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Systemic risk and CO_2 emissions in the U.S.[☆,☆☆]

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ABSTRACT

We provide both a theoretical framework and empirical results for the relationship between CO_2 emissions and systemic risk in the U.S. Based on a modified structural distance-to-default model that integrates physical risk effects, a theoretical framework is developed, documenting a positive link between CO_2 emissions and systemic risk. Network VAR analysis, Diebold and Yilmaz variance decomposition, and conditional Granger causality provide empirical support for this positive link. Bank assets are found to be negatively related to CO_2 emissions, which indicates an adjustment of the banking sector's assets towards a lower-carbon economy. Policy implications include government-sponsored insurance support for banks facing insured losses.

1. Introduction

In the aftermath of the 2015 Paris Climate Conference, significant attention has been paid to the relationship between environmental degradation as measured by CO_2 emissions and financial system risk. A recent report by the Network for Greening the Financial System (NGFS, 2019) highlighted that climate change affects the financial system and is a contributor to systemic risk. Central banks identify this as an issue of great importance. Bank of England Governor Mark Carney highlighted the threat of climate change to the stability of the financial system (Carney, 2015). Additionally, regulators acknowledge that climate change is a source of risk relevant to the soundness of financial institutions.[1] Various contributions have explored the link between climate change and firm credit risk (Capasso et al., 2020), showing that companies with a high carbon footprint are more likely to default. This result has implications for financial stability (NGFS, 2019), and opens up the issue of exploring the link between CO_2 emissions and aggregate systemic risk from a macro-prudential policy perspective. The present paper explores the relationship between CO_2 emissions and systemic risk at an aggregate level in the U.S. for the period 1973–2018. Systemic risk refers to the chance that the financial system may become so impaired that severe negative consequences on various facets of economic activity would be inevitable. Systemic risk affects real economic activity (Giglio et al., 2016) and has implications for the banking sector and financial stability (Teteryatnikova, 2014).

To motivate the present work, CO_2 emissions and systemic risk are theoretically linked on the basis of a physical risk effect and a transition risk effect (Bank of England, 2018). The physical risk effect focuses on the impact of CO_2 emissions-driven events (heat waves, droughts, floods, storms) on asset values, the creditworthiness of borrowers, and the losses they face. Extreme weather-related events result in losses for borrowers, reducing their ability to repay loans and increasing the credit risk to banks. Furthermore, the physical risk effect can result in a deterioration of borrowers' ability to repay their debt and thus cause depreciation in the value of assets used for collateral by banks, thereby negatively affecting their assets in turn. In addition, banks hit by such risks may find themselves in a difficult position to refinance themselves, thereby facing liquidity risks with a detrimental effect on both sides of

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[1] https://currency.com/climate-change-will-threaten-banks-profitability-report (accessed 10 July 2020).

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their balance sheets.[2]

The transition effect refers to an adjustment towards a low-carbon economy by reducing CO_2 emissions over a long period in accordance with a carbon abatement agreement such as the Paris Agreement or the Kyoto Protocol. To achieve this goal, the financial system may need to make adjustments in asset financing, such as fossil fuel assets and investment financing,[3] which could prompt a reassessment of the value of such assets (Delis et al., 2018). In a recent report, it was argued that banks produce emissions from loans, with the sector facing pressure to pare back lending to oil companies in order to achieve a net-zero carbon future.[4] Similarly, Lamperti et al. (2021) suggested financial policies to mitigate the physical risk effect on the economy. Although they acknowledge the direct relationship between climate change and credit risk as well as the mediating role of the banking system, they do not shed light on the transmission channels of the physical risk to the economy, which is one of the contributions of this study.

The extant literature covers the link between systemic risk and firms' profitability. For instance, Schied (2006), Acharya et al. (2010), and Chen et al. (2013) identified the inverse relationship between systemic risk and firms' profits using aggregated and individual firms' data. Yang and Zhou (2013) highlighted that the interconnectedness of financial institutions is responsible for financial distress spillover and increased systemic risk. Moreover, Tang et al. (2019) and Hirata and Ojima (2020) emphasized the relationship between the banking system and systemic risk. Specifically, these scholars discussed the impact of systemic risk and portfolio size, and heterogeneity on portfolio performance and vice versa. Hirata and Ojima (2020) pointed out the direct relationship between financial institutions' competition and systemic risk. This unexpected finding is explained by the portfolio structure of Japan's regional banks.

To our knowledge, the present work is the first attempt to explore the impact of CO_2 emissions on systemic risk and makes several contributions. Firstly, we utilise Merton (1974)'s distance-to-default approach to integrate physical risk effect. Moreover, we provide a simple theoretical framework that documents a positive impact of CO_2 emissions on systemic risk, namely that systemic risk increases after an increase in CO_2 emissions. Secondly, we empirically explore the link between CO_2 emissions and systemic risk using network-based methodologies, including network VARs, the Diebold and Yilmaz (2014) variance decomposition approach, and conditional Granger causality. Thirdly, we provide robust empirical evidence that CO_2 emissions positively impact systemic risk, in line with our theoretical conjecture. Finally, we reveal evidence of a negative link from bank assets to CO_2 emissions, suggesting that increasing bank assets is linked to decreasing CO_2 emissions, which is in line with the adoption of financial policies towards a low-carbon economy and the transition effect.

The rest of the paper is structured as follows. Section 2 discusses the literature on systemic risk measurement. Section 3 provides the theoretical framework. Section 4 describes the data. Section 5 outlines the network-based empirical methodologies used in the study. Section 6 discusses the empirical results. Section 7 outlines policy implications, and Section 8 concludes the paper.

2. Measurement of systemic risk

Several authors have attempted to quantify systemic risk through measures of interconnectedness of the financial system or connectedness of financial institutions and sectors. Greater interconnectedness can increase systemic risk and the probability of contagion, and this may signal authorities to take steps to manage or prevent systemic risk.

Most previous work on systemic risk focuses on alternative approaches to its measurement and characterization. One strand of this literature (Kaminsky and Reinhart, 2003; McGuire and Tarashev, 2008) consider information on aggregate country-level bilateral exposures. In an important contribution, Giudici et al. (2020) introduced a measure of systemic risk that complements direct exposures with common exposures and compares them to each other. Another strand uses market data on Credit Default Swaps (CDS), bond spreads, and equity prices (Huang et al., 2009; Acharya et al., 2010), whilst Arvai et al. (2009) adopted simulation techniques to determine probabilities of various potential contagion mechanisms.

Allen et al. (2012) quantified systemic risk by focusing on aggregate catastrophic risk in the financial sector. Based on a Value-at-Risk (VaR) approach, they proposed the CATFIN measure of systemic risk estimated from a cross-section of financial firms at any point in time. CATFIN is a macro-measure of systemic risk, adopting the view that systemic risk can emerge through general factors that cause markets to freeze up. In other words, CATFIN determines the macroeconomic implications of aggregate risk-taking in the financial system. CATFIN has been widely used in the literature (Shan, 2018) as a macro-level aggregate cross-sectional measure of systemic risk that identifies the overall level of systemic risk in the financial system at a point in time.

Billio et al. (2012) measured systemic risk by focusing on four financial sectors, namely hedge funds, banks, broker/dealers, and insurance companies, and proposed a Granger causality network measure of connectedness. The focus on such institutions is motivated by their extensive business ties. The authors concluded that linkages within and across all four sectors are highly dynamic, varying quantifiably over time. In addition, they concluded that all four sectors have become highly interrelated, increasing the channels through which shocks can propagate throughout the finance and insurance sectors. Finally, the authors were able to identify important asymmetry in the connections characterizing these sectors and suggested that banks may be more central to systemic risk than the shadow banking system. An additional feature of the systemic risk characterized by Billio et al. (2012) was that, by competing with other financial institutions in non-traditional business, banks and insurers may have taken on risks more appropriate for hedge funds.

Ahelegbey et al. (2016) proposed a Bayesian, graph-based approach to identify systemic risk using a VAR model known as a BGVAR, which can capture contemporaneous and temporal causal structures and present these in a graphical format. The BGVAR approach of Ahelegbey et al. (2016) provided a data-driven identification of the structural relationships among economic variables and sectors in the Eurozone. Systemic risk is thus measured on the basis of the representation of the linkages between financial and non-financial super-sectors through the application of the BGVAR approach and, ultimately, through an assessment of interconnectedness of the system and potential vulnerabilities.

Diebold and Yilmaz (2014) focused on the empirical concept of connectedness and advanced a framework for conceptualizing and measuring connectedness using variance decompositions from various approximating models. Diebold and Yilmaz (2014)'s connectedness measure refers to both pairwise and systemwide levels and is based on determining shares of forecast error variation (at firm, market, or country level) due to shocks arising elsewhere. Thus, this approach

[2] See Berger et al. (2020), Section 3.3, for a summary of recent studies that look at how severe weather events impact banks.

[3] Wall Street's Carbon Bubble Report (2021), Center for American Progress and the Sierra Club, available at https://www.carbonbubble.net/.

[4] Bloomberg (2021). Banks produce 700 times more emissions from loans than offices. Available at: https://www.bloomberg.com/news/articles/2021-04-27/banks-produce-700-times-more-emissions-from-loans-than-offices?leadSource=uverify%20wall (accessed 28 September 2022).

allows for a multivariate framework in which both direct and indirect linkages can be taken into account. In this approach, the forecast error variance of variable i is decomposed into parts attributed to the other variables in the network (or system), and thus, it is related to the notion of variance decomposition.

Avdjiev et al. (2019) proposed a methodology merging the market price approach and the exposure approach mentioned above. They put forward a network-based distress measure for national banking systems that allows for both banks' CDS spreads and their interaction with the global financial system via various linkages. The derived network measure can be interpreted in terms of a banking system's credit risk or funding risk.

Departing from the previous studies aiming to measure and characterize systemic risk, the current work aims to identify the relationship between systemic risk and CO_2 emissions. Thus, the present study does not aim to contribute alternative systemic risk measures. We use the well-known measure of CATFIN (Allen et al., 2012) as our measure of systemic risk for the U.S. (this measure is publicly available on a monthly basis from 1973), and we seek to identify its connectedness with CO_2 emissions within a multivariate framework, taking into account possible network effects characterizing this relationship.

3. Theoretical framework

Systemic risk emerges from economic conditions that cause banks to reduce the provision of credit (Allen et al., 2012), and from widespread catastrophic events creating risk factors common among banks (Kashyap and Stein, 2000). In the present paper, we consider CO_2 emissions as such to be a risk factor. To model the impact of CO_2 emissions on systemic risk, we adopt Merton's (1974) options-theoretic distance-to-default approach and integrate the physical risk effect.

Merton's (1974) approach is based on the probability of default (*PD*), a determinant of systemic risk (Carlson et al., 2011; Giesecke and Kim, 2011; Allen et al., 2012; Financial Stability Review, 2015; Giudici and Parisi, 2018). To define *PD*, let A_t be the value of the aggregate banking sector's assets, which follows a geometric Brownian motion, and its dynamics is (Merton, 1974):

$$dA_t = \mu A_t dt + \sigma A_t dz_t \tag{1}$$

where dA_t is the banking sector's asset value change, μ is the drift term, σ is the annualized assets volatility, and dz is a Wiener process. Assuming that the log of A_t is normally distributed, we get:

$$lnA_T \sim N(lnA_t + (\mu - \frac{\sigma^2}{2})(T-t), \sigma^2(T-t)) \tag{2}$$

Debt is assumed to consist of a single bond with maturity T and face value K (Capasso et al., 2020). At time T, the shareholders' payoff is the residual value of the assets once the debt is repaid, $(A_T - K)$. The probability of default at time t (PD_t) is the probability that the value of A_T will be less than or equal to the value of liabilities (K) at the time of maturity (T), is $PD_t = \Pr(A_T \leq K)$. Based on Merton (1974), and considering logs, the probability of default (*PD*) is:

$$PD_t = \Pr(\ln(A_T) - \ln(K) \leq 0)$$
$$= \Phi\left(-\frac{\ln(A_t - \left(\mu - \frac{\sigma^2}{2}\right)(T-t) - \ln(K)}{\sigma\sqrt{T-t}}\right) = PD_t|c^{*} \tag{3}$$

where Φ is the cumulative distribution function of the standardized normal variable. Denoting the level of CO_2 emissions by c and the *benchmark* level of CO_2 emissions by c^*, *PD* in (3) is the *PD* conditional on c^*, $PD|c^*$. The physical risk effect is integrated into (3) through K and A_t.

The physical risk effect arises after an increase in CO_2 emissions, $\Delta c > 0$. This leads to climate change risk and weather-related events,[5] causing financial losses to businesses and households. If these CO_2-driven losses are insured, the financial sector will bear the cost with the sector's liabilities, K', going up, $K' > K$. From (3), the new *PD* conditional on $\Delta c > 0$, $PD = \Delta c > 0$, is:

$$PD_t|\Delta c > 0 = \Phi\left(-\frac{\ln(A_t) - \left(\mu - \frac{\sigma^2}{2}\right)(T-t) - \ln(K')}{\sigma\sqrt{T-t}}\right) \tag{4}$$

Additionally, the physical risk effect can induce a deterioration of borrowers' ability to repay their debt and cause depreciation in the value of assets used for collateral by banks, thereby negatively affecting bank assets. In terms of (1), this is reflected in a reduction of μ, $\mu' < \mu$, and thus $A_t' < A_t$. In this case, the *PD* is written as:

$$PD_t|\Delta c > 0 = \Phi\left(-\frac{\ln(A_t') - \left(\mu - \frac{\sigma^2}{2}\right)(T-t) - \ln(K')}{\sigma\sqrt{T-t}}\right) \tag{5}$$

Expression (5) provides an adjusted Merton (1974) theoretical framework that integrates the physical risk effect and reflects the impact of CO_2 emissions on *PD* and, consequently, on systemic risk (Carlson et al., 2011; Giesecke and Kim, 2011). If losses are insured, an increase in CO_2 emissions leads to an increase in K, K', which subsequently causes the distribution Φ to shift. Fig. 1A illustrates this shift, showing that an increase in CO_2 emissions causes an increase in *PD* and, thus, to systemic risk. In addition, the physical risk effect can negatively affect the value of bank assets, rendering $A_t' < A_t$ and causing a further shift of Φ to the right. Fig. 1B illustrates this shift. The combined shift of the distribution Φ to the right, namely the sum of the two shifts shown in Fig. 1A and 1B, establishes a positive impact of CO_2 emissions on systemic risk. The validity of this conclusion is empirically examined next.[6]

4. Variables and data sources

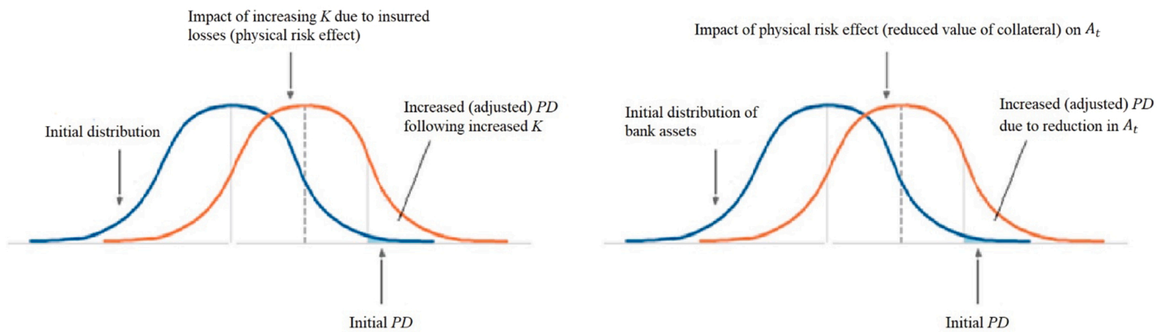
We consider annual CO_2 emissions (in kt) for the period 1973–2018. The 1973–2016 data are from the World Bank, whereas the 2017–2018 data are from FRED.[7] The series is expressed in annual percentage changes. Systemic risk is measured using the CATFIN indicator developed by Allen et al. (2012)[8] CATFIN measures the aggregate catastrophic risk in the financial sector and is a Value-at-Risk (VaR) measure estimated from a cross-section of financial firms at a given point in time. It is defined as the average of three different VaR measures: two using parametric distributions and one using the nonparametric method. It is a macro-measure of systemic risk, adopting the view that systemic risk can

[5] Climate change risk is caused by CO_2 emissions: According to the Anon (2014), CO_2 emissions accounted for 78% of the total green house gas emission increase from 1970 to 2010. A fraction of CO_2 emissions remains in the atmosphere for centuries and causes irreversible damage to climate (Fuss et al., 2014). Thus, climate changes arise from CO_2 emissions into the atmosphere over all time periods (Batten et al., 2016).

[6] This framework could also accommodate the transition risk effect that arises from a long-term *reduction* in c, $\Delta c < 0$ in accordance with a carbon abatement agreement. Such analysis, however, is beyond the scope of the present paper.

[7] The series from FRED starts from 1980, hence we considered the World Bank as the data source starting from 1960. See: U.S. Energy Information Administration, Total Carbon Dioxide Emissions From All Sectors, All Fuels for United States [EMISSCO2TOTVTTTOUSA], retrieved from Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/EMISSCO2TOTVTTTOUSA. https://data.worldbank.org/indicator/EN.ATM.CO2E.KT?locations=US.

[8] Although several other systemic risk measures have been proposed in the literature, we rely on CATFIN because publicly available CATFIN data are available from 1973.



Panel A: Impact of K

Panel B: Impact of reduction in A_t

Fig. 1. An adjusted Merton framework for the impact of CO_2 emissions on systemic risk.

emerge through general factors that cause markets to freeze up. The data for CATFIN is from Turan Bali's website.[9]

We also obtain annual data for real GDP growth.[10] The inclusion of real GDP growth is based on two reasons. First, Giglio et al. (2016) have shown that systemic risk and macroeconomic activity are linked. Second, based on the well-known relationship between real GDP and CO_2 emissions (Kuznets, 1955), real GDP is the main determinant of CO_2 emissions, highlighting the need to account for a possible link between real GDP growth and CO_2 emissions. To explore whether bank assets play a role in the relationship, we consider data for the total assets of all commercial banks in the U.S. from FRED.[11] We also consider data on insured losses (expressed in annual percentage changes) using https://www.iii.org/graph-archive/218221.[12] Table 1 presents descriptive statistics and the augmented Dickey-Fuller unit root test for the variables used in this study. The sample extends over the period 1973–2018, except for insured losses data available from 1981. Based on ADF unit root tests, all variables are stationary. All series are pictorially presented in Fig. 2.

Table 1
Descriptive statistics.

Variables	Mean	Standard deviation	ADF
CATFIN ('catfin')	0.29	0.13	-3.87
Percentage change in bank assets ('Assets')	0.03	0.02	-4.57
Percentage change in CO_2 emissions ('CO_2')	0.003	0.03	-5.63
Real GDP growth ('GDP')	2.75	1.98	-5.25
Percentage change in insured losses ('dl_insured_losses')	0.23	0.75	-9.46

Notes: ADF stands for the augmented Dickey-Fuller unit root test. The number in parenthesis next to the ADF test statistic is the number of augmentation terms in the Dickey-Fuller regression based on the SIC criterion. The 5% critical value of the ADF test is − 2.877. Based on this, all series are stationary at the 5% level.

[9] https://sites.google.com/a/georgetown.edu/turan-bali/

[10] U.S. Bureau of Economic Analysis, Real Gross Domestic Product [GDPC1], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/GDPC1

[11] Board of Governors of the Federal Reserve System (US), Total Assets, All Commercial Banks [TLAACBW027SBOG], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/TLAACBW027SBOG

[12] Insurance Information Institute, https://www.iii.org/graph-archive/218221, and Munich Re, Geo Risks Research, NatCatSERVICE, https://www.munichre.com/en/solutions/for-industry-clients/natcatservice.html. Data are obtained using a digital reader.

5. Empirical methodology[13]

5.1. Network Vector Autoregression (Network VAR)

The introduction of networks in Vector Autoregressions (VARs) enables modelling the serial, temporal and contemporaneous relationships in a multivariate time-series framework. In a network model capturing the relationships between variables, each variable is defined by a node. The statistical relationship between a pair of variables is reflected by "arrows" joining the nodes. The network VAR approach for modelling the connecting relations between systemic risk, CO_2 emissions, bank assets, and real GDP growth for the USA is presented below.

Let $Y_t = (Y_t^1, Y_t^2, \ldots Y_t^n)$, where Y_t^i is the realization of the i-th variable at time t. For our purposes, Y_t can be a 4×1 vector that depicts the behavior of systemic risk, CO_2 emissions, bank assets, and real GDP growth at time t. The dynamic evolution of Y_t is described by a Vector Autoregressive process of order p, VAR(Y_t), as shown below:

$$Y_t = \sum_{s=1}^{p} B_s Y_{t-s} + U_t \tag{6}$$

and

$$U_t = B_0 U_t + \varepsilon_t \tag{7}$$

where B_s is a 4×4 matrix of coefficients, with $B_{ij|s}$ measuring the effect of $Y_{j,t-s}$ on $Y_{i,t}$, U_t is the vector of independent and identically normally distributed (iid) residuals with covariance matrix Σ_u, B_0 is a zero diagonal matrix where $B_{ik}(0)$ measures the contemporaneous effect of a shock to Y_k on Y_i, and ε_t stands for a vector of orthogonalized disturbances with covariance matrix Σ_ε. Based on (7), Σ_u can be expressed in B_0 and Σ_ε as follows:

$$\Sigma_u = (I - B_0)^{-1} \Sigma_\varepsilon (I - B_0)^{-1'} \tag{8}$$

To introduce networks into (6) and (7), we assign to each coefficient

[13] We wish to thank an anonymous Referee for insightful comments on methodology and for suggesting network-based approaches. We also considered using a simple VAR and a mixed frequency VAR model (Ghysels, 2016), in which all variables are treated as endogenous. As pointed out by the Referee, considering all variables (including GDP) as endogenous implies a more refined chain of correlations amongst the 4 endogenous variables (or 5 endogenous variables, as later in the analysis insured losses will be added). Given the sample size, a simple or mixed frequency VAR might not be totally capable of reflecting higher-order relationships (namely, potential links from GDP to CO_2 emissions, from CO_2 emissions to catfin, from catfin to GDP, from GDP to CO_2 emissions, etc). Hence, we follow the Referee's recommendation to use network-based approaches, which are more appropriate to capture higher-order relationships that may arise amongst the endogenous variables of real GDP, catfin, CO_2 emissions, bank assets, and insured losses.

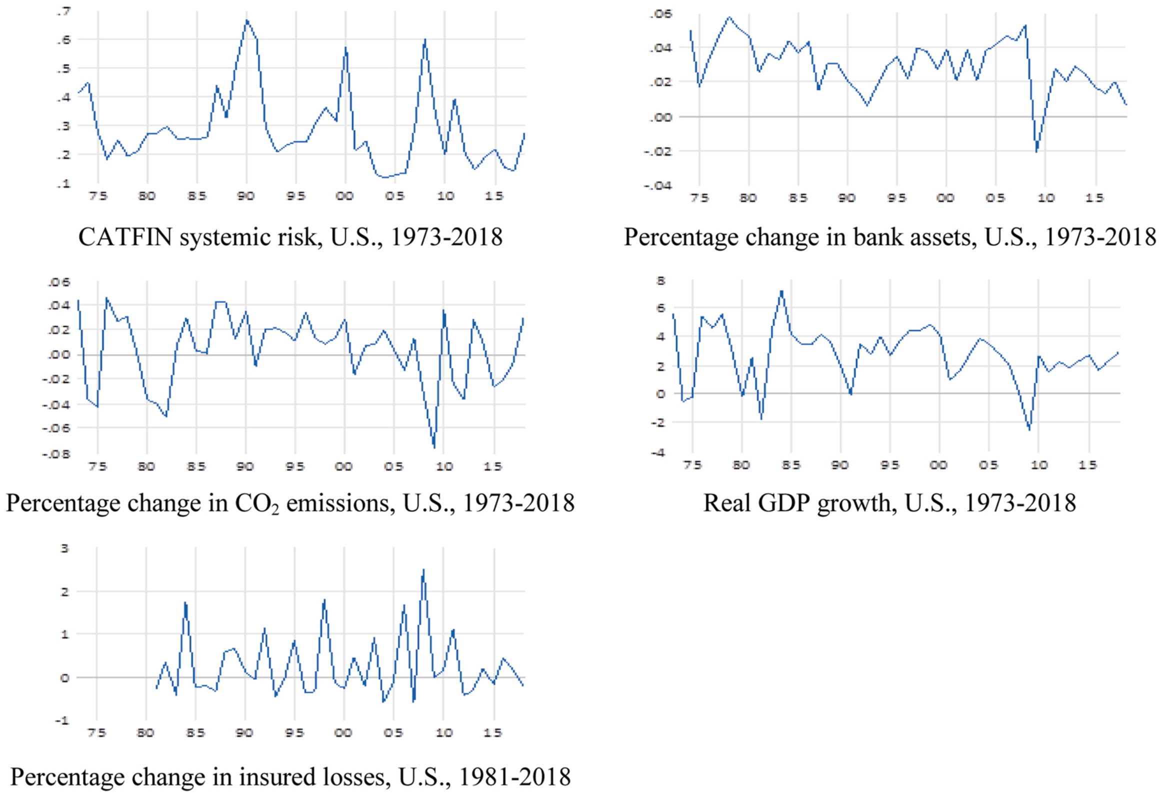


Fig. 2. Graphical presentation of the variables.

in B_s a corresponding latent indicator in $G_s \in \{0,1\}^{4\times4}$, such that for $i,j = 1,\ldots,4$ and $s = 0,1,\ldots p$, we have:

$$B_{ij|s} = \left\{ \begin{array}{lll} 0 \quad if & G_{ij|s} = 0 & \Rightarrow Y_{j,t-s} \nrightarrow Y_{i,t} \\ \beta_{ij} \in \mathbb{R} if & G_{ij|s} = 1 & \Rightarrow Y_{j,t-s} \rightarrow Y_{i,t} \end{array} \right\} \tag{9}$$

where $Y_{j,t-s} \nrightarrow Y_{i,t}$ means that Y_j does not influence Y_i at lag s, and $Y_{j,t-s} \rightarrow Y_{i,t}$ means that Y_j does influence Y_i at lag s. Furthermore, $Y_j \rightarrow Y_i$ means that there is a contemporaneous or lagged directed link from Y_j to Y_i.[14]

The specification reflected in (6) and (7) forms the structural VAR (SVAR) model, which suffers from identification issues (Ahelegbey et al., 2021). These issues are avoided following the Bayesian Graphical Vector Autoregressive Approach (BGVAR) discussed in Ahelegbey et al. (2016).[15] An important feature of the BGVAR approach is that it introduces restrictions directly on the structural model. Following Ahelegbey et al. (2021), this is an innovation in resolving the identification issues with the SVAR models. Indeed, the BGVAR model uses the natural interpretation of the graph structures and acyclic constraints on the contemporaneous relationships.

Following Ahelegbey et al. (2016), Eq. (6) can be represented in the form of a graphical model with a one-to-one correspondence between the coefficient matrices and a directed acyclic graph (DAG):

$$Y^j_{t-s} \rightarrow Y^i_t \quad \Leftrightarrow \quad B^*_{ij|s} \neq 0, \quad 0 \leq s \leq p \tag{10}$$

where $B^*_{ij|s} = B_0$, for $s = 0$, and $B^*_s = (B_s, C_s)$, for $1 \leq s \leq p$. By considering structural dynamics as a causal dependence among variables (Ahelegbey et al., 2016), the relationship in (10) for $1 \leq s \leq p$ can be referred to as lagged (temporal) dependence, and as contemporaneous dependence for $s = 0$. Temporal dependence is based on time flow and is dependent upon the assumption that causes precede effects in time. Contemporaneous causal relationships are dependent upon distinguishing between instantaneous causation from correlations (Ahelegbey et al., 2016, p. 361).

5.2. *Diebold and Yilmaz (2014)'s variance decomposition*

As discribed above, networks are represented in graphs with nodes (variables) and edges (arrows). Directed networks, specifically, represent those that allow for asymmetries (from A to B). One example of a directed network is the forecast error variance decomposition (FEVD) (Caloia et al., 2018). Diebold and Yilmaz (2009) computed a spillover index among a number of variables using the Cholesky decomposition of the VAR residuals covariance matrix.

Diebold and Yilmaz (2014) discussed connectedness between financial and/or macroeconomic variables on the basis of a generalized VAR and the variance decomposition matrix. They developed and applied a unified framework for measuring connectedness using variance decompositions from approximating models. Their approach is based on assessing shares of forecast error variation in various settings (firms, variables, countries, and so on) due to shocks arising elsewhere, and is related to variance decomposition. In variance decomposition, the forecast error variance of variable i is decomposed into parts attributed to the various variables in the system (or network). Denoting by d^H_{ij} the ij-th H-step variance decomposition component (namely. the fraction of variable i's H-step forecast error variance due to shocks in variable j), Diebold and Yilmaz's (2014) measures are based on the non-own (cross) variance decompositions $d^H_{ij}, i,j = 1,\ldots,N, i \neq j$. The 'non-own' is represented by $i \neq j$.

Diebold and Yilmaz (2014) presented measures in a connectedness table. Variance decompositions are reported in the upper-left NxN block of the connectedness table. This block is referred to as a variance decomposition matrix, denoted by $D^H = \left[d^H_{ij}\right]$. The connected table

[14] For a more analytical discussion of the network VAR model, see Ahelegbey et al. (2021)

[15] See also, Giudici and Spelta (2016) on graphical network models.

augments the variance decomposition matrix D^H with the rightmost column containing row sums for $i \neq j$, a bottom row containing column sums for $i \neq j$, and a bottom-right element capturing the grand average for $i \neq j$. Measurements of pairwise directional connectedness from (variable) j to (variable) i, defined as $C^H_{i\leftarrow j} = d^H_{ij}$, appear at the off-diagonal entries of D^H and are parts of the N forecast error variance decompositions of relevance from a connectedness perspective. Based on the two measurements such as $C^H_{j\leftarrow i} = d^H_{ji}$ and $C^H_{i\leftarrow j} = d^H_{ij}$, the net pairwise directional connectedness is defined as $C^H_{ij} = C^H_{j\leftarrow i} - C^H_{i\leftarrow j}$.

The connectedness table of Diebold and Yilmaz (2014) also reported off-diagonal row or column sums. For instance, in the first row, the sum of the off-diagonal elements measures the share of the H-step forecast error variance on variable x_1 coming *from* shocks arising in all *other* variables (as opposed to a single other variable) ('From others' in the connectedness table). Total directional connectedness from others to variable x_i is defined as $C^H_{i\leftarrow\bullet} = \sum_{j=1, j\neq i}^{N} d^H_{ij}$.

In the first column, the sum of off-diagonal elements measures the total directional connectedness from variable x_1 *to* all other variables ('To others' in the connectedness table). In general, the total directional connectedness to others from variable j is denoted as $C^H_{\bullet\leftarrow j} = \sum_{i=1, j\neq i}^{N} d^H_{ij}$. Based on the above measures of total directional connectedness from others and to others for variable i, net total directional connectedness is defined as $C^H_i = C^H_{\bullet\leftarrow i} - C^H_{i\leftarrow\bullet}$. The grand total of the off-diagonal elements in D^H measures the total connectedness, C_H, and is given by $C_H = \frac{1}{N} \sum_{i,j=1, i\neq}^{N} d^H_{ij}$.

Variance decompositions are based on the generalized variance decomposition of Koop et al. (1996), and Pesaran and Shin (1998), which has the feature of being invariant to ordering. The H-step generalized variance decomposition matrix $D^{gH} = [d^{gH}_{ij}]$ has elements given by $d^{gH}_{ij} = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_i'\Theta_h \quad \sum e_j)^2}{\sum_{h=0}^{H-1}(e_i'\Theta_h \sum \Theta_h' e_i)}$, where $e_j$is a selection vector with jth element unity and 0 s elsewhere, Θ_h is the coefficient matrix multiplying the h-lagged shock vector in the infinite moving-average representation of the non-orthogonalized VAR, Σ is the covariance matrix of the shock vector in the non-orthogonalized VAR, and $\sigma_{jj}$is the jth diagonal element of Σ. Generalized connectedness measures are based on $\tilde{D}^g = [\tilde{d}^g_{ij}]$ where $\tilde{d}^g_{ij} = \frac{d^g_{ij}}{\sum_{j=1}^{N} d^g_{ij}}$, and $\sum_{j=1}^{N} \tilde{d}^g_{ij} = 1$ and $\sum_{i,j=1}^{N} \tilde{d}^g_{ij} = N$.

5.3. Conditional Granger causality

Based on Geweke (1982), (1984), conditional Granger causality can be applied in a multivariate framework.[16] Assume that we wish to test whether variable x_j (dlco2) Granger causes variable x_i (catfin) ($x_j \rightarrow x_i$) and that x_j is linked with a set of L variables ($x_1.x_L$), which are the conditioning variables. Consider that the conditioning set of variables comprises the $L = 1$ variable (real_gdp *or* dlassets, one at a time) or $L = 2$ variables (real_gdp, dlassets). The null hypothesis is that variable x_j does not Granger cause variable x_i, conditional on the set of variables L.

In the conditional Granger causality approach, we run an *unrestricted* model and a *restricted* model. Assume that we seek to test whether $x_j \rightarrow x_i$, in both models the dependent variable is x_i. In the unrestricted model, the right-hand side part of the model comprises x_j, with a lag length denoted by Q and the set of L conditioning variables with a lag length denoted by R. In the restricted model, we exclude variable x_j (the causal variable). Denoting by $SSR_U$and SSR_R the sum of squared residuals from the unrestricted and the restricted models respectively, by n the sample size, and letting $Q = R = 1$, the F_{RATIO}, given by $F_{RATIO} = \frac{SSR_R - SSR_U}{SSR_U} * (n - L - 1)$, follows an F-distribution with $(1, n - L - 1)$ degrees of freedom (Greene, 2012; Bressler and Seth, 2011; Duggento et al., 2016).

6. Empirical findings

6.1. Network VAR results

In terms of network terminology, each of the variables is depicted as a node (circle), and the temporal relationships among the nodes are graphically represented as edges (arrows, with each arrow indicating the directionality of the depicted temporal relationship). The color of the arrows (edges) represents the sign of the relationship: green indicates a positive relationship and red indicates a negative relationship. The thickness (width) of each arrow indicates the strength of the relationship: the higher the thickness the stronger the relationship. Finally, line thickness reflects the temporality of the relationship: a solid line indicates a contemporaneous relationship, and a dashed line indicates a dynamic relationship. Self-loops indicate autoregression, and the thickness of lines of self-loops indicates the strength (size) of autoregression. We consider a VAR model comprising (the percentage change of) CO_2 emissions ('CO_2'), CATFIN ('catfin'), real GDP growth ('GDP'), and (the percentage change of) bank assets ('Assets').[17]

Fig. 3 graphically portrays the obtained network representation. As we have four variables, the network contains four nodes named accordingly. The first point that emerges from Fig. 3 is that for all four variables in the network, there exist positive self-loops. All self-loops are green, indicating that a positive autocorrelation exists for all four network variables. Of the four self-loops, the one for catfin is the strongest. We next assess the interconnectedness of the network variables. Based on the shape, color, and direction of the corresponding arrows, we identify a positive (green) link from CO_2 *to* catfin. This relationship is dynamic (dashed arrow). Thus, past percentage changes

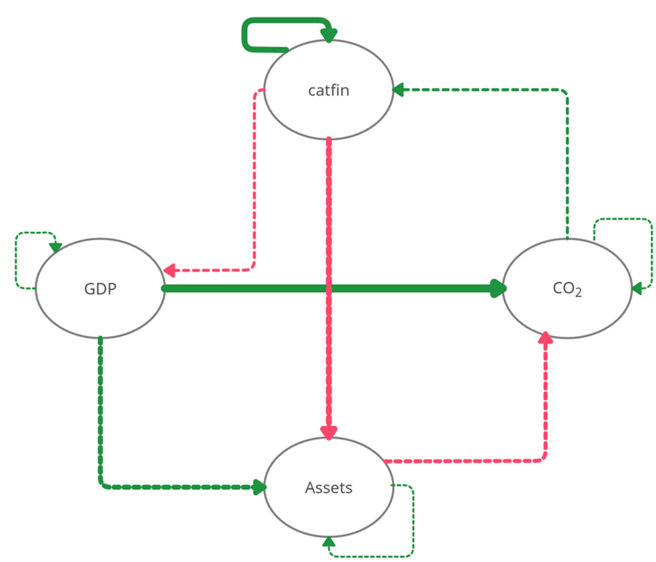


Fig. 3. Network VAR for systemic risk, CO_2 emissions, bank assets and real GDP growth for the U.S.

[16] For applications, see Duggento et al. (2016) and Marica and Horobet (2019).

[17] A lag order of 1 is used for parsimony.

in CO_2 emissions are positively interconnected with catfin (systemic risk). This is in line with our theoretical conjecture.

The network representation of Fig. 3 further reveals a rich set of additional interconnectedness links. As indicated by the red dashed arrow from catfin to assets, systemic risk (catfin) exercises a dynamic negative effect on bank assets, with the strength of the relationship being relatively strong. In addition, catfin exercises a dynamic negative effect on real GDP growth. This result is in line with the findings of Giglio et al. (2016) on the detrimental impact of systemic risk on economic activity. From GDP, two green arrows depart. One arrow reveals a strong contemporaneous link from GDP to CO_2 emissions, which is in line with the well-known literature on macroeconomic activity and CO_2 emissions (Holtz-Eakin and Selden, 1995). There is also a positive dynamic link from GDP to bank assets, which echoes the findings of previous studies linking economic growth and bank performance (Bikker and Hu, 2002; Demirguc-Kunt and Huizinga, 1999). Importantly, there is a dynamic negative link from bank assets to CO_2 emissions, which is in line with the transition effect of the adjustment to a low-carbon economy. As contended by Delis et al. (2018), to achieve this goal, the financial system may need to make asset adjustments. This finding is also in line with the ongoing discussion[18] that banks must follow green transition plans towards a more responsible finance industry by promoting green finance and sustainable investment.[19] Indeed, several major international banks have committed to measuring and reporting carbon emissions resulting from their lending and investments (namely, their bank assets).[20]

This finding is also in line with anecdotal evidence of banks in the U. S. investing in and switching to greener technology. Indeed, Green Investment Banks (GIBs) in the U.S. as well as in other countries have been established both at the state (California, Connecticut, Hawaii, New Jersey, New York and Rhode Island) and country level to facilitate private investment in domestic low-carbon, climate-resilient (LCR) infrastructure and to finance clean energy projects.[21] In addition, green financial products and green bonds have been developed as vehicles to provide funding for clean energy projects. These products are targeted to home or business owners and retail and investment banks. Connecticut Green Bank, for example, has driven growth in its residential and commercial segments through a residential solar loan and lease program, credit support mechanisms for energy efficiency, and a commercial property-assessed clean energy product for a variety of energy conservation measures (https://www.nrel.gov/state-local-tribal/basics-green-banks.html).

To assess the reliability of network results, goodness of fit statistics are reported in Table 2. The goodness of fit measures includes the Root Mean Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), and the Standardised Root Mean Square Residual (SRMR). Based on Hooper et al. (2008), Yang et al., (2019, 2018), and Xia and Yang (2018) a network model is deemed as a good fit based on a '3 out of 4′ rule, namely that CFI and TLI should be at least 0.95, and that RMSEA and SRMR should be no greater than 0.08. On the basis of the results shown in Table 4, the estimated network meets all 4 of these criteria; hence, its goodness of fit is confirmed.

Table 2
Goodness of fit statistics for network (catfin, GDP, Assets, CO_2).

	RMSEA (should be < 0.08)	CFI (should be > 0.95)	TLI (should be > 0.95)	SRMR (should be < 0.08)	Goodness of Fit result
Network (catfin, GDP, Assets, CO_2)	0	1	1.085	0.055	YES

Table 3
Connectedness Table based on Diebold and Yilmaz (2014).

	catfin	CO_2	Assets	GDP	From others
catfin	71.31	15.04	4.92	8.73	28.69
CO_2	5.62	57.29	10.05	27.13	42.70
Assets	24.60	9.00	48.33	18.07	51.69
GDP	11.69	20.64	9.84	57.83	42.17
To others	41.80	44.68	24.81	53.92	41.30
Net	13.11	1.98	-26.88	11.75	

Table 4
Conditional Granger causality.

Null hypothesis: CO_2 does not Granger cause catfin conditional on the set of variables L

Set of variables (L =)	SSR_U	SSR_R	F_{RATIO}	p-value
Assets	0.707	0.757	2.97^+	0.09
GDP	0.711	0.771	3.63^+	0.06
Assets and GDP	0.69	0.749	3.51^+	0.07

$^+$ statistically significant at the 10% level.

Impulse response analysis can be conducted on the basis of the network configuration (Yang et al., 2018, 2019). Such analysis proceeds by perturbing the estimated network one node (variable) at a time, producing an impulse response analysis matrix (Yang et al., 2018, 2019).[22] This matrix consists of equilibrium values, namely how many steps are required for variable j to reach equilibrium after a perturbation from variable i (e_{ij}). Fig. 4 reports the results. As evidenced in Fig. 4, comparing the dynamic negative impact from assets to CO_2 ('from.3. to.2′) with the dynamic positive effect from CO_2 to catfin ('from.2.to.1′), the former is relatively shorter than the latter. The main conclusion from the network VAR analysis is that there is evidence supporting the positive link between CO_2 emissions and systemic risk that can last for a relatively prolonged period.

6.2. Diebold and Yilmaz (2014)'s variance decompositions

We next apply the approach of Diebold and Yilmaz (2014), which captures both pairwise and multivariate connectedness through variance decompositions through the amount of information that each variable can contribute to discerning other variables in the autoregression.[23] The results are reported in Table 3.[24]

As shown in Table 3, in the network of the four variables, three

[18] In September 2019, many global banks met for New York Climate Week and signed the United Nations Principles for Responsible Banking, which call for evidence-based targets in the banking industry. Although this is not within our sample period, it still is indicative of the trend in the sector for pursuing responsible green finance policies driven by assets adjustment.See https://www.triodos.co.uk/articles/2019/how-finance-can-help-the-low-carbon-transition.

[19] https://www.santander.com/en/stories/why-do-banks-measure-their-carbon-footprinthttps://sponsored.bloomberg.com/article/business-reporter/how-banks-can-be-key-enablers-in-the-fight-against-climate-change

[20] https://member.fintech.global/2021/07/21/how-banks-can-offset-their-carbon-emissions-amid-the-current-climate-crisis/

[21] According to the Green Bank Network (www.greenbanknetwork.org), there are 72 green banks in the U.S.

[22] The evaluation of recovery times relies on a bootstrap approach, which accommodates uncertainty in the model parameters. See Yang et al. (2018), (2019).

[23] This is based upon the General Forecast Error Variance Decomposition introduced by Pesaran and Shin (1998).

[24] Results are based on a lag order of 1.

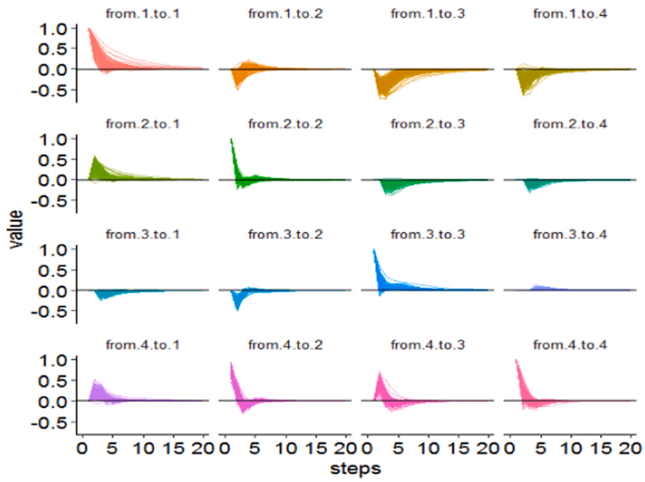


Fig. 4. Impulse responses.

(catfin, GDP, and CO_2) are net spillover transmitters, with bank assets being net spillover recipient. CO_2 is a net exporter (transmitter) of spillovers. Excluding the own connectedness measure (from CO_2 to CO_2 which is71.31), the spillover from CO_2 to catfin is 15.04, which is the highest measure compared to the spillover measures from the other two variables, namely from assets to catfin (4.92) and from GDP to catfin (8.73). In terms of total spillover from the other three variables (CO_2, GDP and Assets), which is 28.69, the spillover from CO_2 only accounts for more than half, which highlights the important role of CO_2 in exporting effects to catfin within the multivariate framework of Diebold and Yilmaz (2014)'s variance decomposition. In other words, CO_2 is the most important transmitter of spillovers to systemic risk in the estimated network.

The connectedness parameter from assets to CO_2 is 10.05. Excluding the own spillovers (from CO_2 to CO_2) (which is 57.29) and spillovers from GDP to CO_2 (which is 27.13 and captures the well-known link between growth and CO_2), the link from bank assets amounts for nearly 23.4% of the total spillovers from others to bank assets. Thus, as bank assets increase, CO_2 emissions decrease. As outlined above, an interpretation of this finding is that as bank assets increase, banks invest in and switch to greener technology in the course of adjusting to greener finance.

6.3. Conditional Granger causality

We next turn to another multivariate framework to assess the importance of dynamic effects from CO_2 to systemic risk, namely the conditional Granger causality approach (Geweke, 1982, 1984). The conditionality refers to the inclusion in the information set (conditioning) variable(s). The null hypothesis is that CO_2 does not Granger cause catfin conditional on the set of variables L, where L = {GDP}, L = {Assets}, and L = {GDP and Assets}. Table 4 reports the results of the F_{RATIO} and its corresponding p-value.

The null hypothesis that CO_2 does not Granger cause catfin conditional on assets yields an F_{RATIO} of 2.97 with a p-value of 0.09, thereby rejecting the null at the 10% level. When conditioning is in terms of GDP, the p-value of the F_{RATIO} just misses the 5% level (p-value = 0.06). When conditioning involves both assets and GDP, the p-value is 0.07. Thus, by-and-large, the multivariate conditional Granger causality approach is not incompatible with the conclusion that some degree of causality exists from CO_2 with respect to systemic risk.

6.4. Insured losses

The empirical evidence presented above supports the existence of the physical risk effect, which may have implications for bank assets. Indeed, as the physical risk effect focuses on the impact of CO_2 emissions-driven events (heat waves, droughts, floods, storms) on asset values, it can induce a deterioration of borrowers' ability to repay their debts and cause a depreciation in the value of assets used for collateral by banks thereby negatively affecting their assets. In addition, banks hit by such risks may find themselves in a difficult position to refinance themselves, with detrimental effects on both sides of their balance sheets (Berger et al., 2020).

Climate-related events may hit businesses and households, which therefore pay an insurance premium and thus pass the risk of losses to the financial (banking) sector. The latter receives the insurance premium and undertakes the risk of covering the insured losses. Hoeppe (2016) showed high insurance penetration for all convective weather-related loss events in the U.S. over most of the sample period. Based on the NatCatSERVISE data from Munich RE,[25] Hoeppe (2016) concluded that the ratio of insured losses in terms of overall losses in the last years in the U.S. has been far above 50%, and the insurance industry had to pay about 2/3 of the overall losses. The fraction of insured losses to overall losses regarding convective storm events in the U.S. over the period 1980–2018 is graphically shown in Fig. 5. As shown in this Figure, insured losses account for more than 50% of overall losses.

In 2017 for the U.S., as presented in the TOPICS Geo Natural Catastrophes (2017), all major loss events were characterized by high insurance coverage. A summary of these events in 2017 is provided in Table 5. In almost all these events, the insured losses were more than 60% of the overall losses. Since most losses are insured, a significant part of the cost of climate change-related losses is carried by the financial system, which raises the issue of the relationship between insured losses and bank assets.

To assess the relationship between insured losses and bank assets, we incorporate the percentage change of insured losses ('dl_insured_losses') in the empirical analysis.[26] Specifically, we re-estimate the network VAR by including dl_insured_losses as a 5th variable (node) in order to identify possible arrows directed from or to this variable. The graphical representation of the newly estimated network VAR model is given in Fig. 6. As shown in this Figure, there is a dynamic negative (red colored) effect from dl_insured_losses to bank assets. Combining this negative link from insured losses to bank assets with the negative link from bank assets to CO_2 emissions (also present in Fig. 6 as well as in Fig. 3), one can argue that an increase in insured losses will have a detrimental effect on bank assets (link from insured losses to bank assets), possibly leaving less room for banks to make greater asset adjustments towards a greener and more responsible finance (link from bank assets to CO_2 emissions).

7. Policy implications

One way in which regulators can manage the positive impact of increasing CO_2 emissions on systemic risk is through government-sponsored insurance schemes that cover natural disasters, including the National Flood Insurance Program (NFIP), the Texas Windstorm Insurance Association (TWIA), and the Louisiana Citizens Property Insurance Corporation. Federal or state explicit insurance support (reinsurance) for the financial and banking sector facing increasing insured losses after a climate change-related natural disaster would also be a step towards neutralizing K from CO_2 emissions in terms of (4) and thus rendering K independent of changes in c, Δc (ΔK=0).

Integrating climate change into the supervisory framework is a further policy implication of our research. Regulators may use their financial stability authority under Section 165 of the Dodd- Frank Act to implement the recently introduced climate-focused macro-prudential legislation (Gezlinis and Steele, 2019). This action would be compatible

[25] https://www.munichre.com/en/solutions/for-industry-clients/natcatservice.html

[26] We wish to thank an anonymous referee for this suggestion

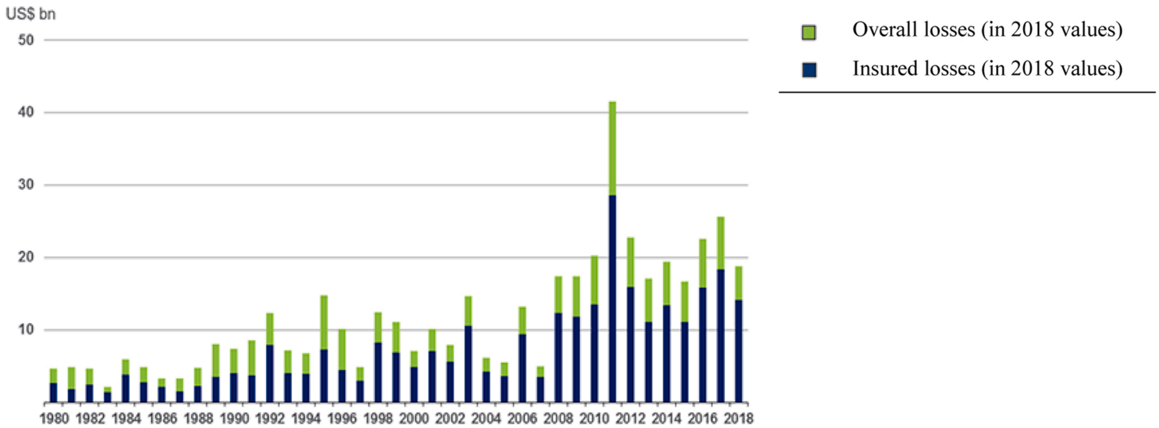


Fig. 5. Overall and insured losses in the U.S., 1980–2018.
Source: © 2019 Munich Re, Geo Risks Research, NatCatSERVICE. As of March 2019. https://www.iii.org/graph-archive/218221.

Table 5
Overall losses vs. insured losses (U.S.$ m): Summary of 2017 major weather-related loss events in the U.S.

No	Date	Loss event	Overall losses (US$ m)	Insured losses (US$ m)
1	28/02–2/3	Tornadoes, severe storms	1900	1400
2	6/3–9/3	Severe storms, tornadoes	2200	1600
3	25/3–28/3	Hailstorms, severe storms	2700	2000
4	8/5–11/5	Hailstorms, severe storms	3100	2500
5	9/6–12/6	Severe storms	2000	1500
6	27/6–29/6	Severe storms, hail, tornado	1400	1100
7	8/10–20/10	Wildfires	13,000	9800
8	4/12–31/12	Wildfire	2200	1700

Source: TOPICS Geo Natural Catastrophes (2017), pp. 64–65.

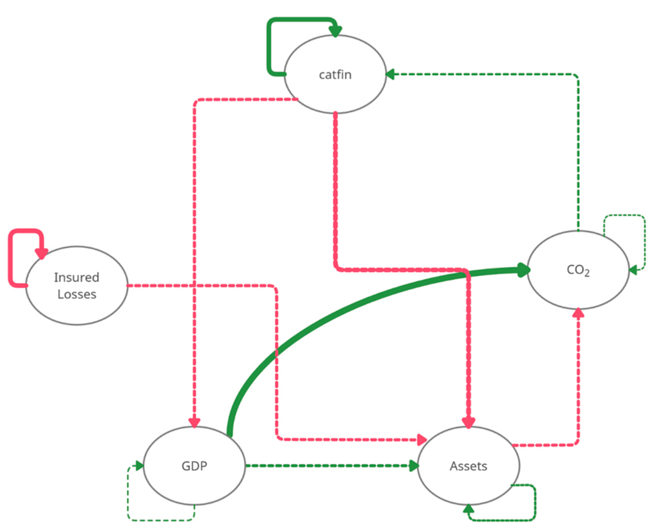


Fig. 6. Insured losses in the network VAR model.

with the Fed conducting climate change stress tests taking physical risks into account. Such policies are currently being implemented by the Bank of England, the Dutch National Bank, and the European Systemic Risk Board. Regulators may also integrate climate risk into their supervisory frameworks by setting higher risk-weighted bank capital requirements for assets sensitive to the carbon price.

8. Conclusions

This study presents both a theoretical framework for and empirical evidence of the relationship between CO_2 emissions and systemic risk in the U.S. We advance a modified structural distance-to-default model that incorporates physical risk effects to illustrate the positive link in theoretical terms from CO_2 emissions to systemic risk. Our empirical analysis uses a range of approaches – Network VAR analysis, Diebold and Yilmaz variance decomposition, and conditional Granger causality – that empirically support the aforementioned relationship.

We further illustrate the negative dynamic impact of bank assets on CO_2 emissions, which reflects an adjustment by banks towards a low-carbon economy. This finding suggests that the financial system tends to move towards more responsible green finance policies driven by asset adjustment. We also show that insured losses exercise a negative impact on bank assets. An increase in insured losses will have a detrimental effect on bank assets (link from insured losses to bank assets), leaving less room for banks to make proper adjustments in terms of assets towards greener finance (link from bank assets to CO_2 emissions). These findings indicate that relevant policies would include federal or state insurance support to banks and measures to integrate climate change into the regulatory framework.

Data Availability

Data will be made available on request.

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