Journal of Financial Stability 66 (2023) 101132

Contents lists available at ScienceDirect

Journal of Financial Stability

journal homepage: www.elsevier.com/locate/jfstabil

Climate change and financial systemic risk: Evidence from US banks and insurers☆

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ARTICLE INFO

JEL classification:
G15
G18
G20
Q54

Keywords:
Systemic risk
Climate risk
Financial stability
Sustainable finance

ABSTRACT

We study the relationship between climate change and financial systemic risk. First, we test whether, to what extent and how quickly the systemic risk of US banking and insurance sectors reacts to billion-dollar weather and climate disasters. We prove that some extreme events can exacerbate financial systemic risk and provide insights about the different timing at which the reaction of the systemic risk measures takes place. Second, we investigate through quantile regressions how the performance of green and brown market indexes affects the systemic risk of the two US financial sectors. We observe that higher levels of the green indexes reduce systemic risk more than a raise in brown indexes, with an increasing magnitude in tail conditions. A raise in the riskiness of the green indexes seems to significantly increase systemic risk, with the effect being stronger than that of an increase in the riskiness of brown indexes. Our results confirm the importance of the adoption of appropriate policies aiming at contrasting the raise in the frequency and severity of climate disasters. Our findings are also important in the perspective of the likely increase (decrease) in the exposure of financial firms towards green (brown) companies, induced by the policy decisions taken to combat climate change, and in terms of the implications for banks' and insurers' risk management models and procedures.

1. Introduction

After Mark Carney's famous speech *"Breaking the Tragedy of the Horizon"* (Carney, 2015), addressing the threats that climate change poses to financial markets and institutions has become one of the top priorities in the agenda of financial regulators and supervisors, despite the difficulties of integrating climate related risk analysis into financial stability monitoring and prudential supervision (Bolton et al., 2020). Climate change gives rise to risks that are generally classified as physical risks — i.e., those referring to the damages caused by natural catastrophic events to physical assets, natural capital and human lives; and transition risks — i.e., those associated with the economic and financial losses stemming from the re-evaluation of carbon-intensive and low-carbon assets, caused by the transition to a low-emission economy (Monasterolo, 2020; Battiston et al., 2021). According to the Financial Stability Board (2020), even if the current estimates of the impact of physical risks on asset prices seem to be relatively contained, it may be subject to considerable tail risk, and their manifestation could lead to a significant fall in asset prices and growing uncertainty. Transition risks materialize when the green transition occurs in a disorderly and unpredicted way, following for example technological shocks inducing a rapid decrease (increase) in the costs (performance) of renewable energy production, or policy and regulatory shocks, like the sudden introduction of a carbon tax or of measures affecting banks' capital requirements (High-Level Expert Group on Sustainable Finance, European Commission, 2018; Network for Greening the Financial System, 2019).

It has been widely recognized that physical and transition risks are intertwined and represent a major source of systemic risk when they cause losses to financial intermediaries, disruption in financial

☆ We thank Iftekhar Hasan, Radu Tunaru and Mattia Bevilacqua for many useful discussions and suggestions. We thank all the participants at the 3rd International Conference CGRM 2021 "Climate risk and sustainability: the emerging impacts and future perspectives for the financial intermediaries" for their valuable comments and suggestions. We would like to thank reviewers for taking the time and effort necessary to review the manuscript. We sincerely appreciate all valuable comments and suggestions, which helped us to improve the quality of the manuscript.

Views expressed are solely those of the authors and so cannot be taken to represent those of the European Banking Authority (EBA), or to state the EBA's policy.

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https://doi.org/10.1016/j.jfs.2023.101132
Received 5 January 2022; Received in revised form 20 April 2023; Accepted 25 April 2023
Available online 4 May 2023

markets functioning, and sudden increases in the volatility of large asset classes, with knock-on effects for the real economy (Monasterolo et al., 2017; Alogoskoufis et al., 2021; Brunetti et al., 2021). The interconnectedness across financial markets and institutions might easily amplify the effects of climate related risks through second-round/indirect equity losses and self-reinforcing feedback loops (Battiston et al., 2017; Stolbova et al., 2018; Financial Stability Board, 2020). Adopting a systemic perspective is therefore necessary when studying the way how climate related issues interact with the financial system. The analysis of the effects on financial systemic risk of climate change and of the policies adopted to face it is a relatively new research field and previous research generally uses a financial network approach to tackle these issues (see, among others Battiston et al., 2017; Roncoroni et al., 2019; Barucca et al., 2020). Prior studies have scantly examined the impact that climate change driven extreme weather events might have on financial systemic risk, mostly neglecting when and how fast this may occur. Scholars have also devoted few efforts to study the relationship between financial systemic risk and how green and brown companies perform.

Compared to this literature, we follow a more direct and straightforward approach and develop an empirical analysis where: first, through the Wilcoxon signed rank sum test, we investigate whether, to what extent and how quickly the systemic risk of US banking and insurance sectors reacts to billion-dollar weather and climate disasters; second, by using quantile regressions, we study the relationship between the systemic risk of US banks and insurers and the performance of green and brown market indexes, as measured through their levels and two risk measures — i.e., the Value at Risk (VaR) and the Expected Shortfall (ES). The two parts of our empirical investigation are strictly interconnected since they are both linked with the adoption of climate policies, which are intended to contrast the rise in the frequency and severity of extreme weather events, on the one hand, and are expected to change the degree of greenness (brownness) of financial firms' asset portfolios, on the other hand. Our findings are valuable in both perspectives.

We estimate the systemic risk of US banks and insurers through two consolidated market-based systemic risk measures (SRMs), namely the delta conditional Value at Risk ($\Delta CoVaR$) developed by Adrian and Brunnermeier (2016) and the marginal expected shortfall (MES) of Acharya et al. (2017). The decision to use these SRMs is in line with the Basel Committee on Banking Supervision's claim (2021), according to which frameworks to systematically translate climate change impacts into standard financial risks are not in place and standard financial risk metrics must be enhanced to account for co-movements among financial institutions, given the interconnectedness within the financial system. Since market-based SRMs are among the best suited measures to take the interconnectedness into account (Cai et al., 2018), our approach addresses these issues.

Our empirical analysis takes a backward-looking approach and is based on past events, both climate disasters and historical time series of brown and green firms' equity performance. This means that our findings might not be confirmed by future investigations since the way the transition policies will be designed and implemented might significantly change the frequency and severity of climate-related events and green/brown companies' performance. Nevertheless, we believe to provide some new and interesting insights, useful in the perspective of policy makers, financial regulators and supervisors and financial intermediaries, all involved in the efforts to contrast and manage climate-related risks.

To the best of our knowledge, prior literature has never investigated financial system reaction, as measured by consolidated systemic risk metrics, to climate disasters, especially in terms of the speed at which this reaction occurs. We first prove that the size and nature of climate events are not necessarily a relevant factor in determining a significant impact on financial systemic risk. 88% of the events that can significantly increase SRMs have a cost between 1 and 10 USD billion, which is a small value if compared with the damages that some of these disasters have caused in the recent past. As far as the speed of the reaction is concerned, we show that financial systemic risk sensitivity exhibits a certain delay since SRMs mainly rise after the climate event terminates.

Relative to prior studies, this research also provides some new evidence as concerns the study of the relationship between green and brown firms' performance and systemic risk of the banking and insurance sectors. Overall, the sensitivity of SRMs of both sectors is more pronounced in the tails of the green/brown indexes distributions, which confirms the need of climate policies that can ensure an orderly and easily predictable transition to a green economy. Since we find that higher $VaRs$ and ESs of green indexes seem to increase SRMs more than brown indexes, we show that the riskiness of green firms, if not adequately managed, might have an even worse impact on the financial system, if compared with brown firms. Finally, we also highlight that banks are overall more exposed than insurers to green companies' performance. This calls for further efforts by academic research, policy makers, financial supervisors and institutions to explain the peculiarities underlying the relationship between different financial intermediaries and their green counterparties and to consistently design and implement effective climate policies and risk management practices.

The evidence of a significant relation between some extreme weather events and financial systemic risk confirms the importance of the adoption of appropriate policies aiming at contrasting the raise in the occurrence probability and magnitude of such catastrophes and highlights the necessity to effectively embed the risk stemming from these events into the risk management practices of financial intermediaries and into the practices of financial supervisors. By highlighting how differently the performance of green and brown companies, as reflected by the performance of the respective market indexes, affects financial systemic risk, our results contribute to the current policy debate about the actions to take to effectively contrast climate change, and to the related previous literature, which mainly focuses on the reduction in the value of brown companies' stranded assets. Our findings are important in the perspective of the likely increase (decrease) in the exposure of financial firms towards green (brown) companies, induced by the policy decisions that will be taken to combat climate change, and in terms of the implications for banks' and insurers' risk management models and procedures. The way how financial intermediaries manage risk and financial supervisors exert their function should account for the different contribution of green and brown companies' riskiness to systemic risk.

The remainder of the paper is organized as follows. In Section 2 we describe how climate change issues are linked to financial systemic risk, discuss our reference literature, the differences of the approach we use and the contribution we can provide. Section 3 outlines the systemic risk models focusing on the estimation of $\Delta CoVaR$ and MES, the main hypotheses and the methodologies we use to test them. Section 4 describes the data used for the empirical analysis. Results are examined in Section 5. Section 6 provides concluding remarks and discusses some policy implications.

2. Climate change and financial systemic risk: a literature review

The rise in the frequency and severity of extreme weather events hitting non-financial firms negatively affects the stability of banks and insurers in a direct way, which is to a major extent linked to the specific business these financial companies run. Insurers are directly affected because they provide guarantees to cover losses on physical assets and property. The shock caused by a climate-induced disaster can be passed from them on to banks and other financial firms through: (i) an exposure effect, triggered if the latter are creditors or counterparties to the insurance companies; (ii) an asset liquidation effect, according to which insurers might be forced to sell assets at fire-sale prices to pay huge claims, causing a price fall which might negatively affect banks' and other financial firms' asset portfolio value. Even the banking sector is directly exposed to physical risks as they undermine borrowers' ability to repay and reduce the value of damaged assets, which affects banks' capacity to fully recover the value of the loan in case of default, if the assets are used as collateral. Extreme weather events may also lead to liquidity strains by inducing banks' counterparties to withdraw deposits and draw on credit lines. The transmission of the shock from banks to insurers and other financial institutions follows the exposure and asset liquidation effects described above (Gros et al., 2016). Nevertheless, banks and insurance companies are exposed to the impact of climate change on non-financial firms even because they invest in securities issued by these latter, whose value might be affected both by climate induced disasters and climate policies. In other words, if we still focus on the risk transmission mechanism starting from their counterparties and leading to them, banks and insurers are exposed to climate change and to climate policies because they hold, directly or indirectly (e.g., through investment funds), financial contracts, mainly shares/stocks and bonds issued by firms whose performance is affected both by extreme weather events and by the way how climate policies are designed and implemented. Being able to drive their performance, extreme weather events and climate policies can change the value of those financial contracts, thus affecting the value of banks' and insurers' assets.

Studying how financial companies react to climate change is difficult because climate risks and their impact are difficult to assess (Battiston et al., 2021). By moving from Taleb (2007)'s "black swan", Bolton et al. (2020) warn that climate change could lead to "green swan" events and be the cause of a systemic crisis. Green swans share some features with black swans, namely non-linearity, fat tailed distributions and uncertainty, that cannot be effectively captured and modelled by traditional pricing and risk management approaches (Balint et al., 2017; Monasterolo et al., 2019). The complexity of climate change events is even of a higher order because of the chain reactions, cascade effects and feedback loops that might generate unpredictable social, economic, and financial dynamics (Battiston et al., 2016; Gros et al., 2016; Bolton et al., 2020; Battiston et al., 2021). From a policy perspective, the absence of well-established knowledge about their effects on real economy and financial markets and institutions makes the design of green public policies quite a challenging task. This has called for the development of forward-looking methods, grounded in scenario-based analyses, to capture the systemic risk emerging from the interaction between climate change and financial system (Monasterolo et al., 2017; Morana and Sbrana, 2019; Bolton et al., 2020; Financial Stability Board, 2020; Monasterolo, 2020). Research has tried to account for the nature of climate risks and their interplay with financial risks. Works in this area use stock-flow consistent (SFC) and agent-based models to explore macroeconomic and financial consequences of climate risk. Studies combine climate scenarios with financial risk metrics and methods proposed by academics (Battiston et al., 2017) and apply modelling approaches based on complexity economics and network models (Battiston et al., 2012, 2016) to specifically assess how financial interconnectedness contributes to systemic risk.

Dafermos et al. (2017) develop a stock-flow-fund ecological macroeconomic model to investigate the trajectories of key environmental, macroeconomic and financial variables under different assumptions about the sensitivity of economic activity to the leverage ratio of firms and different types of green finance policies. They highlight that environmental changes cause economic damages that are reinforced as the contractionary effects of a higher leverage ratio become stronger. Green finance policies turn out to have beneficial effects on environmental variables and firms' financial fragility, which are even boosted when the expansion of green credit occurs together with the conventional credit restriction. Bovari et al. (2018) adopt an integrated ecological macroeconomic model that combines global warming and private over-indebtedness. They show that short-term results of climate change on economic fundamentals may lead to severe consequences for the economy in case of a too rapid application of climate policies; in the long run, negative effects might be due to the lack of proactive climate policies. Monasterolo and Raberto (2018) develop an SFC model rooted on a balance sheet approach, through which they show that green public policies can promote green growth by influencing firms' expectations and the credit market. Lamperti et al. (2019) adopt an agent-based climate-macroeconomic model and argue that climate change will increase the frequency of banking crises. An additional fiscal burden of approximately 5%–15% of gross domestic product per year and an increase of the ratio of public debt to gross domestic product by a factor of 2 will be required to rescue insolvent banks. Macroprudential regulation can attenuate bailout costs only modestly.

Since the global financial crisis, scholars have been developing financial network models to assess the role of financial interconnectedness and complexity on the emergence of systemic risk (Battiston et al., 2012; Castrén and Rancan, 2014). Due to their ability to capture loss amplification mechanisms, central banks and financial supervisors use network models in stress test exercises (Monasterolo, 2020). In the perspective of the integration of climate risks, Battiston et al. (2017) apply financial valuation in network models to analyse investors' exposure to equity holdings issued by some economic activities defined as climate-policy relevant sectors (CPRS), such as fossil fuels, utilities and energy-intensive sectors. Based on the DebtRank algorithm (Battiston et al., 2012), the authors develop a climate-stress test of the financial system in which they assess not only the first-round effects, but also the indirect losses caused by the devaluation of counterparties' debt obligations on the interbank market (second-round effects). Their results confirm that EU and US financial firms are largely exposed to financial contracts whose issuers belong to CPRS and that network effects — i.e., mutual exposures of financial intermediaries; might amplify potential losses.

Stolbova et al. (2018) develop a methodology based on multi-layer financial-real economy networks, through which they study the direct and indirect chains of contracts at the basis of the chains of financial exposures across multiple financial instruments. They account for the amplification of climate policy shocks, with the transmission channel given by the changes in the valuation of equity and debt securities conditional upon a shock on the asset side of the security issuer. Based on the findings referred to a dataset of financial exposures between the institutional sectors in the Euro Area, even a small shock on the banking system could create a great amplification in the banks-households chain and the consequent large gains (losses) for the banks would positively (negatively) affect the real economy. Battiston et al. (2019)'s CLIMAFIN provides a science-based approach to climate scenarios adjusted financial pricing models and risk metrics, which is built on the definition of a risk-adverse investor information set, risk management strategy and portfolio of risky financial contracts and securities. To define a climate spread — i.e., the change in the spread of a corporate or sovereign bond conditional to a given climate policy shock scenario; and a climate VaR — i.e., the "worst-case loss" under future climate shock scenarios, given a certain confidence level; CLIMAFIN adopts a valuation model to price equity risk and credit risk conditioned to forward-looking climate transition risk. The approach was applied to the analysis of development banks' project loans, conditional to climate related risk scenarios (Monasterolo and Stefano, 2016; Monasterolo and Raberto, 2018), and to provide a forward-looking climate transition risk assessment of the sovereign bond portfolios of insurance companies in Europe (Battiston et al., 2019).

Dietz et al. (2016) use a standard integrated assessment model and the "climate VaR" framework. Assuming that climate change can reduce the dividend payments of firms and the price of financial assets, they provide various estimates about the climate-induced loss in the value of financial assets, finding that the expected "climate VaR" of global financial assets is 1.8% along a business-as-usual emissions path. In examining the physical effects of climate change on financial stability, the study by Dafermos et al. (2018) moves beyond Dietz et al. (2016)'s analysis. Within their SFC-based approach, the authors consider the balance sheets and the financial flows in the financial sector, thus being able to model the climate-induced fragility of firms' and banks' financial structures. By using a multiple financial asset portfolio choice framework and accounting for a non-neutral impact of the financial system on the economic activity, they capture the implications of a fire sale of certain financial assets and consider the interactions between economic performance and financial (in)stability. According to the results obtained by calibrating the model using global data and running simulations for the years 2016–2120, in a business-as-usual scenario climate change is likely to negatively affect the default of firms, the leverage of banks and the price of financial assets. The paper also shows that climate-induced financial instability reinforces the adverse effects of climate change on economic activity and that the implementation of a green corporate quantitative easing program can reduce climate-induced financial instability and restrict global warming.

Another stream of literature deals with the link between climate change and financial system by looking at how financial markets react to climate announcements. The financial system has started to consider climate issues only in recent times, particularly after the 2015 Paris Agreement, and the scant existing research has not reached conclusive evidence. Two papers specifically examine the consequences of Trump's presidential election and the nomination of the climate skeptic Scott Pruitt to head the Environmental Protection Agency (EPA): according to Ramelli et al. (2018), investors rewarded companies in high-emissions industries, at least in the short run; Wagner et al. (2018) find that investors rewarded companies demonstrating more responsible climate strategies. Mukanjari and Sterner (2018) study the stock market reaction to the 2015 Paris Agreement announcement and the presidential election of Donald Trump, without finding a different effect on the financial performance of fossil energy firms. Monasterolo and De Angelis (2020) test if financial EU, US and global stock markets priced the Paris Agreement by decreasing (increasing) the systematic risk and increasing (decreasing) the portfolio weights of low-carbon (carbon-intensive) indexes afterwards. Their results show that overall systematic risk for the low-carbon indexes decreased consistently, while stock markets' reaction was mild for most carbon-intensive indexes, suggesting that investors started to consider low-carbon assets as an attractive opportunity after the Paris Agreement, with no penalization for carbon-intensive assets though.

Relative to prior literature, we take a different approach and rest interested in a different target variable, since this research examines the relationship between climate change and financial system by specifically focusing on this latter's stability, as measured by market-based SRMs. Therefore, our analysis is also valuable for the research dealing with financial systemic risk, as we verify whether and how climate change related issues can affect this risk. We focus on two different aspects of climate change, by looking at the effects of extreme weather events and by detecting whether and how the performance of green and brown companies influences banks' and insurers' systemic risk. The two issues we are interested in both depend on the adoption of policies to combat climate change, which are intended to contrast the rise in the frequency and severity of extreme weather events, on the one hand, and are expected to increase (decrease) the degree of greenness of banks' and insurers' asset portfolios, on the other hand.

The approach we use in our empirical analysis shares to some extent the logic of a stress test exercise, since we look at how market-based SRMs of US banks and insurers react in "stressed situations", namely when a climate disaster happens and when the performance of green and brown companies is observed under tail conditions. Nevertheless, unlike what we do in our investigation, to stress test portfolios of financial institutions against forward-looking climate risks, previous literature discussed above has developed approaches based on complexity economics and network science. Relative to traditional economic and financial risk models, these approaches enable to capture some key characteristics of the climate-finance relationship: feedback loops that could cause amplification effects, and cascade effects; non-linearities and tipping points, after which a system changes its core characteristics and is no more able to go back to the original status; the possibility that a measure introduced with a specific goal could have completely different yet long-standing effects on the system (Monasterolo, 2020). Further, such methods can be used to conduct a climate stress test of the banking system based on microeconomic data at the level of individual banks (Battiston et al., 2017).

Under the network-based approach, systemic risk is quantified and measured by analysing the evolution of the nodes and the structure of the network, where the nodes are the financial institutions and the links connecting them are the financial contracts, such as equity, bonds and loans. Assessing financial risk through network models benefits from their ability to consider the potentially relevant impact of indirect exposures on losses, diversification of risk across counterparties and external assets, and interconnectedness. By accounting for imperfect information and incomplete risk markets, network models allow to understand how externalities affect financial contracts and contribute to create and boost systemic risk. Finally, network models can estimate the feedback effects between the financial system and the real economy and grant a more comprehensive explanation of the macroeconomic aggregate phenomena.

Our method neither allows to analyse the exposures of banks and insurers to sectors of the economy that can be considered relevant in a climate policy perspective, nor makes it feasible to examine the exposures among banks and insurers themselves, across several types of financial instruments. We are not able to analyse how, once transferred on to the financial system, climate risk spreads through the different financial actors. We miss the second-round effects of climate-related shocks, both caused by physical risks and transition policy measures, and directly look at the market-based measures of systemic risk. Nevertheless, we believe that the methodology we adopt, which has the advantages to be straightforward, grounded on consolidated metrics, namely the $\Delta CoVaR$ and MES, fed by objective market-based data, and very easy to replicate, is well suited to address the specific issues we want to tackle: first, whether, how and at which speed financial systemic risk is sensitive to physical risks; second, how the market reacts to brown and green companies' equity performance.

In their stress testing exercises and scenario analyses aimed at assessing the resilience of financial institutions, supervisory authorities make recourse to hypothetical climate scenarios covering both transition and physical risk, as well as short-term and long-term perspectives. Even if these scenarios must be considered hypothetical and do not necessarily represent the most likely future outcomes, by accounting for a range of possible future climate pathways, as well as the associated economic and financial developments, their analysis can help to understand how climate-related financial risks may materialize. In this sense, supervisors' approaches are forward looking by nature. Nevertheless, running such exercises is not an easy task: in comparing climate stress testing with traditional solvency stress tests, Baudino and Svoronos (2021) find that the main issues are those referred to data availability, capturing financial risks over long horizons, modelling physical risk and developing models that can convert climate scenarios into financial variables. Further, the likelihood of the realization of a given climate scenario pathway is uncertain and depends on the ability of countries to introduce coordinated climate policies and on the rational reaction of socioeconomic agents in terms of their consumption and production behaviour (Monasterolo, 2020).

In this regard, our method does not rely on hypotheses concerning the evolution of climate factors. We study the impact on financial systemic risk of climate events actually occurred and of the historical market performance of green and brown companies. In this paper we do not need to identify future scenarios about the evolution of climate change-related factors, in terms neither of physical (e.g., global temperature rise) nor institutional (e.g., carbon tax) shocks. Our analysis accounts for the fact that, even if the timescale of climate change impacts is two decades or more, investors might base their decisions on a much shorter time horizon and on a market backward-looking benchmark that is estimated on past companies' performance (Monasterolo, 2020). Even if we acknowledge that the past does not necessarily represent a good guide for the future, looking at what has already happened can give us some useful insights on what can happen and how policy makers and financial institutions and supervisors can act to better combat the climate change and more effectively manage the transition to a low carbon economy.

3. Methodology

In Section 3.1, we present the methodology used to estimate systemic risk of the US banking and insurance sectors. We use the $\Delta CoVaR$, as proposed by Adrian and Brunnermeier (2016), and the MES by Acharya et al. (2017). As discussed in Section 3.2, we perform a formal test to investigate whether, to what extent and how quickly these market-based SRMs incorporate the information deriving from a sample of climate-induced catastrophes observed in the US from December 12, 2015 to July 30, 2022. In Section 3.3, we describe the quantile regression method through which we investigate the impact of the performance of green and brown market indexes on the stability of the US banks and insurers during the same period.

3.1. Measuring financial systemic risk

Adrian and Brunnermeier (2016) introduced the $\Delta CoVaR$ as a measure for market-based systemic risk, which hinges on the most common risk measure used by financial institutions, namely the VaR.[1] This latter focuses on the risk of an individual institution in isolation, which does not necessarily represent its contribution to the overall systemic risk. To emphasize the systemic nature of this risk measure, Adrian and Brunnermeier (2016) added the prefix "Co", which stands for "conditional".

We estimate $\Delta CoVaR^i$ of the US banking and insurance sector (i) as the difference between the $CoVaR$ of sector i conditioned on the distress of the financial system and its $CoVaR$ conditioned on the median state. We denote the q%-VaR quantile by $VaR_{q,Market}$:

$$Pr(X_{Market} \leq VaR_{q,Market}) = q\% \tag{1}$$

where X_{Market} is the US financial system's *"return loss"* for which $VaR_{q,Market}$ is defined. $CoVaR_q^{i|C(X_{Market})}$ is the VaR of sector i that is conditional on some event $C(X_{Market})$ in the financial system. Event C is an event equally likely across institutions, such as the financial system's loss at or above its $VaR_{q,Market}$. $CoVaR_q^{i|C(X_{Market})}$ is implicitly defined by the q%-quantile of the conditional probability distribution:

$$Pr(X^{i|C(X_{Market})} \leq CoVaR_q^{i|C(X_{Market})}) = q\% \tag{2}$$

The $\Delta CoVaR$ of sector i that is conditional on the entire financial system being under distress is computed as follows:

$$\Delta CoVaR_q^i = CoVaR_q^{i|X_{Market}=VaR_{q,Market}} - CoVaR_q^{i|X_{Market}=VaR_{50^{th},Market}} \tag{3}$$

We use a quantile regression to estimate $\Delta CoVaR$. In particular, following Adrian and Brunnermeier (2016), we estimate the following:[2]

$$X_{q,i} = \alpha_q + \beta_q X_{q,Market} \tag{4}$$

where $X_{q,i}$ and $X_{q,Market}$ denote sector i and the financial system return loss, respectively. Using the predicted value of $X_{Market} = VaR_{q,Market}$, we yield the $CoVaR_{q,i}$ measure as follows:

$$CoVaR_q^i = VaR_q^{i|X_{Market}=VaR_{q,Market}} = \hat{\alpha}_q + \hat{\beta}_q VaR_{q,Market} \tag{5}$$

where $VaR_{q,Market}$ is the q%-quantile of the financial system losses. Based on Eq. (3), we estimate $\Delta CoVaR_q^i$ as:

$$\Delta CoVaR_q^i = CoVaR_q^i - CoVaR_q^{i|X_{Market}=VaR_{50^{th},Market}} = \hat{\beta}_q(VaR_{q,Market} - VaR_{50^{th},Market}) \tag{6}$$

Based on Eq. (6), we estimate $\Delta CoVaR_{95^{th}}^i$ as the difference between the predicted $CoVaR$ at the 95th quantile and the one at the 50th quantile.

Our study considers equity losses with positive values. For this reason, in the empirical results, we consider only positive values for $VaR_{q,t}^i$ and $CoVaR_{q,t}^i$, because a negative capital shortfall indicates a capital surplus.[3]

In addition, as an alternative measure for market-based systemic risk, we estimate the MES proposed by Acharya et al. (2017), which is defined as the ES of sector i in the tail of the financial system's loss distribution.[4] This measure can be interpreted as the losses of the US banking and insurance sectors when the entire financial system is in a tail event.

We estimate the MES as the average return of sector i portfolio during the 5% worst days for the financial system. This measure estimates the equal-weighted average return of any given sector (R^i) for the $q = 5\%$ worst days of the financial system returns (R^m):

$$MES_{q\%}^i = \frac{1}{\#days} \sum R_t^i \tag{7}$$

Both the $\Delta CoVaR$ and the MES are estimated considering a 1-year moving window.

The $SRISK$ by Brownlees and Engle (2017) might also be used to identify the contribution of each financial sector to systemic risk as it measures the capital shortfall conditional on a severe market decline.[5] Since it is computed by also accounting for balance-sheet variables, the $SRISK$ is less volatile compared to $\Delta CoVaR$ and MES, but also less suitable when investigating the reactions of systemic risk to volatile events such as climate-induced catastrophes, which is the reason why we choose not to adopt this systemic risk measure in our analysis.

3.2. Testing the impact of climate-induced catastrophes on financial systemic risk

As in Morelli and Vioto (2020), to analyse the impact of physical risks associated with climate disasters on financial systemic risk, we use the Wilcoxon signed rank sum test for paired data,[6] which allows to test

[1] For several studies providing extensions of the $\Delta CoVaR$ estimation method see among others Girardi and Ergün (2013), López-Espinosa et al. (2012), Reboredo and Ugolini (2015), Sedunov (2016).

[2] For simplicity of exposition we drop the index notation and the error term from the regression equation.

[3] We estimate negative values for $VaR_{q,t}^i$ and $CoVaR_{q,t}^i$ only at the 50th quantile, which represents the median state, so the absence of a distress for sector i.

[4] For extensions and further studies on the relevance of the MES, see Idier et al. (2014) and Banulescu and Dumitrescu (2015).

[5] Other systemic risk measures have also been proposed. For a comprehensive description of the main systemic risk measures, readers can refer to the survey papers by Bisias et al. (2012) and Silva et al. (2017).

[6] We chose the Wilcoxon signed rank sum test because it requires no or very limited assumptions to be made about the format of the data. It can be useful for dealing with unexpected, outlying observations that might be problematic with a parametric approach. Nevertheless, we are aware that non-parametric methods may lack power as compared with more traditional approaches, which is a particular concern if the assumptions for the corresponding parametric method hold, and adjustments to the test statistic may be necessary. For a detailed description of the Wilcoxon signed rank sum test, readers can refer to Wilcoxon (1945).

whether, to what extent and how quickly SRMs of the US banking and insurance sectors react to the billion-dollar weather and climate disasters occurred during our sample period. We first investigate whether the systemic risk of US banks and insurers observed during the h days a natural catastrophe lasts — i.e., between day h and day $t+h$; is greater than that recorded h days before, thus applying the Wilcoxon signed rank sum test to the following null hypothesis:

$$H_0 : SRM^i_{t:t+h} \leq SRM^i_{t-h-1:t-1} \tag{8}$$

$$H_1 : SRM^i_{t:t+h} > SRM^i_{t-h-1:t-1} \tag{9}$$

where i indicates the sector under analysis and t is the day when the extreme climate event starts. The failure to reject the null hypothesis (8) implies that the market does not perceive an increase in systemic risk for the sector i during a specific climate-induced catastrophe.

In addition, we apply the Wilcoxon signed rank sum test to two more null hypotheses. We first test whether the systemic risk of the banking and insurance sectors during the h days after the event — i.e., from day $t+h+1$ to day $t+2h+1$; is greater than that referred to the h days preceding the start of the event — i.e., between day $t-h-1$ and day $t-1$; with the following hypotheses to be tested:

$$H_0 : SRM^i_{t+h+1:t+2h+1} \leq SRM^i_{t-h-1:t-1} \tag{10}$$

$$H_1 : SRM^i_{t+h+1:t+2h+1} > SRM^i_{t-h-1:t-1} \tag{11}$$

Finally, we test whether the systemic risk of the US banking and insurance sectors observed during the h days after the end of the event, from day $t+h+1$ to day $t+2h+1$, is greater than that experienced by the two financial sectors during the event. The associated hypotheses are as follows:

$$H_0 : SRM^i_{t+h+1:t+2h+1} \leq SRM^i_{t:t+h} \tag{12}$$

$$H_1 : SRM^i_{t+h+1:t+2h+1} > SRM^i_{t:t+h} \tag{13}$$

3.3. Investigating the relationship between the performance of green and brown companies and financial systemic risk

To detect the potential impact of the performance of green and brown companies on the systemic risk of US banks and insurers, we use green and brown market indexes, by accounting for their levels and two risk measures — i.e., the Value at Risk (VaR) and the Expected Shortfall (ES). To study the relationship between these indexes and our SRMs, we use Koenker and Bassett Jr. (1978)'s quantile regression method. Unlike classical linear regression methods, which can only provide inference on the conditional mean functions, thus losing information about the tails of the distribution, quantile regressions allow to estimate models for the conditional median function and for the full range of all the other conditional quantile functions. Therefore, we test whether the relationship between green and brown indexes and market-based SRMs is sensitive to different quantiles.

In the simplest terms, we run the following quantile regression:

$$y_i = \alpha_\tau + \beta_\tau x'_i + \varepsilon_{\tau,i} \tag{14}$$

where y_i is the measure for systemic risk — either, $\Delta CoVaR$ or MES; x'_i is the independent variable represented by the level and extreme risk measures of green and brown indexes; α_τ is the constant; β_τ is the vector of the estimated relationship coefficients, and ε_τ is the error term. The subscript $\tau \in (0,1)$ represents the quantile. We write the τ^{th} conditional quantile function as $Q_\tau(y|x) = \beta_\tau x'$.

The estimator $\hat{\beta}_\tau$ is computed by minimizing the weighted sum of the absolute errors, where the weights are dependent on the quantile values:

$$\hat{\beta}_\tau = arg\ min\left(\sum_{i=y_i>x'_i\beta_\tau} \tau \left| y_i - x_i\beta_\tau \right| + \sum_{i=y_i<x'_i\beta_\tau} (1-\tau) \left| y_i - x_i\beta_\tau \right| \right) \tag{15}$$

Overall, we expect a negative relationship between US banks' and insurers' systemic risk and the level of both green and brown market indexes, since a raise in these latter would be associated with an increase in the value of the share of their assets represented by investments in green and brown sectors. Vice versa, SRMs are expected to have a positive relationship with VaR and ES measures calculated on the market indexes. We estimate non-parametric historical VaR and ES at 5% confidence level, using a 1-year moving window. The VaR is the realized loss of the index at the 95th quantile each day t; while the ES is the average of the worst 5% realizations of the index each day t.

As previously explained, the quantile regression focuses on estimating the interrelation between the dependent variables and their predictors at the median level ($\tau = 0.5 = 50$th) and at any other specific quantile. In our study, we consider estimates at the 5th, 10th, 50th, 90th and 95th quantiles. In the literature, low quantiles (e.g., up to the 50th) are considered tranquil periods in the market; while high quantiles (e.g., above the 75th) represent distressed conditions in the market (see, e.g., Adrian and Brunnermeier, 2016).

4. Data

To estimate our measures of systemic risk, we collect data on the daily values of the S&P 500 Banks Industry Group GICS Level 2, S&P 500 Insurance Industry Group GICS Level 2 and S&P 500 Financials Sector GICS Level 1 Index, which is used as proxy for the whole US financial system. We are strongly motivated to consider the GICS framework[7] because it has become widely recognized by market participants worldwide and enables meaningful comparisons of sectors and industries. Moreover, MSCI and Standard & Poor's review the entire framework annually to ensure an accurate representation of the marketplace.

We consider the following two green indexes: (i) MSCI USA Select Green 50 3% Decrement Index, which is designed to track the performance of the largest 50 stocks from the MSCI USA Investable Market Indexes that offer products and services that contribute to an environmentally sustainable economy; and, (ii) the NASDAQ OMX Green Economy US Index, which aims to track the performance of companies across the spectrum of industries most closely associated with the economic model around sustainable development through every economic sector and involved in the reduction of fossil-sourced fuels, products, services, and lifestyles domiciled in the United States.

We calculate three capitalization weighted indexes of listed US polluters, as identified by the Political Economy Research Institute at the University of Massachusetts Amherst, defined as the Greenhouse 100 Polluters Index, Toxic 100 Air Polluters Index and Toxic 100 Water Polluters Index. They comprise the top greenhouse gas emitters and the top corporate air and water polluters using the most recent data available from the US Environmental Protection Agency.[8]

Market data are all downloaded from Bloomberg. As argued by Monasterolo and De Angelis (2020) and Ehlers et al. (2022), financial markets started paying attention to climate issues only after the 2015 Paris Agreement. For this reason, we study both green and brown indexes over the period from December 12, 2015, when the final wording of the Paris Agreement was adopted by consensus by the 195 states and the European Union, to July 31, 2022.

We select climate-induced disasters from the list of billion-dollar weather and climate disasters published by the National Centers for Environmental Information (NCEI). As part of its responsibility of monitoring and assessing the climate, NCEI tracks and evaluates climate

[7] For a detailed description of the GICS methodology, readers can refer to: "Global Industry Classification Standard (GICS) Methodology", Standard & Poor's, 2009; or, https://www.msci.com/gics.

[8] For a detailed description of the Top 100 Polluter indexes, readers can refer to: https://peri.umass.edu/top-100-polluter-indexes.

Table 1
Descriptive statistics of the market-based SRMs and the green and brown indexes.

	Mean	Median	Std. dev.	Skewness	Min	Max	1 percent Stress
$\Delta CoVaR^{Banks}$	4.12	2.72	4.04	2.32	0.62	21.08	17.24
$\Delta CoVaR^{Insurers}$	3.01	1.91	3.25	2.65	0.54	15.07	14.22
MES^{Banks}	3.17	2.46	2.28	1.44	0.57	11.63	11.01
$MES^{Insurers}$	2.71	2.07	1.99	1.50	0.61	8.52	7.98
MSCI USA Select Green 50 3% Decrement Index	2032.45	1748.22	665.62	0.85	1132.73	3640.92	3527.15
VaR	1.63	1.60	0.64	0.58	0.66	3.04	3.04
ES	2.34	2.03	1.13	1.24	0.85	4.94	4.94
NASDAQ OMX Green Economy US Index	2949.98	2697.31	920.47	1.59	1493.42	5128.20	5038.38
VaR	1.92	1.82	0.71	0.52	0.80	3.42	3.42
ES	3.02	2.69	1.27	1.30	1.53	5.87	5.87
Greenhouse 100 Polluters Index	38643.18	38606.48	6018.67	0.01	22373.11	52213.88	28022.08
VaR	1.87	1.61	0.95	1.66	0.73	4.88	3.44
ES	2.74	2.19	1.56	1.62	0.94	6.94	5.77
Toxic 100 Air Polluters Index	38132.22	38126.31	5803.55	−0.21	20240.48	52267.21	34334.33
VaR	1.88	1.64	0.93	1.40	0.63	4.63	4.21
ES	2.76	2.25	1.53	1.47	0.85	6.84	6.52
Toxic 100 Water Polluters Index	42875.47	43164.28	6268.94	−0.35	22127.37	58843.82	27990.57
VaR	1.81	1.63	0.88	1.26	0.64	4.32	4.21
ES	2.69	2.27	1.48	1.46	0.86	6.36	5.35

Notes: The descriptive statistics for the market-based SRMs of the US banking and insurance sectors, and the green and brown indexes. The 1 percent stress corresponds to the variable realizations in the worst 1 percent of S&P 500 Financials Sector GICS Level 1 Index returns. Note that, as stated in Section 3, market-based SRMs are estimated considering an equity loss with positive values.

events in the US and globally that have great economic and societal impacts.[9] From this list of weather and climate events that had overall damages reaching or exceeding 1 USD billion from 1980, we select those occurred between January 1, 2005 and July 31, 2022 and lasting more than two and less than thirty days.[10] Our selection of climate-induced disasters (122 in total) includes 74 severe storms, 20 tropical cyclones, 17 floodings, 6 winter storms, 3 freezes and 2 wildfires, with an average cost of 2.3, 30.4, 3.1, 2.1, 1.8 and 11.2 USD billion, respectively. We use these events to test the hypotheses discussed in Section 3.2.

Table 1 presents the summary statistics of: (i) the market-based SRMs of the US banking and insurance sectors; and (ii) the level, VaR and ES of both green and brown indexes. The column labelled "1 percent Stress" shows the value of each variable in the worst 1 percent realization of the financial system returns — i.e., S&P 500 Financials Sector GICS Level 1 Index returns. The mean $\Delta CoVaR$ tends to be larger than the mean MES for both banks and insurance companies. On average, banks appear to be more exposed to systemic risk than insurance companies and show a larger difference between minimum and maximum values for both SRMs.

Green indexes have a positive skewness, which turns negative for brown indexes, except for the case of the Greenhouse 100 Polluters Index, which shows a skewness close to zero. In the period we consider, investing in green companies generates frequent small losses and few large gains, whereas an investor in brown firms may expect frequent small gains and few extreme losses. Moreover, both VaR and ES referred to brown indexes reach higher mean values and are characterized by a greater volatility if compared to the VaR and ES calculated for green indexes.

Table 2 shows the correlation coefficients from the time series of both green and brown indexes. The two green indexes have a strong positive and statistically significant correlation among them, with a Pearson correlation coefficient equal to 97.1%. The same result is found among brown indexes, where correlation coefficients are greater than 92.4%. Though statistically significant, green indexes show much lower correlation coefficients with brown ones, with values ranging from 34.9% to 35.5%.

5. Results

In Section 5.1 we present the results of the statistical tests on US banks' and insurers' SRMs reaction to billion-dollar weather and climate disaster events. Section 5.2 shows how the equity performance of green and brown indexes affects SRMs of the US banking and insurance sectors. The issues investigated in these two subsections are strictly interconnected under the perspective of the adoption of climate policies, which are meant to combat the increase in the frequency of extreme weather events and in the damages they produce, on the one hand, and are going to change the greenness (brownness) of financial companies' asset portfolios, on the other.

5.1. Climate-induced catastrophes and financial systemic risk

Table 3 presents the results of the Wilcoxon signed rank sum test used to verify the hypotheses discussed in Section 3.2, aiming at testing whether, how and at which speed SRMs of the financial system react to physical risk.[11] For each of the three null hypotheses we calculate the success ratio — i.e., the percentage of climate catastrophes for which we reject the hypothesis, by adopting a confidence level of 1%, 5% and 10%, respectively.

Overall, our results show that 51 extreme weather events have an impact on financial systemic risk considering all the three significance thresholds. We have also performed a case-by-case control to check that no other macroeconomic or financial major event has affected our impact study.[12] 45 of these events have a cost between 1 and

[9] For a detailed description of the NCEI, the methodology to identify climate-inducted disasters and the data sources used, readers can refer to: https://www.ncdc.noaa.gov/billions/. The complete list of climate-induced disasters is available at: https://www.ncdc.noaa.gov/billions/events.

[10] The average length of our sample climate related extreme events is 4 days and around 95% lasted less than 6 days.

[11] The table containing individual results for each of the 122 climate-inducted disasters is available upon request.

[12] We performed the following testing procedure: 1. We isolated the dates of potentially relevant events — i.e., main financial and geo-political events, namely FED's decisions on monetary policy interest rates and communications about stress tests results, presidential elections, global financial crisis (GFC), USA-China trade war and COVID-19 pandemic, for a total of 211 dates (4 for the GFC, 3 for COVID-19, 11 for stress tests, 142 for interest rates changes, 47 for USA-China trade war, and 4 for presidential elections). 2. For each of the climate disasters that increased financial systemic risk at least in one of the hypotheses discussed in Section 3.2, irrespective of the measure ($\Delta CoVaR$ vs. MES) and of the confidence interval, we performed a matching analysis on the days each event lasts and the dates of the potentially relevant events mentioned above. None of such dates is included in the period the climate disasters able to significantly affect systemic risk measures lasted. The excel file where we run this procedure is available upon request.

Table 2
Pearson correlation matrix for the green and brown indexes.

	MSCI USA Select Green 50 3% Decrement Index	NASDAQ OMX Green Economy US Index	Greenhouse 100 Polluters Index	Toxic 100 Air Polluters Index	Toxic 100 Water Polluters Index
MSCI USA Select Green 50 3% Decrement Index	1	0.9713***	0.3524***	0.3496***	0.3554***
NASDAQ OMX Green Economy US Index	0.9713***	1	0.3501***	0.3494***	0.3554***
Greenhouse 100 Polluters Index	0.3524***	0.3501***	1	0.9243***	0.9284***
Toxic 100 Air Polluters Index	0.3496***	0.3494***	0.9243***	1	0.9816***
Toxic 100 Water Polluters Index	0.3554***	0.3554***	0.9284***	0.9816***	1

Notes: The Pearson correlation coefficients from the time series of the green and brown indexes. The ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 3
Climate-induced catastrophes and US banks' and insurers' market-based SRMs.

Panel A: Success ratio of the Wilcoxon signed rank sum test for $\Delta CoVaR$						
	Banks			Insurers		
Significance threshold	*1%*	*5%*	*10%*	*1%*	*5%*	*10%*
H_0: $\Delta CoVaR^i_{t:t+h} \leq \Delta CoVaR^i_{t-h-1:t-1}$	1.64%	9.02%	18.85%	0.82%	7.38%	16.39%
H_0: $\Delta CoVaR^i_{t+h+1:t+2h+1} \leq \Delta CoVaR^i_{t-h-1:t-1}$	1.64%	11.48%	18.85%	1.64%	10.66%	18.85%
H_0: $\Delta CoVaR^i_{t+h+1:t+2h+1} \leq \Delta CoVaR^i_{t:t+h}$	0.82%	5.74%	9.84%	1.64%	7.38%	10.66%
Panel B: Success ratio of the Wilcoxon signed rank sum test for MES						
	Banks			Insurers		
Significance threshold	*1%*	*5%*	*10%*	*1%*	*5%*	*10%*
H_0: $MES^i_{t:t+h} \leq MES^i_{t-h-1:t-1}$	2.46%	4.92%	9.02%	2.46%	5.74%	8.20%
H_0: $MES^i_{t+h+1:t+2h+1} \leq MES^i_{t-h-1:t-1}$	4.10%	9.02%	13.93%	3.28%	8.20%	13.93%
H_0: $MES^i_{t+h+1:t+2h+1} \leq MES^i_{t:t+h}$	1.64%	4.92%	6.56%	0.82%	3.28%	7.38%

Notes: The Wilcoxon signed rank sum test aims to determine whether the systemic risk of the US banking and insurance sectors during (after) the h days of the selected climate-induced catastrophes, is greater than the systemic risk h days before (during, before). t is the starting date of the climate-induced catastrophe and h is its length. Rows indicate the null hypotheses tested (H_0), which are described in Section 3.2. The success ratio indicates the number of climate-induced catastrophes for which we reject each null hypothesis, by adopting a confidence level of 10%, 5% and 1%, respectively.

10 USD billion,[13] entailing that the size of the event in terms of the costs it generates is not the only factor explaining its relevance from a financial systemic risk perspective. Even if not all the extreme events we consider are able to affect the systemic risk of US banks and insurers, by highlighting the presence of a significant impact for some of them, our findings support the prompt adoption of climate policies able to contrast the potential increase of such events frequency and severity in the next future.

As far as the speed at which physical risk transmits to the financial system is concerned, we notice that: (i) relative to the period before their initial day, the number of the events able to determine a significant increase in the SRMs after their final day is equal or higher than the number of those that produce a significant increase in the SRMs during the days they last (the success ratios of row n. 1 are not higher than those of row n. 2 for both Panels A and B). This implies that the market perceives the impact of an extreme weather event in terms of financial systemic risk mainly after it terminates, and not necessarily when it occurs; (ii) there is a smaller number of cases in which SRMs experience a significant increase after the events end, relative to the days they last, which signals either a further raise in the financial systemic risk relative to the period before the events start, or the first time the market reacts (the success ratios of row n. 3 are never higher lower than those of rows n. 1 and 2 for both Panels A and B).

Focusing on the 1% confidence level and the $\Delta CoVaR$, the systemic risk sensitivity of US banks and insurers to climate disasters is driven by two tropical cyclones, namely, the Southern Tornado Outbreak (March 2022), when the success ratio is at least 0.82%, together with the Hurricane Dorian (September 2019), when the success ratio equals 1.64%. By measuring systemic risk through the MES, three more climate related disasters have an impact on US banks' systemic risk, namely Southeast Tornadoes and Severe Weather (March 2021), Arkansas River Flooding (June 2019) and Missouri and Arkansas Flooding and Central Severe Weather (May 2017), of which the last two affect also insurers' MES. Under the 5% (10%) confidence level, the $\Delta CoVaR$ of both the US banking and insurance sectors raises 10 (16) times due to severe storms, 3 (6) times because of tropical cyclones and in just 1 (1) case of floodings. Correspondingly, the MES increases 5 (15), 3 (6) and 1 (2) time.

The level of systemic risk measured by $\Delta CoVaR$ during a climate-induced catastrophic event is significantly higher than that observed before the disaster in 9.02% (18.85%) of our sample events for US banks and in 7.38% (16.39%) of the cases for US insurance companies (row n. 1 of Panel A) according to the 5% (10%) significance threshold, respectively. Measuring systemic risk through the MES, the corresponding values are 4.92% (9.02%) for banks, and 5.74% (8.20%) for insurers (row n. 1 of Panel B).

As for the hypotheses of a significant increase in the level of SRMs after the end of the extreme climate event — i.e., in the h-day period starting after the final day of the event, in comparison with the h-day period before its initial day (rows n. 2 of both Panel A and Panel B), the success ratios referred to US banking sector's $\Delta CoVaR$ are higher than those of the insurance one according to the 5% and 10% significance thresholds. When the systemic risk measured during the h-day period following the event is compared with the h-day period the event lasts (rows n. 3 of both Panel A and Panel B), US insures' $\Delta CoVaR$ is higher than that observed for the banking sector under both 5% and 10% significance thresholds. US banks' MES calculated after the end of the event is also higher than that observed during the h day period the event lasts (equal to) and before (lower) the event starts under the 5% (10%) significance threshold.

5.2. Green and brown companies' performance and financial systemic risk

Policies to combat climate change are expected to have a tremendous impact in the asset portfolios of banks and insurers, presumably

[13] Hurricane Rita (September 2005), Hurricane Katrina (August 2005), Southeast/Ohio Valley/Midwest Tornadoes (April 2011), Hurricane Matthew (October 2016), Hurricane Irma (September 2017) and Hurricane Harvey (August 2017) had a cost higher than 10 USD billion, amounting at 11.1, 12.1, 25.5, 53.5, 133.7 and 172.5 USD billion, respectively.

Table 4
$\Delta CoVaR$ and green indexes.

	Panel A: $\Delta CoVaR^{Banks}$					
	MSCI USA Select Green 50 3% Decrement Index			NASDAQ OMX Green Economy US Index		
	$Index$	VaR	ES	$Index$	VaR	ES
OLS	−0.4312***	2.9125***	1.5459***	−0.0710***	3.2569***	1.3031***
$adj.R^2$	21.83%	86.11%	94.75%	20.04%	90.84%	91.74%
Quantile Regression						
τ = 5th	−0.3710***	2.7143***	1.7102***	−0.0312***	2.6043***	1.4229***
$adj.R^2$	15.39%	22.84%	53.38%	21.76%	39.68%	51.12%
τ = 10th	−0.2918**	1.9024***	1.6933***	−0.0314***	3.0090***	1.3881***
$adj.R^2$	16.16%	29.50%	56.77%	20.66%	41.49%	54.94%
τ = 50th	−0.3147***	2.9051***	1.5402***	−0.0567***	3.2898***	1.3208***
$adj.R^2$	20.33%	51.21%	73.89%	22.41%	62.47%	68.51%
τ = 90th	−0.8512***	2.9792***	1.4665***	−0.1300***	3.0966***	1.0934***
$adj.R^2$	27.21%	75.84%	82.04%	37.52%	80.27%	73.31%
τ = 95th	−0.9333***	2.9759***	1.4629***	−0.1271***	3.0670***	1.0724***
$adj.R^2$	38.33%	74.94%	77.85%	32.96%	77.94%	70.61%
	Panel B: $\Delta CoVaR^{Insurers}$					
	MSCI USA Select Green 50 3% Decrement Index			NASDAQ OMX Green Economy US Index		
	$Index$	VaR	ES	$Index$	VaR	ES
OLS	−0.2340***	1.6492***	0.8455***	−0.0612***	1.8269***	0.7191***
$adj.R^2$	21.59%	92.45%	94.92%	21.00%	95.71%	93.57%
Quantile Regression						
τ = 5th	−0.1811**	1.2281***	0.8929***	−0.0410***	1.9116***	0.7491***
$adj.R^2$	18.34%	65.64%	64.55%	22.82%	74.73%	64.19%
τ = 10th	−0.1825***	1.1909***	0.8502***	−0.0512***	1.8823***	0.7377***
$adj.R^2$	19.34%	66.57%	67.89%	22.19%	75.32%	67.27%
τ = 50th	−0.2642***	1.5605***	0.8375***	−0.0981***	1.8049***	0.6938***
$adj.R^2$	24.13%	67.94%	74.08%	21.95%	75.94%	68.82%
τ = 90th	−0.4310***	1.8535***	0.8769***	−0.1212***	1.8557***	0.7131***
$adj.R^2$	27.45%	79.56%	80.47%	31.64%	80.92%	81.00%
τ = 95th	−0.5043***	1.8632***	0.8304***	−0.1423***	1.8091***	0.7116***
$adj.R^2$	26.32%	78.07%	77.04%	27.87%	78.98%	77.36%

Notes: The coefficients from the time series regression analysis with the $\Delta CoVaR$ as the dependent variable. The independent variables are listed in the header of each column. Intercept results are not reported for the sake of space. The ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

with an increase of their exposure towards green companies and a reduction of their commitment towards brown ones. From a financial stability perspective, this calls for a more in-depth analysis of the relationship between green companies' performance and banks' and insurers' systemic risk. We tackle this issue by investigating whether and how green indexes affect market-based SRMs of the US banking and insurance sectors (see Tables 4 and 5). Moreover, we compare these estimates with those obtained when brown indexes are regressed against the same SRMs (see Tables 6 and 7). This allows us to draw policy implications about the potential effects that the prospective changes in the greenness (brownness) of financial asset portfolios might have on the stability of the financial system. To perform this analysis, we implement a classical linear regression model, together with quantile regressions providing detailed and specific information about the tails of the distribution, where SRMs are the dependent variables and the level, VaR and ES of the green (brown) market indexes are the explanatory variables.

Tables 4 and 5 show the estimates of the regressions with $\Delta CoVaR$ and MES as dependent variables, respectively, and with Panel A of both tables referring to the banking sector, and Panel B to the insurance one. In the column labelled "Index", we study the relation between the level of the specific green index and our SRMs; in the columns labelled "VaR" and "ES", we investigate the impact on $\Delta CoVaR$ and MES of the performance of green indexes, as measured by their VaR and ES.

Overall, in correspondence of the 90th and 95th quantiles of the explanatory variables distributions, we find higher values of the adjusted-R^2 for both $\Delta CoVaR$ and MES, which suggests that systemic risk of US banks and insurers is more dependent on tail performance of green indexes.

The relationship between the level of green indexes and SRMs is overall negative for both banks and insurers, with a larger magnitude observed in the regressions referred to the 90th and 95th quantiles of the explanatory variables' distributions. This indicates that, when green indexes raise, financial systemic risk decreases, both if measured through $\Delta CoVaR$ and MES, and suggests that the better their performance, the stronger is this mitigation effect. In contrast, both the market-based SRMs are positively related to the VaR and ES of green indexes, with a more intense reaction than that observed for their levels. Moreover, when comparing the two financial sectors, systemic risk of the US banks appears to be more affected by green indexes, if compared to what we observe for the insurers. This seems to imply that, from a systemic risk perspective, the market perceives banks as more exposed to a change in the greenness of their asset portfolios. We argue this is the evidence of the stronger and more direct link, in comparison with the insurance companies, between banks and green firms, which might be due to the financial support banks ensure to such firms through their lending activity.

Following the same structure of Tables 4 and 5, Tables 6 and 7 present the results of the regression models used to detect the impact of the brown indexes' performance on $\Delta CoVaR$ and MES, respectively. Again, Panel A and Panel B of both the tables show the estimates referred to the banking and insurance sectors, respectively.

The evidence we find is qualitatively similar to that discussed for green indexes, with a negative (positive) relationship between the level (VaR and ES) of brown indexes and SRMs. Nevertheless, the coefficients estimated using the level of the indexes as regressor are always close to zero, indicating that the contribution of an increase in brown indexes in terms of systemic risk mitigation is not significant from an economic point of view. As far as the relationship between

Table 5
MES and green indexes.

	Panel A: MES^{Banks}					
	MSCI USA Select Green 50 3% Decrement Index			NASDAQ OMX Green Economy US Index		
	$Index$	VaR	ES	$Index$	VaR	ES
OLS	−0.2341***	2.9466***	1.5959***	−0.1111***	3.3121***	1.3576***
$adj.R^2$	21.72%	86.02%	98.57%	22.17%	91.69%	97.22%
Quantile Regression						
τ = 5th	−0.1097***	2.2083***	1.6290***	−0.0712***	3.2814***	1.4028***
$adj.R^2$	23.58%	52.99%	82.38%	22.52%	54.61%	76.34%
τ = 10th	−0.2091***	2.3333***	1.6216***	−0.0615***	3.2898***	1.3890***
$adj.R^2$	25.65%	52.35%	82.88%	24.79%	54.73%	77.13%
τ = 50th	−0.2912***	2.8609***	1.5406***	−0.0808***	3.3469***	1.3466***
$adj.R^2$	21.37%	47.08%	83.60%	21.75%	61.44%	76.49%
τ = 90th	−0.3511***	3.1950***	1.5945***	−0.1501***	3.2364***	1.2713***
$adj.R^2$	23.05%	72.34%	91.28%	33.37%	79.50%	87.55%
τ = 95th	−0.4196***	2.9588***	1.6063***	−0.2800***	3.1554***	1.2521***
$adj.R^2$	25.96%	68.28%	90.8%	25.51%	75.54%	87.01%
	Panel B: $MES^{Insurers}$					
	MSCI USA Select Green 50 3% Decrement Index			NASDAQ OMX Green Economy US Index		
	$Index$	VaR	ES	$Index$	VaR	ES
OLS	−0.3681***	2.5391***	1.3456***	−0.0900***	2.8334***	1.1498***
$adj.R^2$	21.99%	90.17%	98.91%	22.54%	94.73%	98.44%
Quantile Regression						
τ = 5th	−0.2371***	1.5140***	1.4170***	−0.0701***	2.6672***	1.2113***
$adj.R^2$	22.16%	62.30%	82.00%	22.77%	69.87%	72.87%
τ = 10th	−0.2551***	1.6575***	1.3755***	−0.0600***	2.8228***	1.1825***
$adj.R^2$	22.29%	62.11%	83.58%	24.6%	71.68%	76.72%
τ = 50th	−0.3180***	2.5244***	1.3388***	−0.1309***	2.9921***	1.1280***
$adj.R^2$	19.91%	58.12%	86.67%	23.62%	69.83%	86.14%
τ = 90th	−0.3116***	2.5778***	1.3052***	−0.1425***	2.6827***	1.0966***
$adj.R^2$	25.90%	77.64%	93.20%	35.81%	83.29%	92.27%
τ = 95th	−0.3122***	2.5161***	1.3020***	−0.2254***	2.6850***	1.068***
$adj.R^2$	32.90%	74.37%	92.43%	27.16%	79.37%	90.69%

Notes: The coefficients from the time series regression analysis with the MES as the dependent variable. The independent variables are listed in the header of each column. Intercept results are not reported for the sake of space. The ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

SRMs and the VaR and ES of the brown indexes is concerned, the regression coefficients are generally lower than those referred to the green indexes. This finding turns out to be always verified in tail market conditions and when the VaR is used as the explanatory variable. Therefore, we argue that if the economic environment gets worse and overall non-financial firms' riskiness increases — i.e., higher VaR and ES calculated on the green and brown market indexes; market might perceive investments in brown companies systemically safer than those in green ones.

Different factors can explain this evidence. For example, shifting business practices to be more environmentally friendly can be expensive. To reduce costs, companies have been teaming up with each other and with environmentally focused institutions. While this might be beneficial, allowing companies to grow faster, it might also be a drawback because the same companies might end up to be exposed to common risks, thus increasing the contagion risk under negative market conditions. Moreover, it has been also argued that there could be an excessive investment in green companies, which could lead to unsustainable levels of debts. In particular, as the interest rate rises many of the green young companies that are on the market today could fail.[14] In turn, losses from green companies could spill over to institutions providing financial support, triggering systemic complications within the financial system.

6. Concluding remarks

In recent years the relationship between climate change and financial stability has taken central stage in the policy debate and academic literature (Roncoroni et al., 2021). Nevertheless, from a financial systemic risk perspective, further studies are still needed about the implications stemming from climate-related catastrophes and from the prospective change in the greenness of financial institutions' asset portfolios. We adopt an empirical perspective to tackle these issues by firstly examining whether, to what extent and how quickly $\Delta CoVaR$ and MES of US banking and insurance sectors react to billion-dollar weather and climate catastrophes. Then, we investigate the link between the systemic risk of US banks and insurers and the performance of green and brown companies, as proxied by green and brown market indexes.

Based on our evidence, even if climate-induced disasters do not necessarily have an impact on financial systemic risk, the presence of a statistically significant relation between some of the billion-dollar weather and climate catastrophes and US banks' and insurers' SRMs confirms that physical risks caused by climate change might represent a serious threat to financial stability. This stresses the urgency to design appropriate policies to avoid further increase in the frequency and severity of systemically relevant climate events. As for the implications stemming from the potential increase in the greenness of banks' and insurers' asset portfolios, we observe that higher levels of the green market indexes mitigate systemic risk, unlike a raise in brown indexes, with an increasing magnitude in the higher quantiles. However, a raise in the VaR or ES of green indexes worsens financial systemic risk more than an increase in the two risk measures calculated for brown indexes.

[14] Satoshi Kambayashi (May 21, 2021). "A green bubble? We dissect the investment boom", *The Economist*. Retrieved from: https://www.economist.com/finance-and-economics/2021/05/17/green-assets-are-on-a-wild-ride.

Table 6
$\Delta CoVaR$ and brown indexes.

	Panel A: $\Delta CoVaR^{Banks}$								
	Greenhouse 100 Polluters Index			Toxic 100 Air Polluters Index			Toxic 100 Water Polluters Index		
	$Index$	VaR	ES	$Index$	VaR	ES	$Index$	VaR	ES
OLS	−0.0001***	2.4937***	1.1854***	−0.0001***	2.3766***	1.2424***	−0.0001***	2.2122***	1.1625***
$adj.R^2$	9.59%	92.2%	94.33%	10.14%	87.20%	91.75%	7.18%	89.19%	92.30%
Quantile Regression									
$\tau = 5$th	−0.0001***	2.0349***	1.2434***	−0.0001***	2.6833***	1.4376***	−0.0001***	2.7421	1.3092
$adj.R^2$	5.05%	46.94%	59.79%	14.94%	32.90%	46.89%	3.26%	36.45%	47.00%
$\tau = 10$th	−0.0001***	2.2010***	1.2899***	−0.0001***	2.1569***	1.4064***	−0.0001***	2.6197	1.3096
$adj.R^2$	6.34%	48.81%	61.93%	15.39%	33.51%	49.16%	4.59%	38.91%	48.98%
$\tau = 50$th	−0.0001***	2.5238***	1.1696***	−0.0001***	2.3873***	1.2534***	−0.0001***	2.2684	1.1773
$adj.R^2$	8.53%	64.76%	71.58%	15.36%	53.80%	65.61%	7.92%	58.58%	67.46%
$\tau = 90$th	−0.0003***	2.4673***	1.8000***	−0.0002***	2.3293***	1.1090***	−0.0001***	2.1138	1.0406
$adj.R^2$	15.45%	80.19%	80.08%	16.57%	76.18%	77.14%	10.14%	77.90%	77.30%
$\tau = 95$th	−0.0001***	2.4814***	2.2583***	−0.0001***	2.369***	1.2693***	−0.0001***	2.1533	1.1688
$adj.R^2$	15.78%	76.77%	77.48%	16.29%	72.61%	74.55%	11.95%	74.64%	74.46%
	Panel B: $\Delta CoVaR^{Insurers}$								
	Greenhouse 100 Polluters Index			Toxic 100 Air Polluters Index			Toxic 100 Water Polluters Index		
	$Index$	VaR	ES	$Index$	VaR	ES	$Index$	VaR	ES
OLS	−0.0001***	1.3625***	1.6506***	−0.0001***	1.3506***	0.6940***	−0.0001***	1.2513***	0.6466***
$adj.R^2$	7.63%	92.17%	95.15%	11.51%	94.30%	95.87%	6.64%	95.56%	95.61%
Quantile Regression									
$\tau = 5$th	−0.0001***	1.1283***	1.6656***	−0.0001***	1.4434***	0.6889***	−0.0001***	1.3489	0.6487
$adj.R^2$	7.10%	65.76%	69.48%	15.78%	68.62%	74.65%	8.69%	71.57%	73.62%
$\tau = 10$th	−0.0001***	1.1193***	1.6578***	−0.0001***	1.2151***	0.6833***	−0.0001***	1.2702	0.6431
$adj.R^2$	5.78%	65.06%	71.51%	15.45%	70.23%	77.03%	8.03%	73.04%	75.83%
$\tau = 50$th	−0.0001***	1.3501***	1.6448***	−0.0001***	1.2792***	0.6845***	−0.0001***	1.2077	0.6473
$adj.R^2$	8.34%	65.67%	73.47%	16.34%	73.03%	75.48%	10.53%	74.67%	74.73%
$\tau = 90$th	−0.0001***	1.4226***	1.6495***	−0.0001***	1.4762***	0.7112***	−0.0001***	1.3168	0.6635
$adj.R^2$	9.75%	78.80%	81.92%	15.05%	80.64%	83.98%	13.43%	83.38%	82.64%
$\tau = 95$th	−0.0001***	1.3809***	1.6329***	−0.0001***	1.5698***	0.7056***	−0.0001***	1.3779	0.6401
$adj.R^2$	10.01%	77.35%	79.22%	15.36%	78.34%	79.86%	14.41%	81.40%	78.70%

Notes: The coefficients from the time series regression analysis with the $\Delta CoVaR$ as the dependent variable. The independent variables are listed in the header of each column. Intercept results are not reported for the sake of space. The ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 7
MES and brown indexes.

	Panel A: MES^{Banks}								
	Greenhouse 100 Polluters Index			Toxic 100 Air Polluters Index			Toxic 100 Water Polluters Index		
	$Index$	VaR	ES	$Index$	VaR	ES	$Index$	VaR	ES
OLS	−0.0001***	2.4683***	1.217***	−0.0001***	2.4085***	1.2935***	−0.0001***	2.2426***	1.2102***
$adj.R^2$	8.52%	88.16%	97.04%	10.69%	87.41%	97.08%	7.40%	89.47%	97.64%
Quantile Regression									
$\tau = 5$th	−0.0001***	2.0666***	1.3086***	−0.0001***	2.7839***	1.3735***	−0.0001***	2.6443	1.2806
$adj.R^2$	6.84%	55.69%	71.18%	12.07%	56.17%	74.16%	9.39%	59.33%	75.51%
$\tau = 10$th	−0.0001***	1.9871***	1.2924***	−0.0001***	2.4384***	1.3680***	−0.0001***	2.6760	1.2647
$adj.R^2$	7.38%	54.49%	70.81%	10.06%	56.73%	74.36%	8.35%	59.79%	76.46%
$\tau = 50$th	−0.0001**	2.5361***	1.2035***	−0.0001***	2.5531***	1.2625***	−0.0001***	2.3703	1.1987
$adj.R^2$	7.24%	54.33%	77.15%	13.02%	51.32%	76.64%	12.86%	55.68%	79.45%
$\tau = 90$th	−0.0003***	2.5611***	1.158***	−0.0003***	2.4463***	1.2566***	−0.0003***	2.1138	1.1583
$adj.R^2$	11.69%	74.62%	88.37%	15.42%	71.61%	88.48%	12.83%	73.91%	88.12%
$\tau = 95$th	−0.0001**	2.5111***	1.2212***	−0.0001***	2.5366***	1.2854***	−0.0001***	2.1025	1.1557
$adj.R^2$	15.41%	69.88%	87.34%	13.17%	66.71%	87.17%	12.71%	69.89%	87.18%
	Panel B: $MES^{Insurers}$								
	Greenhouse 100 Polluters Index			Toxic 100 Air Polluters Index			Toxic 100 Water Polluters Index		
	$Index$	VaR	ES	$Index$	VaR	ES	$Index$	VaR	ES
OLS	−0.0001***	2.0848***	1.0287***	−0.0001***	2.0771***	1.102***	−0.0001***	1.9271***	1.0285***
$adj.R^2$	7.29%	88.78%	97.87%	10.63%	91.76%	99.46%	6.57%	93.26%	99.54%
Quantile Regression									
$\tau = 5$th	−0.0001***	1.4746***	1.0914***	−0.0001***	1.6647***	1.1389***	−0.0001***	1.4254	1.0597
$adj.R^2$	4.85%	55.22%	78.97%	13.65%	69.18%	88.78%	7.80%	69.90%	87.61%
$\tau = 10$th	−0.0001***	1.4462***	1.0835***	−0.0001***	1.5547***	1.1326***	−0.0001***	1.4544	1.0430
$adj.R^2$	7.52%	55.17%	81.52%	15.43%	69.20%	89.65%	13.06%	69.71%	89.74%
$\tau = 50$th	−0.0001***	2.1751***	1.0324***	−0.0001***	2.226***	1.0977***	−0.0001***	1.9994	1.0315
$adj.R^2$	9.41%	56.49%	80.81%	13.11%	61.52%	90.93%	11.98%	65.85%	91.88%
$\tau = 90$th	−0.0003***	2.1295***	0.9529***	−0.0002***	2.0516***	1.0827***	−0.0002***	1.8045	0.9930
$adj.R^2$	11.57%	77.63%	90.17%	14.94%	76.15%	94.19%	12.20%	80.67%	94.86%
$\tau = 95$th	−0.0001***	2.0278***	0.9777***	−0.0001***	2.1663***	1.0866***	−0.0001***	1.8196	0.9965
$adj.R^2$	13.34%	72.13%	89.02%	15.02%	70.67%	93.23%	13.00%	76.25%	94.19%

Notes: The coefficients from the time series regression analysis with the MES as the dependent variable. The independent variables are listed in the header of each column. Intercept results are not reported for the sake of space. The ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Overall, our results confirm that climate change and financial system are strictly interconnected and that the former might jeopardize the stability of the latter. Understanding how the systemic risk of the banking and insurance sectors could be impacted by climate disasters and changes in the performance of green and brown companies provides useful insights to prevent potential episodes of financial instability. The evidence that a significant impact on the systemic risk of US banks and insurers is produced by only some of the climate disasters taken into account deserves attention from a policy point of view, due to the potentially increasingly devastating impacts of global warming in the long run. Consequences for banks and insurance companies must not be underestimated since physical risks directly cause losses characterized by a huge magnitude and the ability to rapidly spread and severely impact other financial intermediaries.

Again, from a policy perspective, our results are relevant since they also allow us to argue that, based on the evidence referred to green and brown market indexes, investing in green companies contributes to mitigating financial systemic risk when these companies' performance gives rise to an increase in the respective market indexes. This result does not hold for brown companies: changes in the levels of the corresponding market indexes do not affect the systemic risk of US banks and insurers. When the performance of green and brown companies turns out in a raise in the VaR and ES calculated on the respective market indexes, green firms contribute more than brown ones to the growth of financial systemic risk. Even if the performance and health of green and brown companies might depend on different factors, not necessarily related to the adoption of climate change policies, our findings suggest that these policies should be set considering that, from a financial system stability perspective, issues may come not only from the reduction in the value of brown companies' stranded assets, as mainly pointed out by prior studies, but also from some specific characteristics of the green companies (e.g., newer technology, higher financial fragility, and lower market share), which distinguish them from the brown ones and, under a negative market environment, might determine a larger increase in the systemic risk of their financial counterparties.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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