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Abstract
We examine the relationship between climate-related financial policies (CRFPs) and banks' systemic risk. Using a sample of 458 banks in 47 countries over the period 2000-2020, we document that more stringent CRFPs are detrimental to overall financial stability and contribute to increased system-wide distress, where excessive regulatory constraints may impose burdens on banks. Decomposing systemic risk shows that stricter climate-related financial policies raise bank-level volatility but not interbank correlation, indicating that higher systemic risk stems from increased individual bank fragility rather than stronger synchronization. We investigate the bank-level transmission channels through which climate-related financial policies may contribute to higher systemic risk. Tighter policies are associated with slower loan growth, lower profitability, an increase in non-performing loans and compressed net interest margins, as funding costs rise faster than lending rates. At the same time, capital adequacy ratios decline, indicating mounting balance sheet pressures. However, the implementation and ratification of the Paris Agreement, more robust adaptation strategies to cope with climate shocks and a higher incidence of natural disasters and a larger number of people affected by extreme climate events may counteract the amplifying effects of CRFPs on systemic risk. Moreover, banks with stronger environmental, social, and governance (ESG) commitments experience less systemic distress when exposed to green financial policies.

Keywords: systemic risk; climate change; climate-related financial policy
JEL classification: G21; G32; Q54

1. Introduction

Climate-related financial policies (CRFRs) and systemic vulnerabilities share common characteristics and involve both dimensions of systemic risk: they pose a common risk to the financial system and build up over time (Hiebert and Monnin, 2023). Against this backdrop, a series of green financial policies have been advanced to mitigate climate hazards. Although numerous studies document a beneficial effect of macroprudential tools in curtailing system-wide financial fragility (see, e.g., Meuleman and Vander Vennet, 2020; Neill, 2024), the nexus between green financial policies and systemic risk is not clear and may not necessarily limit its accumulation (Coelho and Restoy, 2023). This may be attributable to the novel regulatory environment that endeavors to establish a framework for mitigating CRFRs, which has the potential to engender undesirable outcomes, such as the alteration of the availability and affordability of funds in the economy. As a result, this could impede the feasibility of a smooth transition to a low-carbon economy and exacerbate transition risks, affecting overall financial stability (Punzi, 2024).

Building on the database gathered by D'Orazio and Thole (2022), we investigate whether and to what extent climate-related financial policies mitigate or amplify banks' systemic distress. Using a panel data sample composed of 458 international banks from 47 advanced markets (AMs) and emerging market and developing economies (EMDEs) over the period 2000-2020, we document that a higher engagement of authorities in green policymaking is detrimental to overall financial stability and leads to higher systemic risk for banks. The results are also economically significant: a one standard deviation increase in the lagged CRFP index is associated to an increase in systemic risk of 5.24 percentage points (pp) of a standard deviation, or 3.83 pp of mean systemic risk, holding all other dependent variables constant, a very large effect compared to an average of 1.07% and a standard deviation of 0.78% for our measure of systemic risk (which is the MES, discussed below).

This finding can be explained by the fact that overly stringent climate-related financial policies could lead to a disorderly transition. Hence, measures that restrict banks' exposure to carbon-intensive counterparties, both directly and indirectly, may result in fewer loans being granted to the real economy and higher lending rates. The ability of businesses to invest in energy-saving and emission-reduction technologies and make their business models sustainable may then be in jeopardy. This could therefore have an impact on companies' capacity to pay back and service

their outstanding debt, which could lower the value of the pledged collateral. Consequently, this could lead to substantial credit losses, diminished bank profitability, and spillover effects with the potential to undermine systemic resilience, giving rise to a "green bubble" (Coelho and Restoy, 2023; Noth and Schüwer, 2023). By the same token, the common exposures of banks to sectors subject to climate regulation, such as those from polluting industries, can potentially generate shocks that propagate throughout the financial system.

To shed light on the channels through which climate-related financial policies (CRFPs) affect systemic risk, we decompose the marginal expected shortfall into its volatility and correlation components. We find that stricter CRFPs increase bank-level volatility, but do not increase interbank correlation. This suggests that the increase in systemic risk is primarily driven by greater fragility and variability at the level of individual banks, rather than by stronger co-movement or interconnectedness within the banking system.

Furthermore, we investigate the transmission channels at bank level through which climate-related financial policies may contribute to higher systemic risk. Our findings suggest that tighter climate-related financial policies are linked to slower loan growth, declining profitability and deteriorating asset quality, as evidenced by an increase in non-performing loans. At the same time, banks appear to increase loan prices, but rising funding costs lead to compressed net interest margins. Despite an increase in realized credit risk, loan loss provisions do not adjust significantly. This suggests that climate-related risks may not yet be fully embedded in forward-looking provisioning practices. These pressures, combined with weaker profitability and higher risk-weighted assets, are linked to declines in capital adequacy ratios.

However, the implementation and ratification of the Paris Agreement by each country, as well as a stronger adaptation strategy to cope with climate shocks, have a negative moderating effect, mitigating the exacerbating effect of climate-related financial policies. In addition, banks that are more sustainable in terms of environmental, social and governance (ESG) factors exhibit less systemic distress when are subject to green financial policies.

The findings remain robust to a variety of tests, including variations in the dependent and independent variables, different estimation techniques (both static and dynamic) to address endogeneity concerns and cross-sectional and temporal dependencies, the inclusion of different fixed effects to mitigate potential omitted variable bias, and alternative sample selections. Although our study does not seek to establish causality, it offers strong associative and even

predictive insights and underscores the significant implications of climate-related financial strategies on financial stability.

Climate change has become a significant threat to both the financial system and the real economy (ESRB, 2016; Kahn et al., 2021; Bilal and Känzig, 2024). As Mark Carney, former Governor of the Bank of England, eloquently stated, it is the "Tragedy of the Horizon" (Carney, 2015). The Paris Agreement (PA), adopted by 195 countries and the European Union (hereinafter "Parties") at the United Nations Climate Change Conference (COP21) on 12 December 2015, and which entered into force on 4 November 2016, replacing the Kyoto Protocol, establishes the framework for the coordinated action by the Parties, with the objective of transitioning to a net-zero economy by 2050 and reducing greenhouse gas (GHG) emissions, thereby contributing to the mitigation efforts aimed at maintaining the global average temperature well below 2°C and, ideally, at 1.5°C above pre-industrial levels. However, the international community has yet to make substantial progress in achieving these objectives. According to the Climate Action Tracker (2025), given current policies and actions in place, the global median temperature is projected to raise by 2.6°C above pre-industrial levels by the year 2100.

A major concern in the direction of green and sustainable development is the path in adopting policies aimed at addressing climate change, which is heterogeneous across countries. The Enhanced Transparency Framework (ETF), established under the auspices of the Paris Agreement, mandates that countries report transparently on their actions and progress regarding climate change mitigation, adaptation, and assistance provided or received. This requirement started to be implemented in 2024. In this context, it is crucial to track the progress of each country because, given a coordination failure problem, these policies can generate a sub-optimal outcome and entail unintended consequences that can put the whole financial system at risk (Coelho and Restoy, 2023).

[Figure 1 goes around here]

Figure 1 illustrates how 74 countries worldwide have adopted CRFPs to address the issue of climate change.[1] It displays a composite index for 2020, calculated as the weighted sum of different policies with policy bindingness, with equal weights for all policy categories (see Section 3.3 for details). In this respect, France, South Korea and Indonesia are the most committed to climate-related financial planning, while Bahrain, Ghana, Israel, Lebanon, Lithuania, Mongolia, Nepal, Panama, Saudi Arabia and Ukraine are the least committed, with important differences among these countries. This highlights the substantial heterogeneity in the adoption of green finance policies among different countries.

In the wake of the Paris Agreement, numerous authorities - both national and supranational - have recognized climate change as a potential source of financial risk (e.g., NGFS, 2019; ECB, 2019; FSB, 2020; BIS, 2021; BGFRS, FDIC, and OCC, 2023). These authorities have also recognized that climate-related financial risks (CRFRs) are systemic in nature (Bolton et al., 2020; Battiston et al., 2021; Hiebert and Monnin, 2023).[2] The channels through which climate-related shocks propagate to the financial sector are usually referred to as physical, transition, and liability risks (Carney, 2015).[3] Physical risks stem from financial institutions' exposure to extreme climate events, including heat waves, storms, floods, hurricanes, and other natural disasters. These risks can materialize directly through their impact on households, businesses, or countries affected by such events, and indirectly through the broader effects of climate change on the real economy and feedback loops within the financial system. As a result, they can lead to higher default rates in loan portfolios (credit risk) and contribute to market, liquidity, and operational risks (Grippa et al., 2019; Chenet et al., 2021; Sole Pagliari, 2023). Transition risks arise from uncertainties surrounding a rapid and disorderly shift to a low-carbon economy and encompass regulatory changes, technological advancements, and evolving consumer and investor expectations in response to climate policies (Liu et al., 2024b). Liability (or litigation) risks manifest when entities held responsible for climate-related damages or losses are required to compensate affected economic agents (Campiglio et al., 2023). Recent studies have shown that transition risks have the greatest

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[1] These policies should be distinguished from general climate policies, such as carbon taxes (e.g., Kaldorf and Rottner, 2025). They are usually a subset of financial policies, focusing primarily on addressing climate change or facilitating the transition to a green economy. See Baer et al. (2021) for details.

[2] Systemic risk refers to the possibility of a disruption in financial services resulting from the failure of all or part of the financial system, which could have severe adverse consequences for the real economy (FSB, IMF and BIS, 2009). See also Allen and Carletti (2013) for a discussion on different types of systemic risk.

[3] For a thorough exposition of these risks and their transmission channels to the financial system, see BCBS (2021).

impact on companies due to regulatory changes that can increase carbon costs and ultimately exacerbating financial fragility (Roncoroni et al., 2021; Battiston et al., 2021; Stroebel and Wurgler, 2021).

To mitigate these risks and prevent system-wide distress, regulators should implement a risk-based prudential framework (Hiebert and Monnin, 2023). This approach must operate at both the microprudential level, focusing on individual financial institutions, and the macroprudential level, addressing interconnected entities to account for the systemic nature of climate-related shocks. Given that systemic risk manifests itself in two dimensions, i.e., cross-sectional and temporal, macroprudential policy addresses both.[4] With respect to the first dimension, it captures the interconnectedness of financial institutions and the propagation of spillover effects through the financial system arising from exposures to common shocks or, in the case of banks, the interbank market. Commonly used macroprudential tools to mitigate the cross-sectional dimension of systemic risk can include systemic capital and liquidity surcharges, or levies on non-core liabilities. As for the time-series dimension, which captures the evolution of risk over time and the procyclicality of the financial system, macroprudential regulation aims to enhance the resilience of the financial system to aggregate shocks and to contain the accumulation of financial imbalances by imposing, for example, countercyclical capital buffers or time-varying systemic liquidity surcharges (Freixas et al., 2015).

Our research advances the existing literature in several key directions. To our knowledge, this is one of the first study to examine the relationship between financial policies implemented by regulators to enhance the resilience of the financial system to climate-related shocks and facilitate the transition to a greener economy and banks' systemic risk.[5] This is particularly important given that, as firms and households exposed to climate-related risks interact with them through credit, deposits and financial services, banks are key actors in climate dynamics (Berger et al., 2025) and their role in the economy, stimulating economic growth (i.e., the finance-growth nexus) (King and Levine, 1993; Berger et al., 2020). In the same vein, banks may be more vulnerable to increases in market volatility and the emergence of bankruptcies among borrowing firms triggered by climate-related shocks and may direct resources toward "green" or "brown" projects through credit

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[4] In contrast, microprudential policy ignores the cross-sectional dimension of systemic risk (see Freixas et al., 2015).
[5] Other papers (e.g., Covi et al., 2025) investigate the effectiveness of general climate policies through the banking sector. However, there are far fewer studies that specifically assess the role of climate-related financial policies in driving banking activity.

selection, thereby influencing the likelihood of transition to sustainable growth (Lamperti et al., 2021). Second, we use a novel and comprehensive dataset that includes cross-country CRFPs adopted in line with the Paris Agreement's goals of curbing carbon emissions over a long period of time, constructed as indices to better capture the multifaceted dimension of these prudential policies, thus not limiting the analysis to a single instrument or a particular country. Third, we provide evidence on the importance of the Paris Agreement as a legally binding international treaty, the role of countries' adaptation strategies in dealing with climate disruption, the impact of the increasing frequency of natural disasters, and the importance of banks' sustainability, as measured by ESG factors, in mitigating the negative impact of climate-related financial policies on financial stability. Last but not least, we extend the literature on the drivers of systemic risk, which typically includes bank, banking system, and macroeconomic factors.

The paper is organized as follows: Section 2 provides a discussion of the prior literature. Section 3 describes the sample, data, and empirical strategy. Section 4 presents the results, robustness checks, and further analysis. Finally, Section 5 concludes the paper.

2. Related literature

Our study belongs to the growing literature on climate-related risks, climate-related financial policies, and financial stability. Investors, academics, practitioners, central banks, and supervisors are taking climate events very seriously, according to a large body of evidence (NGFS, 2019; ECB, 2019; FSB, 2020; Krueger et al., 2020; Stroebel and Wurgler, 2021; BIS, 2021; BGFRS, FDIC, and OCC, 2023). This has significant ramifications for financial stability (Chenet et al., 2021) and economic activity, as the macroeconomic damages from climate change are six times greater than previously estimated (Bilal and Känzig, 2024). In their 2021 survey, Stroebel and Wurgler (2021) examine the perspectives of 861 financial academics, professionals, regulators, and policy economists on the most pressing climate risks for companies and investors. The survey revealed that regulatory risk emerged as the predominant concern over the ensuing five-year period, while physical risk was identified as the most significant risk over a 30-year timeframe. Numerous scholars investigate how climate-related financial risks are associated with financial stability (Battiston et al., 2017; Roncoroni et al., 2021; Curcio et al., 2023; Noth and Schüwer, 2023; Do et al., 2023; Chen and Lin, 2024; Ge et al., 2024; Liu et al., 2024b; Vollmar and Wening, 2024; Wu et al., 2024; Ojea-Ferreiro et al., 2024), financial institutions performance (Li and Pan, 2022;

Boungou and Urom, 2023; Chen and Lin, 2024) or the macroeconomy (Tol, 2009; Burke et al., 2015; Diluiso et al., 2021; Kahn et al., 2021; Bilal and Känzig, 2024; Bettarelli et al., 2025; Chavleishvili and Moench, 2025).[6] For example, Ge et al. (2024) find that climate transition hazards increase the risk of corporate defaults in China, leading to elevated credit risk for banks, while Wu et al. (2024) document that enhanced systemic risk is associated with a country's exposure to climate risk for a global sample of banks.

To address these risks and to align with the Article 2.1(c) of the Paris Agreement, a series of climate-related financial measures have been proposed. Broadly, these policies can be categorized as follows (D'Orazio and Popoyan, 2019; D'Orazio and Thole, 2022; D'Orazio and Dirks, 2022): (i) Basel III-style climate-related prudential regulations, which include governance and risk management measures, climate stress testing, and climate risk disclosure for the banking sector; (ii) green credit allocation initiatives, such as green lending quotas; (iii) green finance principles, which focus on the development of green financial markets, including green finance principles and taxonomies; and (iv) additional climate-related disclosure requirements for non-financial institutions and other non-bank intermediaries. Moreover, the growing recognition of green monetary policy initiatives as pivotal instruments in confronting CRFRs is of paramount importance. This is due to the fact that climate risks stemming from event-driven hazards have the potential to compromise the effectiveness of conventional monetary policy by dampening output growth and amplifying inflation volatility and uncertainty (Roy, 2024). Following the Paris Agreement, the number of countries adopting lender-based regulations increased significantly, from 43 in 2015 to 81 in 2023 (D'Orazio and Pham, 2025).

An increasing number of studies showcase that CRFPs can produce undesirable outcomes. Among them, Dafermos and Nikolaidi (2021) demonstrate that the Green Supporting Factor (GSF) and the Brown Penalising Factor (BPF), which fall under the category of climate-related prudential regulations, have the potential to engender transition risks. This phenomenon occurs because the GSF has been observed to increase bank leverage, given its propensity to enhance green credit, whereas the BPF has been shown to elevate loan defaults, a consequence of its effect on reducing economic activity. Lamperti et al. (2021) posit that green capital requirements, green public loan guarantees, and carbon risk adjustments in credit ratings have the potential to moderately reduce carbon emissions and mitigate climate impacts. Nevertheless, it is imperative to note that certain

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[6] For a systematic literature review, see Carè (2023).

policy configurations may inadvertently culminate in credit booms, escalate financial instability, and augment public debt. Along the same lines, Punzi (2024) reveal that climate-related policies can lead to an increase in default rates across both the green and brown sectors, thereby impeding a seamless transition to a low-carbon economy. This impact is manifested through two primary channels: (i) the banking capital channel, where a decline in bank capital leads to a reduction in loan supply, thereby hindering the financing of new projects, and (ii) the banking funding channel, where banks increase lending rates in both sectors to regain profitability. The aforementioned effect is corroborated by Chan et al. (2024) within the framework of green monetary and macroprudential policies. The authors propose a policy mix that combines a dual interest rate policy with a fiscal strategy that redistributes carbon tax revenues to households via vouchers. This approach aims to support the green transition while maintaining financial stability.

Another stream of research identifies positive effects of CRFPs.[7] As posited by Diluiso et al. (2021), capital requirements, conceived as a means to encourage the decarbonization of banks' balance sheets, have the potential to mitigate the severity of a recession following a disorderly climate policy. However, this intervention may also result in a substantial prolongation of the recovery phase, primarily by impeding a swift economic recovery. D'Orazio and Dirks (2022) posit that CRFPs effectively reduce carbon dioxide emissions in G20 nations. Annicchiarico et al. (2023) find that macroprudential tools in the form of reserve requirements, effectively reduce the welfare costs associated with business cycles. Furthermore, macroprudential policy, even without a green-specific component, can enhance the welfare conditions necessary for implementing climate policies. By the same token, Carattini et al. (2023) theorize that that climate policy shocks have the potential to precipitate macroeconomic instability. However, this effect can be alleviated through the implementation of macroprudential policies, such as the imposition of taxes or subsidies on bank assets. A salient finding of the study, in contrast to Annicchiarico et al. (2023), is the assertion that macroprudential policies, when utilized in isolation from a climate policy, demonstrate limited efficacy in addressing climate externalities. More recently, Wang et al. (2025) show that climate disruptions increase country-level financial risk. However, it has been demonstrated that the implementation of more robust central bank green policies - such as

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[7] General climate policies, such as carbon taxes, tend to promote long-term financial stability. However, in the short term, they increase financial distress, giving rise to "Climate Minsky Moments" (Kaldorf and Rottner, 2025).

regulatory mandates, green finance programs, and macroprudential measures - weakens this effect and reduces the financial risks associated with climate change.

Notwithstanding these contributions, no previous studies have hitherto examined the relationship between climate-related financial policies and banks' systemic risk. Moreover, the empirical and theoretical evidence regarding the impact of these policies on financial stability is ambiguous. In this study, we endeavor to address this gap in the extant literature.

3. Sample, data, and empirical strategy

3.1 Sample and data

Our sample encompasses 458 banking institutions from 47 advanced markets and emerging market and developing economies, extending from 2000 to 2020. The mean asset size of these institutions at the conclusion of 2020 was \$224 billion, amounting to a total of over 6,900 bank-year observations. Initially, we considered a larger sample of 593 banks from 57 countries included in the Refinitiv Global Banks Index. However, we excluded banks with insufficient data for systemic risk analysis and those from countries with limited information on climate-related financial policies. The final sample includes both large and small banks, recognizing that smaller institutions can contribute to systemic risk, especially if they engage in herding behavior and build portfolios similar to their larger peers, as noted by Brunnermeier et al. (2009).

Market data is sourced from Reuters Eikon, balance sheet and income statement variables are obtained from Worldscope, and banking system and macroeconomic controls are sourced from the World Bank and International Monetary Fund.

3.2 Systemic risk indicator

To capture financial instability at the bank level, the marginal expected shortfall (MES) indicator - as proposed by Acharya et al. (2017) - is utilized. This indicator measures a bank's expected equity loss during extreme market downturns.[8] We use the dynamic version of MES proposed by Brownlees and Engle (2017). It can be represented as follows:

$$MES_{t-1}^i = E_{t-1}(r_t^i | r_t^m < c) \tag{1}$$

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[8] This metric is frequently utilized in the extant literature to measure systemic risk, and it has been employed, *inter alia*, by Atasoy et al. (2024) and Andrieș et al. (2025).

where r_t^i represents the daily log return of bank i and r_t^m is the daily log return of the aggregate market index, which we proxy by the MSCI World Financials Index similar to other studies (e.g., Bostandzic and Weiß, 2018; Andrieș et al., 2025), and c is the 5% threshold for financial distress. Following Brownlees and Engle (2017), the bivariate process of bank and market log returns is modeled with the following relations:

$$r_t^m = \sigma_t^m \varepsilon_t^m \tag{2}$$

$$r_t^i = \sigma_t^i \varepsilon_t^i = \sigma_t^i \rho_t^i \varepsilon_t^m + \sigma_t^i \sqrt{1 - \rho_t^{2i}} \varphi_t^i \tag{3}$$

where σ_t^m and σ_t^i denote daily volatilities of the market index and bank i, respectively, and ρ_t^i is the daily time-varying correlation between r_t^m and r_t^i. ε_t^m and φ_t^i are the *iid* error terms. Thus, the conditional MES can be expressed as a function of time-varying conditional correlations, the banks' equity price volatility, and the comovement of the distribution tails:

$$MES_{t-1}^i = E_{t-1}\left(r_t^i \middle| r_t^m < c\right) = \sigma_t^i E_{t-1}\left(\varepsilon_t^i \middle| \varepsilon_t^m < \frac{c}{\sigma_t^m}\right) = \sigma_t^i \rho_t^i E_{t-1}\left(\varepsilon_t^i \middle| \varepsilon_t^m < \frac{c}{\sigma_t^m}\right) +$$

$$\sigma_t^i \sqrt{1 - \rho_t^{2i}} E_{t-1}\left(\varphi_t^i \middle| \varepsilon_t^m < \frac{c}{\sigma_t^m}\right) \tag{4}$$

Stock return conditional volatilities are modeled using an asymmetric GJR-GARCH specification to capture leverage effects on volatility, while time-varying conditional correlations are estimated through a modified dynamic conditional correlation (DCC) method, as outlined by Cappiello et al. (2006), which accounts for potential asymmetries. The estimation is performed using quasi-maximum likelihood methods.[9]

Kleinow et al. (2017) show that of four risk measures, MES is the most consistent and reliable indicator of systemic risk across industries and time periods. In addition, Acharya et al. (2024) present evidence that market-based indicators of systemic risk, such as MES, have significant and consistent predictive power for forecasting future cross-sectional market outcomes

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[9] For more technical details, please refer to Cappiello et al. (2006) and Idier et al. (2014).

and predicting bank failures. We compute MES using daily data and then take the median to obtain annual values, as the median is less prone to outliers than averaging.[10] Higher MES values indicate greater systemic risk, and a more systemically important bank.

[Figure 2 goes around here]

Figure 2 shows the evolution of the average marginal expected shortfall over time and across countries. There are notable spikes in systemic risk, particularly during the global financial crisis, the European sovereign debt crisis, and the COVID-19 shock. Banks from France, Germany, and Belgium experienced the highest levels of systemic risk, while banks from India, Pakistan, and Morocco experienced the lowest levels of systemic distress.

3.3 Climate-related financial policies

Climate-related financial policies are regulations introduced by central banks and financial regulators designed to reduce the impact of climate-related financial shocks and promote green finance (D'Orazio, 2023). These measures fall into five categories: (i) green prudential regulations, which focus on identifying potential risks to financial stability arising from climate-related factors. These are enforced through capital requirements, governance adjustments, risk management strategies, climate-related stress tests, and risk disclosures aimed at the banking sector; (ii) green lending policies, which are adopted to promote environmentally sustainable financial practices, including the allocation of credit in a manner that supports green lending and investments. These policies encompass several actions, including setting green lending quotas, offering concessionary loans to support environmentally sustainable projects, prioritizing financing for eco-friendly sectors, and limiting loans to industries considered harmful to the environment, often referred to as "brown" sectors; (iii) green financing guidelines: To foster the development of green financial markets, it is crucial to develop clear principles and robust taxonomies. These taxonomies are vital for accurately evaluating the environmental impact of investments. Additional measures include sustainability reporting guidelines and compliance standards; (iv) additional environmental disclosure requirements related to measures that require or encourage specific environmental criteria for pension funds, insurance companies and other non-financial institutions; and (v) the

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[10] We also use averages and the results remain consistent.

taxonomy and issuance of green bonds, which are financial instruments, such as bonds, specifically designed to provide long-term financial support for environmentally friendly initiatives.

For each policy category, a policy indicator is calculated that takes into account the binding nature of the policy (i.e., non-binding, voluntary or mandatory measure), normalized, and then aggregated into a composite index using weights for all policy categories that captures a country's commitment to green policies, with higher index values indicating a more advanced adoption of such policies. We normalize the index between 0 and 1 using the min-max approach and use it in the empirical setting.

[Figure 3 goes around here]

Figure 3 showcases the average value of the CRPF index over time and across the 47 countries that make up our international sample, normalized between 0 and 1. The index is calculated as the weighted sum of policies with policy bindingness using equal weights for all policy categories. As we can see, the value of the index increases over time, especially after 2006, when the six Principles for Responsible Investment were adopted,[11] reflecting a greater level of participation among countries worldwide. As of 2020, the index registered the highest value, when the Taskforce on Nature-related Financial Disclosures (TNFD) initiative was announced.[12] At the national level, France, Indonesia, and Brazil adopted the most CRFPs, while Georgia, the Philippines, and the United Arab Emirates adopted the fewest over the 2000-2020 period.

3.4 Empirical design

Our data consist of two hierarchical levels: countries and banks. Specifically, individual banks are nested within countries, i.e., bank-level observations are grouped within country-level observations. To address this two-level data structure and to account for potential interdependencies resulting from nesting effects, a hierarchical linear modeling (HLM) approach is employed, also referred to as mixed-effects or multilevel analysis. This model facilitates variance partitioning across disparate aggregation levels while obviating the necessity for homogeneity. Furthermore, the HLM estimator addresses cross-level interaction effects between

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[11] https://www.unpri.org/about-us/about-the-pri
[12] https://tnfd.global/about/history/

bank-level and country-level variables, without making the assumption of independent errors (Mourouzidou-Damtsa et al., 2019). As noted by Vauclair (2013), mixed-effects models are generally more conservative than traditional statistical methods, such as the ordinary least squares (OLS), which often exhibit biases in multilevel data, leading to incorrect standard errors, confidence intervals, and significance tests.

The HLM's ability to capture commonalities in banking activities across countries is a significant advantage over competing models. For example, Islamic banks, which have distinct business strategies, generally have lower risk profiles than conventional peers (Abedifar et al., 2013). In addition, bank-based financial systems - such as those found in Europe - are more susceptible to systemic distress than market-based systems due to their reliance on bank funding. This increased vulnerability is attributed to the presence of debt and asset-liability mismatches, as shown in studies by Langfield and Pagano (2016) and Bats and Houben (2020).

The empirical model takes the following form:

$$MES_{i,j,t} = \underbrace{\alpha_0 + \beta_1 \times CRFP_{j,t-1} + \beta_2 \times \Theta_{i,j,t-1} + \beta_3 \times \Omega_{j,t-1}}_{fixed\ components} + \underbrace{\vartheta_{i,j} + \mu_j + \varepsilon_{i,j,t}}_{random\ components} \qquad (5)$$

where $MES_{i,j,t}$ is the systemic risk of bank i from country j at time t, $CRFP_{j,t-1}$ is the climate-related financial policy index corresponding to country j at time t-1 computed as the weighted sum of policies with policy bindingness, $\Theta_{i,j,t-1}$ is a vector of bank-specific variables that reflect the cross-sectional variation in systemic risk as outlined in the literature[13] at time t-1, including factors such as size (natural log of total assets in USD), capitalization (common equity to total assets), lending activities (loans as a percentage of total assets), credit risk ratio (non-performing loans/total loans), funding structure (deposits over total liabilities), income diversification (non-interest income to total revenues), and profitability (return on equity – net income to common equity ratio). $\Omega_{j,t-1}$ represents a set of one-year lagged control variables at both the banking system and macroeconomic levels, such as bank concentration, the level of development of financial institutions, and economic growth and inflation. In addition, we include year dummies to account for time-varying shocks, such as financial crises, that affect all banks across different countries.

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[13] See Laeven et al. (2016); Andrieș et al. (2022); Altunbas et al. (2022); Beck et al. (2022); Nistor and Ongena (2023); Andrieș et al. (2024); Atasoy et al. (2024); Wu et al. (2024); Andrieș et al. (2025).

We are interested in estimating β_1, which captures the sensitivity of bank fragility to green financial policies. Table A1, located in the Appendix, displays the pairwise correlation matrix for the regressors pointing the absence of multicollinearity issues.

Given the emphasis on mean differences as opposed to variations in slopes stemming from the multilevel structure, the variables are regarded as fixed factors (Raudenbush and Bryk, 2002). In addition, $\vartheta_{i,j}$ and μ_j permit unique variations in the intercept ($\alpha_0 + \vartheta_{i,j} + \mu_j$) at both levels of aggregation. Thus, we estimate the HLM model with random intercepts and fixed slopes, employing the maximum likelihood (ML) estimation technique.

To reduce potential endogeneity concerns associated with climate-related financial policies and systemic distress, stemming from possible reverse causality, we lag the explanatory control variables by one year. This approach accounts for the fact that an increase in systemic distress can influence all control variables, while also controlling for the speed of systemic distress adjustment (Andrieș et al., 2022; Nie et al., 2023). Extreme values are addressed through winsorization at the 1st and 99th percentiles.

4. Empirical results

4.1 Descriptive statistics

Table 1 provides summary statistics for the primary winsorized variables utilized in this study. The average systemic risk is 1.07%, with a standard deviation of 0.78%, ranging from -0.77% to 3.62%. This indicates that the mean expected short-term equity loss across all banks is 1.07%, assuming the MSCI World Financials Index experiences a loss greater than 5%. The normalized climate-related financial policy index averages 0.23 for the 2000-2020 period, with a standard deviation of 0.22, and spans from a minimum of 0 to a maximum of 0.85.

[Table 1 goes around here]

4.2 Results and discussion

Table 2 provided the baseline results of the study in which we test the link between climate-related financial policies and banks' systemic distress. We started with a baseline model introducing only the CRFP index as a regressor as well as year fixed effects (Model (1)) and then proceeded to include only bank-level controls (Model (2)) and both microeconomic and macroeconomic factors

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(Model (3)). As observed in Model (1), the estimated coefficient of the CRFP index is positive and statistically significant at the 1% level, implying that greater involvement of financial authorities in green policies is detrimental to financial stability. This is also true for Model (2) and Model (3) when we control for specific factors related to systemic risk, both at the bank, banking system and country levels. Taking the outcome from Model (3) as the primary result, this study reveals economically meaningful effects: a one standard deviation increase in the lagged CRFP index is associated with a boost in systemic risk of 5.24 percentage points of a standard deviation, or 3.83 percentage points of mean systemic risk, compared to an average of 1.07% and a standard deviation of 0.78% for MES, keeping all other explanatory factors unchanged. The probability of the likelihood ratio (LR) test, which follows a chi-squared distribution, is zero for all models, indicating that the mixed-methods are preferable to the OLS specification.

[Table 2 goes around here]

Our fundings underscore that excessively strict climate-related financial policies could lead to a disorderly transition. Policies that directly or indirectly limit banks' exposure to carbon-intensive counterparties may reduce lending to the real economy and drive up borrowing costs. As a result, companies might struggle to invest in energy-efficient and emission-reducing technologies, jeopardizing the sustainability of their business models. This could weaken firms' ability to service their debt, diminishing the value of collateral and potentially leading to significant credit losses. Such losses could erode bank profitability and trigger spillover effects that threaten financial stability, ultimately contributing to the formation of a "green bubble" (Coelho and Restoy, 2023; Noth and Schüwer, 2023). In addition, banks' common exposure to climate-regulated sectors, particularly polluting industries, could amplify financial shocks across the system. The results of this study align with those of Chan et al. (2024), who highlight a trade-off in the implementation of green monetary or macroprudential policies. Their research suggests that while such policies can promote the green transition, they may also undermine financial stability by increasing default rates. In addition, D'Orazio (2025) finds that climate-related financial policies are associated with reduced bank solvency, as measured by the Z-score. This suggests that the introduction of transition risks, such as stricter regulatory requirements, shifts in credit allocation,

and asset revaluations in carbon-intensive sectors, could potentially exacerbate financial instability.

In terms of control variables, we document that higher levels of total assets, non-performing loans, and economic growth have a destabilizing impact on banks' marginal expected shortfall, while deposit funding, income diversification, increased profitability, elevated levels of bank concentration, and higher inflation are beneficial for overall financial stability. Large banking institutions have been shown to be more prone to contributing to systemic risk buildup for a number of reasons. First, these institutions often possess diminished capital and net stable funding ratios, coupled with augmented exposure to high-risk activities (Laeven et al., 2016). Second, banks with higher asset levels may leverage their size to benefit from future government intervention, thereby increasing their exposure to excessive risk-taking (Nistor and Ongena, 2023). This phenomenon, known as "too big to fail," has been shown to create moral hazard (Farhi and Tirole, 2012). Existing research suggests that an elevated stock of non-performing loans is a common feature of banks' risk-taking (Fang et al., 2014) and banking crises (Ari et al., 2021), as it reduces bank profitability and efficiency, weakens bank balance sheets, and reduces lending capacity (Aiyar et al., 2015). Regarding real gross domestic product (GDP) growth, a plethora of studies indicate a procyclical behaviour of financial stability (see, e.g., Ben Bouheni and Hasnaoui, 2017). In other words, during economic expansions, financial imbalances tend to build up in the financial system. This process is driven by excessive market optimism, rising credit and asset prices, narrowing credit spreads, and weakened bank capital buffers and provisions.

Greater reliance on deposit funding is associated with less bank fragility, in line with Anginer et al. (2014). This is because this type of funding is relatively stable, as customer deposits benefit from insurance schemes, while wholesale funding responds quickly to changes in a bank's risk profile (Demirguc-Kunt and Huizinga, 2010). Non-traditional banking activities, such as non-interest income from fees and commissions, help mitigate risk by providing portfolio diversification benefits (De Jonghe et al., 2015). This can act as a safety net when income from traditional activities is reduced in the context of deteriorating borrower repayment capacity in the face of climate-related financial policies. Another channel of banks' systemic risk reduction is profitability. Profitable banks can accumulate capital, reducing the constraints of capital requirements and enhancing their ability to absorb losses (Perotti et al., 2011). By the same token, enhanced profitability results in elevated "charter value" (i.e., long-term expected profitability)

and, consequently, reduced risk-taking by banking institutions (Xu et al., 2019). When it comes to bank concentration, we find that banking systems with a greater proportion of assets held by the largest banking institutions exhibit enhanced financial stability. This may be due to the fact that supervisory and regulatory authorities are able to more effectively monitor a limited number of large banking institutions as opposed to numerous small banks. This is consistent with the conclusions of Beck et al. (2006), who show that national bank concentration tends to decrease the probability of systemic banking crises. Finally, higher inflation adds negatively to banks' marginal expected shortfall, in line with Sánchez García and Cruz Rambaud (2023).

To disentangle the channels through which climate-related financial policies impact the systemic risk and provide more direct evidence, we reran the baseline model using the subcomponents of the MES: time-varying volatility and time-varying correlation. The findings are presented in Table A2 in the Appendix. The results indicate that more stringent climate-related financial policies are associated with increased volatility, though no significant effect on interbank correlation was found. This suggests that climate policy acts as a source of financial uncertainty and adjustment pressure, resulting in greater fluctuations in risk indicators at the level of individual banks. At the same time, the absence of a significant increase in correlation implies that these effects are heterogeneous across institutions and do not reflect common exposures or synchronised movements. Therefore, the observed increase in systemic risk is due to greater fragility of individual banks, rather than amplified interconnectedness or contagion channels. Therefore, these green financial policies generate firm-specific uncertainty and risk, suggesting a microprudential policy response focused on the capital and banks' risk management processes to mitigate systemic vulnerability.[14]

Furthermore, we examine several alternative transmission mechanisms through which climate-related financial policies may contribute to higher systemic risk at the bank level. First, the lending channel captures potential contractions in credit supply and is proxied by loan growth, measured as the annual change in the natural logarithm of total loans. Second, the profitability channel considers pressures on banks' earnings capacity, captured by return on equity. Third, the credit risk channel reflects a deterioration in asset quality and is assessed using the ratio of non-performing loans to total loans and loan loss provisions relative to total assets. Fourth, the pricing channel reflects changes in the cost of financial intermediation and is measured through interest

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[14] We would like to thank an anonymous referee for this suggestion and proposed explanation.

income to assets, interest expenses to assets, and net interest income to assets. Finally, the capital adequacy channel captures potential erosion of banks' capital buffers and is proxied by the total Capital Adequacy Ratio (CAR) and Tier 1 capital ratio.

As shown in Table A3 in the Appendix, tighter climate-related financial policies are correlated with decreased loan growth, higher non-performing loans and reduced profitability. The empirical results suggest that tighter climate-related financial policies are associated with a contraction in bank loan growth (Model (1)) and a decline in return on equity (Model (2)). The observed decline in loan growth indicates that banks are adjusting their credit supply in response to more stringent climate-related financial policies. These policies are designed to reduce the impact of climate-related financial shocks and promote green finance, and they may make lending to carbon-intensive sectors less attractive and increase the perceived riskiness of certain exposures. Consequently, banks appear to adopt a more cautious lending stance, consistent with a reallocation of credit away from climate-vulnerable activities. This contraction in lending activity is accompanied by a reduction in return on equity, indicating that the tightening of climate-related financial policies also affects bank profitability.

The results of Model (3) reveal a significant increase in the non-performing loan (NPL) ratio, pointing to a deterioration in borrower credit quality following the introduction or strengthening of climate-related financial policies. This effect likely reflects the transition pressures faced by firms operating in carbon-intensive or environmentally exposed sectors. However, the lack of a statistically significant response in loan loss provisions (Model (4)) suggests that banks may not be fully incorporating climate-related risks into their forward-looking provisioning frameworks. This difference between realized credit deterioration (captured by NPLs) and provisioning behavior may imply that climate-related risks have not yet been fully incorporated into expected credit loss models or internal risk assessment frameworks. In this sense, credit risk appears to materialise before being comprehensively reflected in accounting-based measures.

Table A4 in the Appendix presents the results for testing the pricing and capital adequacy channels. The results of Models (1) to (3) highlight an important pricing channel. The results of Model (1) reveal that the interest income relative to assets increases following the introduction or strengthening of climate-related financial policies, suggesting that banks reprice loans upward in response to higher risk or regulatory costs. Model (2) shows that tighter climate-related financial

policies are associated with a greater increase in interest expenses. This implies that funding conditions tighten more than lending rates adjust, possibly because investors perceive a higher risk or a greater reliance on more expensive funding sources. Consequently, net interest income declines, signalling a compression of interest margins. The reduction in net interest margins further amplifies the negative impact on return on equity, highlighting how climate-related financial tightening can undermine bank profitability through the pricing channel.

The results of Models (4) and (5) in Table A4 of the Appendix indicate that tighter climate-related financial policies are associated with declines in both the total capital adequacy ratio and the Tier 1 capital ratio. Lower profitability constrains banks' ability to generate capital internally through retained earnings, while heightened credit risk may lead to an increase in risk-weighted assets. These dynamics weaken capital buffers and may reduce banks' resilience and their capacity to sustain future lending.

These findings suggest that, particularly during the transition phase, climate-related financial policies can generate short- to medium-term pressures on banks' balance sheets. In line with previous studies (Alessi et al., 2024; Bartsch et al., 2025; Pozdyshev et al., 2025) our results underscore the importance of supervisory guidance and risk management improvements to ensure that climate-related risks are adequately reflected in provisioning, capital adequacy, and stress-testing frameworks. While climate policies are designed to support long-term environmental and economic sustainability, the evidence suggests that their financial stability implications during the transition period warrant careful monitoring.

4.3 Further analysis

4.3.1   The role of the Paris Agreement

The Paris Agreement, which was adopted at the 21st United Nations Climate Change Conference on December 12, 2015, and entered into force in 2016, is a legally binding international treaty designed to motivate governments to take concrete actions in tackling climate-related challenges.[15] The agreement stipulates that countries submit nationally determined contributions (NDCs) outlining their plans for mitigation and adaptation. The primary objective of the agreement is to

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[15] Prior to the establishment of the Paris Agreement, no globally binding climate change agreement had been instituted, though certain international accords, including the Kyoto Protocol from 2005 and the Copenhagen Accord from 2009, addressed climate-related issues.

restrict the rise in global temperatures to well below 2 degrees Celsius above pre-industrial levels, with a target of limiting the increase to 1.5 degrees Celsius (UNFCCC, 2016). Subsequent to ratifying the Paris Agreement, signatory countries initiated the implementation of novel policies and climate initiatives to expedite corporate decarbonization, incentivizing companies to disclose environmental aspects and adopt ESG targets (Bingler et al., 2024). A substantial body of research has identified 2015 as a pivotal year for analyzing climate-related financial risks, suggesting a notable increase in government climate policies thereafter (Li and Pan, 2022) as well as climate-related financial policies (D'Orazio, 2026). For instance, following the adoption of the Paris Agreement, banking institutions began integrating the risk associated with carbon emissions into their loan portfolios, imposing elevated loan rates on fossil fuel enterprises (Delis et al., 2024).

[Table 3 goes around here]

We take the Paris Agreement as an exogenous policy shock[16] and construct two dummy variables, one for the adoption in 2016 and another for ratification at the country level, and interact them with the CRFP index in Table 3. We document that this global accord has a negative moderating effect on the marginal expected shortfall, reducing the systemic vulnerability of banks. This finding aligns with Li and Pan (2022), who show that the signing of the Paris Agreement limited the inhibitory effect of transition risk on bank performance. One potential explanation for this phenomenon is that the Agreement prompted financial institutions to curtail their risk-taking behaviour by tightening lending standards for carbon-intensive sectors and reallocating assets away from high-risk categories (Zhang and Ming, 2025) and served as a potent and credible signal, thereby reducing policy uncertainty and enabling banking institutions and firms to make long-term capital allocation decisions with greater confidence, secure in the knowledge that climate national policies were less likely to be erratic or reversed.[17]

4.3.2 Adaptation of countries to climate disruption

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[16] Seltzer et al. (2025) note that the outcome of the negotiations that led to the Paris Agreement was highly uncertain, making the event a genuine exogenous shock.

[17] We thank an anonymous referee for suggesting this last explanation.

Climate adaptation encompasses a country's vulnerability to climate hazards - its susceptibility to adverse impacts, capturing both transition and physical risks - and its capacity to mobilize private and public investment for adaptation, which is shaped by economic, governance, and social readiness. Previous research indicates that climate-related investments are more prevalent in countries with greater climate readiness or robust adaptation strategies to tackle climate risks (Klaaßen and Steffen, 2023). In situations where significant green bank lending is crucial for climate action, banks are more inclined to invest in climate technologies and support sustainable development (Liu et al., 2024). Moreover, financial risks stemming from climate shocks can be mitigated through climate readiness (Setyowati, 2023), and high climate readiness capacity acts as a catalyst for climate policy uncertainty that tends to reduce system-wide fragility (Liu et al., 2024).

[Table 4 goes around here]

The Notre Dame Global Adaptation Initiative's (ND-GAIN) index is employed to assess a nation's capacity to contend with climate-related disruptions. We construct a dummy variable derived from the median of the sample in a given year, designated as "high ND-GAIN". This dummy variable is then interacted with the primary variable of interest. As presented in Table 4, Model (1)), banks operating in countries with lower climate vulnerability and higher ND-GAIN scores experience less systemic risk compared to those in more climate-exposed nations.

4.3.3   The role of climate-related disasters

Countries that are most vulnerable to natural disasters, including droughts, extreme temperatures, floods, landslides, storms, and wildfires, stand to benefit the most from adopting climate-related financial policies. The experience with these events can inform the design of regulations intended to address potential vulnerabilities (Gramlich et al., 2023). Furthermore, the efficacy of these policies in mitigating the adverse impacts of major disasters is contingent, at least in part, on the capacity of the financial system to support adaptation, response, and recovery efforts (Zhou et al., 2023). In the same spirit, banks have been shown to play a pivotal role in the economic recovery process following a natural disaster. This is evidenced by an increase in credit supply to affected borrowers, with the aim of preventing foreclosures (Duqi et al., 2021). In their analysis, Nie et al. (2023) document that natural disasters exert a negative and persistent impact on banks' balance

sheets, leading to elevated levels of non-performing loans, which is a factor that drives up systemic risk. Building upon this, the study by Noth and Schüwer (2023) reveals that property damage resulting from weather-related hazards and natural disasters led to a decline in the stability of banking institutions with operations in affected regions within a period of two to three years.

We attempt to test this hypothesis by using data for climate-related disaster frequency and individuals affected by these events, which are derived from the Climate Change Dashboard of the International Monetary Fund. A dichotomous variable is constructed based on the median of the sample in a given year and is interacted with the CRFP index. Table 4, Models (2) and (3) reveal that banking institutions headquartered in countries with a higher incidence of natural disasters exhibit a reduced exposure to systemic risk when subject to climate-related financial policies, as well as in scenarios where a significant population is impacted by these hazards.

4.3.4   The role of environmental, social and governance factors

The environmental, social, and governance (ESG) attributes of a company can be used to capture its sustainability practices. Prior research has shown that these attributes can have a negative effect on banks' individual risk (Chiaramonte et al., 2022) and systemic vulnerability (Aevoae et al., 2023), while also enhancing bank profitability (Gangi et al., 2019). The mechanism in question is associated with the risk mitigation perspective grounded in stakeholder theory. This theory posits that investment in corporate social responsibility initiatives functions as a form of insurance, thereby mitigating bank-specific risks and generating moral capital among stakeholders.

[Table 5 goes around here]

Using data from Reuters Eikon, we test whether high ESG banks, in conjunction with green financial policies at the country level, alleviate systemic risk. We employ the ESG Combined Score to capture banks' overall sustainability behavior, which takes into account corporate controversies, which have been shown to have a material impact on firm performance (Elamer and Boulhaga, 2024), as well as bank risk-taking (Galletta and Mazzù, 2023). As demonstrated in Table 5, banks with higher ESG performance benefit more from climate-related financial policies, reducing their

marginal expected shortfall.[18] This result is consistent with Chiaramonte et al. (2024) who demonstrate that baning institutions with a high degree of environmental commitment exhibit a reduced likelihood of default in the event of an escalation in nation-wide climate-related expenditures.

4.3.5   Advanced markets vs. emerging market and developing economies

Emerging market and developing economies (EMDEs) face significant physical risks, including severe weather events and resource scarcity. These economies also have a significant reliance on carbon-intensive sectors, further exacerbating environmental concerns (Puyo et al., 2024). Despite structural and institutional constraints, including but not limited to reduced financial capacity and weaker enforcement mechanisms and procedures, EMDEs have made important steps toward adopting CRFPs (D'Orazio and Pham, 2025). However, banks in EMDEs make a minimal contribution to climate finance, allocating 5% or less of their lending to finance green and low-carbon projects (NGFS, 2024). Aevoae et al. (2023) show that while banking institutions in advanced economies benefit from improved sustainability practices with lower systemic risk, those in EMDEs tend to exacerbate financial instability.

[Table 6 goes around here]

We test whether being incorporated in Advanced Economies (AEs) or EMDEs plays a moderating role in the relationship between climate-related financial policies and banks' systemic distress. In this regard, we interact the AE and EMDE dummies with the CRFP index in Table 6. We find that there is no difference for banks between operating in AEs or EMDEs, as the estimated coefficients are statistically insignificant in both models.

4.3.6   Short-term dynamics

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[18] Note, however, that the standalone coefficient of High ESG Combined Score is positive and statistically significant. This result can be attributed to the tendency of high-ESG firms to be large (Bissoondoyal-Bheenick et al., 2023), systemically important institutions that frequently undertake significant green investments, long-term transition projects, and balance sheet reallocations towards innovative or illiquid assets, which may lead to elevated levels of systemic risk, irrespective of the policy environment. In conjunction with CRFPs, where high-ESG firms can adapt more smoothly to increasing regulation, sustainability becomes a risk mitigation strategy, disciplining ESG investments, internalising climate externalities, and reducing greenwashing and speculative flows.

Because the linkages between climate-related financial policies and systemic risk may differ in the short- and long-term, we analyze how changes in these policies, capturing the short-run dynamics, differentiate from their long-run behavior (captured by CRFP index used in levels).

[Table 7 goes around here]

As shown in Table 7, Models (1) and (3), changes in the CRFP index (considering all policies with bindingness) and CRFP3 index (considering only policies without bindingness) are not associated with financial stability. However, when considering the CRFP2 and CRFP4 indices, the estimated coefficients are negative and statistically significant at the 5% level. Thus, the change in the climate-related financial policy indices with bindingness and differentiated weights for green prudential regulations implemented to promote the development of green prudential regulations and identify threats to, and safeguard, financial stability in the presence of climate-related financial risks (Model (2)) and green credit allocation designed to promote green lending and investments through credit allocation and/or lending limits (Model (4)) policy areas are negatively correlated with banks' systemic distress in the short-run.

4.3.7   Non-linear effects

Going further, we investigate the hypothesis that the nexus between climate-related financial policies on systemic risk exhibits non-linearity.[19] In this regard, we incorporate the quadratic term of the CRFP index into Eq. (5). The incorporation of non-linearity in our model, captured by the CRFP term squared, signifies that the regression equations are estimated as a second-degree polynomial. This allows for alterations in slopes as a function of changes in the independent variable. Consequently, the slope of the estimating equation may fluctuate in response to variations in the CRFP index, thereby enabling the discernment of turning points in the correlation between climate-related financial policies and banks' systemic distress.

[Table 8 goes around here]

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[19] For example, Liu et al. (2024) demonstrate that climate policy uncertainty exerts a non-linear, U-shaped influence on systemic risk.

As demonstrated in Table 8, the relationship between climate-related financial policies and financial stability is indeed non-linear, exhibiting an inverted U-shaped form. This indicates that as the stringency of green prudential regulations approaches a specific threshold, their correlation with systemic risk becomes negative. Thus, initial policies have the potential to engender uncertainty and increase systemic vulnerabilities, whereas well-established, comprehensible frameworks offer a degree of clarity and serve to mitigate risk. The CRFP index (Model (1)), which encompasses all policies with bindingness, exhibits a turning point at 0.34, a value that is proximate to the 75th quartile of the distribution of 0.38. In the 47 countries constituting the sample, 28 have CRFP indices that are greater than or equal to the turning point. In contrast, for the CRFP3 index (Model (3)), which includes all policies without bindingness, the turning point is considerably higher, i.e., 0.52. This finding suggests that fewer mandatory policies may yield superior outcomes in comparison to a higher number of voluntary and non-binding measures.

4.4 Robustness checks

In this section, we conduct a series of robustness checks to ensure that our results hold across different specifications. First, in addition to MES, we use two others widely used metrics of systemic risk, namely ΔCoVaR developed by Adrian and Brunnermeier (2016) and SRISK by Brownlees and Engle (2017). ΔCoVaR measures the contribution of a given bank to systemic distress, and thus measures contagion spillovers when a stressed bank performs poorly. SRISK measures a bank's expected capital shortfall during a systemic event, specifically a 40% drop in the MSCI World Financials Index over a six-month period. It is determined by its size, leverage, and long-run marginal expected shortfall (LRMES). As showcased in Table 9, our baseline results hold for both ΔCoVaR and SRISK.

[Table 9 goes around here]
[Table 10 goes around here]
[Table 11 goes around here]
[Table12 goes around here]
[Table 13 goes around here]

Second, we employ alternative indices to assess countries' commitment to green financial policies. These indices, developed by D'Orazio and Thole (2022), differ from the CRFP index used in the baseline model in terms of weighting schemes and policy bindingness. Specifically, the CRFP2 index assigns different weights to prudential and lending policies, the CRFP3 index applies equal weights to all policy categories but includes only non-binding policies, and the CRFP4 index assumes equal weights while including a detailed policy indicator for the prudential policy area. Again, the main conclusion of the paper remains unaffected (Table 10).

Third, we run the model depicted in Eq. (5) using different static models. The results are reported in Table 11. In Model (1) the HLM model is estimated with restricted maximum likelihood (REML) instead of maximum likelihood in which the number of parameters in the model is restricted and has the advantage to obtain unbiased estimates of variance and covariance parameters (Høj-Edwards and Sørensen, 2022). Model (2) estimates the model with bank fixed effects to capture bank-specific unobserved heterogeneity, whereas Model (3) does the same using country fixed effects. In Model (4) we include multiple levels of fixed effects, that is, bank, country, and year fixed effects using the high-dimensional fixed effects (HDFE) procedure proposed by Guimarães and Portugal (2010). In Model (5), the coefficients are estimated using Driscoll and Kraay's (1998) standard errors, which are robust to common forms of cross-sectional and temporal dependence. This estimation accounts for heteroskedasticity, autocorrelation up to the first lag, and correlation across groups. Finally, in Model (6) we specifically address potential endogeneity issues arising from the fact that more stringent climate-related financial policies may be adopted in response to rising systemic risk rather than causing changes in systemic risk in a limited-information maximum likelihood (LIML) setting which is robust to weak instruments. Following a similar approach to Checherita-Westphal and Rother (2012) in macroeconomics and Leary and Roberts (2014) in finance, we instrument the lagged CRFP index variable using the average CRFP index levels of the other countries (peers) in the sample. This instrument must meet two conditions: (i) relevance, meaning it should correlate with the lagged CRFP index, and (ii) exogeneity, i.e., it should not directly affect the systemic risk. The rationale underlying this selection is that the pressure to adopt CRFPs, in conjunction with peer imitation, can exert a significant influence on countries, prompting them to implement green financing policies. This suggests a potential correlation between a country's adoption status and that of its peers. However, the implementation of CRFPs in other countries does not directly impact the systemic risk of a

bank from a specific country. Thus, this instrumental variable fulfills the requirement of being correlated with the CRFP index, and not directly related to the dependent variable. A recent study by Covi et al. (2025) finds evidence of international spillovers through banks' cross-border lending portfolios: banks reduce their exposure to brown projects in countries that tighten their climate policies relative to others in their portfolio. Conversely, banks increase their exposure to brown projects in countries with relatively lax climate regulations. Furthermore, in the case of the European Union, the disclosure and taxonomy frameworks are anchored in legislation, generating direct compliance incentives and extraterritorial effects (D'Orazio, 2026). The model is just-identified since it uses only a single instrument. In all cases, the robustness of the results is maintained while the LIML specification passes the goodness-of-fit tests, i.e., the first-stage F-test and the and the Kleibergen-Paap rk LM statistic.[20]

Fourth, we assume an autoregressive structure of the marginal expected shortfall and employ two dynamic models, namely the bias-corrected least squares dummy variable (LSDVC) proposed by Bruno (2005a) and the quasi-maximum likelihood (QML) linear dynamic panel data estimator (DPDQML) of Kripfganz (2016). Both estimators can circumvent the Nickell (1981) bias and have specific features that make them more appropriate than other dynamic estimators, such as the generalized method of moments (GMM), which is hampered by weak instruments and overidentification problems in the presence of strong data persistence, and suffers from finite sample bias (Blundell and Bond, 1998). In particular, the LSDVC tends to perform better than the instrumental variable (IV) GMM estimators in terms of bias and mean squared error (Bruno, 2005b) and is also suitable for unbalanced panels, as in our case. To initialize the bias correction procedure we use the Blundell-Bond consistent estimator (Blundell and Bond, 1998). In a similar vein, the DPDQML estimator demonstrates particular efficacy in scenarios characterized by a large number of cross-sectional units and a fixed time dimension. This configuration fosters enhanced efficiency and finite sample performance when contrasted with alternative estimation methodologies (Kripfganz, 2016). In addition, the QML estimator is robust to initial conditions, conditional and time-series heteroskedasticity, and log-likelihood misspecifications (Phillips, 2018). As demonstrated in Table 12, the findings obtained from both estimators are consistent.

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[20] In an alternative specification, we follow Kim et al. (2025) and employ lagged temperature anomaly as an instrument for CRFPs given that climate policies are usually adopted in response to changes in temperature in an attempt to limit temperature rise, as set out in the Copenhagen Accord. The results remain consistent and are available upon request.

Furthermore, the lagged coefficient for MES is statistically significant at the 1% level and less than one, indicating the suitability of these models for our analysis.

Finally, we re-estimate the baseline model using alternative sample structures and present the results in Table 13. Specifically, we first exclude the countries with the largest number of banks in our sample, namely Japan and the United States (Model (1)). Next, we exclude countries with three or fewer banks (Model (2)). Finally, we combine these two approaches in Model (3). The results obtained from this analysis are consistent and robust, suggesting that the conclusions derived are not contingent upon the specific sample structure employed.

To further assess the dynamic response of banks' MES to climate-related financial policies shocks at the country level, we use impulse response functions (IRFs). We employ local projections (LPs) à la Jordà et al. (2005), adapted to panel data. Compared to vector autoregression (VAR) models, LPs have the advantage of being robust to lag length misspecification, non-stationarity and highly persistent data. Moreover, LPs allow the direct estimation of impulse responses at each horizon without imposing restrictions across periods. To ensure the robustness of our inferences, we adopt a conservative approach and use two lags for the shock variable, following Montiel Olea and Plagborg-Møller (2021), as well as for the dependent variable to control for own dynamics and persistence (Nie et al., 2023). The LP specification for different horizons (h = 0, 1, 2, 3, 4) in years is modeled as follows:

$$MES_{i,j,t+h} = \zeta^h \times CRFP_{j,t-1} + \eta^h \times MES_{i,j,t-1} + \vartheta \times \Theta_{i,j,t-1} + \lambda \times \Omega_{j,t-1} + \gamma_i^h + \delta_t^h + \varepsilon_{i,j,t+h}$$

(6)

where γ_i^h and δ_t^h are bank and year fixed effects, respectively, and $\varepsilon_{i,j,t+h}$ is the error term. The impulse responses are constructed on the basis of the estimated ζ^h coefficients at each horizon. The confidence interval is derived from the respective estimated standard errors. Standard errors are clustered at the bank level.

[Figure 4 goes around here]

As shown in Figure 4, the results align with the baseline model, revealing an increase in banks' systemic risk following a one percentage point shock to the CRFP index. Notably, the effect

is more pronounced in the second year after the shock, indicating that a country's involvement in green policymaking has a lasting influence on financial stability.

5. Conclusions

Climate change has become a significant threat to both the financial system and the real economy. It is imperative to recognize that this process is a source of financial risk and that climate-related financial risks are systemic. In this regard, the Paris Agreement establishes a framework for coordinated action by signatory nations, with the overarching goal of transitioning to a net-zero economy and reducing greenhouse gas emissions by 2050. However, the international community has yet to make significant progress in achieving these goals. Against this backdrop, a number of green financial policies have been proposed to mitigate climate risks. A major concern in this direction is the adoption path of these policies, which is heterogeneous across countries. As such, it is crucial to track the progress of each country, as in the presence of a coordination failure problem, these policies may lead to a sub-optimal outcome and entail unintended consequences that can put the entire financial system at risk.

Building upon the database compiled by D'Orazio and Thole (2022), this study explores the extent to which climate-related financial policies mitigate or intensify systemic distress within the banking sector. Utilizing a panel dataset encompassing 458 international banks across 47 advanced markets (AMs) and emerging market and developing economies (EMDEs) from 2000 to 2020, our analysis reveals that augmented public pledges to green policies exert a negative influence on financial stability, thereby contributing to escalated systemic risk. This suggests that excessively strict climate-related financial policies could lead to a disorderly transition. Furthermore, measures that restrict banks' exposure to carbon-intensive counterparties, both directly and indirectly, may result in fewer loans being granted to the real economy and higher lending rates. This, in turn, gives rise to substantial credit losses, diminished bank profitability, and spillover effects with the potential to undermine systemic resilience.

In order to shed light on the channels through which climate-related financial policies (CRFPs) affect systemic risk, we decompose the marginal expected shortfall into its volatility and correlation components. We find that stricter CRFPs increase bank-level volatility, but do not increase interbank correlation. This suggests that the increase in systemic risk is primarily driven

by greater fragility and variability at the level of individual banks, rather than by stronger co-movement or interconnectedness within the banking system.

Furthermore, we investigate the transmission channels at bank level through which climate-related financial policies may contribute to higher systemic risk. Specifically, we examine lending, profitability, credit risk, pricing and capital adequacy using the following indicators: loan growth; return on equity; non-performing loans; loan loss provisions; interest income and expenses relative to assets; net interest income; and regulatory capital ratios. Our findings suggest that tighter climate-related financial policies are linked to slower loan growth, declining profitability and deteriorating asset quality, as evidenced by an increase in non-performing loans. At the same time, banks appear to increase loan prices, but rising funding costs lead to compressed net interest margins. Despite an increase in realized credit risk, loan loss provisions do not adjust significantly. This suggests that climate-related risks may not yet be fully embedded in forward-looking provisioning practices. These pressures, combined with weaker profitability and higher risk-weighted assets, are linked to declines in capital adequacy ratios. Overall, the findings suggest that climate-related financial tightening can put strain on banks' balance sheets during the transition phase through multiple interconnected channels, with potential implications for financial stability.

However, the implementation and ratification of the Paris Agreement, a more robust adaptation strategies to cope with climate shocks and a higher incidence of natural disasters and a larger number of people affected by extreme climate events act as negative moderators, counteracting the amplifying effects of climate-related financial policies on systemic risk. In addition, banks with stronger environmental, social and governance (ESG) performance experience less systemic distress when exposed to green financial policies. The findings of this study have important policy implications, given the increasing involvement of public authorities in formulating green policy actions to meet the objectives of the Paris Agreement. The development and implementation of climate-related financial policies may inadvertently amplify transition risks and trigger systemic shocks, potentially undermining the mandate of central banks and supervisors to safeguard financial stability. To avoid these unwanted consequences, it is incumbent upon policymakers to carefully delineate the scope of application of such policies, which could be a difficult task to achieve due to the lack of clear and granular data and robust standards and globally harmonized taxonomies. In order to circumvent the potential impediments to the availability of funds for firms adapting their business models to low-carbon environments

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posed by these regulations, authorities must deliberate on the most suitable level for implementing green lending policies - whether the firm or project level. In addition, as the Network for Greening the Financial System (NGFS) suggests, a series of additional measures must be taken in this regard, including transition plans for climate alignment within financial and non-financial institutions, as well as the strengthening of international coordination within the financial system.

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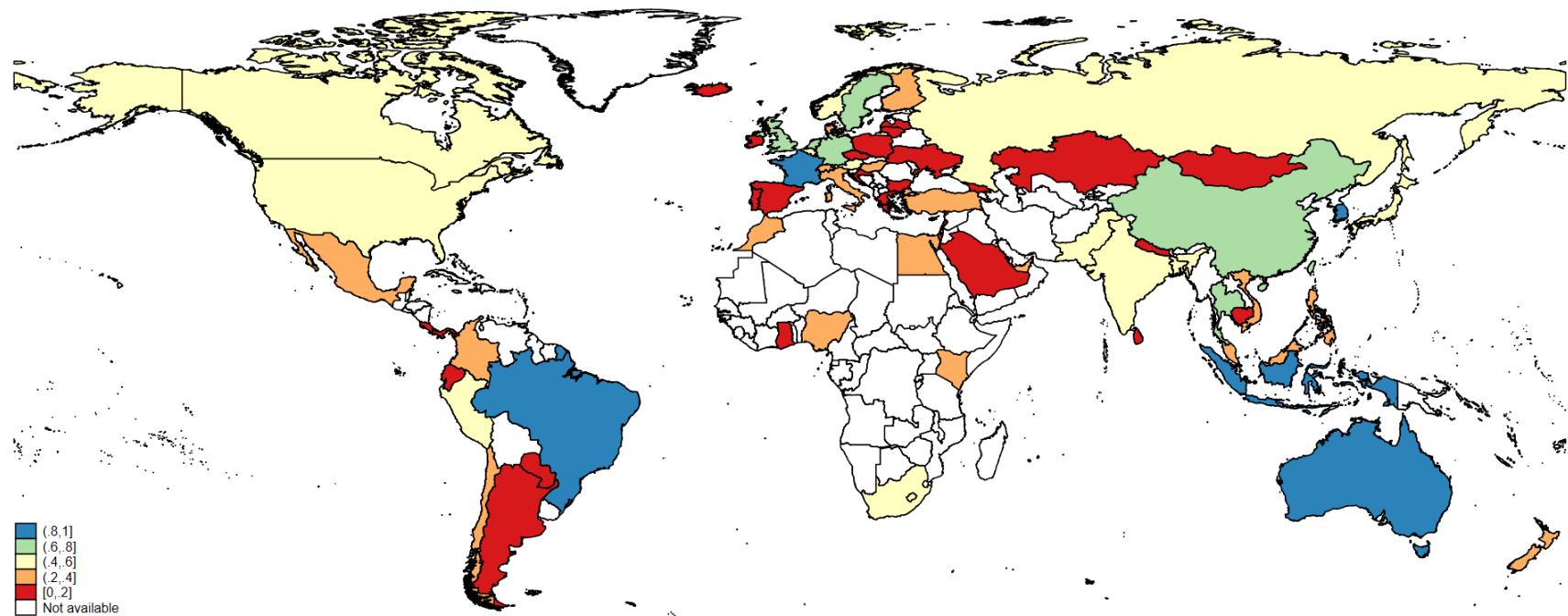
Figure 1. Climate-related financial policy index around the world in 2020, normalized between 0 and 1.
Source: D'Orazio and Thole (2022).
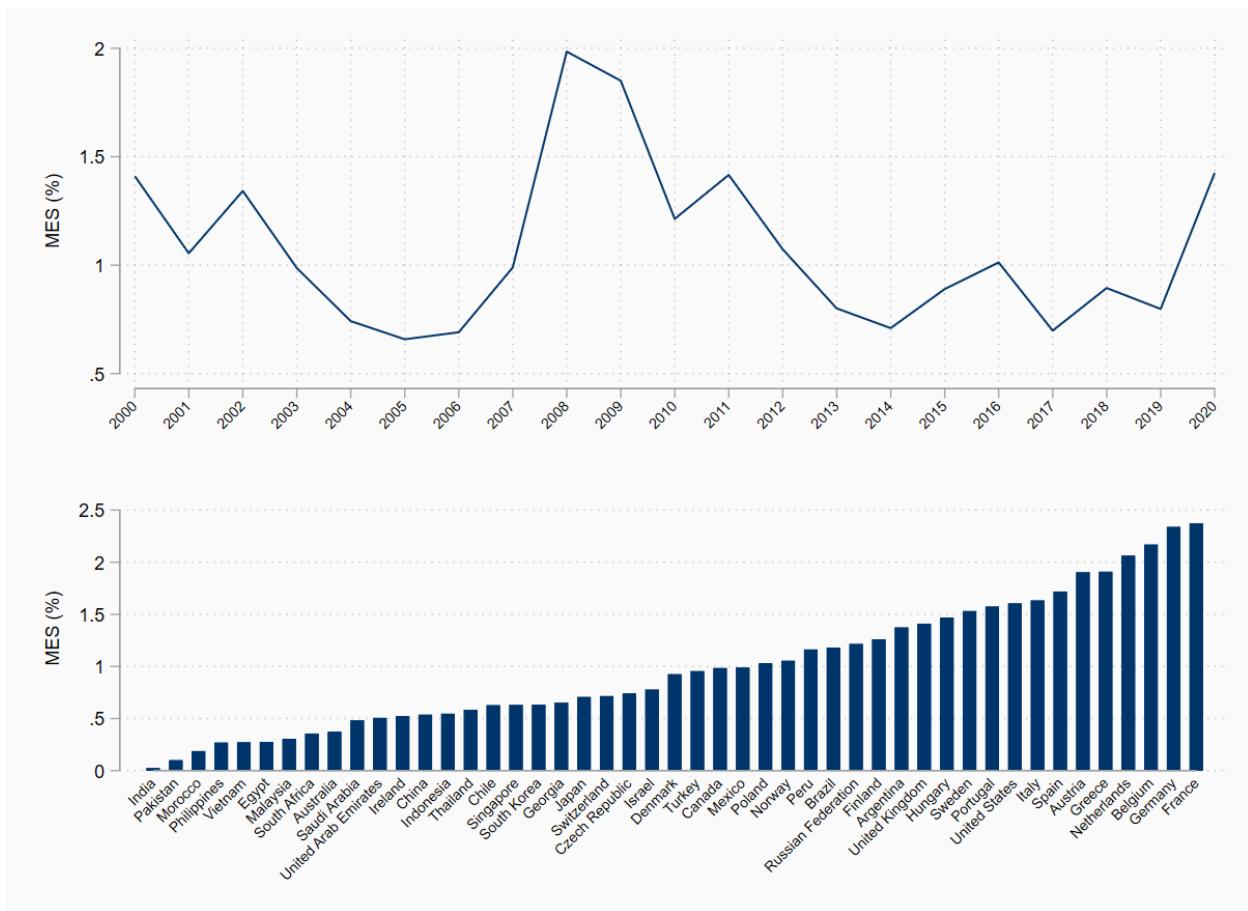
Figure 2. The average evolution of MES over time and across countries.
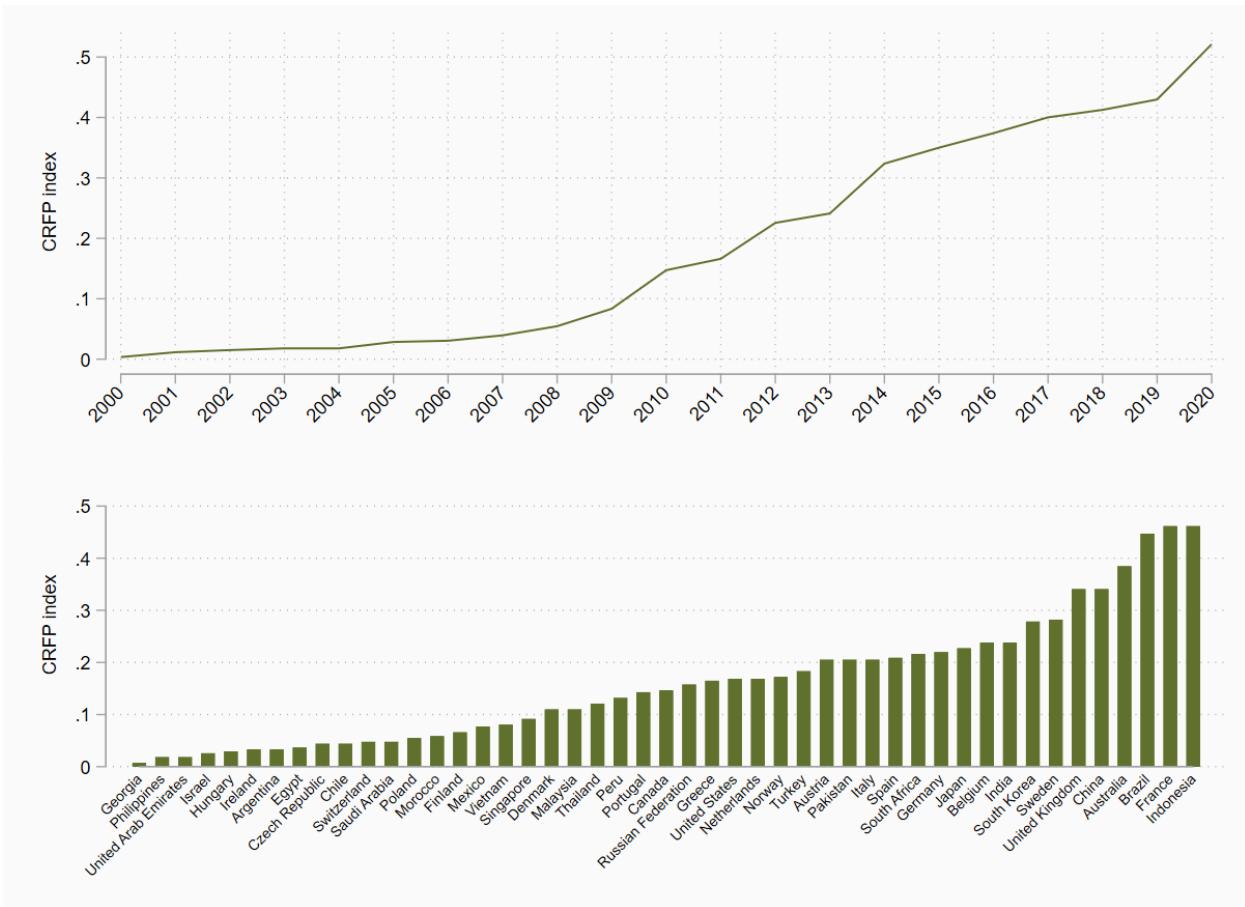
Figure 3. The average evolution of CRPF index over time and across countries, normalized between 0 and 1.
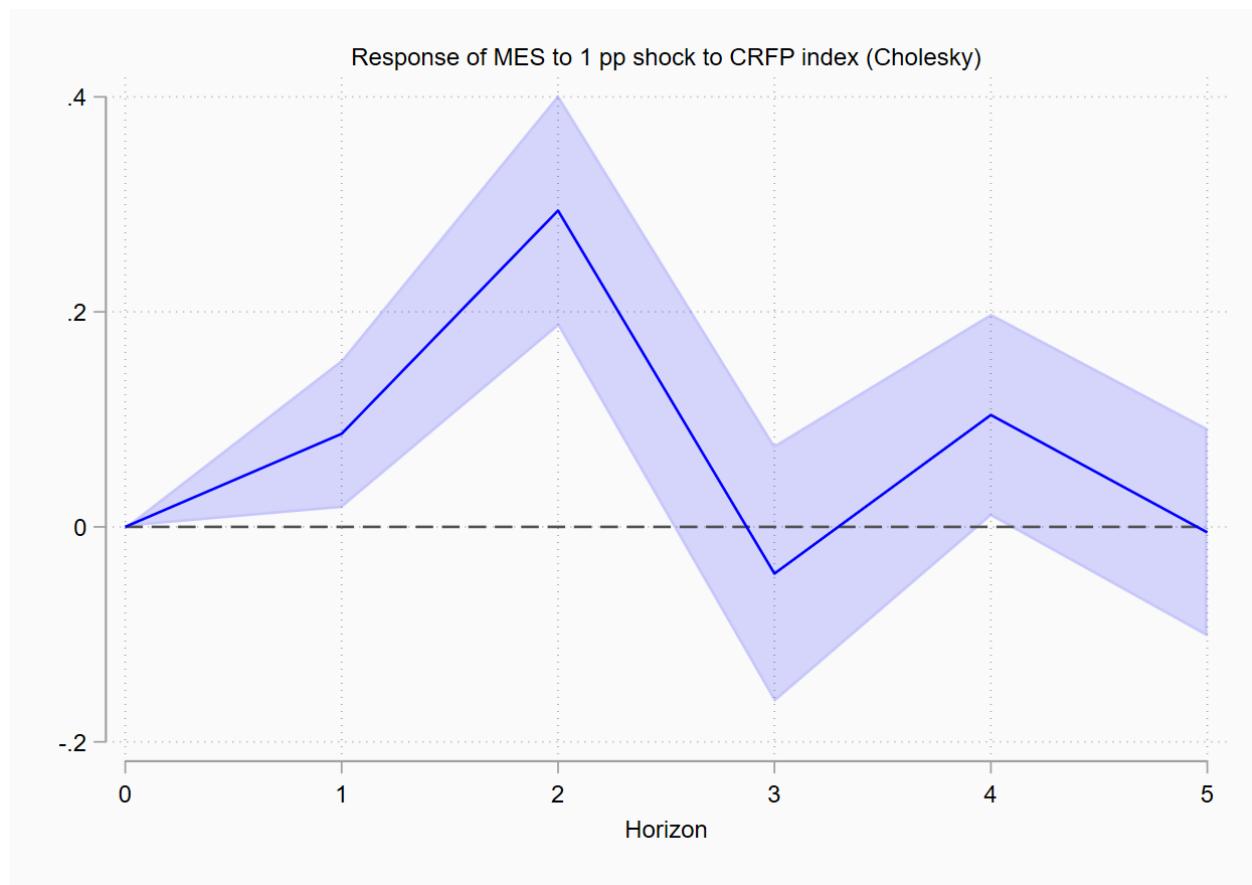
Figure 4. Panel local projections.
Note: Shaded area represents 90% confidence band.

Table 1. Summary statistics.

Variables	Mean	St. dev.	p25	Median	p75	Min	Max	Obs.
MES	1.0712	0.7834	0.5187	0.9438	1.4784	-0.7718	3.6203	6937
CRFP index	0.2258	0.2214	0.0000	0.2308	0.3846	0.0000	0.8462	6937
Size	24.1529	1.7865	22.8491	23.9923	25.1744	20.1517	28.4862	6935
Capitalization	8.6057	3.7296	5.8497	8.0848	10.6952	2.0553	25.9390	6935
Lending	64.4455	13.0623	57.2994	65.9299	73.3929	23.0906	91.2124	6924
Credit risk ratio	3.0850	3.7285	0.8250	1.8324	3.8231	0.0249	24.3661	6869
Funding structure	77.1620	18.3391	67.9525	82.5222	91.5433	17.0417	98.8034	6935
Income diversification	25.7808	12.8693	16.2402	24.2003	33.3144	2.7741	68.1073	6933
Profitability	10.2941	8.7995	5.8400	10.2100	14.9800	-30.3600	36.1500	6924
Bank concentration	49.2618	20.8463	34.7131	40.0176	63.0877	22.3073	99.9418	6902
Financial institutions index	0.7271	0.2056	0.6159	0.8442	0.8721	0.2342	0.9556	6499
Real GDP growth	2.1396	2.8759	0.9543	2.2419	3.4832	-5.9185	10.1136	6937
Inflation	2.5292	3.3931	0.9442	1.8706	3.0856	-2.3493	21.4137	6937

Note: This table display descriptive statistics of the winsorized variables used in the empirical setting.

Table 2. Baseline model results.

Dependent: MES	(1)	(2)	(3)
Fixed-effects parameters			
CRFP index (t-1)	0.1872***	0.1726***	0.1963***
	(0.0332)	(0.0355)	(0.0358)
Size (t-1)		0.0795***	0.0672***
		(0.0075)	(0.0077)
Capitalization (t-1)		-0.0006	0.0003
		(0.0018)	(0.0018)
Lending (t-1)		-0.0004	-0.0004
		(0.0005)	(0.0005)
Credit risk ratio (t-1)		0.0019	0.0031**
		(0.0012)	(0.0013)
Funding structure (t-1)		-0.0015***	-0.0016***
		(0.0005)	(0.0005)
Income diversification (t-1)		-0.0014***	-0.0015***
		(0.0005)	(0.0005)
Profitability (t-1)		-0.0013***	-0.0013***
		(0.0005)	(0.0005)
Bank concentration (t-1)			-0.0009**
			(0.0004)
Financial institutions index (t-1)			0.1645
			(0.1075)
Real GDP growth (t-1)			0.0074***
			(0.0025)
Inflation (t-1)			-0.0135***
			(0.0015)
Constant	0.8566***	-0.8520***	-0.5776***
	(0.0860)	(0.2062)	(0.2181)
Random-effects parameters			
Country-level variance	-0.5974***	-0.7036***	-0.6978***
	(0.1143)	(0.1134)	(0.1144)
Bank-level variance	-1.0700***	-1.2268***	-1.2054***
	(0.0366)	(0.0396)	(0.0402)
Residual variance	-1.3427***	-1.3555***	-1.3672***
	(0.0084)	(0.0088)	(0.0088)
Observations	7624	7004	6937
Banks	458	458	458
Countries	47	47	47
LR test Chi-square p-value	0.0000	0.0000	0.0000
Year FE	Yes	Yes	Yes

Note: Standard errors in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 3. Further analysis: the role of the Paris Agreement.

Dependent: MES	(1)	(2)
Fixed-effects parameters	Implementation	Ratification
CRFP index (t-1)	0.2811***	0.2745***
	(0.0435)	(0.0427)
After Paris Agreement	0.3714***	0.1580***
	(0.0327)	(0.0239)
CRFP index (t-1) × After Paris Agreement	-0.1678***	-0.1666***
	(0.0489)	(0.0484)
Size (t-1)	0.0652***	0.0757***
	(0.0077)	(0.0078)
Capitalization (t-1)	0.0003	0.0010
	(0.0018)	(0.0018)
Lending (t-1)	-0.0004	-0.0000
	(0.0005)	(0.0005)
Credit risk ratio (t-1)	0.0034***	0.0033**
	(0.0013)	(0.0013)
Funding structure (t-1)	-0.0017***	-0.0015***
	(0.0005)	(0.0005)
Income diversification (t-1)	-0.0014***	-0.0018***
	(0.0005)	(0.0005)
Profitability (t-1)	-0.0014***	-0.0012**
	(0.0005)	(0.0005)
Bank concentration (t-1)	-0.0009**	-0.0006*
	(0.0004)	(0.0004)
Financial institutions index (t-1)	0.1876*	0.1133
	(0.1075)	(0.1080)
Real GDP growth (t-1)	0.0063**	0.0072***
	(0.0025)	(0.0025)
Inflation (t-1)	-0.0138***	-0.0131***
	(0.0015)	(0.0015)
Constant	-0.5317**	-0.8147***
	(0.2182)	(0.2222)
Observations	6937	6937
Banks	458	458
Countries	47	47
LR test Chi-square p-value	0.0000	0.0000
Year FE	Yes	Yes

Note: The output for the random-effects parameters is suppressed due to space constraints. Standard errors in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 4. Further analysis: country-level events.

Dependent: MES	(1)	(2)	(3)
Fixed-effects parameters			
CRFP index (t-1)	0.1964***	0.3029***	0.5269***
	(0.0392)	(0.0445)	(0.0455)
High ND-GAIN (t-1)	0.1915***		
	(0.0178)		
CRFP index (t-1) × High ND-GAIN (t-1)	-0.1861***		
	(0.0402)		
High number of disasters (t-1)		0.0603***	
		(0.0157)	
CRFP index (t-1) × High number of disasters (t-1)		-0.1078***	
		(0.0387)	
High number of people affected (t-1)			0.1058***
			(0.0150)
CRFP index (t-1) × High number of people affected (t-1)			-0.4252***
			(0.0376)
Size (t-1)	0.0750***	0.0688***	0.0776***
	(0.0076)	(0.0080)	(0.0079)
Capitalization (t-1)	0.0013	0.0000	0.0012
	(0.0018)	(0.0019)	(0.0019)
Lending (t-1)	-0.0002	-0.0002	0.0002
	(0.0005)	(0.0005)	(0.0005)
Credit risk ratio (t-1)	0.0028**	0.0029**	0.0026*
	(0.0013)	(0.0014)	(0.0014)
Funding structure (t-1)	-0.0014***	-0.0020***	-0.0019***
	(0.0005)	(0.0005)	(0.0005)
Income diversification (t-1)	-0.0016***	-0.0017***	-0.0018***
	(0.0005)	(0.0005)	(0.0005)
Profitability (t-1)	-0.0012**	-0.0013**	-0.0015***
	(0.0005)	(0.0005)	(0.0005)
Bank concentration (t-1)	-0.0007**	-0.0011***	-0.0008**
	(0.0004)	(0.0004)	(0.0004)
Financial institutions index (t-1)	0.0249	0.0423	0.0411
	(0.1108)	(0.1233)	(0.1223)
Real GDP growth (t-1)	0.0061**	0.0051*	0.0041
	(0.0025)	(0.0028)	(0.0028)
Inflation (t-1)	-0.0136***	-0.0156***	-0.0156***
	(0.0015)	(0.0018)	(0.0018)
Constant	-0.7728***	-0.5026**	-0.8076***
	(0.2171)	(0.2313)	(0.2297)
Observations	6937	6269	6259
Banks	458	450	450
Countries	47	46	46
LR test Chi-square p-value	0.0000	0.0000	0.0000
Year FE	Yes	Yes	Yes

Table 5. Further analysis: the role of ESG.

Dependent: MES	(1)
Fixed-effects parameters	
CRFP index (t-1)	0.2851***
	(0.0646)
High ESG Combined Score (t-1)	0.0465**
	(0.0192)
CRFP index (t-1) × High ESG Combined Score (t-1)	-0.1806***
	(0.0547)
Size (t-1)	0.1510***
	(0.0119)
Capitalization (t-1)	0.0069**
	(0.0033)
Lending (t-1)	0.0026***
	(0.0008)
Credit risk ratio (t-1)	-0.0052**
	(0.0022)
Funding structure (t-1)	-0.0007
	(0.0008)
Income diversification (t-1)	-0.0014**
	(0.0007)
Profitability (t-1)	-0.0016**
	(0.0008)
Bank concentration (t-1)	-0.0000
	(0.0005)
Financial institutions index (t-1)	0.4056**
	(0.1614)
Real GDP growth (t-1)	0.0100***
	(0.0033)
Inflation (t-1)	-0.0055**
	(0.0025)
Constant	-3.1320***
	(0.3407)
Observations	3194
Banks	367
Countries	45
LR test Chi-square p-value	0.0000
Year FE	Yes

Note: The output for the random-effects parameters is suppressed due to space constraints. Standard errors in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 6. AEs vs. EMDEs.

Dependent: MES	(1)	(2)
Fixed-effects parameters		
CRFP index (t-1)	0.1889***	0.2012***
	(0.0418)	(0.0420)
AEs	0.4594***	
	(0.1437)	
CRFP index (t-1) × AEs	0.0124	
	(0.0437)	
EMDEs		-0.4594***
		(0.1437)
CRFP index (t-1) × EMDEs		-0.0124
		(0.0437)
Size (t-1)	0.0665***	0.0665***
	(0.0077)	(0.0077)
Capitalization (t-1)	0.0005	0.0005
	(0.0018)	(0.0018)
Lending (t-1)	-0.0004	-0.0004
	(0.0005)	(0.0005)
Credit risk ratio (t-1)	0.0030**	0.0030**
	(0.0013)	(0.0013)
Funding structure (t-1)	-0.0017***	-0.0017***
	(0.0005)	(0.0005)
Income diversification (t-1)	-0.0015***	-0.0015***
	(0.0005)	(0.0005)
Profitability (t-1)	-0.0013**	-0.0013**
	(0.0005)	(0.0005)
Bank concentration (t-1)	-0.0009**	-0.0009**
	(0.0004)	(0.0004)
Financial institutions index (t-1)	0.1015	0.1015
	(0.1138)	(0.1138)
Real GDP growth (t-1)	0.0071***	0.0071***
	(0.0025)	(0.0025)
Inflation (t-1)	-0.0135***	-0.0135***
	(0.0016)	(0.0016)
Constant	-0.7525***	-0.2931
	(0.2210)	(0.2379)
Observations	6937	6937
Banks	458	458
Countries	47	47
LR test Chi-square p-value	0.0000	0.0000
Year FE	Yes	Yes

Note: The output for the random-effects parameters is suppressed due to space constraints. Standard errors in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 7. Further analysis: the short-run dynamics.

Dependent: MES	(1)	(2)	(3)	(4)
Fixed-effects parameters	CRFP index	CRFP2 index	CRFP3 index	CRFP4 index
ΔCRFP index (t-1)	0.0008	-0.1265**	-0.0642	-0.1290**
	(0.0551)	(0.0595)	(0.0482)	(0.0542)
Size (t-1)	0.0737***	0.0737***	0.0737***	0.0738***
	(0.0078)	(0.0078)	(0.0078)	(0.0078)
Capitalization (t-1)	0.0002	0.0002	0.0001	0.0002
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Lending (t-1)	-0.0003	-0.0003	-0.0003	-0.0003
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Credit risk ratio (t-1)	0.0030**	0.0029**	0.0030**	0.0029**
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Funding structure (t-1)	-0.0018***	-0.0018***	-0.0018***	-0.0018***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Income diversification (t-1)	-0.0015***	-0.0015***	-0.0015***	-0.0015***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Profitability (t-1)	-0.0016***	-0.0016***	-0.0016***	-0.0016***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Bank concentration (t-1)	-0.0007*	-0.0007*	-0.0007**	-0.0007*
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Financial institutions index (t-1)	0.2256**	0.2178**	0.2213**	0.2142*
	(0.1112)	(0.1111)	(0.1111)	(0.1111)
Real GDP growth (t-1)	0.0084***	0.0091***	0.0087***	0.0092***
	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Inflation (t-1)	-0.0131***	-0.0132***	-0.0131***	-0.0133***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Constant	-0.4191*	-0.4164*	-0.4173*	-0.4181*
	(0.2222)	(0.2221)	(0.2221)	(0.2221)
Random-effects parameters				
Country-level variance	-0.7017***	-0.6982***	-0.7000***	-0.6979***
	(0.1143)	(0.1143)	(0.1143)	(0.1143)
Bank-level variance	-1.2230***	-1.2238***	-1.2236***	-1.2237***
	(0.0401)	(0.0401)	(0.0401)	(0.0401)
Residual variance	-1.3581***	-1.3584***	-1.3582***	-1.3585***
	(0.0090)	(0.0090)	(0.0090)	(0.0090)
Observations	6724	6724	6724	6724
Banks	458	458	458	458
Countries	47	47	47	47
LR test Chi-square p-value	0.0000	0.0000	0.0000	0.0000
Year FE	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 8. Non-linear effects.

Dependent: MES	(1)	(2)	(3)	(4)
Fixed-effects parameters	CRFP index	CRFP2 index	CRFP3 index	CRFP4 index
CRFP index (t-1)	0.3456***	0.4755***	0.3834***	0.3024***
	(0.0670)	(0.0727)	(0.0670)	(0.0823)
CRFP index squared (t-1)	-0.2340***	-0.4473***	-0.3950***	-0.1230
	(0.0887)	(0.0953)	(0.0888)	(0.1085)
Size (t-1)	0.0665***	0.0704***	0.0668***	0.0714***
	(0.0077)	(0.0077)	(0.0077)	(0.0077)
Capitalization (t-1)	0.0002	0.0007	0.0003	0.0007
	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Lending (t-1)	-0.0004	-0.0002	-0.0002	-0.0003
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Credit risk ratio (t-1)	0.0032**	0.0035***	0.0033**	0.0035***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Funding structure (t-1)	-0.0018***	-0.0017***	-0.0020***	-0.0015***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Income diversification (t-1)	-0.0015***	-0.0015***	-0.0015***	-0.0016***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Profitability (t-1)	-0.0014***	-0.0014***	-0.0014***	-0.0014***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Bank concentration (t-1)	-0.0008**	-0.0008**	-0.0007**	-0.0008**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Financial institutions index (t-1)	0.1914*	0.1426	0.2197**	0.1110
	(0.1078)	(0.1087)	(0.1080)	(0.1101)
Real GDP growth (t-1)	0.0065***	0.0054**	0.0060**	0.0065***
	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Inflation (t-1)	-0.0139***	-0.0139***	-0.0136***	-0.0138***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Constant	-0.5638***	-0.6458***	-0.5812***	-0.6580***
	(0.2177)	(0.2177)	(0.2175)	(0.2179)
Random-effects parameters				
Country-level variance	-0.7105***	-0.7004***	-0.7190***	-0.6922***
	(0.1147)	(0.1144)	(0.1149)	(0.1143)
Bank-level variance	-1.2059***	-1.2107***	-1.2064***	-1.2118***
	(0.0402)	(0.0400)	(0.0401)	(0.0400)
Residual variance	-1.3677***	-1.3683***	-1.3673***	-1.3685***
	(0.0088)	(0.0088)	(0.0088)	(0.0088)
Turning point	0.3385	0.4703	0.5151	0.2034
Observations	6937	6937	6937	6937
Banks	458	458	458	458
Countries	47	47	47	47
LR test Chi-square p-value	0.0000	0.0000	0.0000	0.0000
Year FE	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 9. Robustness checks: alternative independent variables.

	(1)	(2)
Fixed-effects parameters	ΔCoVaR	SRISK
CRFP index (t-1)	0.0613***	2.8701**
	(0.0167)	(1.2798)
Size (t-1)	0.0308***	1.0907***
	(0.0033)	(0.2735)
Capitalization (t-1)	-0.0019**	-0.3109***
	(0.0008)	(0.0657)
Lending (t-1)	-0.0007***	-0.1385***
	(0.0002)	(0.0164)
Credit risk ratio (t-1)	0.0013**	0.0973**
	(0.0006)	(0.0461)
Funding structure (t-1)	-0.0008***	-0.1342***
	(0.0002)	(0.0178)
Income diversification (t-1)	-0.0005**	0.0335*
	(0.0002)	(0.0176)
Profitability (t-1)	-0.0003	-0.1526***
	(0.0002)	(0.0181)
Bank concentration (t-1)	-0.0007***	-0.0157
	(0.0002)	(0.0129)
Financial institutions index (t-1)	0.0909*	14.4568***
	(0.0494)	(3.7564)
Real GDP growth (t-1)	0.0037***	-0.4431***
	(0.0011)	(0.0883)
Inflation (t-1)	-0.0032***	0.0893
	(0.0007)	(0.0547)
Constant	0.1331	-7.4539
	(0.0956)	(7.5514)
Random-effects parameters		
Country-level variance	-1.5401***	2.5763***
	(0.1140)	(0.1209)
Bank-level variance	-2.1352***	2.3726***
	(0.0415)	(0.0381)
Residual variance	-2.1217***	2.2110***
	(0.0088)	(0.0088)
Observations	7062	6937
Banks	458	458
Countries	47	47
LR test Chi-square p-value	0.0000	0.0000
Year FE	Yes	Yes

Note: Standard errors in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 10. Robustness checks: alternative dependent variables.

Dependent: MES	(1)	(2)	(3)
Fixed-effects parameters	CRFP2 index	CRFP3 index	CRFP4 index
CRFP index (t-1)	0.1757***	0.1325***	0.2158***
	(0.0348)	(0.0362)	(0.0307)
Size (t-1)	0.0709***	0.0670***	0.0720***
	(0.0077)	(0.0077)	(0.0077)
Capitalization (t-1)	0.0007	0.0003	0.0008
	(0.0018)	(0.0018)	(0.0018)
Lending (t-1)	-0.0003	-0.0003	-0.0003
	(0.0005)	(0.0005)	(0.0005)
Credit risk ratio (t-1)	0.0032**	0.0030**	0.0034***
	(0.0013)	(0.0013)	(0.0013)
Funding structure (t-1)	-0.0015***	-0.0018***	-0.0014***
	(0.0005)	(0.0005)	(0.0005)
Income diversification (t-1)	-0.0016***	-0.0015***	-0.0016***
	(0.0005)	(0.0005)	(0.0005)
Profitability (t-1)	-0.0013**	-0.0013**	-0.0013**
	(0.0005)	(0.0005)	(0.0005)
Bank concentration (t-1)	-0.0008**	-0.0008**	-0.0008**
	(0.0004)	(0.0004)	(0.0004)
Financial institutions index (t-1)	0.1013	0.1650	0.0867
	(0.1087)	(0.1077)	(0.1082)
Real GDP growth (t-1)	0.0073***	0.0076***	0.0069***
	(0.0025)	(0.0025)	(0.0025)
Inflation (t-1)	-0.0132***	-0.0130***	-0.0136***
	(0.0015)	(0.0015)	(0.0015)
Constant	-0.6576***	-0.5827***	-0.6667***
	(0.2185)	(0.2184)	(0.2180)
Random-effects parameters			
Country-level variance	-0.6821***	-0.6962***	-0.6848***
	(0.1142)	(0.1145)	(0.1140)
Bank-level variance	-1.2095***	-1.2038***	-1.2123***
	(0.0401)	(0.0402)	(0.0400)
Residual variance	-1.3668***	-1.3661***	-1.3684***
	(0.0088)	(0.0088)	(0.0088)
Observations	6937	6937	6937
Banks	458	458	458
Countries	47	47	47
LR test Chi-square p-value	0.0000	0.0000	0.0000
Year FE	Yes	Yes	Yes

Note: Standard errors in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 11. Robustness checks: alternative static estimation models.

Dependent: MES	(1)	(2)	(3)	(4)	(5)	(6)
			Country	HDFE	Driscol-	LIML
	REML	Bank FE	FE		Kraay	
CRFP index (t-1)	0.1963***	0.1987***	0.1964***	0.1987***	0.1987*	0.1947***
	(0.0359)	(0.0513)	(0.0523)	(0.0515)	(0.1048)	(0.0510)
Size (t-1)	0.0672***	-0.0031	0.0692***	-0.0031	-0.0031	-0.0030
	(0.0077)	(0.0140)	(0.0104)	(0.0140)	(0.0188)	(0.0139)
Capitalization (t-1)	0.0003	0.0012	0.0002	0.0012	0.0012	0.0012
	(0.0018)	(0.0020)	(0.0020)	(0.0020)	(0.0023)	(0.0020)
Lending (t-1)	-0.0004	-0.0001	-0.0004	-0.0001	-0.0001	-0.0001
	(0.0005)	(0.0006)	(0.0005)	(0.0006)	(0.0008)	(0.0006)
Credit risk ratio (t-1)	0.0031**	0.0033**	0.0030*	0.0033**	0.0033	0.0033**
	(0.0013)	(0.0016)	(0.0016)	(0.0016)	(0.0036)	(0.0016)
Funding structure (t-1)	-0.0016***	-0.0021***	-0.0015**	-0.0021***	-0.0021	-0.0021***
	(0.0005)	(0.0007)	(0.0007)	(0.0007)	(0.0018)	(0.0007)
Income diversification (t-1)	-0.0015***	-0.0027***	-0.0015***	-0.0027***	-0.0027**	-0.0027***
	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0013)	(0.0006)
Profitability (t-1)	-0.0013***	-0.0011	-0.0013*	-0.0011	-0.0011	-0.0011
	(0.0005)	(0.0007)	(0.0007)	(0.0007)	(0.0013)	(0.0007)
Bank concentration (t-1)	-0.0009**	-0.0010**	-0.0009**	-0.0010**	-0.0010	-0.0010**
	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0007)	(0.0004)
Financial institutions index (t-1)	0.1635	0.2101	0.1131	0.2101	0.2101	0.2103
	(0.1078)	(0.1319)	(0.1365)	(0.1324)	(0.3724)	(0.1315)
Real GDP growth (t-1)	0.0074***	0.0081***	0.0078***	0.0081***	0.0081	0.0081***
	(0.0025)	(0.0028)	(0.0028)	(0.0028)	(0.0058)	(0.0028)
Inflation (t-1)	-0.0135***	-0.0154***	-0.0135***	-0.0154***	-0.0154**	-0.0154***
	(0.0015)	(0.0019)	(0.0018)	(0.0019)	(0.0061)	(0.0019)
Constant	-0.5786***	1.1496***	0.1895	1.2449***	1.4767***	
	(0.2188)	(0.3583)	(0.2647)	(0.3759)	(0.4447)	
Observations	6937	6937	6937	6932	6937	6932
Banks	458	458	458	453	458	453
Countries	47	47	47	47	47	47
LR test Chi-square p-value	0.0000					
R-squared		0.6917	0.6893	0.9020	0.6917	
F-test (first stage) p-value						0.0000
Underidentification - Kleibergen-Paap rk LM statistic p-value						0.0000
Bank FE	No	Yes	No	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The output for the random-effects parameters is suppressed due to space constraints. Standard errors in parentheses for Model (1), robust standard errors in parentheses for Models (2), (3), (4) and (6), and Driscol and Kraay (1998) standard errors in parentheses for Model (5). ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 12. Robustness checks: alternative dynamic estimation models.

Dependent: MES	(1)	(2)
	LSDVC	DPDQML
CRFP index (t-1)	0.1551***	0.0723**
	(0.0455)	(0.0327)
Size (t-1)	0.0163	0.0256***
	(0.0131)	(0.0091)
Capitalization (t-1)	0.0003	0.0005
	(0.0026)	(0.0013)
Lending (t-1)	0.0004	0.0011***
	(0.0006)	(0.0004)
Credit risk ratio (t-1)	0.0015	0.0029**
	(0.0019)	(0.0011)
Funding structure (t-1)	-0.0002	-0.0013***
	(0.0006)	(0.0004)
Income diversification (t-1)	-0.0023***	-0.0022***
	(0.0006)	(0.0005)
Profitability (t-1)	-0.0002	0.0002
	(0.0005)	(0.0006)
Bank concentration (t-1)	-0.0005	-0.0006*
	(0.0005)	(0.0003)
Financial institutions index (t-1)	0.0974	0.0356
	(0.1596)	(0.0931)
Real GDP growth (t-1)	0.0135***	0.0132***
	(0.0023)	(0.0023)
Inflation (t-1)	-0.0064***	-0.0049***
	(0.0017)	(0.0010)
MES (t-1)	0.6175***	0.5891***
	(0.0113)	(0.0103)
Observations	6684	5381
Banks	456	357
Countries	47	45
Bank FE	Yes	Yes
Year FE	Yes	Yes

Note: Bootstrap standard errors based on 50 repetitions in parentheses for Model (1) and robust standard errors in parentheses for Model (2). ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 13. Robustness checks: different sample structures.

Dependent: MES	(1)	(2)	(3)
	No US and	No countries with less than	
Fixed-effects parameters	Japan	3 banks	(1) + (2)
CRFP index (t-1)	0.2077***	0.2165***	0.2026***
	(0.0433)	(0.0373)	(0.0445)
Size (t-1)	0.1041***	0.0662***	0.1018***
	(0.0124)	(0.0077)	(0.0127)
Capitalization (t-1)	0.0081***	-0.0004	0.0074***
	(0.0027)	(0.0018)	(0.0028)
Lending (t-1)	-0.0018***	-0.0004	-0.0020***
	(0.0006)	(0.0005)	(0.0006)
Credit risk ratio (t-1)	-0.0001	0.0032**	-0.0002
	(0.0014)	(0.0013)	(0.0015)
Funding structure (t-1)	0.0002	-0.0015***	0.0004
	(0.0006)	(0.0005)	(0.0006)
Income diversification (t-1)	-0.0033***	-0.0014***	-0.0031***
	(0.0007)	(0.0005)	(0.0007)
Profitability (t-1)	0.0015**	-0.0017***	0.0014*
	(0.0007)	(0.0005)	(0.0007)
Bank concentration (t-1)	-0.0009**	-0.0010***	-0.0010**
	(0.0004)	(0.0004)	(0.0004)
Financial institutions index (t-1)	0.0212	0.3010***	0.1481
	(0.1200)	(0.1139)	(0.1262)
Real GDP growth (t-1)	0.0160***	0.0059**	0.0151***
	(0.0027)	(0.0026)	(0.0028)
Inflation (t-1)	-0.0095***	-0.0143***	-0.0097***
	(0.0017)	(0.0015)	(0.0018)
Constant	-1.4787***	-0.6883***	-1.5706***
	(0.3214)	(0.2243)	(0.3315)
Random-effects parameters			
Country-level variance	-0.6303***	-0.7565***	-0.6881***
	(0.1177)	(0.1322)	(0.1374)
Bank-level variance	-1.1551***	-1.2052***	-1.1471***
	(0.0545)	(0.0408)	(0.0563)
Residual variance	-1.3416***	-1.3855***	-1.3744***
	(0.0124)	(0.0091)	(0.0131)
Observations	3540	6547	3150
Banks	311	429	228
Countries	45	33	31
LR test Chi-square p-value	0.0000	0.0000	0.0000
Year FE	Yes	Yes	Yes

Note: Standard errors in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table A1. Pairwise correlation matrix of the main regressors.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) CRFP index	1.0000											
(2) Size	0.2854*	1.0000										
(3) Capitalization	0.0164	-0.3716*	1.0000									
(4) Lending	-0.1019*	-0.2357*	0.0894*	1.0000								
(5) Credit risk ratio	-0.0336*	0.0414*	-0.0848*	-0.0234*	1.0000							
(6) Funding structure	-0.0451*	-0.4621*	0.1535*	0.1899*	-0.0707*	1.0000						
(7) Income diversification	0.0921*	0.3708*	-0.1520*	-0.3343*	0.0201*	-0.2152*	1.0000					
(8) Profitability	-0.0853*	-0.0340*	0.1100*	-0.0928*	-0.2313*	-0.0819*	-0.0181	1.0000				
(9) Bank concentration	-0.0190	0.3415*	-0.2092*	0.0128	0.2124*	-0.4524*	0.1049*	0.1144*	1.0000			
(10) Financial institutions index	0.0836*	0.0247*	-0.1295*	0.0877*	-0.3349*	0.0659*	0.1698*	-0.3276*	-0.2533*	1.0000		
(11) Real GDP growth	-0.1314*	-0.0367*	0.0834*	-0.0223*	-0.0375*	0.0303*	-0.1478*	0.3776*	0.0376*	-0.4886*	1.0000	
(12) Inflation	-0.0522*	-0.0903*	0.1856*	-0.0927*	0.0752*	-0.1225*	-0.1782*	0.3818*	0.1540*	-0.5630*	0.2918*	1.0000

Table A2. Results for the subcomponents of MES.

Dependent: MES	(1)	(2)
	Volatility	Correlation
Fixed-effects parameters		
CRFP index (t-1)	0.0930***	0.0037
	(0.0172)	(0.0112)
Control variables	Yes	Yes
Observations	6937	6937
Banks	458	458
Countries	47	47
LR test Chi-square p-value	0.0000	0.0000
Year FE	Yes	Yes

Note: Standard errors in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table A3. Testing possible channels: lending, profitability and credit risk

Dependent: MES	(1)	(2)	(3)	(4)
	Loan growth	ROE	NPL/TL	Provisions/TA
Fixed-effects parameters				
CRFP index (t-1)	-0.0367**	-1.6539**	0.6290**	-0.0643
	(0.0169)	(0.8419)	(0.3157)	(0.0504)
Control variables	Yes	Yes	Yes	Yes
Observations	7201	7745	7189	7133
Banks	458	458	457	458
Countries	47	47	47	47
LR test Chi-square p-value	0.0000	0.0000	0.0000	0.0000
Year FE	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table A4. Testing possible channels: pricing and capital adequacy.

Dependent: MES	(1)	(2)	(3)	(4)	(5)
	Interest Income/TA	Interest Expense/TA	NII/TA	CAR	CAR Tier 1
Fixed-effects parameters					
CRFP index (t-1)	0.7516***	1.0666***	-0.2749***	-1.2029***	-1.4143***
	(0.1096)	(0.0869)	(0.0649)	(0.3336)	(0.3487)
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	7211	7207	7208	5946	5435
Banks	458	458	458	415	406
Countries	47	47	47	46	46
LR test Chi-square p-value	0.0000	0.0000	0.0000	0.0000	0.0000
Year FE	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

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