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By *Angelos Kanas* and *Philip Molyneux*

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Systemic risk and CO_2 emissions in the U.S.

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Abstract

We provide evidence that annual CO_2 emissions in the U.S. exercise a positive, statistically significant, and robust impact on the U.S. economy's systemic risk. The transmission channel of the impact is through bank profitability: we reveal a negative effect from CO_2 emission to bank profitability, suggesting that an increase in CO_2 emission has a detrimental effect on bank profitability. This finding is supported by the relatively high percentage of insured losses shifting the cost of CO_2-driven climate change risks on to the financial system. In addition, we document a negative effect from bank profitability to systemic risk, indicating that decreasing bank profitability entails an increase in systemic risk. Policy implications include government sponsored insurance support for banks facing insured losses**.**

Keywords: CO_2 emissions, systemic risk, mixed-frequency VAR, bank profitability, insured losses.

J.E.L.: G01, G02, G21, G28, C5

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1. Introduction

In the aftermath of the 2015 Paris Climate Conference, significant attention has been placed on the relation 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 is affecting the financial system, and is a contributor to systemic risk. Central banks have identified this as an issue of great importance. The 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 for the soundness of financial institutions[1]. Contributions have explored the link between climate change and *firm* credit risk (Capasso et al., 2020), showing that companies with 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 the *aggregate* systemic risk from a macro-prudential policy perspective.

The present paper explores the relation between CO_2 emissions and systemic risk at an aggregate level in the U.S. for the period 1973-2017. Systemic risk refers to the risk 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 to losses for borrowers, reduce their ability to repay loans, and increase the credit risk of banks. If losses from physical risks are *insured*, the cost is borne by the financial sector thereby increasing liabilities. Furthermore, the physical risk effect can induce 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 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 their balance sheets[2].

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[1] https://currency.com/climate-change-will-threaten-banks-profitability-report (accessed 10 July 2020).
[2] See Berger et al. (2020), section 3.3, for a summary of recent studies that look at how severe weather events impact banks.

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, which could prompt a re-assessment of the value of assets with many carbon-intensive assets becoming 'stranded' (Delis et al., 2018). In the present study, we focus on the physical risk effect, as implementation of CO_2 emissions reduction agreements (Kyoto Protocol and Paris Agreement) by the U.S., necessary for transition risks to arise, is rather limited.

The present work is the first attempt, to our knowledge, to explore the impact of CO_2 emissions on systemic risk, and makes several contributions. Firstly, we integrate the physical risk effect into the Merton's (1974) distance-to-default approach and provide a simple theoretical framework which documents a positive impact of CO_2 emissions on systemic risk, namely, systemic risk increases after an increase in CO_2 emissions. Secondly, we use annually available data for CO_2 emissions, monthly and quarterly data for CATFIN (Allen et al., 2012) as an indicator for systemic risk, and a mixed frequency VAR (MF-VAR) approach (Ghysels, 2016) which is flexible enough to accommodate variables measured at different frequencies within a vector autoregressive (VAR) framework. Thirdly, we provide robust empirical evidence that CO_2 emissions have a positive impact on systemic risk, confirming the physical risk effect. Lastly, we illustrate that increasing CO_2 emissions are linked with decreasing bank profitability, and that decreasing bank profitability is associated with increasing systemic risk. This highlights that bank profitability is the channel through which the CO_2 emissions impact is transmitted to systemic risk.

The rest of the paper is as follows. Section 2 provides the theoretical framework. Section 3 describes the data and the methodology. Section 4 discusses the empirical results, tests their robustness, and ascertains that bank profitability is the transmission channel. Section 5 concludes.

2. 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 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 adjust it by integrating the physical risk effect.

Merton's (1974) approach is based on the probability of default (*PD*), a determinant of systemic risk (Carlson et al., 2008; Giesecke and Kim, 2011; Allen et al., 2012; Financial Stability Review, 2015; Giudici and Parisi, 2016). 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), that 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:

$$PD_t = \Pr(\ln(A_T) - \ln(K) \leq 0) \Rightarrow$$

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

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[3], causing financial losses to business and households. If

[3] Climate change risk is caused by CO_2 emissions: According to the Intergovernmental Panel on Climate Change (2014), CO_2 emissions accounted for 78% of the total green house gas emission increase during 1970 -2010. Fraction of CO_2

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:

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

The physical risk effect, in addition, can induce a deterioration of borrowers' ability to repay their debt if weather-related losses are not insured, 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:

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

Expression (4B) provides an adjusted Merton (1974) theoretical framework which integrates the physical risk effect, and reflects the impact of CO_2 emissions on *PD* and consequently (Carlson et al., 2008; Giesecke and Kim, 2011) on systemic risk. An increase in CO_2 emissions leads, if losses are insured, to an increase in *K*, *K'*, which subsequently causes the distribution Φ to shift. Figure 1A illustrates this shift. This Figure shows 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. Figure 1B portrays this shift. The combined shift of the distribution Φ to the right, namely the sum of the two shifts shown in Figures 1A and 1B, establishes a positive impact of CO_2 emissions on systemic risk. The validity of this conclusion is empirically examined next[4].

3. Variables and methodology: the mixed frequency VAR (MF-VAR) model

3.1 Variables and data sources

We consider annual CO_2 emissions (in kt) for the period 1973-2017. The 1973-2016 data are from World Bank, whereas the 2017 data are from FRED[5]. The series is expressed in terms of

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emissions remains in the atmosphere for centuries and causes irreversible damage on climate (Fuss et al., 2009). Thus, climate changes arise from CO_2 emissions into the atmosphere over all time periods (Batten et al., 2016).

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

[5] The series from FRED starts from 1980, hence we considered the World Bank as the data source with a start 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;

annual percentage changes. Systemic risk is measured using the CATFIN indicator developed by Allen et al. (2012). 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 any 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 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 used widely 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 each point in time[6].The data for CATFIN is from Turan Bali's web site and are available on a monthly basis from 1973[7].

We also obtain annual data for the real GDP growth[8] to be used as a control variable. 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, suggesting that one needs to control for any macro impact on systemic risk. Second, based on the well known relation between real GDP and CO_2 emissions (Kuznets, 1955), the main determinant of CO_2 emissions is real GDP. This highlights the need to account for the impact of real GDP growth on CO_2 emissions. To explore whether bank profitability is an impact transmission channel, we consider data for both ROA and ROE[9]. The sample extends over the period 1973-2017, except for bank profitability data available from 1984Q1 on a quarterly basis. Based on ADF unit root tests, all variables are stationary. All series are pictorially presented in Figure 2.

3.2 Mixed-frequency VAR model and estimation

Modeling the bilateral link between annual percentage changes in CO_2 emissions, Δc, and monthly (and quarterly) CATFIN can be achieved using the mixed frequency VAR (MF-VAR) approach by Ghysels (2016). To illustrate the MF-VAR model, we consider two frequencies of data, a monthly

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https://fred.stlouisfed.org/series/EMISSCO2TOTVTTTOUSA.https://data.worldbank.org/indicator/EN.ATM.CO2E.KT?locations=US.

[6] Although several other systemic risk measures have been proposed in the literature, we rely on CATFIN due to the fact that publically available CATFIN data are available from 1973.

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

[8] 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

[9] Federal Financial Institutions Examination Council (US), Return on Average Equity for all U.S. Banks [USROE], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/USROE.
And Federal Financial Institutions Examination Council (US), Return on Average Assets for all U.S. Banks [USROA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/USROA.

(high) frequency and a low (annual) frequency, so there are m=12 high frequency periods per low frequency. The endogenous variables in the VAR include Δc (y_L^i) observed at low frequency and CATFIN (y_H^i) observed at high (monthly) frequency.

To briefly characterize the MF-VAR model, let the annual Δc be stacked in matrix Y_L, and the 12 monthly variables of CATFIN be stacked in Y_H. Let Y_{L,t_L} represent Δc observed at the low frequency period t_L, and $Y_{L,t_L,t}$ represent CATFIN observed at the t-th high frequency period during low frequency period t_L. By stacking Δc into Y_L and the 12 monthly variables of CATFIN into Y_H, the MF-VAR model is written (ignoring the intercepts and exogenous variables) as:

$$\begin{bmatrix} Y_{H,t_L,1} \\ Y_{H,t_L,2} \\ \vdots \\ Y_{H,t_L,12} \\ Y_{L,t_L} \end{bmatrix} = \sum_{j-1}^{p} \begin{bmatrix} \Pi_j^{1,1} & \cdots & \Pi_j^{1,13} \\ \vdots & \ddots & \vdots \\ \Pi_j^{13,1} & \cdots & \Pi_j^{13,13} \end{bmatrix} \begin{bmatrix} Y_{H,t_L-j,1} \\ Y_{H,t_L-j,2} \\ \vdots \\ Y_{H,t_L-j,12} \\ Y_{L,t_{L-j}} \end{bmatrix} + \begin{bmatrix} E_{H,t_L,1} \\ E_{H,t_L,2} \\ \vdots \\ E_{H,t_L,12} \\ E_{L,t_L} \end{bmatrix} \tag{5}$$

where $\Pi_j^{a,b}$ is 1×1, $\Pi_j^{13,b}$ is 1×1, and $\Pi_j^{a,13}$ is 1×1 for all j, a, b = 1,...13, and $\Pi_j^{13,13}$ is $k_L \times k_L$. To interpret (5), we stack the months of January…, and December of the systemic risk indicator of year t together with the year t data of Δc. Estimation of (5) is carried out using the unrestricted MIDAS (U-MIDAS) or the Bayesian method (Ghysels, 2016). The former applies VAR least squares to estimate the stacked matrix of coefficients, and is our main estimation approach. For robustness, we also consider Bayesian estimation[10]. Lastly, Granger causality and impulse response analysis between annual CO_2 emissions and monthly CATFIN is conducted based on Ghysels (2016).

In the empirical analysis, and for robustness purposes, we also consider a MF-VAR model comprising of annual Δc and quarterly CATFIN. In this model, m=4 and $\Pi_j^{a,b}$ is 1×1, $\Pi_j^{5,b}$ is 1×1, and $\Pi_j^{a,5}$ is 1×1 for all j, a, b = 1,...5, and $\Pi_j^{5,5}$ is $k_L \times k_L$ in terms of the above notation. The quarterly CATFIN data is based on the CATFIN value of March for the 1st quarter, June for the 2nd quarter, September for the 3rd quarter and December for the 4th quarter of each year. Lastly, for further robustness checks, we consider an 'annual' VAR model, comprising of annual Δc and annual CATFIN data obtained as the average of the monthly CATFIN values.

[10] This is analogous to Bayesian VAR, and requires the specification of prior distributions for the parameters and the residual covariance matrix. For obtaining the prior distributions and more technical details, we follow Ghysels (2016).

4. Empirical evidence

4.1. Main results

We start by estimating the MF-VAR model including the *monthly* CATFIN and the annual percentage changes in CO_2 emissions (Δc), as reflected in (5). Table 2 reports the results based on the U-MIDAS approach[11]. For the estimation, CATFIN is transformed into twelve separate variables, one variable for each month in the year. In terms of notation in Table 2, CATFIN_1 is the variable for the 1st month of the year, CATFIN_2 is for the 2nd month, ... and CATFIN_12 is for the 12th month. In line with the discussion of the MF-VAR model in (5), CATFIN_1, CATFIN_2, ... CATFIN_12 appear as endogenous variables along with Δc. Further, CATFIN_1(-1) refers to the 1st month of the *previous* (*lagged*, denoted by '(-1)') year. For example, if the reference year is 2000, 'CATFIN_1' refers to January 2000, 'CATFIN_2' to February 2000, ..., and 'CATFIN_12' to December 2000. Furthermore, 'CATFIN_1(-1)' refers to January 1999, 'CATFIN_2(-1)' to February 1999, etc.

Starting with the impact of real GDP growth on CO_2 emissions and on the basis of the Δc equation (last column in Table 2), we find that growth has a positive and significant effect on CO_2 emissions (t-statistic=5.741). This is in line with literature suggesting a positive link between macro activity and CO_2 emissions (Holtz-Eakin and Selden, 1995). The effect of growth on systemic risk is negative and statistically significant at the 6% level (t-statistic=-1.940), suggesting that the stronger the real GDP growth the lower will be the systemic risk. These results justify the use of real GDP growth as a control variable in the empirical model.

We next turn to assessing the impact of lagged annual Δc (Δc (-1)) on monthly systemic risk in the following year. In other words, we examine the impact of an increase in CO_2 emissions, say, in 2000 on the systemic risk in January 2001, February 2001, ..., December 2001. As Table 2 illustrates, an increase of lagged Δc (Δc(-1)) exercises a positive and statistically significant at the 5% level impact on the systemic risk of the last 2 months of the subsequent year (t-statistic=1.987 and 3.158 for the equations of CATFIN_11 and CATFIN_12 respectively). Additionally, a positive and statistically significant at the 10% level impact is traced for the systemic risk of the 4th and 9th months of the subsequent year (equations for CATFIN_4 and CATFIN_9) (t-statistic=1.900 and 1.708, respectively).

[11] In this model as well as in all additional MF-VAR and VAR models, a lag length of 1 is used for parsimony.

To shed further light into the relationship between annual changes in CO_2 emissions and the monthly systemic risk, we follow Ghysels (2016) and perform Granger causality tests using the MF-VAR results in Table 2. We explore whether there is Granger causality from CO_2 emissions to the systemic risk of each of the 12 months in the following year. The results are reported in Table 3. The findings suggest that there is a statistically significant at the 5% level causality from CO_2 emissions to the systemic risk of November and December of the following year, in line with the results in Table 2. We lastly conduct impulse response and accumulated impulse response analysis for each of the 12 monthly systemic risk values to impulses from CO_2 emissions. The results are reported graphically in Figures 3A and 3B. In line with the findings in Tables 2 and 3, the findings suggest that CO_2 emissions trigger a statistically significant response of the November and December systemic risk of the following year. Based on accumulated responses, the results are statistically significant for the March and April systemic risk as well.

We can interpret these results as evidence supporting the physical risk effect. Furthermore, one could infer that an increase in the U.S. CO_2 emissions in 2020 will contribute to an *increase* in the economy's systemic risk in November and December 2021 (with possibly early signs as early as April 2021). Given that an increase in systemic risk has been found to cause detrimental effects on the U.S. macro-economy (Giglio et al., 2016), this time window provides an opportunity for policy makers to take actions in order to control increasing systemic risk associated with CO_2 emissions, and thus avoid its negative knock on effect on the macro-economy.

4.2. Robustness

We perform two types of robustness checks on the previous findings. The first refers to alternative methods of time aggregation of the systemic risk (CATFIN) data, and the second to adopting the Bayesian estimation method of the MF-VAR model.

We start by considering quarterly data on CATFIN, based on the March, June, September, and December CATFIN values. Hence, instead of 12 monthly CATFIN variables in Table 2, we now have 4 quarterly CATFIN variables, CATFIN_1 for the 1^{st} quarter, ..., and CATFIN_4 for the 4^{th} quarter. Using the quarterly CATFIN and the annual CO_2 emissions data, a new MF-VAR model is estimated using the U-MIDAS approach. Results are reported in Table 4. In line with the results in Table 2, the real GDP growth enters in the Δc equation (last column in the Table) with a positive sign and a statistically significant coefficient (t-statistic = 6.884). Also in line with Table 2, CO_2 emissions have a positive and statistically significant (t-statistic = 2.675) impact on CATFIN_4, namely the CATFIN value in the 4th quarter of the following year. We next test, using this MF-VAR model, the null hypothesis that there is no Granger causality from CO_2 emissions to the systemic risk of the 4th quarter. Testing this hypothesis yields a chi-squared statistic of 7.150 with a p-value of 0.007, thereby rejecting the null in favor of the alternative of causality. Impulse response and accumulated impulse response analysis, presented in Figures 4A and 4B, provide further support to the robustness of our results with respect to using quarterly, instead of monthly, data for systemic risk.

In a further time-aggregation robustness check, we consider annual data on CATFIN based on the simple average of the 12 monthly values within a year. Using this series and annual CO_2 emissions, we estimate an 'annual' VAR and the results are reported in Table 5. Consistently with the MF-VAR results on monthly and quarterly CATFIN data, Table 5 shows that CO_2 emissions exercise a positive and statistically significant (at the 5% level) effect on the average systemic risk of the following year. Testing the null that CO_2 emissions do not Granger cause next year's systemic risk yields a chi-squared statistic of 3.830 with a p-value of 0.05.

In the second type of robustness checks, we consider the Bayesian, instead of the U-MIDAS, approach to re-estimate the MF-VAR model with quarterly CATFIN (and annual changes in CO_2 emissions). The results, reported in Table 6, indicate that changing the estimation method does not qualitatively alter the results. The main conclusion from these robustness checks is that the evidence documenting a positive impact of the U.S. CO_2 emissions on the systemic risk of the following year is robust to alternative time aggregation and estimation methods.

4.3. Identifying the channel of impact transmission: bank profitability

Having revealed a robust impact from CO_2 emissions to the systemic risk of the U.S. economy, we proceed to identify the channel through which this impact is transmitted. 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. If assets are insured, then physical risks may cause a detrimental effect on bank profitability. 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 their balance sheets. These arguments suggest that a possible candidate channel through which CO_2 emissions impact the systemic risk is through bank profitability.

To empirically assess the role of bank profitability as a possible transmission channel, we revisit the MF-VAR model in Table 4, with the quarterly CATFIN and annual CO_2 emissions data, and allow for the change in bank profitability (change in ROE, ΔROE) as an additional variable[12]. Thus, we estimate an MF-VAR model comprising of 3 endogenous variables, namely the annual percentage changes in CO_2 emissions Δc, the quarterly CATFIN and the quarterly change in bank profitability (ΔROE), and control for real GDP growth. The results are reported in Table 7.

Table 7 shows that the positive and statistically significant impact of real GDP growth on CO_2 emissions is preserved, providing further justification for the inclusion of real GDP growth as a control variable. In addition, the impact of CO_2 emissions on CATFIN_4 (the systemic risk in the following 4^{th} quarter) is still present: the coefficient is positive and statistically significant (t-statistic = 2.342), in line with the previous results.

Importantly, we reveal a bilateral relation between CO_2 emissions and bank profitability. Changes in bank profitability (ΔROE) are shown to be negatively related with changes in CO_2 emissions in the following year. Indeed, ΔROE_2 and ΔROE_3 enter with a negative and statistically significant value in the Δc equation (last column in Table 7). Thus, as bank profitability increases, CO_2 emissions decrease, and vice versa. A possible interpretation of this finding is that as bank profitability increases, banks invest in and switch to a greener technology. Importantly, Green Investment Banks (GIBs) in the U.S. (as well as in other countries) have been established both at state level (California, Connecticut, Hawaii, New Jersey, New York and Rhode Island) and at country level, to facilitate private investment into domestic low-carbon, climate-resilient (LCR) infrastructure and to finance clean energy projects[13]. In addition, green financial products and green bonds have been developed as vehicles to provide funding for clean energy projects[14].

An opposite link is also traced: CO_2 emissions are found to exercise a negative and statistically significant effect on the change in bank profitability in the following quarter (ΔROE_1), suggesting that an increase in CO_2 emissions is perceived as entailing a decrease in bank profitability. In addition, Table 7 illustrates that changes in bank profitability exercise a negative impact on systemic risk in the following year. Indeed, ΔROE_4(-1), the change in bank profitability in the 4^{th}

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[12] As the bank profitability data are only available on a *quarterly* (and not on a monthly) basis, we consider the MF-VAR model with *quarterly* CATFIN in Table 4.

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

[14] 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).

quarter of the previous year, is shown to exercise a negative impact on CATFIN_1, CATFIN_2, CATFIN_3, and CATFIN_4 (namely, the systemic risk in the 1^{st}, 2^{nd}, 3^{rd}, and 4^{th} quarters of the following year). Further, ΔROE_2(-1) also exercises a negative an statistically significant impact on CATFIN_2[15].

To ensure robustness of the results with respect to ROE, we also consider the change in ROA (ΔROA) as an alternative measure of bank profitability. Results are reported in Table 8. The Table shows that the previously identified link between CO_2 emissions and ΔROE is preserved: CO_2 emissions exercise a negative and statistically significant effect on ΔROA__1, and ΔROA_4(-1) has a negative impact on CATFIN_1, CATFIN_2, CATFIN_3, and CATFIN_4. Thus, the previously identified relations hold irrespective of whether ROA or ROE is used.

The combination of the two previously revealed links, namely from CO_2 emissions to bank profitability, and from bank profitability to systemic risk, echoes the existence of a bank profitability channel in the transmission of the impact from CO_2 emissions to systemic risk: bank profitability is the interim variable, which receives the impact of the CO_2 emissions and subsequently transmits this impact on to systemic risk. The main conclusion which arises is that CO_2 emissions in the U.S. have an impact on the economy's systemic risk in the next year, with the main channel through which this impact is transmitted being bank profitability.

4.4. Insured losses

Climate-related events may hit businesses and households which, in order to insure themselves, pay an insurance premium and pass the risk of losses to the financial (banking) sector. The latter receives the insurance premium and undertakes the risk of covering the insurred losses. The revealed link from CO_2 emissions to bank profitability is based on the argument that firms and households insure themselves against climate-related losses thereby shifting these losses to banks. This argument is supported by Hoeppe (2016), who shows that there is 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[16], Hoeppe (2016) concludes that in the U.S. the ratio

[15] Table 7 also shows that ΔROE_1(-1) exercises a positive impact on CATFIN_2. Taking, however, the cumulative impact on CATFIN_2 which arises from all 4 quarters of ΔROE of the previous year (i.e. from ΔROE_1(-1), ΔROE_2(-1), ΔROE_3(-1), and ΔROE_4(-1)), the cumulative impact is strongly negative.
[16] https://www.munichre.com/en/solutions/for-industry-clients/natcatservice.html

of the insured losses in terms of the overall losses in the last years has been far above 50%, and the insurance industry had to pay even 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 1980-2017 is graphically shown in Figure 5. As shown in this Figure, insured losses account for more than 50% of overall losses for all years in this period. Especially 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 is provided in Table 9. In almost all these events, the insured losses were more than 60% of the overall losses. Thus, since most losses are insured, a significant part of the cost of climate change related losses is carried by the financial system, which explains the negative impact of CO_2 emissions on bank profitability.

5. Policy implications

One way of managing by regulators of the positive impact of increasing CO_2 emissions on systemic risk would involve government-sponsored insurance schemes for natural disasters, such as 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 be a step towards neutralizing K from CO_2 emissions (in terms of (4A)), 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 (Gelzinis and Steele, 2019). This action would be compatible with the Fed conducting climate change stress tests taking into account physical risks. 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 the supervisory framework by setting higher risk-weighted bank capital requirements for assets that are sensitive to the price of carbon.

6. Conclusions

This research has provided evidence that CO_2 emissions in the U.S. have a robust impact on the economy's systemic risk in the following year. The present findings are supportive of the physical risk effect of increases in CO_2 emissions, and suggest that, if CO_2 emissions in 2020 increase, the U.S. systemic risk will increase in November and December 2021. As systemic risk affects the macro-economy in a detrimental manner, this evidence indicates that policy makers have a 10-month period to act in order to control for this negative CO_2-driven impact on systemic risk.

We further illustrate that the impact of CO_2 emissions on systemic risk is channeled through bank profitability. We show that there is a negative effect from CO_2 emissions to bank profitability and a negative effect from bank profitability to systemic risk. Bank profitability is the recipient of a detrimental impact of CO_2 emissions, which is then transmitted on to the financial system as a contributor to systemic risk. This implies that policy makers, in order to control the effects of CO_2 emissions on systemic risk, may act to control the effect of CO_2 emissions on bank profitability. Policies, which are compatible with this objective, include federal or state insurance support to banks and measures of integrating climate change into the regulatory framework.

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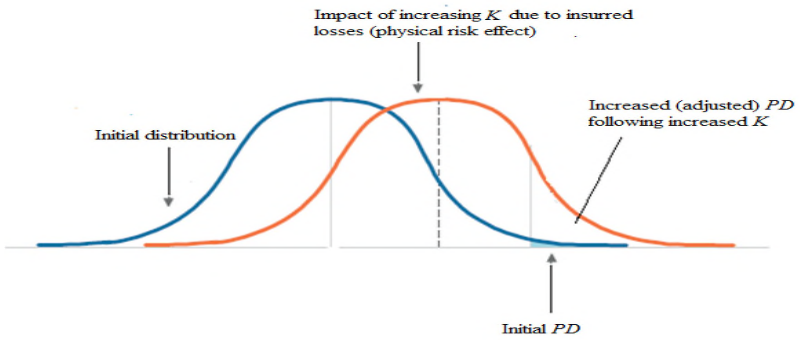
Figure 1: An adjusted Merton framework for the impact of CO_2 emissions on systemic risk

Panel A: Impact of *K*



Panel B: Impact of reduction in A_t

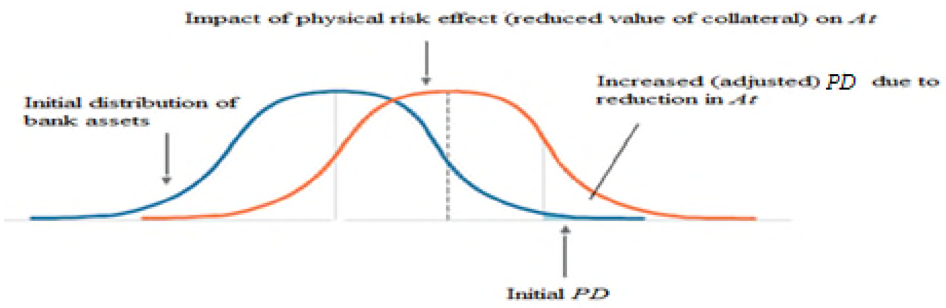


Figure 2: Graphical presentation of the variables

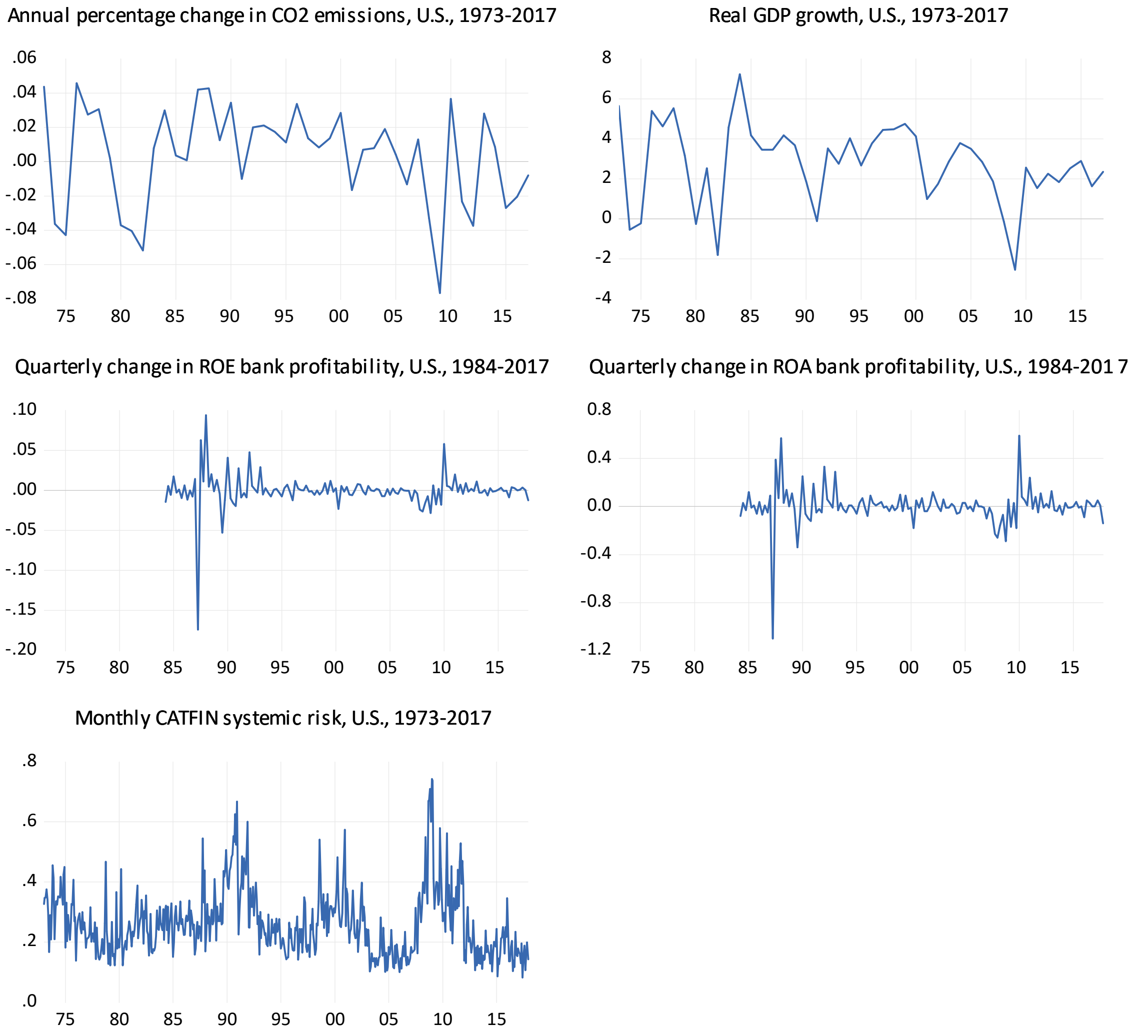


Figure 3A: Impulse response of the 12 monthly systemic risk variables to CO_2 emissions

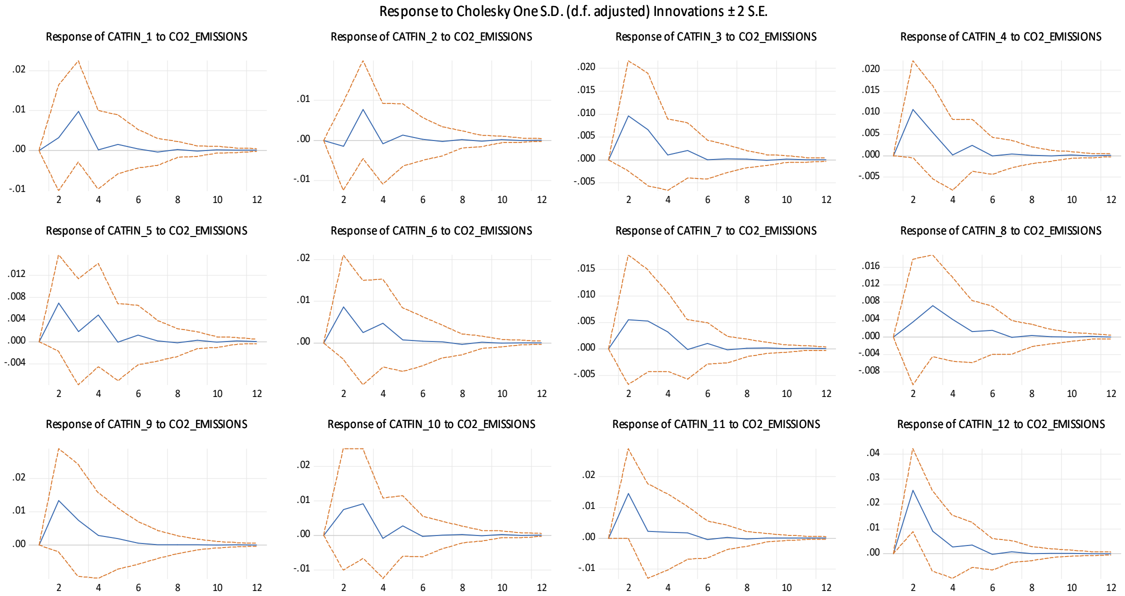


Figure 3B: Accumulated impulse response of the 12 monthly systemic risk variables to CO_2 emissions

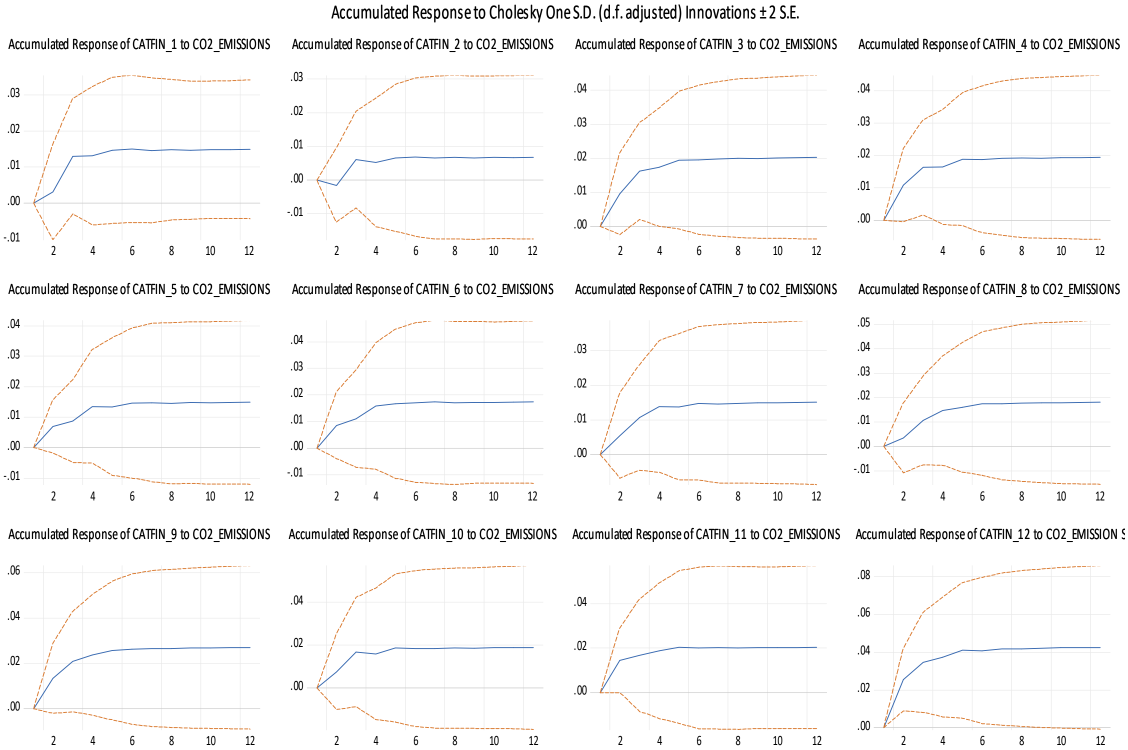


Figure 4A: Impulse response of the 4 quarterly systemic risk variables to CO_2 emissions

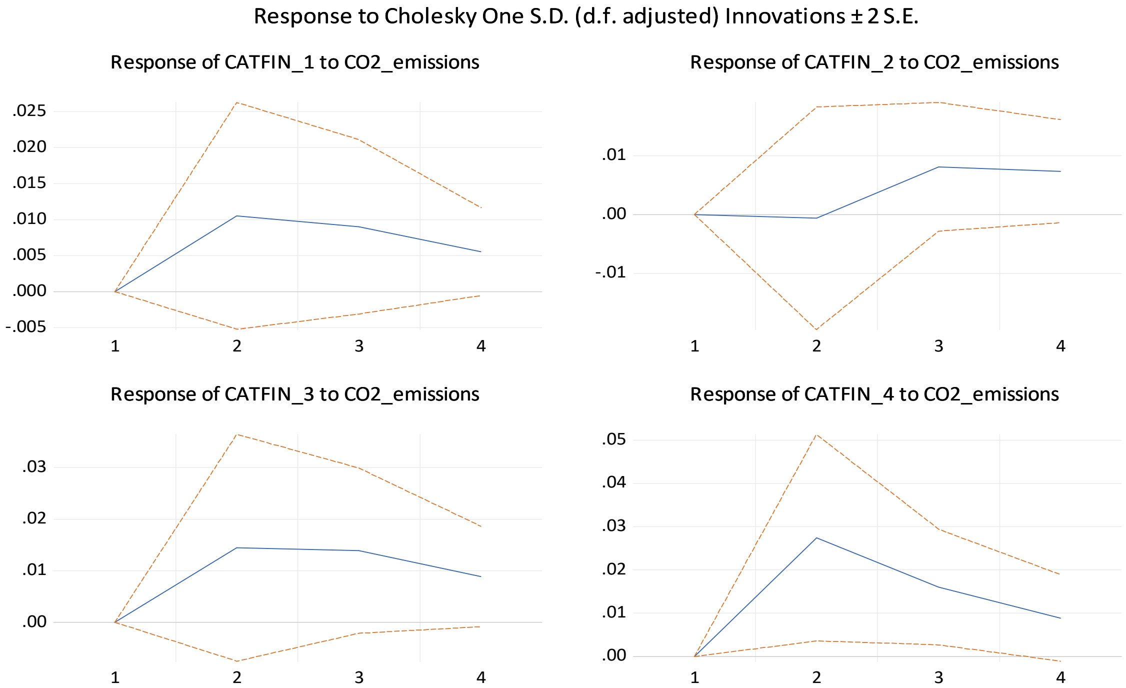


Figure 4B: Accumulated impulse response of the 4 quarterly systemic risk variables to CO_2 emissions

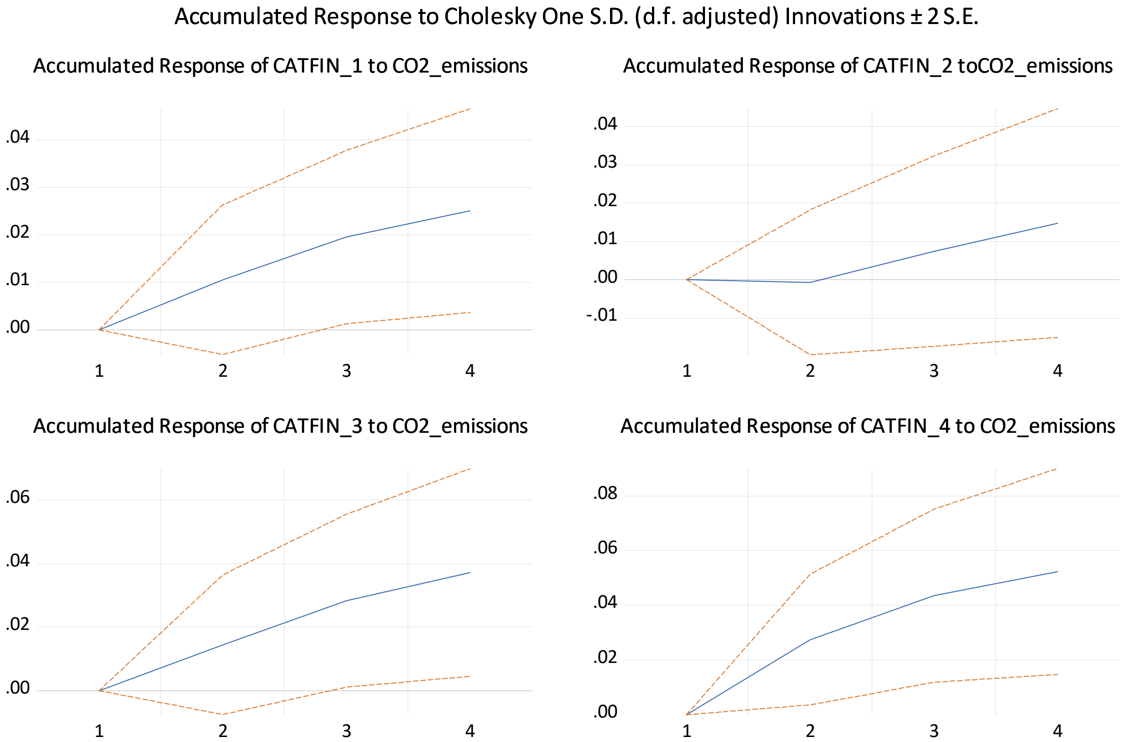
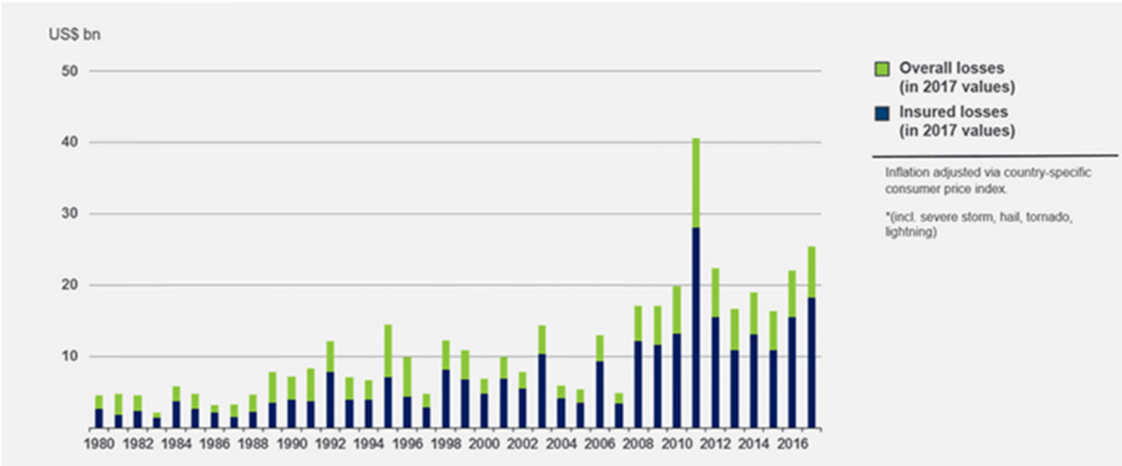


Figure 5: Overall and insured losses in the U.S., 1980-2017



Source: © 2018 Munich Re, Geo Risks Research, NatCatSERVICE. As of January 2018., https://www.iii.org/graph-archive/218221

Table 1: Descriptive statistics

Variable	Mean	Standard deviation	ADF
CATFIN	0.26	0.11	-5.71 (2)
Percentage change in CO_2 emissions ('Δc')	0.003	0.03	-5.56 (0)
Real GDP growth ('Real GDP')	2.75	2.00	-5.12 (0)
Change in bank ROE profitability ('ΔROE')	-0.0002	0.02	-5.97 (5)
Change in bank ROA profitability ('ΔROA')	0.0002	0.15	-5.02 (3)

Notes:

1. 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.

Table 2: MF-VAR model, U-MIDAS estimation: Monthly systemic risk (CATFIN) and annual changes in CO_2 emissions (Δc)

	CATFIN_1	CATFIN_2	CATFIN_3	CATFIN_4	CATFIN_5	CATFIN_6	CATFIN_7	CATFIN_8	CATFIN_9	CATFIN_10	CATFIN_11	CATFIN_12	Δc
CATFIN_1(-1)	-0.039	-0.385	-0.264	-0.289	0.021	0.045	-0.287	-0.328	-0.371	-0.535	-0.238	-0.319	-0.050
	[-0.173]	[-2.031]	[-1.291]	[-1.508]	[0.143]	[0.210]	[-1.363]	[-1.325]	[-1.407]	[-1.763]	[-0.973]	[-1.178]	[-0.915]
CATFIN_2(-1)	-0.055	0.163	0.347	0.271	0.286	0.351	0.494 *	0.520	0.310	0.134	0.324	0.296	0.114
	[-0.214]	[0.763]	[1.500]	[1.252]	[1.697]	[1.452]	[2.071]	[1.860]	[1.042]	[0.391]	[1.172]	[0.965]	[1.848]
CATFIN_3(-1)	0.185	0.150	-0.155	0.154	0.018	0.207	0.185	0.212	0.469	0.284	0.259	0.455	-0.064
	[0.835]	[0.819]	[-0.780]	[0.829]	[0.125]	[1.000]	[0.904]	[0.886]	[1.836]	[0.967]	[1.093]	[1.730]	[-1.212]
CATFIN_4(-1)	-0.468	-0.383	-0.450	-0.429	-0.267	-0.411	-0.353	-0.220	-0.527	-0.765 *	-0.854 *	-1.060 *	-0.001
	[-1.768]	[-1.744]	[-1.899]	[-1.930]	[-1.533]	[-1.657]	[-1.444]	[-0.767]	[-1.724]	[-2.178]	[-3.009]	[-3.370]	[-0.022]
CATFIN_5(-1)	-0.167	0.065	0.405	0.257	-0.209	-0.118	-0.335	-0.130	-0.186	0.334	0.046	0.413	0.052
	[-0.555]	[0.259]	[1.497]	[1.012]	[-1.060]	[-0.417]	[-1.201]	[-0.398]	[-0.534]	[0.833]	[0.145]	[1.152]	[0.723]
CATFIN_6(-1)	0.121	-0.049	-0.227	-0.231	-0.265	-0.333	-0.146	0.117	-0.351	-0.352	-0.390	-0.826	0.025
	[0.413]	[-0.202]	[-0.864]	[-0.936]	[-1.387]	[-1.213]	[-0.540]	[0.369]	[-1.036]	[-0.905]	[-1.240]	[-2.370]	[0.367]
CATFIN_7(-1)	0.174	0.092	0.171	0.206	-0.021	0.541 *	0.149	0.037	0.605 *	0.554	0.772	0.588	-0.029
	[0.682]	[0.433]	[0.749]	[0.960]	[-0.127]	[2.258]	[0.634]	[0.136]	[2.050]	[1.634]	[2.815]	[1.936]	[-0.489]
CATFIN_8(-1)	-0.357	-0.220	-0.132	0.009	0.340 *	0.126	0.006	0.248	0.302	-0.194	0.080	0.075	-0.011
	[-1.616]	[-1.199]	[-0.668]	[0.050]	[2.358]	[0.608]	[0.034]	[1.036]	[1.182]	[-0.663]	[0.338]	[0.289]	[-0.210]
CATFIN_9(-1)	0.372	0.342	0.034	0.043	0.092	-0.172	0.157	-0.449	-0.489	-0.047	-0.451	0.038	-0.010
	[1.437]	[1.593]	[0.150]	[0.198]	[0.549]	[-0.710]	[0.656]	[-1.604]	[-1.636]	[-0.137]	[-1.626]	[0.124]	[-0.161]
CATFIN_10(-1)	-0.081	0.026	0.073	-0.069	0.162	0.058	-0.120	0.001	-0.019	0.151	0.262	-0.072	0.038
	[-0.416]	[0.165]	[0.418]	[-0.418]	[1.265]	[0.316]	[-0.666]	[0.007]	[-0.084]	[0.579]	[1.247]	[-0.310]	[0.829]
CATFIN_11(-1)	0.418	0.541 *	0.168	0.468 *	0.463 *	0.660 *	0.203	0.209	0.724 *	0.560	0.772 *	0.454	-0.090
	[1.693]	[2.640]	[0.760]	[2.257]	[2.875]	[2.852]	[0.890]	[0.784]	[2.541]	[1.710]	[2.919]	[1.550]	[-1.524]
CATFIN_12(-1)	0.115	-0.021	0.360	0.067	-0.075	-0.093	0.288	0.432	0.231	0.240	0.045	0.426	0.059
	[0.501]	[-0.111]	[1.744]	[0.349]	[-0.497]	[-0.434]	[1.354]	[1.728]	[0.867]	[0.783]	[0.182]	[1.556]	[1.076]
Δc(-1)	0.261	-0.124	0.789	0.890	0.569	0.705	0.451	0.284	1.101	0.617	**1.189 ***	**2.095 ***	0.038
	[0.468]	[-0.267]	[1.577]	[1.900]	[1.562]	[1.348]	[0.875]	[0.471]	[1.708]	[0.832]	**[1.987]**	**[3.158]**	[0.284]
C	0.179 *	0.158 *	0.153 *	0.098 *	0.077 *	0.042	0.196 *	0.078	0.074	0.169 *	0.111	0.173 *	-0.037 *
	[3.124]	[3.308]	[2.977]	[2.039]	[2.070]	[0.784]	[3.703]	[1.260]	[1.124]	[2.218]	[1.814]	[2.533]	[-2.715]
REAL_GDP	-0.011	-0.009	-0.009	0.002	0.005	-0.008	-0.007	-0.003	-0.007	-0.004	-0.011	-0.017	0.010 *
	[-1.489]	[-1.510]	[-1.365]	[0.386]	[1.017]	[-1.218]	[-0.987]	[-0.367]	[-0.859]	[-0.443]	[-1.384]	[-1.940]	[5.741]
R-squared	0.609	0.711	0.579	0.570	0.728	0.691	0.499	0.553	0.644	0.529	0.685	0.658	0.691
Adj. R-squared	0.420	0.571	0.376	0.363	0.598	0.542	0.257	0.338	0.472	0.301	0.532	0.493	0.541

Notes:

1. REAL_GDP stands for real GDP growth.

2. * denotes statistical significance at the 5% level.

3. Δc stands for annual percentage changes of CO_2 emissions

4. CATFIN_1 is the variable for the first month of the year, CATFIN_2 is for the second month, ... and CATFIN_12 is for the twelve-th month In line with the discussion of the MF-VAR model in (5), CATFIN_1, CATFIN_2, ... CATFIN_12 appear as endogenous variables along with Δc. Further, CATFIN_1(-1) refers to the first month of the *previous* (*lagged*, denoted by '(-1)') year. For example, if the reference year is 2000, 'CATFIN_1' refers to January 2000, 'CATFIN_2' to February 2000, ..., and 'CATFIN_12' to December 2000. Furthermore, 'CATFIN_1(-1)' refers to January 1999, 'CATFIN_2(-1)' to February 1999, etc.

Table 3: Granger causality tests from annual CO_2 emission changes to the systemic risk of each month of the subsequent year

Causality from: Lagged changes in CO_2 emissions, $\Delta c(-1)$			
Causality to:	Chi-sq	df	Prob.
CATFIN_1	0.22	1	0.639
CATFIN_2	0.07	1	0.789
CATFIN_3	2.49	1	0.114
CATFIN_4	3.60	1	0.058
CATFIN_5	2.44	1	0.118
CATFIN_6	1.82	1	0.177
CATFIN_7	0.76	1	0.381
CATFIN_8	0.22	1	0.637
CATFIN_9	2.92	1	0.087
CATFIN_10	0.69	1	0.405
CATFIN_11	3.95	1	0.047 *
CATFIN_12	9.98	1	0.001 *

Note: * denotes statistical significance at the 5% level.

Table 4: MF-VAR model, U-MIDAS estimation: Quarterly systemic risk (CATFIN) and annual changes in CO_2 emissions, Δc

	CATFIN_1	CATFIN_2	CATFIN_3	CATFIN_4	Δc
CATFIN_1(-1)	-0.153	0.302	0.413	0.231	-0.025
	[-0.927]	[1.512]	[1.795]	[0.945]	[-0.589]
CATFIN_2(-1)	0.044	0.242	0.029	-0.297	0.012
	[0.237]	[1.067]	[0.113]	[-1.072]	[0.257]
CATFIN_3(-1)	0.017	-0.054	-0.189	0.130	-0.007
	[0.099]	[-0.248]	[-0.752]	[0.487]	[-0.156]
CATFIN_4(-1)	0.379	0.213	0.448 *	0.421	0.027
	[2.605]	[1.211]	[2.210]	[1.952]	[0.732]
Δc(-1)	0.649	-0.039	0.891	**1.694 ***	-0.000
	[1.521]	[-0.077]	[1.496]	**[2.675]**	[-0.004]
C	0.176 *	0.091	0.096	0.177 *	-0.031 *
	[3.888]	[1.669]	[1.514]	[2.627]	[-2.720]
REAL_GDP	-0.008	-0.007	-0.007	-0.013	0.011 *
	[-1.292]	[-0.967]	[-0.789]	[-1.360]	[6.884]
R-squared	0.407	0.418	0.413	0.398	0.594
Adj. R-squared	0.311	0.323	0.318	0.300	0.529

Notes: 1. REAL_GDP stands for real GDP growth.

2. * denotes statistical significance at the 5% level.

3. CATFIN_1 refers to the first quarter of the year, CATFIN_2 to the second quarter, CATFIN_3 to the third, and CATFIN_4 to the fourth. CATFIN_1(-1) is the first quarter of the previous (lagged, denoted by '(-1)') year.

4. Δc stands for annual percentage changes of CO_2 emissions.

Table 5: MF-VAR model, U-MIDAS estimation: Average annual systemic risk (CATFIN) and annual changes in CO_2 emissions

	Δc	CATFIN_Annual_average
Δc(-1)	0.024	**0.670 ***
	[0.239]	**[1.960]**
CATFIN_Annual_average(-1)	0.035	0.632
	[0.995]	[5.196]
C	-0.038	0.113
	[-3.200]	[2.803]
REAL_GDP	0.011	-0.008
	[7.312]	[-1.545]
R-squared	0.594	0.494
Adj. R-squared	0.563	0.456

Notes: See notes in Tables 2, and 4.

Table 6: MF-VAR model, *Bayesian* estimation: Quarterly systemic risk (CATFIN) and annual changes in CO_2 emissions

	CATFIN_1	CATFIN_2	CATFIN_3	CATFIN_4	Δc
CATFIN_1(-1)	-0.156 (0.151)	0.300 (0.182)	0.408 (0.210)	0.224 (0.225)	-0.024 (0.039)
CATFIN_2(-1)	0.065 (0.169)	0.251 (0.203)	0.046 (0.234)	-0.270 (0.251)	0.012 (0.045)
CATFIN_3(-1)	-0.001 (0.156)	-0.053 (0.189)	-0.196 (0.219)	0.108 (0.236)	-0.006 (0.043)
CATFIN_4(-1)	0.372 (0.122)	0.195 (0.152)	0.432 (0.177)	0.411 (0.190)	0.026 (0.034)
Δc(-1)	0.264 (0.250)	-0.285 (0.350)	0.559 (0.422)	1.275 (0.471)	-0.007 (0.095)
C	0.177 (0.042)	0.094 (0.051)	0.099 (0.059)	0.179 (0.063)	-0.031 (0.011)
REAL_GDP	-0.007 (0.006)	-0.007 (0.007)	-0.006 (0.008)	-0.012 (0.009)	0.011 (0.001)
R-squared	0.393	0.413	0.408	0.390	0.594
Adj. R-squared	0.407	0.427	0.421	0.404	0.603

Notes: 1. REAL_GDP stands for real GDP growth.

2. * denotes statistical significance at the 5% level.

3. CATFIN_1 refers to the first quarter of the year, CATFIN_2 to the second quarter, CATFIN_3 to the third, and CATFIN_4 to the fourth. CATFIN_1(-1) is the first quarter of the previous (lagged, denoted by '(-1)') year.

4. Δc stands for annual percentage changes of CO_2 emissions.

Table 7: MF-VAR model: Quarterly systemic risk (CATFIN), bank profitability changes (ΔROE), and annual changes in CO_2 emissions (*Δc*)

	ΔROE_1	ΔROE_2	ΔROE_3	ΔROE_4	CATFIN_1	CATFIN_2	CATFIN_3	CATFIN_4	*Δc*
ΔROE_1(-1)	0.331 *	0.046	-0.405 *	-0.106	-0.579	1.818 *	1.635	1.722	0.330
	[3.574]	[0.128]	[-2.844]	[-1.482]	[-0.871]	[2.348]	[1.453]	[1.414]	[1.811]
ΔROE_2(-1)	-0.720 *	0.176	-0.202	0.045	-0.485	-1.504 *	-0.993	-1.046	**-0.490 ***
	[-8.283]	[0.523]	[-1.511]	[0.678]	[-0.778]	[-2.0706]	[-0.940]	[-0.915]	**[-2.863]**
ΔROE_3(-1)	-0.60 *7	0.084	-0.023	0.073	0.282	-2.337	-2.151	-2.101	**-0.831 ***
	[-3.648]	[0.131]	[-0.091]	[0.566]	[0.235]	[-1.679]	[-1.063]	[-0.959]	**[-2.532]**
ΔROE_4(-1)	0.018	1.797	-0.270	0.444	**-7.059 ***	**-11.736 ***	**-9.802 ***	**-11.374 ***	-0.265
	[0.051]	[1.298]	[-0.493]	[1.608]	**[-2.759]**	**[-3.942]**	**[-2.264]**	**[-2.428]**	[-0.378]
CATFIN_1(-1)	0.022	-0.035	0.006	0.023	-0.073	0.383	0.338	0.077	0.034
	[0.855]	[-0.336]	[0.155]	[1.122]	[-0.383]	[1.708]	[1.037]	[0.219]	[0.657]
CATFIN_2(-1)	0.076 *	0.026	0.083*	0.026	0.270	0.141	-0.017	-0.425	-0.001
	[2.936]	[0.262]	[2.082]	[1.327]	[1.445]	[0.647]	[-0.054]	[-1.247]	[-0.024]
CATFIN_3(-1)	-0.027	-0.073	0.018	-0.004	-0.093	-0.297	-0.319	0.152	-0.067
	[-1.048]	[-0.716]	[0.462]	[-0.198]	[-0.490]	[-1.343]	[-0.992]	[0.438]	[-1.290]
CATFIN_4(-1)	0.014	0.088	-0.062	-0.001	0.232	0.028	0.250	0.172	0.010
	[0.653]	[1.037]	[-1.854]	[-0.100]	[1.469]	[0.154]	[0.934]	[0.593]	[0.243]
Δc(-1)	**-0.297 ***	-0.179	0.057	-0.032	**1.338 ***	-0.336	1.606	**2.444***	-0.263
	[-3.747]	[-0.582]	[0.468]	[-0.526]	**[2.349]**	[-0.508]	[1.665]	**[2.342]**	[-1.681]
C	-0.034 *	0.010	-0.018	-0.019 *	0.063	0.105	0.128	0.183	-0.029
	[-4.502]	[0.363]	[-1.606]	[-3.222]	[1.151]	[1.654]	[1.384]	[1.825]	[-1.928]
REAL_GDP	0.005 *	-0.004	0.003	0.002 *	0.018	0.008	0.000	0.009	0.013 *
	[3.637]	[-0.808]	[1.621]	[2.106]	[1.701]	[0.669]	[0.028]	[0.487]	[4.448]
R-squared	0.897	0.124	0.473	0.488	0.668	0.755	0.606	0.582	0.678
Adj. R-squared	0.866	-0.140	0.314	0.334	0.568	0.681	0.487	0.456	0.580

Notes: 1. REAL_GDP stands for real GDP growth. ΔROE stands for the change in bank profitability (Return on Equity).

2. * denotes statistical significance at the 5% level.

3. CATFIN_1 refers to the first quarter of the year, CATFIN_2 to the second quarter, CATFIN_3 to the third, and CATFIN_4 to the fourth. CATFIN_1(-1) is the first quarter of the previous (lagged, denoted by '(-1)') year.

4. *Δc* stands for annual percentage changes of CO_2 emissions.

Table 8: MF-VAR model: Quarterly systemic risk (CATFIN), bank profitability changes (ΔROA), and annual changes in CO_2 emissions (*Δc*)

	ΔROA_1	ΔROA_2	ΔROA_3	ΔROA_4	CATFIN_1	CATFIN_2	CATFIN_3	CATFIN_4	*Δc*
ΔROA_1(-1)	0.301 *	0.094	-0.387 *	-0.095	-0.051	0.333 *	0.339 *	0.313	0.041
	[2.335]	[0.284]	[-3.003]	[-1.037]	[-0.568]	[3.197]	[2.203]	[1.844]	[1.523]
ΔROA_2(-1)	-0.671 *	0.103	-0.186	0.017	-0.080	-0.175	-0.113	-0.088	**-0.062 ***
	[-5.503]	[0.327]	[-1.525]	[0.199]	[-0.950]	[-1.776]	[-0.801]	[-0.554]	**[-2.448]**
ΔROA_3(-1)	-0.574 *	0.115	-0.061	0.015	-0.067	-0.439 *	-0.418	-0.369	**-0.113 ***
	[-2.413]	[0.188]	[-0.256]	[0.093]	[-0.406]	[-2.284]	[-1.515]	[-1.180]	**[-2.291]**
ΔROA_4(-1)	0.280	1.029	0.111	0.569 *	**-0.810 ***	**-1.256 ***	**-1.151 ***	**-1.240 ***	0.010
	[0.757]	[1.074]	[0.300]	[2.156]	**[-3.143]**	**[-4.193]**	**[-2.677]**	**[-2.543]**	[0.134]
CATFIN_1(-1)	0.404	-0.197	0.082	0.244	-0.074	0.383	0.327	0.075	0.036
	[1.549]	[-0.293]	[0.318]	[1.315]	[-0.409]	[1.819]	[1.082]	[0.220]	[0.668]
CATFIN_2(-1)	0.780 *	0.132	0.776 *	0.212	0.312	0.040	-0.135	-0.531	-0.003
	[2.828]	[0.185]	[2.815]	[1.081]	[1.630]	[0.182]	[-0.423]	[-1.466]	[-0.060]
CATFIN_3(-1)	-0.271	-0.530	0.095	-0.016	-0.125	-0.308	-0.331	0.144	-0.063
	[-1.042]	[-0.789]	[0.367]	[-0.088]	[-0.692]	[-1.467]	[-1.100]	[0.422]	[-1.166]
CATFIN_4(-1)	0.048	0.545	-0.484 *	-0.007	0.233	0.175	0.380	0.324	0.026
	[0.225]	[0.976]	[-2.243]	[-0.047]	[1.557]	[1.006]	[1.517]	[1.141]	[0.591]
Δc(-1)	**-2.742 ***	-1.769	0.318	-0.466	**1.506 ***	-0.235	1.663	**2.548 ***	-0.261
	[-3.482]	[-0.869]	[0.404]	[-0.831]	**[2.751]**	[-0.370]	[1.820]	**[2.460]**	[-1.587]
C	-0.311 *	0.056	-0.144	-0.1782 *	0.049	0.085	0.110	0.163	-0.031 *
	[-4.128]	[0.287]	[-1.919]	[-3.317]	[0.950]	[1.401]	[1.267]	[1.650]	[-2.019]
REAL_GDP	0.043 *	-0.023	0.025	0.022 *	0.022 *	0.011	0.004	0.012	**0.013 ***
	[2.785]	[-0.586]	[1.628]	[2.051]	[2.117]	[0.921]	[0.271]	[0.615]	**[4.085]**
R-squared	0.829	0.117	0.503	0.525	0.702	0.780	0.655	0.599	0.654
Adj. R-squared	0.777	-0.150	0.352	0.382	0.611	0.714	0.551	0.478	0.549

Notes: 1. REAL_GDP stands for real GDP growth. ΔROA stands for the change in bank profitability (Return on Assets)

2. * denotes statistical significance at the 5% level.

3. CATFIN_1 refers to the first quarter of the year, CATFIN_2 to the second quarter, CATFIN_3 to the third, and CATFIN_4 to the fourth. CATFIN_1(-1) is the first quarter of the previous (lagged, denoted by '(-1)') year.

4. *Δc* stands for annual percentage changes of CO_2 emissions.

Table 9: Overall losses vs insured losses (US $ 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	13000	9800
8	4/12 - 31/12	Wildfire	2200	1700

Source: TOPICS Geo Natural Catastrophes, 2017, page 64-65.

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