The impact of COVID-19 related policy interventions on international systemic risk*

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Abstract

We examine the relationship between systemic risk, its traditional financial and economic determinants, and the COVID-19 related policy interventions in an international framework. The COVID-19 outbreak period represents for us an ideal hub to test the role of such policies on systemic risk. A cross-country panel analysis shows that bank-specific financial variables do not represent a threat to the financial system, contrary to uncertainty and some economic variables such as inflation and interest rates that are the main channels through which policy interventions increased systemic risk worldwide. A possible explanation for our findings is a milder *disconnect* between the real economy and the financial system, as opposed to the whole equity market, given the higher burden that the financial sector has in an economic recovery.

Keywords: Systemic Risk, International Markets, COVID-19 Pandemic, Policy Interventions, Financial Stability.

JEL classification: G01, G15, G18, G20.

Declarations of interest: none

*We thank Jonathan A. Batten (the editor), five anonymous referees, as well as Sandra Batten, Michele Bagella, Edoardo Chiarotti, Domenico Curcio, David Feldman (discussant), Delphine Lautier and Radoslav Raykov for their valuable comments and suggestions. We thank all the participants at the World Finance Conference 2021, IFABS 2021, International Conference Turkish Economic Association 2021, and the XXXII Villa Mondragone International Economic Seminar. Views expressed are solely those of the authors and so cannot be taken to represent those of the European Banking Authority (EBA) or to state the EBA's policy.

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1 Introduction

The spreading of the coronavirus (COVID-19) dramatically changed the global financial and economic outlooks. Uncertainty due to the rise in COVID-19 cases, the implementation of nationwide lockdowns to contain the spread of the pandemic, the fear related to decreasing firms' profits and the negative economic outlook caused a strong drop in global stock markets, with the S&P 500 losing over $5 trillion in value between February and March 2020, according to Thomson Reuters.[1] The pandemic impacted directly the real economic landscape and all industries in both advanced and emerging markets, with the banking and financial sectors affected mostly indirectly in the first phase through a decline in their stock prices.[2]

The pandemic has put banks in a tricky spot. The role of the financial sector acquires systemic importance when facing firms' increasing demand for credit. When the COVID-19 pandemic struck and economies locked down, with entire industries largely affected, banks faced unprecedented aggregate demand for credit-line drawdowns. In particular, while banks and financial firms are not the triggers of the COVID-19 crisis, a longer slowdown or recession causing financial losses, lower capital buffers, and a reduction in credit provision would have negatively put these firms' loan portfolios, profitability, liquidity and solvency positions under additional pressure. The increasing unemployment rate, families' lower income to repay their loans, and stimulus cheques further reduced demand for loans from households and firms. Given this background, banks' stock prices crashed and systemic risk level increased in most countries, with our results showing systemic risk reaching its absolute peak after the World Health Organization (WHO) characterized COVID-19 as a pandemic on March 11, 2020.

During the global financial crisis (GFC), the regulation of the banking system turned out to be unable to maintain financial stability largely because it overlooked systemic risk (e.g., Allen and Gu, 2018). We are now interested in studying whether policy interventions adopted worldwide to primarily contain the impact of the pandemic on the economy were, this time around, also successful in containing systemic risk and maintaining financial stability. Our main questions are: *did policy interventions in response to the COVID-19 pandemic help decrease systemic risk? Or did the traditional financial and economic channels prevail in affecting systemic risk and shaping the financial systems worldwide?*

[1] For more information about the U.S. and global stock market tumbling around that time, see `https://www.reuters.com/article/us-global-markets-idUSKCN20M001`.

[2] Over the course of 2019, global financial markets have been stressed by the impact of the onset of the trade war between China and the United States, the United States presidential elections and Brexit. Despite these events, the IMF (2019) forecast global growth of 3.2% in 2019, picking up to 3.5% in 2020. However, after less than three months from January 2020, with the spreading of COVID-19, the global financial and economic outlooks dramatically changed causing an adjustment of the projections of global growth in 2020 to a fall of -4.9% (IMF, 2020), defining the COVID-19 crisis the worst economic downturn since the Great Depression.

Starting from March 2020, in response to the pandemic, a fast-paced range of policy interventions was implemented by central banks, regulators and governments. Countries worldwide announced over $13.8 trillion (equal to 13.5% of the global GDP) in total emergency funding, more than four times the support provided during the GFC.[3] The unprecedented measures spanned a great range of actions: support for employment (e.g., wage subsidies, cheques, furlough schemes), support for households (e.g., unemployment benefits, child benefits, cash transfers), and increased credit to households and businesses. Although many of these policies did not primarily aim to reduce systemic risk, it is important for policymakers to be aware of any secondary benefit for financial stability.

Conventional and unconventional monetary policies were adopted by central banks worldwide to allow the banking sector to have the necessary liquidity to continue providing loans to the real economy. Specifically for the financial sector, supervisory authorities reduced certain mandatory capital buffers, allowing banks to continue their lending activity, and encouraged banks not to pay dividends to not undermine their capital positions. Furthermore, regulators delayed the transition to the new IFRS 9 loan loss provisioning rules. These interventions aimed to avoid bank failures in 2020 and supported the banking sector in continuing its critical function of keeping the economy running.

The stocks in many sectors rebounded when the policy interventions took place with the global stock market recovering more than half its losses from 23 March to late May, in what many see as a puzzle.[4] However, the stock prices of financial firms did not react in the same way and the level of systemic risk remained high globally. Financial firms are not like every other sector in the economy and also in this crisis they played (and would need to play) a different role.[5] The pandemic and the government lockdowns put the liquidity insurance function of financial firms to a real-life test. Financial firms had the crucial role of supporting other firms and households during the pandemic containment phase and especially during the economic recovery phase. Our study shed new light on this *disconnect* between financial markets and the real economy from a financial sector firms' perspective.

The COVID-19 pandemic provides us with an extraordinary and unique time period to empirically test some of the traditional channels of systemic risk at work and how these interacted with the unprecedented policy interventions adopted worldwide throughout 2020.

[3]See the related Economist article at `https://www.economist.com/briefing/2021/03/06/covid-19-has-transformed-the-welfare-state-which-changes-will-endure`.

[4]The early disconnect between the quick recovery of financial markets and the sluggish response of the real economy was source of much debate as highlighted by the cover page of The Economist, May 9th, 2020: A dangerous gap: The markets v the real economy at `https://www.economist.com/weeklyedition/2020-05-09`. See also Caballero and Simsek (2020).

[5]The idea that a well-working banking system plays an essential role in promoting economic development in a recovery phase is well-grounded in the literature (see, e.g., Levine, 1997, 1998).

First, our empirical results show a statistically significant and homogeneous increase in international systemic risk – measured as the $\Delta CoVaR$ developed by Adrian and Brunnermeier (2016); amid the COVID-19 outbreak, more precisely after the WHO declared it a global pandemic. Second, by breaking down policy interventions into three different categories, we find mixed results regarding the role of fiscal, regulatory, and monetary policies in reducing systemic risk, with their impact being country and policy dependent.

Next, by focusing on common economic and financial drivers of systemic risk, our panel analysis shows time-varying findings according to the choice of the sub-period. Specifically, during the COVID-19 crisis, bank-specific financial variables do not appear to represent a systemic threat to the financial system as we find during the GFC. In addition, when we interact the policy interventions with the traditional channels, we find positive coefficients mainly related to higher volatility and worsening economic conditions, while negative on firm-specific determinants. These results suggest an increase in systemic risk during the COVID-19 crisis mainly spreading through the economic channels rather than through the financial system conditions.

Therefore, interestingly, when it comes to systemic risk, we find evidence of a milder *disconnect* between the real economy and the financial markets. We find evidence that the banking system fears possible financial distress, losses generated in financial firms, and possible systemic events. The impact of the policy interventions seemed to have generated a short-lived relief but was not sufficient to make the systemic risk level drop. The disconnect between financial markets and the real economy comes to light amid substantial interventions targeting the corporate sectors. Firms certainly benefited from public interventions providing them with a liquidity cushion to absorb income shortfalls (e.g., Acharya et al., 2020). Thus, the stock markets around the world rebounded pushed up by news about policy interventions reflecting an optimistic economic outlook. However, stock prices of financial firms took longer to rebound, with risk perception and systemic risk which remained high.[6] We uncover inflation and interest rate as the main economic channels through which policy interventions posed a higher burden on the financial sector, negatively affected financial firms' prices and, therefore, contributed to the increase in systemic risk globally.

We directly contribute to the existing financial literature examining the systemic risk determinants which are predominantly based on the U.S. financial sector and focus mostly on the GFC and the Eurozone crisis (see, among others, Engle et al., 2015; Adrian and Brunnermeier, 2016; Brownlees and Engle, 2016; Acharya et al., 2017). Our analysis focuses on the recent pandemic which provides us with a distinctive setting for studying systemic

[6] Demirgüç-Kunt et al. (2020) highlight that the effectiveness of policy measures was dependent on bank capitalization and fiscal space in the respective country.

risk and its determinants as compared to previous investigations. We also relate to the recent literature on the relationship between the banking sector and the COVID-19 pandemic (e.g., Acharya et al., 2020; Li et al., 2020; Demirgüç-Kunt et al., 2020; Polyzos et al., 2021; Corbet et al., 2022), on the relationship between the pandemic and systemic risk (e.g. Lan et al., 2020; Rizwan et al., 2020; Wu et al., 2020; Abuzayed et al., 2021; Duan et al., 2021; Borri and Di Giorgio, 2022; Rizwan et al., 2022)[7], and on the dynamics of stock prices, economic activity, and policy actions during the COVID-19 pandemic (e.g., Baker et al., 2020; Caballero and Simsek, 2020; Cox et al., 2020; Gormsen and Koijen, 2020; Apostolakis et al., 2021; Bevilacqua et al., 2021; Davis et al., 2021).

Our paper contributes to the above literature on the relationship between systemic risk and the pandemic in several ways. First of all, we study the dynamics of market-based systemic risk measures ($\Delta CoVaR$ and MES) and the impact of policy interventions in an international framework. Second, we improve upon studies that only discussed or tested the impact of aggregate policy indicators on systemic risk measures (e.g. Rizwan et al., 2020; Duan et al., 2021) since we empirically test the impact of policy interventions on systemic risk measures both as an aggregate indicator and also when classified into different policy categories (e.g. fiscal, monetary). Finally, we drift apart from the above studies as we also study the potential financial and economic channels through which the policy interventions have been affecting systemic risk internationally.[8] We investigate the impact of traditional determinants of systemic risk through the lens of the COVID-19 pandemic and policy interventions, uncovering a *disconnect* between economic and financial drivers which is new in the literature. Financial variables do not represent a threat to the financial system, contrary to some economic variables (e.g. inflation, interest rate) which are the main channels through which policy interventions increase systemic risk worldwide. Hence, compared to other studies, by studying different categories of policy interventions, as well as financial and economic channels through which systemic risk is affected, our results can potentially serve as guideposts for central banks, regulators and policy-makers for the assessment of global market-based systemic risk in the coming years given its fundamental role in the forefront of the economic recovery.

We also touch upon the literature on the role of banks as liquidity providers (see Kashyap et al., 2002; Gatev and Strahan, 2006; Ivashina and Scharfstein, 2010; Acharya and Mora,

[7]For a collection of early ideas regarding systemic risk, resilience tools and strategies during COVID-19, see Linkov et al. (2021).

[8]Duan et al. (2021) studied the transmission of the pandemic through different channels compared to ours. The first is the stringency of the government response, the second is the bank default risk, and, finally, they also study which banks' characteristics are more likely to increase the effect of Covid on banks systemic risk.

2015; Dombret et al., 2019), on the role of banks during times of recession (see Bolton et al., 2016; Beck et al., 2018), and on the positive relationship between the banking sector development and economic growth (see Rajan and Zingales, 1998; Beck et al., 2000). Finally, we connect to studies on the impact of COVID-19 on the economy and financial markets arguing about a *disconnect* between the stock market and the economic conditions generated by the pandemic (see Caballero and Simsek, 2020; Koulischer et al., 2020; Igan et al., 2020; Caballero and Simsek, 2021; Goldstein et al., 2021).

We organize our analysis as follows. In section 2 we illustrate the methodology underlying the $\Delta CoVaR$ and the main hypotheses of the study. In section 3 we describe the data adopted. In section 4 we present the global time-series evolution of systemic risk and test its contribution across countries. In section 5 we provide the results of the empirical analysis. In section 6 we report additional robustness checks, whereas section 7 concludes the paper. Additional results and supplemental material are reported in the paper Appendix.

2 Systemic risk and study hypotheses

2.1 Systemic risk: literature and methodology

Systemic risk is a broad concept with no unique definition which varies according to its many dimensions and measures. Acharya et al. (2017) define systemic risk as a situation in which a market freeze could significantly reduce financial intermediation activities, with potentially adverse consequences for the real economy (e.g., Adrian and Brunnermeier, 2016).

Our paper builds the main analysis on the well-known $\Delta CoVaR$ from Adrian and Brunnermeier (2016) as a measure of systemic risk. The particular choice of the $\Delta CoVaR$ is largely motivated by three considerations. First, this measure allows us to generate time-varying estimates of the systemic risk level for each geographical zone in our sample which accounts for co-movements among financial institutions. Specifically, it is strongly and positively correlated with interconnectedness, and such a positive correlation mainly arises from an elevated effect of interconnectedness on systemic risk during recessions (Cai et al., 2018). Second, Zhang et al. (2015) inspect whether market-based measures of systemic risk offer early warning signals on the systemic importance of large financial institutions. Their results show that the $\Delta CoVaR$ by Adrian and Brunnermeier (2016) is the only measure, among several, that increased the predictive power of conventional early warning models during the GFC. Finally, the $\Delta CoVaR$ has become one of the most widely accepted measures for systemic risk over the past decade (e.g., Morelli and Vioto, 2020). [9]

We define the $\Delta CoVaR^{i|Market}$ as the conditional value-at-risk of the financial sector portfolio of country i conditional on the entire market being in tail conditions.[10] We deliberately choose to estimate systemic risk for each country by conditioning the analysis to the respective domestic equity index due to the unique nature of the COVID-19 crisis. Indeed, while systemic risk usually builds in the financial sector and is then transmitted to the real economy, the pandemic triggered a crisis from the real economy spreading towards the financial sector which could have caused financial turmoils backfiring to the real economy. Thus, estimating the $\Delta CoVaR$ by conditioning the analysis to the domestic financial or banking sector index would not have allowed us to capture the sensitivity of $\Delta CoVaR$ due to information related to COVID-19.

We estimate $\Delta CoVaR^{i|Market}$ as the difference between the $CoVaR$ of the financial sector of country i conditional on the distress of the entire market in the same country and $CoVaR$ conditional on the median state. We denote the $q\%$ value-at-risk quantile by $VaR_{q,Market}$:

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

where X_{Market} is the benchmark equity index of country i's *return loss* – i.e., $-log(P_1/P_0)$; for which $VaR_{q,Market}$ is defined. $CoVaR_q^{i|C(X_{Market})}$ is the VaR of the financial sector in country i conditional on some event $C(X_{Market})$ of the entire market. Event C is an event equally likely across financial institutions. Usually, C is the entire market's loss at or above its $VaR_{q,Market}$. $CoVaR_q^{i|C(X_{Market})}$ is implicitly defined by the $q\%$-quantile of the conditional probability distribution:

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

The $\Delta CoVaR$ of the financial system conditional on the entire market being under

[9]For studies providing extensions of the $\Delta CoVaR$ estimation method see López-Espinosa et al. (2012) Reboredo and Ugolini (2015), and Bevilacqua et al. (2023), among others.

[10]Adrian and Brunnermeier (2016) define $CoVaR$ as the conditional value-at-risk of the whole financial sector j conditional on institution i being in a particular state. Among other properties of this measure, the $\Delta CoVaR_q^{j|i}$ is directional. Thus, the $\Delta CoVaR_q^{j|i}$ of j conditioned to the distress of i is not equal to $\Delta CoVaR_q^{i|j}$ of i conditioned to j being in crisis. The importance of the direction of the conditioning can be understood by using a simple example. If the whole market is in significant distress, the financial sector is also likely to face difficulties. On the other hand, conditioning on the financial sector being in distress does not materially impact the probability that the wider market is in distress as well. For this reason, we decide to use the $\Delta CoVaR^{i|Market}$, which captures the direction from the entire market being in distress to the financial sector, as during the COVID-19 crisis.

distress is computed as follows:

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

We use quantile regression to estimate $\Delta CoVaR$. In particular, following Adrian and Brunnermeier (2016), we estimate the following quantile regression:[11]

$$X_{q,i} = \alpha_q + \beta_q X_{q,Market} \quad (4)$$

where $X_{q,i}$ and $X_{q,Market}$ denote country i's financial sector and equity market return losses, respectively. Using the predicted value of $X_{Market} = VaR_{q,Market}$, we yield the $CoVaR_{q,i}$ measure as follows:

$$CoVaR_{q,i} = VaR_q^{i|X_{Market}=VaR_{q,Market}} = \hat{\alpha}_q + \hat{\beta}_q VaR_{q,Market} \quad (5)$$

where $VaR_{q,Market}$ is the q%-quantile of the equity market of country i losses. Based on equation (3), we estimate $\Delta CoVaR_{q,i}$ as:

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

In addition to the $\Delta CoVaR$, studies have suggested several alternatives to measure systemic risk (see, for instance, the survey paper by Bisias et al. (2012)). While in our main analysis we rely on the $\Delta CoVaR$, we also provide robustness checks by adopting the marginal expected shortfall (MES) by Acharya et al. (2017) in section 6. Both the $\Delta CoVaR$ and the MES are estimated considering a 1-year moving window with daily data.

Another widely adopted measure of systemic risk is the $SRISK$ by Brownlees and Engle (2016) that also identifies the systemic risk contribution of each financial firm and measures the capital shortfall of the same conditional on a severe market decline. It is a function of size, leverage and risk, which is measured with the $long - run - MES$. These additional balance-sheet variables make $SRISK$ less volatile compared to $\Delta CoVaR$ and MES. In particular, while this characteristic is an advantage of $SRISK$ because it stabilizes the ranking of systemically important banks (Benoit et al., 2017), it makes the same measure less suitable when investigating systemic risk reactions to market sentiment. Changes in market systemic risk would be fully reflected in the measure only with the publication of the quarterly balance-sheet data. This issue together with the data availability for all the

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

financial firms in a global context represent a limitation to the adoption of the $SRISK$ in our study.

2.2 Hypotheses

In this sub-section, we draw the main hypotheses of our empirical analysis based on the previous literature or the expected underlying economic intuitions. We first look at the main traditional determinants of systemic risk.

Policies of "too-big-to-fail" have received wide attention in the literature (e.g, Demirgüç-Kunt and Huizinga, 2013; Boyd and Heitz, 2016; Thanassoulis and Tanaka, 2018). Laeven et al. (2016) find that systemic risk grows with bank size, with large banks having a higher degree of complexity in their organizational structures and business models. Moreover, systemic risk increases when the larger players in the financial sector have a larger share of output (Boyd and Heitz, 2016). This background implies that large banks are systemically more important. We measure the size of financial firms through the log of total assets and expect a positive relationship with our dependent variable, namely systemic risk.

Next, we consider the Basel leverage ratio, computed as the Tier 1 Capital over total exposures. This is usually considered as a proxy for the level of solvency of financial firms implying that a higher leverage ratio should be associated with a higher resiliency. Allen and Gu (2018) argue that the degree of leverage in the financial system is not a necessary condition for an asset price bubble to cause financial instability. The price-to-book ratio is usually a proxy for growth opportunities, indicating whether financial firms can generate market value commensurate to the value of their tangible assets (see López-Espinosa et al., 2012). Thus, we expect these two ratios to have a negative relationship with systemic risk.

As part of firm-specific variables, we also include the share of non-performing loans (NPL) as a percentage of total loans as a measure of balance sheet risk. Mayordomo et al. (2014) argue that the NPL ratio has a strong impact on systemic risk. In particular, financial firms with a high share of non-performing loans are likely to become distressed contributing to the build-up of systemic risk with potential spillover effects on interconnected firms (Allen et al., 2012). In this case, we expect a positive impact on systemic risk.

As a risk sentiment variable, we take the realized volatility (log), which is commonly found as an important predictor of systemic risk, with more volatile banks facing a higher probability of default (see Lehar, 2005). Further, López-Espinosa et al. (2013) find that a higher level of volatility tends to increase the magnitude of the loss in the whole financial system. For this reason, we expect a positive relationship with our dependent variable.

We also include five measures of real macroeconomic activity: the consumer price index

(CPI), gross domestic product (GDP), industrial production (IP) growth rate, 3-month Treasury Bill rate (T-Bill) and the unemployment rate. In particular, increases in GDP and industrial production are expected to decrease systemic risk implying a negative relationship with the systemic risk measure adopted. On the other hand, healthy financial systems are commonly associated with low inflation, 3-month treasury bill rate, and unemployment rate. Thus, a higher value of these three variables should be associated with a lower economic capacity to withstand shocks, therefore, we expect a positive relationship with the dependent variable (see e.g., Brownlees and Engle, 2016; Laeven et al., 2016).

The second set of hypotheses we draw in this section includes the COVID-19 specific variables and policy interventions. For the first, even though we only adopt the number of confirmed cases and the lockdown measures as controls, we hypothesize a positive relationship with the systemic risk since both indicators may lead to increased investors' fear and economic slowdown. For the policy interventions, from March 2020, central banks, regulators and governments promptly reacted to the COVID-19 pandemic with a large set of policies and actions aimed to limit the human and economic impact of the pandemic. Hence, it may be logical to expect these policy dummies to have a reducing impact on the economic and financial uncertainty and therefore a reducing impact on systemic risk.

For instance, a role for monetary policy in contributing towards economic growth increasing GDP in the Eurozone is found by Darracq-Paries and De Santis (2015). A similar conclusion is reached by Gambacorta et al. (2014) who study the effects of unconventional monetary policy in advanced economies, including the Eurozone. However, monetary policy measures implemented to save the troubled financial markets may only work in the short-run, as they have found to have worked in the United States given that the unlimited quantitative easing (QE) has somehow stopped the panic of investors (e.g., Zhang et al., 2020). These policies may create inconsistencies between investors' short-term and long-term expectations (see Gormsen and Koijen, 2020), introducing further uncertainty into the global markets especially for emerging economies (e.g., Chen et al., 2016), and may conflict with financial stability. Further, Cox et al. (2020) find that, for instance, Fed conventional monetary policy announcements in response to the COVID-19 pandemic showed no impact in calming the financial markets. Conversely, they show that unconventional monetary policy announcements (e.g., unprecedented actions to provide loans to support the economy) played a role in the market turmoil. Bevilacqua et al. (2021) reach a similar conclusion finding that the most important policies in calming the financial market fear are unconventional tools such as the U.S. dollar liquidity swap lines or macroprudential regulations. Given this background, setting ex-ante hypotheses on the relationship between policy interventions and systemic risk appear to be a hard task, therefore we expect a mixed relationship across countries and policy groups.

Hence, while many relationships between financial and macroeconomic factors and systemic risk are well-grounded in the literature, mixed results have been found in the literature so far regarding the impact of policy interventions on systemic risk. The COVID-19 period represents indubitably a useful environment and a unique opportunity to develop further empirical evidence on the relationships between both traditional determinants and policy interventions, and the global systemic risk. Moreover, during this crisis stock markets have been found to be sensitive to each country's macroeconomic fundamentals (see Capelle-Blancard and Desroziers, 2020). This would imply that the relationship between policy interventions and the stock market may only explain a limited part of the stock market, thus systemic risk, fluctuations worldwide. Addressing the broader picture including financial and economic channels at play when studying the role of policies on systemic risk is the main aim of our empirical analysis.

3 Data

In this section, we describe the data adopted in this study, namely the financial and economic variables, the data related to the COVID-19 pandemic and the policy announcements implemented in response to it. We select the top-ten ranked countries per total confirmed cases as of December 31, 2020, namely Brazil, France, Germany, India, Italy, Russia, Spain, Turkey, the United Kingdom and the United States.[12] We also include China, Japan and South Korea to achieve a more comprehensive worldwide comparison. More information about the data and their sources are reported in Appendix A. Tables A1 to A3 in the Appendix provide the data summary statistics.

3.1 Financial and economic variables

To estimate our measures of systemic risk, we collect stock prices for firms included in the GICS financial sector and benchmark equity indexes of thirteen countries from Bloomberg.[13] The number of financial firms for each country is as follows: 11 in Brazil and India, 73 in China, 4 in France and Germany, 10 in Italy, 22 in Japan, 8 in Russia, 48 in South Korea, 7 in Spain, 16 in Turkey, 19 in the United Kingdom and 65 in the United States.

[12] The ranking is downloaded from: https://www.worldometers.info/coronavirus.

[13] Considering the Global Industry Classification Standard (GICS) framework, the financial sector is composed of the banking, insurance and diversified financial industries. For a detailed description of the GICS methodology, readers can refer to: "Global Industry Classification Standard (GICS) Methodology", Standard & Poor's, 2009; or, https://www.msci.com/gics.

Firms' size, leverage, price-to-book and NPL ratios for each firm in the financial sectors of these countries are also collected from Bloomberg at a monthly frequency. Realized measures of volatility are computed from the stock prices of the GICS financial sector's firms and calculated from the stock prices returns of the GICS financial sector's firms in a model-free manner. This represents an end-of-the-day annualized realized volatility measure computed from daily log-returns (see Schwert, 1989). We adopt the following formula: $RVOL_t = \sqrt{\frac{252}{n}\sum_{i=1}^{n} r_i^2}$, where $r_i = ln(\frac{P_t}{P_{t-1}})$ representing daily log-returns computed from the price difference, with P_i representing the financial firms' daily prices with $i \in \{1, \ldots, n\}$. Among the macroeconomic variables, we collect CPI, GDP, IP, T-Bill and unemployment rate for each country from the World Economic Outlook Database of the International Monetary Fund (IMF) at a monthly frequency.

3.2 COVID-19 data and policy interventions

Regarding the COVID-19 specific variables, we collect the number of confirmed cases in each of the selected countries from the Johns Hopkins Coronavirus Resource Center. To measure governments' lockdown initiatives, we adopt the SIndex developed by the Oxford University, which tracks travel restrictions, trade patterns, school openings, social distancing and other such measures, by country and day.

The WHO declared COVID-19 a public health emergency of international concern on January 30, 2020 and characterized it as a pandemic on March 11, 2020. After that, a fast-paced series of actions and policy interventions aiming to contain the economic contraction and market distress due to the COVID-19 pandemic was announced and implemented worldwide. These policies were announced quite consistently throughout the year, with a clear peak around March and April 2020. We adopt the COVID-19 Financial Response Tracker (CFRT) developed by the Yale Program on Financial Stability (YPFS), which collects economic policy responses from official government websites around the world. In particular, The CFRT follows economic interventions by central banks, fiscal authorities, and international organizations aimed at combating the negative effects of the coronavirus pandemic and restoring financial stability. We collect the dates of the press releases and meetings regarding government, central banks and regulators policy announcements and implementations across the countries in our sample from January to December 2020.

The actions implemented worldwide had spanned a large set of tools. We are also interested in the heterogeneous impact of the COVID-19 led policies and actions on systemic risk. To this end, we classify the policies into three broad categories by the role of the implementing institutions (see also Allen and Carletti (2013) and Bevilacqua et al. (2021)

for a similar classification). This classification a) is according to the different channels through which they might have affected the economy and b) allows for a more homogeneous comparison across countries since not all economies have experienced the same range of policy interventions.

The first is what we define, in a broad sense, the *monetary policy category*: it consists of both conventional (e.g., interest rate changes, open market operations, supply of money and credit into the economy) and unconventional policies (e.g., forward guidance and large scale assets purchases) implemented by monetary authorities worldwide. As a few examples, on March 3rd, the U.S. Federal Open Market Committee lowered the target range for the federal funds rate by 1/2 percentage point, to 1 to 1-1/4 percent. On March 17, the Fed established a commercial paper funding facility (CPFF) to support the flow of credit to households and businesses and a primary dealer credit facility (PDCF) which offers overnight and term funding. On March 31, the Fed established a temporary repurchase agreement facility for foreign and international monetary authorities (FIMA Repo Facility). The beneficiaries targeted by all these Fed actions were several, among which SMEs, banks and financial institutions, households and businesses and also international central banks.

In the Eurozone several monetary policy interventions in response to the COVID-19 pandemic were announced by the European Central Bank (ECB). For instance, on March 18 the pandemic emergency purchase programme (PEPP) was announced as a temporary programme for asset purchases with an initial envelope of EUR 750 billion and it was then increased on June 4 and December 10 2020. In the United Kingdom, the Monetary Policy Committee at the Bank of England (BoE) voted to cut Bank rate to 0.1% and increased its holdings of the U.K. government and corporate bonds by £ 200 billion on March 19. On March 16, the Bank of Japan (BoJ) increased purchases of commercial papers and corporate bonds and enhanced monetary easing by implementing the Special Funds-Supplying Operations to facilitate financing. These were only some of the examples of broad monetary policies interventions in some of the countries in our sample. Some other announcements targeted more economies on the same dates. For instance, international central banks such as, within our sample, BoE, BoJ, ECB and Fed announced on March 19 coordinated action to enhance the provision of liquidity via the standing U.S. dollar liquidity swap line arrangements. In our dataset, this date will be marked as a monetary policy announcement in the United Kingdom, Japan, European Member States and the United States at the same time.

The second policy category is the *macroprudential regulations category*: it consists of actions aimed to relax some of the regulatory restrictions of regulated financial entities to free up capital for credit creation or their own needs for liquid assets. As a few examples, on March 18 a money market mutual fund liquidity facility (MMLF) was announced in the U.S. to ensure that financial institutions receive credit for the low-risk activities. In the Eurozone, the Member States also adopted measures to concentrate all efforts on the COVID-19 response. For instance, on March 17 the Ministry of Economy and Finance of Italy passed the "Cura Italia" law decree for a total amount of EUR 25 billion in response to the COVID-19 pandemic. Further, to allow the banking and financial system in Italy to align with European initiatives, the Bank of Italy has granted delays in reporting regulatory compliance.

The third is the *fiscal policy category*. Fiscal interventions were suitable instruments for addressing the detrimental impact of the pandemic on the economy. Fiscal stimulus can alleviate the negative impact of the crisis by supporting aggregate demand and providing well-targeted aid to vulnerable households and firms. As an example, among the main policies for fiscal stimulus in the United States, we include important acts such as the Coronavirus Aid, Relief, and Economic Security (CARES) Act from March 25 to March 27. On April 24 the U.S. Congress and the President signed the Paycheck Protection Program (PPP) and Health Care Enhancement Act, appropriating an additional \$321 billion. In Europe, the four largest Member States, namely Germany, France, Italy and Spain, implemented their first fiscal emergency packages as of mid-March to support the sectors most hit by lockdown measures and in the summer further packages were announced. For instance, in June Germany announced its "Konjunktur und Zukunftspaket" with measures amounting to EUR 130 billion (i.e., 3.9% of GDP) and in September France launched its "France Relance" package worth EUR 100 billion (i.e., 4.4% of GDP).

We construct three dummy variables representing each one of the three policy category denoted (in broad terms) as fiscal ($D_{i,t|Fis}$), monetary ($D_{i,t|Mon}$) and regulatory ($D_{i,t|Reg}$). When considered daily these dummies will mark 1 when at least one policy was implemented on that day.[14] We also construct a generic policy dummy denoted as $D_{i,t|All}$ which will mark 1 if at least one of these three categories was implemented and will capture any possible policy categories interaction effect. In the main empirical analysis of the paper, the policy interventions are aggregated at the monthly frequency, summing up all policies in each month during the COVID-19 period for each policy category. Figure A1 in Appendix A provides an illustration of the policy frequency for some selected countries.

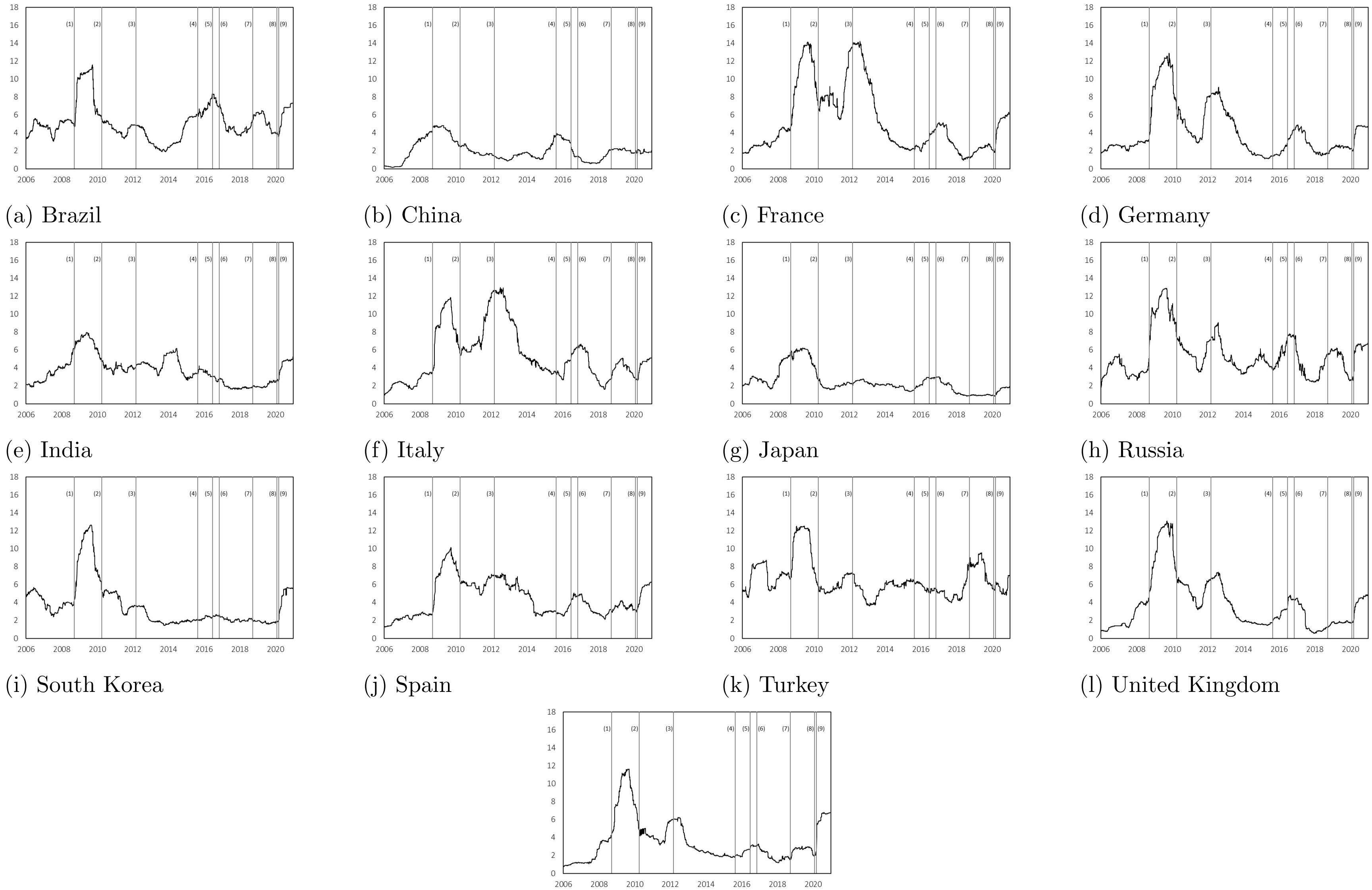
[14] In a few cases, we had more policies implemented on the same day for some countries. These cases were mostly limited to March 2020 and for the U.S.. For instance, on the 17th of March for the U.S. there were 3 fiscal policy announcements, 4 monetary and 4 regulatory. On 23rd March 2020, there were 4 fiscal, 7 monetary and 4 regulatory announcements. In the main analysis of the paper, we mark 1 regardless of the number of policies implemented on that day to be consistent across countries. However, we have also performed the same analysis by changing the dummy variables construction. The dummy variables would just be re-scaled in the few occurrences with multiple policies on the same day, and this leads to results which are qualitatively and quantitatively the same as the main analysis.

4 Dynamics of systemic risk

In this section, we first illustrate the dynamics of systemic risk over our sample period and across the selected countries. Second, we present a ranking of the most systemically risky countries according to our measure. Figure 1 displays the evolution of the systemic risk for the thirteen countries, spanning the period from January 1, 2006 to December 31, 2020. Following Adrian and Brunnermeier (2016) and Brownlees and Engle (2016), we closely look at some of the major dates characterizing the historical magnitude of systemic risk expanding this list of events to include some more recent and some COVID-19 related ones. In particular, the dates we consider are: (1) the Lehman Brothers bankruptcy on September 15, 2008; (2) the agreement between the Greek government and the IMF for the First bailout package of EUR 110 billion on May 2, 2010; (3) the peak of 44.21% reached by the Greek 10-year bond yields on March 9, 2012; (4) the Chinese market crash on August 24, 2015; (5) the Brexit referendum result on June 24, 2016; (6) the U.S. presidential election 2016 results on November 8, 2016; (7) the tech (or cryptocurrency) crash in the U.S. on September 21, 2018; (8) the WHO declaring COVID-19 to be a public health emergency of international concern on January 30, 2019; and (9) the WHO characterizing COVID-19 as a pandemic on March 11, 2020. We first analyze the response of $\Delta CoVaR_{95^{th}}$ to these events and then we specifically focus on the evolution of systemic risk during the COVID-19 period.

From Figure 1 we observe that different countries react in a heterogeneous manner to systemic risk. In particular, all time-series patterns react to the GFC by peaking around the bankruptcy of Lehman Brothers (1) and recovering after interventionist efforts of respective governments to stabilize their economies (2). On the other hand, the Eurozone crisis which peaks around (3) seems to have affected only European financial systems with co-movements observed also in Russia, the U.K. and the U.S.. However, the magnitude of systemic risk measured during the Eurozone crisis is comparable with that observed during the GFC only for European countries. On the contrary, the quick sequence of risky events from 2015 to 2016 – (4) to (6) has an unexpected consequence in global financial systems by hitting their domestic systemic risk, except for South Korea and Turkey. Italy, Russia and Turkey peak again between 2018 and 2019 most likely reflecting domestic political turmoils, increased geopolitical tension and the Turkish Lira crisis for the latter.

The COVID-19 period is characterized by an almost harmonized behavioural timing showing a significant abrupt increase of systemic risk for all of the countries except for China, Japan and Turkey. In particular, systemic risk appears to be stable until March, after which it sharply increases, remaining at high levels until December 2020. A possible reason for this common behavior, especially within developed economies, can be that dominant players



(a) Brazil (b) China (c) France (d) Germany

(e) India (f) Italy (g) Japan (h) Russia

(i) South Korea (j) Spain (k) Turkey (l) United Kingdom

(m) United States

Figure 1: Time series of $\Delta CoVaR_{95^{th}}$.

Time series of $\Delta CoVaR_{95^{th}}$ at a daily frequency from January 1, 2006 to December 31, 2020. The vertical axis reports values of $\Delta CoVaR_{95^{th}}$ in percentage – %. The horizontal axis reports the years. The solid vertical lines mark: (1) the Lehman Brothers bankruptcy; (2) the first bailout package for Greece; (3) the Greek 10-year bond yields peak; (4) the Chinese market crash; (5) the Brexit referendum result; (6) the U.S. election 2016 results; (7) the tech crash; (8) the WHO declaring COVID-19 to be a public health emergency of international concern; and (9) the WHO characterizing COVID-19 as a pandemic.

in financial markets have become more and more alike sharing similar products, risk assessments and models, thus exposing them to a greater number of common risk factors that could exacerbate their interdependencies and heighten systemic risk, especially during economic downturns. In Turkey, the $\Delta CoVaR_{95^{th}}$ reaches a remarkable peak in correspondence with the highest number of confirmed cases reached on December 8, 2020; while systemic risk behaviors of China and Japan result markedly different, which is rather unsurprising considering that the COVID-19 pandemic affected these two countries to a lesser extent. This finding is also in line with Davis et al. (2021) stating that the pandemic had much larger effects on stock prices in the U.S. than in China, this given at least in part by China's greater success in containing the pandemic and also perhaps because COVID-19 erupted first in China playing a different dynamic between stock prices and mobility. However, both China and Japan show higher systemic risk compared to the pre-COVID-19 period.

Table B1 in the Appendix shows the descriptive statistics of the systemic risk estimates of $\Delta CoVaR_{95^{th}}$ for the thirteen countries. An interesting outcome is that $\Delta CoVaR_{95^{th}}$ reached its maximum value, and highest volatility, during the sub-period from 2008 to 2013, which characterizes the GFC and Eurozone crisis, however, during 2020, the mean and median values are higher compared to any other sub-period and less volatile. This entails that the systemic contribution of each financial sector to the respective domestic market had a greater consistency over 2020, remaining less volatile, thus, stagnant, as also shown in Figure 1.

Focusing our attention on the COVID-19 period, we notice a quite abrupt spike in systemic risk around mid-March. We test whether the systemic risk significantly increases in the 30 days after the announcement of the WHO characterizing COVID-19 as a pandemic on March 11, 2020, compared to the 30 days before. We adopt the Wilcoxon signed rank sum test and present the results in Table 1. The null hypothesis is rejected at 1% critical level in all cases excluding Italy, which test statistic is significant at 5% level. Our results show that after this event, the systemic risk of each country has significantly increased. This finding is in line with our previous analysis, which shows a major peak of the systemic risk after March with its level remaining almost constant during the pandemic.

Further, we rank the countries according to their contribution to systemic risk over 2020. We adopt a bootstrap Kolmogorov-Smirnov dominance test which is run for each pair of countries' $\Delta CoVaR_{95^{th}}$ over 2020 and also considering both economies stressed at the 5% level – i.e., considering only the 5% worst realization of $\Delta CoVaR_{95^{th}}$ over 2020. We rank countries at the 1% significance level. This means that the financial sector of countries in a higher position is systemically riskier (at the 1% significance level) than those ranked below them. Table B2 in the Appendix reports the results. Countries like Brazil and Turkey are in the top rank because of a high level of systemic risk not only due to

Table 1: Wilcoxon signed rank sum test on March 11, 2020.

H_0: $\Delta CoVaR^i_{95^{th}; \text{ Mar. 11 – Apr. 10, 2020}} \leq \Delta CoVaR^i_{95^{th}; \text{ Feb. 9 – Mar. 10, 2020}}$			
Brazil	-3.2591***	Russia	-4.3089***
China	-3.5509***	South Korea	-4.3232***
France	-4.3377***	Spain	-4.3150***
Germany	-4.3375***	Turkey	-4.2789***
India	-4.3372***	United Kingdom	-4.3299***
Italy	-2.3957**	United States	-4.3171***
Japan	-4.3382***		

The test statistics of the Wilcoxon signed rank sum test. The failure to reject H_0 means that the systemic risk level of the country i did not increase in the 30 days after March 11, 2020 compared to the 30 days before. The systemic risk is measured by the $\Delta^{\$}CoVaR_{95^{th}}$. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

COVID-19, but which was high already before 2020 reflecting their fragile economy with a high level of unemployment and inflation. The U.S. is ranked first and third, over 2020 when stressing systemic risk at the 1% and 5% level, respectively suggesting the dramatic increase in systemic risk experienced by the U.S. during the pandemic. Italy, France, Russia, South Korea and Spain are in the mid-top ranking followed by Germany, India and the U.K. which systemic risk appears to be contained when compared to the other financial systems. When considering the $\Delta CoVaR_{95^{th}}$ stressed at the 5% level, only France and Spain have the same ranking implying that more countries have systemic risk estimates not significantly different; however, when we deepen our analysis by considering only the 5% worst realization, the difference in systemic risk among countries is amplified since they might have experienced very different extreme systemic tail events due to the pandemic.

In summary, graphical evidence combined with the results of the tests shows that at the peak of the COVID-19 crisis, the international systemic risk raised abruptly. In some cases, the COVID-19 amplified an already existing financial instability. In others, it threatened an otherwise stable and healthy financial system. Further, the increase in systemic risk due to the COVID-19 pandemic is also, according to our measure, not as high as the one reached for some economies during the GFC. It is noteworthy here that there are profound differences between the mechanics of the two recessions. The financial crisis has generated fundamental reforms in the financial regulatory system in the U.S. and internationally in direct response to the weaknesses revealed in the pre-crisis system (e.g., Allen et al., 2016). Hence, the status of the financial system worldwide is healthier at the beginning of 2020 than it was in 2007. Another aspect to note is the absence of a lockdown, which has enormously contributed to the output loss associated with the COVID-19 recession, instead. On the other hand, similarities between the two recessions can also be drawn. The economic uncertainty at the beginning of the two recessions has been quantitatively similar for some economies even though this is due to different reasons. The magnitude of the policies implemented to contain the uncertainty shock in both recessions is comparable, being in both cases an aggressive output stabilization policy scheme. Lastly, the COVID-19 pandemic is a major shock to the whole economy but unlike traditional crises, and the GFC, its origin is exogenous to the financial sector. As a result, in this particular crisis, it would have been hard for systemic risk measures to capture the build-up phase of such risk.

Governments, regulators and central banks worldwide initiated multiple actions in quick succession to combat the pandemic and alleviate the economic and financial crisis from multiple angles; decreasing market uncertainty, stabilizing economic growth, allowing access to credit reducing possible interconnectedness among distresses in the financial sectors, namely containing and decreasing systemic risk. Policy actions may have played a role in attenuating financial instability, however, our graphical analysis and ranking show that most of the countries are still facing elevated systemic risk level at the end of 2020. This analysis entails that increased scrutiny may be needed to achieve domestic and global recovery. Starting from this background, the focus of our empirical analysis is on, first, assessing whether policy actions have played a role in mitigating the level of systemic risk worldwide, and second whether traditional economic and financial drivers of systemic risk still hold over the COVID-19 period.

5 Regression analysis

In this section, we present several sets of empirical results. First, we show the impact of the policy interventions in response to the COVID-19 crisis on international systemic risk in subsection 5.1; second, the relationship between systemic risk and some of the traditional macroeconomic and financial determinants in subsection 5.2; and finally, the impact of the policy interventions through some traditional channels on systemic risk in subsection 5.3.

5.1 International systemic risk and the COVID-19 related policies

In this subsection, we first investigate the impact of policy interventions on $\Delta CoVaR_{i,95^{th}}$ and whether it differs according to the specific policy category. We consider three policy categories for each country, namely monetary (D_{Mon}), fiscal (D_{Fis}), and regulatory (D_{Reg}); we also consider an aggregated variable, (D_{All}), accounting for all types of policies combined to control for potential joint effects. In this analysis, we take all the variables at a daily frequency and our sample period covers the whole of 2020.

We start by conducting a panel regression analysis through model 7 by running the following model:

$$\Delta CoVaR_{95^{th},i,t} = \alpha_i + \beta_{Mon} D_{i,t-1|Mon} + \beta_{Fis} D_{i,t-1|Fis} + \beta_{Reg} D_{i,t-1|Reg} + \beta_{All} D_{i,t-1|All} + \lambda_i \text{Conf. cases}_{i,t-1} + \rho_i \text{SIndex}_{i,t-1} + \gamma_i \text{X}_{i,t-1} + \sum_{j=1}^{n-1} Country_i + \sum_{j=1}^{m-1} Time_j + \epsilon_{i,t} \quad (7)$$

where $\Delta CoVaR_{95^{th},i,t}$ is our dependent variable computed as described in section 2.1; the daily policy dummies mark 1 in case of at least one policy announcement on that day in one of the selected policy categories and countries, and 0 otherwise. We also include the cumulative number of confirmed cases (Conf. cases) and an indicator for governments' lockdown restrictions (SIndex) in each of the selected countries as control variables strictly specific to the COVID-19 pandemic. We have also replaced the number of cases in regression equation 7 with the number of deaths and hospitalizations.[15] These variables are both collected from the Johns Hopkins Coronavirus Resource Center Database. X includes other control variables, namely $Volatility$, each country's daily realized volatility, and also the previous lag of the dependent variable ($CoVaR$). *Country* and *Time* are country and time dummies to control for the individual country and time fixed effects, respectively.[16]

In Table 2, we first present the pooled results regarding the effect of the announced policy interventions when disentangled into the three different categories. We are aware that policy responses may not be allocated randomly but may instead respond endogenously to health, economic, or financial news, which can affect systemic risk.[17] To mitigate this possible causality concern, in addition to controlling for COVID-19 specific variables, we also repeat the same exercise (see columns (3) to (6)), controlling for a proxy for the previous day change in countries' volatility and systemic risk levels, these variables potentially reflecting days that might have prompted policy actions.

We observe a significant and decreasing impact on systemic risk for monetary policies,

[15] We thank an anonymous referee for suggesting this additional check.

[16] We thank two anonymous referees for suggesting this pooled panel regression analysis.

[17] We consider policy action dummies to be exogenous shocks for the financial system. However, one may claim that the systemic risk measures worldwide are likely to be correlated with unobserved factors that guided policy decisions during the pandemic period. Policymakers are presumably trying to optimize response taking into account forward projections of country-specific impacts of the pandemic on the economy in response to a period of high uncertainty.

Table 2: **COVID-19 related policies impact on global systemic risk: Panel analysis.**

Dependent variable	$\Delta CoVaR_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$D_{i,t-1\mid Mon}$	-0.125**	-0.149**	-0.153**	-0.161	-0.155	-0.158
$D_{i,t-1\mid Fis}$	0.113***	0.152***	0.156***	0.010*	0.008*	0.007*
$D_{i,t-1\mid Reg}$	-0.110***	-0.145***	-0.144***	-0.005*	-0.004**	-0.003**
$D_{i,t-1\mid All}$		-0.064	-0.066	0.004	0.005	0.007
$Conf.Cases_{i,t-1}$	0.005***	0.006***	0.005***	0.001**		
$Deaths_{i,t-1}$					0.002	
$Hospitaliz_{i,t-1}$						0.001
$SIndex_{i,t-1}$	0.007***	0.007***	0.007***	0.002*	0.008*	0.009*
$Volatility_{i,t-1}$			0.378**	0.026*	0.026*	0.025*
$CoVaR_{i,t-1}$				0.989***	0.988***	0.987***
Time FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
$adj.R^2$ (%)	82.2	82.4	82.5	94.9	94.7	94.5
Obs.	3376	3376	3376	3376	3376	3376

The regression coefficients from model 8. The analysis is conducted for 2020 at a daily frequency. All equations are estimated with country and time fixed effects. Intercept results are not reported for the sake of space. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

however, this effect goes away when we control for previous market volatility and lagged dependent variable. Thus, this finding implied a limited role of this policy channel in mitigating global systemic risk. On the other hand, fiscal policy interventions are found to increase systemic risk internationally, however, their effect is weak when controlling for previous volatility and systemic risk levels. A possible explanation for the positive impact of the fiscal policies on systemic risk internationally could be the fact that by providing such fiscal stimuli to the consumers and increasing the budget deficit, the governments will have more limited resources to save the too-big-to-fail banks if a crisis happens. For instance, Correa et al. (2014) show that increased sovereign credit risk adversely affects banks that are expected to receive support from the government. Further, we find that regulatory policies show a stronger impact in reducing systemic risk (see, for instance, Cox et al., 2020; Bevilacqua et al., 2021). Finally, we find that the combined policy interventions are found to be not significant in reducing systemic risk. Overall, these findings confirm the mixed relationship we expected from the hypotheses' description in subsection 2.2.

Regarding our controls, we find that the number of confirmed cases as well as lockdown interventions positively and significantly impact the next-day level of systemic risk. This is as expected since the worsening of the COVID-19 cases and more stringent lockdown policies entail a positive contribution to increasing systemic risk. We also find a positive and significant contribution for previous-day market volatility and systemic risk. We detect no significant role for the number of hospitalizations and deaths, therefore we decided to remove these two controls from our next analyses, and to and keep the number of confirmed cases as a better proxy for the worsening of the COVID-19 pandemic.

To further investigate these mixed results, we have also performed the same analysis at the single-country level. We check the role of each policy category for each country in our sample taken individually by running the following model 8:

$$\Delta CoVaR_{95^{th},i,t} = \alpha_i + \beta_{Mon} D_{i,t-1|Mon} + \beta_{Fis} D_{i,t-1|Fis} + \beta_{Reg} D_{i,t-1|Reg} + \beta_{All} D_{i,t-1|All} + \lambda_i \text{Conf. cases}_{i,t-1} + \rho_i \text{SIndex}_{i,t-1} + \epsilon_{i,t} \quad (8)$$

where everything is defined as in equation 7.[18] We present the results in Table 3.

We uncover additional information on policies which could be classified as more or less successful in decreasing systemic risk in specific economies. When looking at the overall impact of the policy interventions combined, we observe a significant and negative impact of the policies dummy for Russia, South Korea and the U.S.. This finding suggests that in these countries the actions aimed at reducing the economic consequences of the pandemic were also able to mitigate systemic risk. Conversely, we find that policies implemented in countries such as Italy and Germany increased] systemic risk. In all the other countries, we find that the combined policy interventions did not significantly affect the systemic risk. Overall, when looking at the effect of the aggregated policy interventions on systemic risk, we uncover heterogenous findings.

Now we look at the effect of the announced policies when disentangled into the three different categories. For the monetary policy results, we find a significant and decreasing impact on systemic risk in Germany and Italy, see, for instance Gambacorta et al. (2014) and Darracq-Paries and De Santis (2015). However, for all the other countries, we detect a not significant impact of monetary policy actions, this finding suggesting a limited role of this policy channel in mitigating global systemic risk.

Interestingly, fiscal policy interventions are found to be significant in reducing systemic

[18]In this exercise, we also include the Euro Area for comparison, whereas we drop it in the panel analysis. The Euro Area is proxied with the S&P Europe 350 Financial Sector GICS Level 1, which is designed to reflect the Eurozone market and accounts for around 70% of the region's market capitalization. It includes 16 countries in the Euro Area.

Table 3: COVID-19 related policies impact on global systemic risk.

Dependent variable	$\Delta CoVaR_{i,t}$						
Country	Brazil	China	Euro Area	France	Germany	India	Italy
$D_{i,t-1\|Mon}$	-0.187	-0.035	-0.145	0.107	-0.677***	-0.142	-0.554*
$D_{i,t-1\|Fis}$	0.025	-0.019	0.322*	-0.621*	-0.425**	-0.401**	-0.435
$D_{i,t-1\|Reg}$	0.042	0.013	-0.677***	-1.271***	-0.491**	-0.573***	-0.557**
$D_{i,t-1\|All}$	0.065	0.001	0.254	-0.186	0.695***	0.152	0.555*
$Conf.Cases_{i,t-1}$	0.006***	0.001*	0.005***	0.003***	0.002**	0.002***	0.003***
$SIndex_{i,t-1}$	0.011***	0.001**	0.028***	0.035***	0.038***	0.021***	0.006**
$adj.R^2$ (%)	84.2	16.2	60.4	51.5	71.2	77.1	20.4
Obs.	261	261	261	261	261	261	261
Country	Japan	Russia	South Korea	Spain	Turkey	UK	US
$D_{i,t-1\|Mon}$	0.047	-0.191	0.043	0.114	0.267	-0.030	-0.121
$D_{i,t-1\|Fis}$	-0.162	-0.054	2.668**	0.061	0.318**	-0.098	-0.229***
$D_{i,t-1\|Reg}$	-0.311***	-0.240	-0.801	-1.898**	0.217	-0.197**	-0.459***
$D_{i,t-1\|All}$	0.002	-0.336*	-1.732**	-0.113	-0.089	-0.167	-0.149*
$Conf.Cases_{i,t-1}$	0.002***	0.007***	0.001***	0.008***	0.001***	0.002***	0.001**
$SIndex_{i,t-1}$	0.008***	0.045***	0.038***	0.019***	0.001	0.036***	0.066***
$adj.R^2$ (%)	43.3	86.1	35.1	47.6	26.6	83.1	94.1
Obs.	261	261	261	261	261	261	261

The regression coefficients from model 8. The analysis is conducted for 2020 at a daily frequency. Intercept results are not reported for the sake of space. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

risk in the U.S., Germany, India and France, however, they are found to increase systemic risk in the broader Euro Area and also in South Korea. An explanation for such heterogeneous impact might be that while the global nature of the crisis has led to a more coordinated response in central banks across the world, the timing and magnitudes of fiscal announcements were more scattered across countries. A possible explanation for the positive impact of the fiscal policies on systemic risk in these two regions could be the fact that by providing such fiscal stimuli to the consumers and increasing the budget deficit, the governments will have more limited resources to save the too-big-too-fail banks if a crisis happens.

Further, we find that regulatory policies show an even stronger impact in reducing systemic risk in our analysis (see, for instance, Cox et al., 2020; Bevilacqua et al., 2021). Regulatory actions are found to be significantly decreasing systemic risk in the U.S., the U.K., all the selected Eurozone countries, Japan, India and also in the broader Euro Area. Finally, for countries such as Brazil, China and Turkey even when policies are decomposed into the three categories, we find no significant impact on their systemic risk. These findings echo the mixed relationships uncovered from the panel analysis in Table 8 and expected from the hypotheses description in subsection 2.2. Regarding our controls, we find quite homogeneous results for the impact of the number of confirmed cases, being positive and significant for all countries in our sample. A similar result is found for the lockdown restrictions, with the only exception of Turkey. Davis et al. (2021) also find that stock prices fall sharply with the stringency of lockdown restrictions worldwide.

These results, however, need to be taken with a grain of salt and serve more as a descriptive guidepost for the relationship between our dependent variable and the policy actions. In fact, clearly isolating the causal impact of the policy interventions on systemic risk is not straightforward due to the potential endogeneity of policy actions. Hence, also in this case, we repeat the same exercise controlling for the previous-day country volatility. We find that the results are overall very similar, with only fiscal policies weakening or losing their significance in a few cases (e.g., France). Fiscal stimulus to households and firms might have been the most unprecedented policy packages put in place to sustain the economy. Most of the time, they were announced and scheduled following periods of high uncertainty and therefore possibly being already priced in by financial firms' stock prices and already reflected in our systemic risk measures. When significant, we detect a positive sign for the measure of uncertainty meaning that a higher uncertainty would lead to a higher systemic risk, as expected. The results are reported in Table C1 in the Appendix.

Moreover, one may also argue that a decreasing impact on systemic risk in our sample could be due to the first news regarding the COVID-19 vaccines. The approval of the COVID-19 vaccines contributed to reducing the uncertainty in the stock market, boosting economic recovery and it might have positively affected systemic risk worldwide. This analysis goes beyond the scope of our paper and the first vaccines' approvals correspond with the end of our sample period. However, we briefly test whether systemic risk significantly decreased after the first COVID-19 vaccine that was granted regulatory approval on December 2, 2020, being this the only vaccine approval date in our sample which allows us a sufficient amount of data to run the Wilcoxon signed rank sum test.[19] We find that the null hypothesis is rejected at the 1% critical level in all cases excluding China in which is rejected at the 5% level implying that after the first vaccine approval, the systemic risk worldwide has significantly decreased. We then control for a dummy reflecting the positive shocks related to the COVID-19 vaccine approval dates in our model 8. In this case, the decreasing impact of some of the policy

[19]The first COVID-19 vaccine was granted regulatory approval on December 2, 2020 by the U.K. medicines regulator MHRA. On December 12, 2020 the U.S. Food and Drug Administration has authorised the Pfizer-BioNTech coronavirus vaccine for emergency use. The European Medicines Agency approved the Pfizer-BioNtech vaccine only at the end of 2020, on the December 29.

interventions does not hold. For instance, the fiscal policies found significant in reducing systemic risk in Italy and France lose their significance, and the regulatory interventions in the U.K. are now significant only at the 10% level. These findings open up for further reflections on the validity of the vast number of policy interventions in mitigating systemic risk as well as on the interactions that such policies might have played with more traditional financial and economic channels of systemic risk.

In addition, one can argue that some policies were implemented outside trading hours but mostly during the day, before the closure of the financial market, therefore could affect the closing prices of the financial stocks in our sample. For this reason, as a robustness check, we also test the role of the policy interventions taken at time t for the specific countries in Tables C2 and C3 in the Appendix. Also in this case, we observe mixed results with respect to the role of the policy interventions, in line with the main results of this section.

Finally, financial firms adopted in our sample can presumably be among the largest in each country and are likely to have international presence. Hence, announcements of financial policies in the United States can affect firms in other countries in case they operate in the U.S. To check this spillover effect of policies across countries, mainly from the U.S., we perform an additional analysis where now we run a pooled panel regression to check the role of the policy categories implemented by the U.S. on all the economies in our sample. We report the results in Table C4 in the Appendix. We observe a spillover effect for the monetary and regulatory policies in other countries, however, this is associated with a higher systemic risk in these countries. Moreover, when we control for the previous levels of volatility and systemic risk in these countries, the policy spillover effect disappears. The dummy including all policies is also found to be significant after controlling for previous volatility, but not after controlling for previous systemic risk. The insignificant role of U.S. policies when controlling for countries' previous risk, as well as the positive sign associated to them when significant, rule out any possible U.S. spillover effect. Thus, we believe our results and the role of policies on systemic risk are mainly country- and economy-dependent.[20]

Overall, both from the pooled panel analysis and from the individual country evidence, we observe a decisive role for regulatory policies successful in mitigating systemic risk. The role for monetary policies is limited to a few economies and a mixed role is detected for fiscal and aggregated policy interventions which, in some cases, have contributed to an increased level of systemic risk. However, when controlling for additional factors (e.g., market volatility or vaccines), the significance of the policy interventions weakens. This first empirical exercise helps us to set the ground for the next empirical analysis. In order to better pinpoint the channels through which policy interventions transmit towards systemic risk, we need to take

[20]We thank an anonymous referee for suggesting this empirical exercise.

into account a broader set of economic and financial factors and interact them with the policy interventions. To be useful as a guide for policy response in the future, one needs to establish which channels were more or less useful to transmit the policy intervention effectiveness onto systemic risk. Thus, we next provide an overview of the main determinants of systemic risk over the last decades with a specific focus on the pandemic year. Finally, we interact these factors with the policy interventions adopted worldwide to uncover the main transmission channels.

5.2 Determinants of systemic risk before and during COVID-19

To disentangle the effects of the policy interventions from other factors, we take a step back and study the set of more traditional drivers of systemic risk. We perform a panel regression analysis with the $\Delta CoVaR$ as the dependent variable and bank-specific characteristics (size, leverage, price-to-book, balance sheet composition), risk sentiment (realized volatility) and macroeconomic factors (GDP, CPI, IP, T-Bill, unemployment rate) as independent variables.[21] We assess whether these factors matter for the financial systems' contribution to the global systemic risk across the whole sample period and sub-periods. Panel regressions are estimated using country and time fixed effects. Standard errors are clustered at the level of the individual country.

We start by conducting a panel regression analysis through model 9. The panel is unbalanced since not all the financial firms in each country have been trading continuously during the January 2001 to December 2020 sample period. We run the following model:

$$\begin{aligned}\Delta CoVaR_{95^{th},i,t} = \alpha_i + \beta_{Firm}\mathrm{Firm}_{i,t-1} + \beta_{RVOL}\mathrm{RVOL}_{i,t-1} + \\ \beta_{Macro}\mathrm{Macro}_{i,t-1} + \sum_{j=1}^{n-1} Country_i + \sum_{j=1}^{m-1} Time_j + \epsilon_{i,t} \quad (9)\end{aligned}$$

where $\Delta CoVaR_{i,95^{th}}$ is computed as described in section 2.1, *Firm* is a (4 x 1) vector of firm-specific systemic-related variables, namely Basel leverage, NPL ratio, price-to-book ratio and

[21] To provide a global overview, firm-specific variables in form of ratios, namely Basel leverage, NPL ratio and price-to-book ratio, are dynamically aggregated at country level, using as weight the market capitalization of the firms included in our sample. The justification for such an approach is that moving weights take better account of composition changes over time, especially those related to changes in relative prices or technologies (see also: https://www.oecd.org/economy/outlook/aggregationmethods.htm). Weights are applied to the variable in level terms: $Y_t = \sum_{i=1}^{n} w_{i,t} * X_{i,t}$ where w is the weight (i.e., the market capitalization) of firm i for period t in the country under consideration, and X is the variable to be aggregated. In contrast, total assets are aggregated at country level by summing up the firms' individual levels: $Y_t = \sum_{i=1}^{n} X_{i,t}$ where X is the total assets, of firm i for period t in the region under consideration, to be aggregated.

financial firm size (total assets), $RVOL$ is the annualized realized volatility proxy for market sentiment, and $Macro$ is a (5 x 1) vector including macroeconomic systemic-related variables, namely CPI, GDP, IP, T-Bill and UR. All the variables are taken at a monthly frequency, end-of-the-month to match the frequency of macroeconomic and balance sheet data. Finally, $Country$ and $Time$ are country and time dummies to control for the individual fixed country and time effects, respectively.[22]

We run our model over five sub-periods. First, we estimate the panel regression model over the period from 2001 to 2020 which we consider as our benchmark model given that it provides an extensive time-period to test the relationship between systemic risk and its determinants. Then, we sub-sample this period focusing on the GFC (from 2008 to 2010), and the latest five years of our sample (from 2016 to 2020). This allows us to conduct a comparison between the turbulent GFC sub-period and a sub-period not characterized by any financial systemic threat in order to check whether the panel coefficients' signs and statistical significance of the selected determinants still hold. Finally, the last two sub-periods of our analysis are the period preceding the Covid-19 crisis (from 2016 to 2019) and the Covid-19 crisis itself over 2020 which allows us to investigate any changes in the panel coefficients' signs and significance before and during the pandemic.

The panel regression estimates for countries' financial sector systemic risk are reported in Table 4. We observe that from 2001 to 2020, countries' systemic risk can be mainly predicted by firm-specific variables, which are all found significant with the expected signs (see subsection 2.2). We find a positive and significant relationship between the NPL ratio and $\Delta CoVaR$ confirming that firms with a worse quality of their credit portfolios contributed more strongly to systemic risk. Similarly, an increase in the size of the financial sector exacerbates systemic risk. Hence, both variables are strong determinants of systemic risk, in line with previous literature (e.g., Beltratti and Stulz, 2012). In contrast, the Basel leverage and the price-to-book ratio are both found to be significantly in alleviating systemic risk.

The results related to firm-specific systemic-related variables are strengthened during the GFC but do not hold over the other three sub-periods spanning the last five years. In particular, we find only the Basel leverage to be negative and significant at the 1% level over the four years preceding the COVID-19 outbreak, highlighting the importance of such variable to strengthen the resiliency of the financial sector. However, firms' size, leverage, NPL and price-to-book ratios are not significantly related to systemic risk during 2020. This finding is particularly relevant when comparing panel estimates for firm-specific variables during the GFC vis-a-vis the COVID-19 crisis. The regulatory changes after 2008 initiated

[22] When the 1-month lag of the dependent variable is included the results are found to be similar and are available from the authors upon request.

Table 4: Determinants of systemic risk across sub-periods.

Dependent variable	$\Delta CoVaR_{i,t}$				
	2001–2020	GFC	2016–2020	2016–2019	COVID-19
Firm-specific variables					
$Basel\ leverage_{i,t-1}$	-0.0125*	-0.0425*	-0.0131	-0.0709***	-0.0477
$NPL\ ratio_{i,t-1}$	0.0168***	0.0425**	-0.0011	-0.0423	0.0218
$Price\text{-}to\text{-}book\ ratio_{i,t-1}$	-0.0246*	-0.8992***	-0.0165	0.0408	0.1069
$Total\ assets\ (log)_{i,t-1}$	0.3749***	1.8393***	0.3105	-0.1159	-0.869
Risk sentiment variable					
$Volatility_{i,t-1}$	1.3175***	0.6925***	0.4976***	0.1848	0.2543*
Macroeconomic variables					
$CPI_{i,t-1}$	0.0093	-0.1309	0.1922***	0.1643**	0.2826**
$GDP_{i,t-1}$	-0.0543***	-0.0719**	-0.0432**	-0.057*	-0.0116
$IP_{i,t-1}$	-0.0014	-0.1361***	-0.001	0.0213	-0.0029
$T\text{-}Bill_{i,t-1}$	0.1445***	0.6378***	0.1589***	0.1711***	0.1657***
$Unempl.\ rate_{i,t-1}$	0.0053*	-0.0039	0.0032*	0.0038	0.0015
Time FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
$adj.R^2$ (%)	76.09	89.21	81.09	82.77	89.93
Obs.	3107	468	780	624	156

The panel regression coefficients from model 9. All the variables are taken at a monthly frequency. The panel regression is run for the whole sample (2001-2020) and four sub-samples, namely GFC, 2016-2020, 2016-2019 and the COVID-19 period. All equations are estimated with country and time fixed effects. Intercept results are not reported for the sake of space. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

through the Basel Process emphasized increasing regulatory requirements for banks, with stress tests leading to improvements in banks' internal risk management practices. As a result, unlike 2008, we find that bank-specific variables do not represent a threat to systemic risk in the post-GFC sub-samples as they were used to be before and during the GFC.

Interestingly, the adjusted-R^2 in 2020 is found to be equal to 89.93%, similar to the one during the GFC and greater than its value achieved during the other three sub-periods. This implies a higher explanatory power of the model during downturns justifying our choice of the dependent variable ($\Delta CoVaR$) and showing a better performance of model 9 when examining systemic risk during a market-downturn period. Also, it is to note that, despite the similar adjusted-R^2 values, Table 4 shows the importance of idiosyncratic drivers of firms' systemic risk during the GFC. In contrast, there is no sign of persistence in the major idiosyncratic drivers of firms' systemic risk during the COVID-19 crisis.

Stock market volatility is highly significant (at the 1% level) in explaining systemic risk over the whole time-period, during the GFC and between 2016 and 2020; it then loses its significance during the pre-pandemic period (2016 to 2019), but it becomes significant again during the COVID-19 crisis. Our results show the importance of such predictor of systemic risk in turbulent times. Regarding the macroeconomic variables, CPI is found to be significant at the 5% level and positively related to systemic risk only during the last five years, with a greater coefficient reached during the COVID-19 crisis. A possible reason for the opposite findings of the role of inflation between the GFC and the COVID-19 crisis can be due to the central bank interventions that have, this time around, inducted liquidity in many markets such as the U.S., the U.K., Europe and Japan, which consequently experienced a notable rise in monetary aggregates (e.g. Suardi et al., 2022). Conversely, in 2008, massive increases in bank reserves largely sat at the central bank and without generating a leveraged effect on the broader monetary aggregates and economy (see Ilzetzki et al., 2020).[23]

The coefficients associated with the T-Bill are always found to be positive and significantly associated with systemic risk (at 1%), with a greater coefficient estimated during the GFC. This confirms previous literature arguing that an increase in the T-Bill rate is associated with higher levels of downside risk (see, e.g., Adrian and Brunnermeier, 2016). Finally, the unemployment rate seems to play a marginal role in increasing systemic risk, becoming statistical insignificant over the COVID-19 sub-period. The IP growth rate is not significant, except during the GFC, whereas GDP is found to be significant in all sub-periods analyzed, except 2020. Another interesting finding is that the coefficients of the dummies used to control for time fixed effects are found positive and statistically significant from March to December 2020, when running model 9 during 2020.[24]

Our results highlight that the COVID-19 crisis cannot be recognized as an endogenous financial sector systemic crisis. In particular, firm-specific variables do not appear to have significant relationships with the $\Delta CoVaR$ as found during the GFC, instead. Thus, the COVID-19 crisis does not represent an event of financial market disruption with adverse effects on the real economy. In contrast, the high level of systemic risk seems to be driven by irrational waves in market volatility due to growing pandemic risks, and by almost stagnant estimates of CPI and T-Bill during the period from 2016 to 2020. These results provide a

[23] We expand on the role of inflation in contributing to increased systemic risk during the COVID-19 crisis when interacting it with the policy interventions.

[24] Results are available from the authors upon request.

first insight on the relevance of systemic-related determinants important for the surveillance of systemic risk and relevant for macroprudential policy interventions.

Overall, we observe how, first, changing the sub-sample period of interest may lead to different relationships between the selected determinants and systemic risk. Second, some drivers strengthened or weakened their impact according to the selected time-period. Lastly, we notice a different impact of firm-specific variables between the GFC and the COVID-19 crisis suggesting a shift in potential channels driving systemic risk worldwide over the two crises. The main systemic risk determinants time-varying features uncovered in this section lay the ground for the next empirical analysis in which we investigate how these channels are affected when interacted with the decisive amount of policy interventions during the COVID-19 period.

5.3 The impact of COVID-19 policies and traditional determinants on systemic risk

The shift in behavior of some of the most traditional financial and macroeconomic determinants of systemic risk during COVID-19 calls for a more in-depth analysis of such relationships. Here, we focus on the effects of the policy interventions on the relationships between systemic-related variables and $\Delta CoVaR$. In particular, we have observed a heterogeneous impact of these policies on systemic risk in subsection 5.1, either increasing it or decreasing it according to the country and policy category. We now assess whether these policy actions might have driven the change in systemic risk indirectly through common economic and financial channels, and (if so) in which direction.

We study the effect of each policy category on systemic risk, in either mitigating or strengthening the coefficients' sign and significance of the systemic risk determinants during the COVID-19 period. To this end, we consider the three policy categories as well as the aggregated policy variable. To perform this panel analysis, the daily dummies are aggregated at a monthly frequency to match the frequency of the other economic and financial variables. In particular, for every month we estimate the intensity of each policy category, which is given by the number of policies in the specific category and country in that month. As an example, a month with several policy announcements in any policy category such as March 2020 would take greater values compared to a less active month in terms of interventions such as October 2020 (see also Figure A1).

We expand model 9 including also the interaction terms ($Inter$) which is a (10 x 1) vector multiplying each policy category dummy for each country and the systemic-related variables as described in model 9 ($Firm$, $RVOL$, and $Macro$), lagged of 1-month. We also control for the corresponding policy category dummy alone (D) and variables strictly specific to the COVID-19 pandemic, namely the number of confirmed cases (Conf. cases) and the lockdown restrictions indicator (SIndex) in each of the selected countries, also aggregated at the monthly frequency, end-of-the-month. We run the following model:

$$\Delta CoVaR_{95^{th},i,t} = \alpha_i + \beta_{Firm}\text{Firm}_{i,t-1} + \beta_{RVOL}\text{RVOL}_{i,t-1} + \beta_{Macro}\text{Macro}_{i,t-1} + \beta_{Inter}\text{Inter}_{i,t-1} + \beta_D D_{i,t-1} + \lambda_i \text{Conf. cases}_{i,t-1} + \rho_i \text{SIndex}_{i,t-1} + \sum_{j=1}^{n-1} Country_i + \sum_{j=1}^{m-1} Time_j + \epsilon_{i,t} \quad (10)$$

Table 5 shows the panel estimates of model 10 estimated with country and time fixed effects. The first key finding of this analysis is the higher value of the adjusted-R^2 of this model, for all equations, compared with model 9 during 2020. This highlights the important role which is played in this model by the interaction and the COVID-19 related variables, which increase the explanatory power of the model.

When looking at the variables without policy interactions, the Basel leverage maintains its negative sign and it is significant at the 10% level in the models when adding fiscal and monetary policies, similar to the estimates from model 9. The estimates for the T-Bill rate are also comparable in terms of their sign and significance with the estimates from model 9. The unemployment rate is also significant at the 10% level, with a positive coefficient in the model including monetary policy only. In sharp contrast with the results from model 9, when adding the policy interventions, volatility and CPI alone do not seem to play a significant role in propagating systemic risk.

Regarding the interaction variables, the panel estimates for the leverage ratio are found negative and significant under all policy categories. Another key finding is the unveiling of the NPL ratio with opposite effects in the prediction of systemic risk when policies are taken into account. The negative sign and significant relationship between systemic risk and these two variables can be explained by the relaxing in credit rules introduced by regulators (e.g., the postponement of the transition to the new IFRS 9 loan loss provisioning rules) and by the liquidity injection by central banks that allowed the financial sector to continue providing the lending activities to the real economy.

Firm size is also found significant at the 5% and 10% levels when interacting with regulatory and aggregated policies, respectively. This result should be interpreted considering that all financial firms in our sample are large-scale firms, which are commonly subject to stricter capital requirements compared to smaller firms. When banks already risk adjust their total capital, a change in capital requirements may not affect the risk profile of financial firms'

Table 5: Traditional determinants and policies on systemic risk.

Dependent variable	$\Delta CoVaR_{i,t}$				
	$D_{i,t-1\|Fis}$	$D_{i,t-1\|Mon}$	$D_{i,t-1\|Reg}$	$D_{i,t-1\|All}$	$D_{i,t-1\|Banks}$
			Firm-specific and macro variables		
$Basel\ leverage_{i,t-1}$	-0.079*	-0.069*	-0.035	-0.051	-0.058*
$NPL\ ratio_{i,t-1}$	0.018	-0.007	-0.034	-0.009	-0.016
$Price\text{-}to\text{-}book\ ratio_{i,t-1}$	0.390	0.404	0.151	0.295	0.383
$Total\ assets\ (log)_{i,t-1}$	-0.283	-0.479	0.305	0.065	-0.043
$Volatility_{i,t-1}$	0.203	0.179	0.167	0.174	0.134
$CPI_{i,t-1}$	0.072	0.034	0.117	0.067	0.095
$GDP_{i,t-1}$	-0.043	-0.042	-0.029	-0.036	-0.016
$IP_{i,t-1}$	0.005	0.025	0.003	0.007	0.002
$T\text{-}Bill_{i,t-1}$	0.165***	0.150***	0.165***	0.170***	0.172***
$Unempl.\ rate_{i,t-1}$	0.003	0.002*	0.001	0.002	0.002
			Interaction with policies		
$Basel\ leverage_{i,t-1}$	-0.002*	-0.006**	-0.003**	-0.002**	-0.005***
$NPL\ ratio_{i,t-1}$	-0.030**	-0.048***	-0.026***	-0.019***	-0.040***
$Price\text{-}to\text{-}book\ ratio_{i,t-1}$	0.014	0.016	0.009	0.003	0.003
$Total\ assets\ (log)_{i,t-1}$	0.003	0.002	0.005**	0.003	0.011***
$Volatility_{i,t-1}$	0.017	0.071*	0.005	0.006	0.043
$CPI_{i,t-1}$	0.064**	-0.001	0.056*	0.038**	0.071*
$GDP_{i,t-1}$	0.006	0.015	-0.001	0.002	-0.002
$IP_{i,t-1}$	-0.003*	-0.006	-0.001	-0.002	-0.004
$T\text{-}Bill_{i,t-1}$	0.022**	0.039**	0.009	0.008*	0.053**
$Unempl.\ rate_{i,t-1}$	-0.001	-0.001	-0.001	-0.001	-0.001
			Policy Dummy		
$D_{i,t-1}$	0.116	0.239	0.099	0.098	0.248
			COVID-19 variables		
$Conf.\ cases_{i,t-1}$	0.005**	0.005**	0.006**	0.005**	0.006**
$SIndex_{i,t-1}$	0.008*	0.008*	0.009**	0.008**	0.008*
Time FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
$adj.R^2$ (%)	92.43	92.72	92.26	92.71	92.81
Obs.	156	156	156	156	156

The panel regression coefficients from model 10. The interaction factors between the independent variables and each of the policy interventions dummy, namely ($D_{i,t-1|Fis}$), ($D_{i,t-1|Mon}$), ($D_{i,t-1|Reg}$), and ($D_{i,t-1|All}$) are included. The panel regression is run for the COVID-19 period. All equations are estimated with country and time fixed effects. All the variables are taken at a monthly frequency. Intercept results are not reported for the sake of space. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

portfolio as much as expected (e.g., Jokipii and Milne, 2011). Thus, financial firms may maintain the same risk profile with a lower capital buffer. This implies that total assets may return a significant predictor of systemic risk resembling the "too-big-to-fail" issue preceding the implementation of the Basel framework.

Market volatility is found positive and significant only when interacting with monetary policy interventions. This finding may be because market participants and investors had higher expectations for policymakers' responses to the COVID-19. Cox et al. (2020) and Bevilacqua et al. (2021) also find that among the policy interventions, the conventional channels were the least effective. Another reason might be related to the unprecedented nature of the COVID-19 shock, which has also been characterized by other potential mechanisms at play. Moreover, Caballero and Simsek (2020) highlight a novel role of financial markets in the transmission of the COVID-19 shock, which they call the "Wall Street/Main Street disconnect". That is, in their case, in the U.S., asset prices reacted quickly to news about the pandemic and then recovered sharply. Similarly, U.S. corporate bond yields rose sharply during February and March 2020 but have rebounded quickly and returned to pre-crisis averages within the same year. This quick recovery of financial markets in the U.S. followed, in part, the Fed's monetary expansion. However, these patterns led many to wonder about a possible disconnect between financial markets and the real economy and the relevance of financial market indicators for economic recovery (see Goldstein et al., 2021), thus ascribing this disconnection as a possible reason for such high volatility in the market.

Turning on the macroeconomic variables, we confirm that inflation is found to increase systemic risk, as in model 9, when interacted with fiscal, regulatory and aggregated policies. Our results suggest that the increased pressure in the financial system triggering instability therein and increased systemic risk has come through the inflation channel especially due to fiscal and regulatory interventions. The rationale for these findings is as follows. As we mentioned earlier, the unprecedented policy interventions worldwide have generated high levels of market liquidity during the COVID-19 pandemic. According to Ilzetzki et al. (2020), the benign inflationary environment of the past two decades could have made policymakers willing to take more risks on inflation to promote growth. Monetary aggregates worldwide have grown at an unprecedented rate since COVID-19, partially due to firms calling on lines of credit.

Moreover, banks received large inflows of deposits mainly originated by the vast fiscal stimulus interventions, pay wage subsidies, cheques, benefits, and cash transfers, and also extra liquidity through unwind mechanism waiver. Hence, liquidity supplied to banks increased at the same time that liquidity demanded from banks spiked (see Li et al., 2020). This mechanism posed a potential threat to systemic risk, and central bankers and economists started to wonder whether, as the economy heals, this higher liquidity could bleed over into inflation.[25] Conversely, the not significant impact of the monetary policy interventions through the inflation channel may be due to the greater coherence across central banks worldwide in their responses to real economic shocks and inflation, which the financial sector does not appear to see monetary policy as a threat to its stability going forward.

T-Bill is also found to increase systemic risk when interacting with fiscal, monetary and aggregated policy interventions. The positive impact of the interaction between T-Bill rate and monetary policies on systemic risk may be since such policies harmed risk-taking and financial stability. A prolonged period of low-interest rates could impact affect valuations, incomes and cash flows which in turn could modify how banks measure estimated risks as well as affect risk-taking, contributing to an increase in banks' risk (e.g., Altunbas et al., 2014). According to Allen and Gu (2018), loose monetary policy is arguably one of the main causes for the emergence of bubbles (e.g., 2007–2009 crisis), and excessively low levels of interest rates should not be implemented. The IP growth rate turns statistically significant when interacted with fiscal policy helping to slightly mitigate systemic risk during the pandemic.

Finally, we detect a positive and statistically significant contribution of COVID-19 related variables such as the number of confirmed cases and lockdown restrictions (SIndex) to systemic risk. These two variables are external to financial and economic activities, but rather specific to the pandemic. Hence, these findings confirm our argument that the COVID-19 crisis cannot be recognized as a systemic crisis, as already discussed in subsection 5.2, and our hypothesis of an increased perceived uncertainty as discussed in subsection 2.2.

Overall, we notice that in general, policy interventions have succeeded in reducing systemic risk through some financial channels, such as leverage and NPL exploiting an overall global healthy financial system, and up to that point, providing a cushion for absorbing economic losses. On the other hand, policy interventions appear to increase systemic risk worldwide through economic factors such as inflation and low interest rates. These economic variables are therefore found to be the main channels through which the pandemic has spread risk towards the financial system. The joint effects of the financial and economic channels lead towards a still-high level of systemic risk consistent with the *disconnect* between the whole equity market and the real economy, seeing the financial system lying in between.

In fact, according to Igan et al. (2020), for instance, monetary policies in the U.S. but also in Europe led to this disconnect through interest rates, in line with our results. Our findings are also in line with Caballero and Simsek (2020), discussing that the recovery of asset markets was primarily due to the aggressive monetary (and fiscal) policy response to

[25]For some economists, the wartime levels of fiscal deficits and massive expansions of the money stock will combine with reductions in supply and a sharp recovery in demand to bring high inflation when the epidemic passes. For some indications of underlying inflationary pressures (see Jaravel and O'Connell, 2020).

the COVID-19 shock. Monetary policy stabilized and supported asset prices by containing and then reversing the large spike in the risk-premium as well as by keeping short and long interest rates low (see also Caballero and Simsek, 2021). Our findings relate to this debate by showing that interest rate is found to be a main channel of policy transmission on systemic risks, mainly in relation to monetary policies with a positive and significant coefficient equal to 0.039, being almost double the one associated with fiscal policies and four times the one associated to regulatory policies.

Thus, according to Caballero and Simsek (2020) and Koulischer et al. (2020), the initial recovery from the COVID-19 recession featured a rebound of firms' prices alongside a worsening in the condition of the real economy, this leading to a disconnect between the performance of the real economy and financial markets.[26] However, the linkage between the financial sector with the real economy as a provider of payment, deposit, credit, and risk management services will be critical for the economic recovery in the coming years, contributing to higher systemic risk.

We uncover a *disconnect* between policy interventions and systemic risk. While the majority of the policy actions had as a main target the real economy, aiming to contain the negative impact of the pandemic, and succeeding also in calming the financial markets, systemic risk remained high. The financial firms do differ from any other sectors, with their role being crucial in a recovery. In fact, within the *disconnect* between the real economy and the whole equity market, our results provide evidence of the financial sector lying in between. This is possibly related to the still high-risk perceptions of the financial system identified as a crucial actor for the containment of economic distress and future recovery. The decisive policy interventions aided the majority of sectors, households, and the economy in general, at the possible expense of a bigger burden for the financial system to carry.

The results detected for the interaction effects are also robust to the inclusion of the policy interventions dummies taken alone. None of the policy categories considered in the model alone are found to be significant. These checks further confirm the fact that the policy interventions worldwide do not appear to be efficient in decreasing systemic risk when studied on their own but their effect emerge through the financial and economic channels.

As a robustness check, we also run model 10 without interaction factors, but including all the three policy groups and the aggregated policy dummy at the same time in the

[26] For the U.S., Caballero and Simsek (2020) highlight a novel role of financial markets in the transmission of the COVID-19 shock denoted as the "Wall Street/Main Street disconnect". The U.S. asset prices reacted quickly to news about the pandemic and recovered even more sharply following the Fed's monetary expansion. For Europe, Koulischer et al. (2020) document that a few months after the outbreak of the pandemic, stock markets have rebounded almost completely from an unprecedented initial shock, despite the deterioration of real economic indicators.

regression together with the financial and macroeconomic variables. This exercise further isolates the impact of the policy interventions on systemic risk after taking into account their potential endogeneity connected to all the other factors. We find only the fiscal and monetary categories to be significant, however, with positive coefficients' signs implying that they contributed to increase systemic risk. These findings confirm the mixed sign relationship between policies and systemic risk. We also run model 10 by adding the previous lag of the dependent variable, again finding that our results hold robust.

Finally, we also check the direct impact of the policy interventions on the financial and macroeconomic variables of interest. Interestingly, we observe that monetary policies significantly increase the level of inflation, interest rates, GDP, and volatility, while decreasing PTB, and have an insignificant relationship with the other variables. Fiscal policies are mainly (and positively) impacting interest rates, the unemployment rate, and NPL, while decreasing volatility and PTB. Regulatory policies are found to be significant only in decreasing leverage, whereas increasing GDP and NPL. Overall, we find that these results are consistent with the main channels uncovered in the main findings of Table 5 in relation to systemic risk and, especially, in confirming a key role for monetary and fiscal policies on inflation and interest rate, and for regulatory policy on firm-specific variables.[27]

5.4 Policies targeting banks and financial institutions

In this final subsection, we repeat the same empirical analysis focusing only on the policy interventions which had banks and financial institutions as ultimate beneficiaries, being these mostly a subset of the regulatory category in all countries. For example, on March 15 in the United States, the Board of Governors announced that depository institutions may borrow from the discount window for periods as long as 90 days, pre-payable and renewable by the borrower daily. The Fed also encouraged banks to use their capital and liquidity buffers as they lend to households and businesses. On May 5, the Fed announced an interim final rule that modifies the agencies' Liquidity Coverage Ratio (LCR), and on May 15 a temporary change to the supplementary leverage ratio to provide balance sheets flexibility to depository institutions as to provide credit to households and businesses. On March 15, in the United Kingdom, the Financial Policy Committee (FPC) reduced the U.K. countercyclical capital buffer rate to 0% of banks' exposures to U.K. borrowers to support further the ability of banks to supply credit. In the Euro Area, for instance, on March 16, EU-wide stress testing for 2021 was suspended to allow banks to focus on the continuity of their core operations. As an example of a banks-related policy targeting only one of the EU state

[27] We thank an anonymous referee for suggesting this empirical exercise. The whole set of results is available from the authors upon request.

members, on September 21, in Germany BaFin allowed supervised institutions to exclude specific central bank exposures from the calculation and evaluation of its leverage ratio to align the supervision with the ECB announcement of exceptional circumstances.

We first repeat the exercise conducted in section 5.1 to check whether or not policy interventions directly targeting banks and financial institutions had a stronger reducing impact on systemic risk. We replace the three main policy categories with a policy dummy for banks-related policies ($D_{i,t-1|Banks}$) in equation 7 and 8. We show the results in Table C5 and C6 in the Appendix. From the panel analysis, we observe an overall significant and decreasing effect of the banks policies on systemic risk globally, even after controlling for previous risk levels. When we look at the individual country, we still find mixed results for the impact of $D_{i,t-1|Banks}$ on systemic risk. The banks' policies were successful in reducing systemic risk only in France, Spain, the U.K., the U.S. and in the broader Euro Area, while not significant in the other countries. Overall, the results are similar to the ones from Table 2 and 3 for the regulatory policy category.

We also include the bank policies dummy in regression model 10 and run the same analysis. We present the results in the last column of Table 5. We observe that now the coefficients associated with the interacted variables with $D_{i,t-1|Banks}$ for the firm-specific characteristics, in particular for leverage, NPL ratio and total assets, are found to be almost double the estimates found for the regulatory dummy, all being significant at the 1% level. The banks' policies are found to significantly increase systemic risk when interacted with CPI (0.071) and T-Bill (0.053), at the 10% and 5% levels, respectively. This exercise shows that when we focus only on policy interventions targeting banks and financial institutions, the results suggest a stronger calming channel through the financial-firms characteristics, however also a greater impact in increasing systemic risk from the economic channels, validating the *disconnect* finding and the channels at work.

6 Additional robustness checks

6.1 MSCI World Index

As a first robustness check, we calculate the $\Delta CoVaR$ conditional to the MSCI ACWI World Index as the benchmark market index in place of the national stock market indices.[28] We run all three main models in the empirical sections, namely 8, 9 and 10 with our dependent variable being now the $\Delta CoVaR$ based on the MSCI global index which we believe can

[28]The MSCI ACWI Index is collected from Bloomberg and it represents a global equity index reflecting the performance of stocks across 23 developed and 27 emerging markets, including all the countries in our analysis.

capture the exposure of each countries' financial system to global shocks, in the whole sample period but especially during the COVID-19 period. The global stock market benchmark is reasonable as COVID-19 has been a global crisis. Moreover, measuring the $\Delta CoVaR$ conditional on a unique shock provides a homogeneous metric of comparison across all the countries in our sample.[29] Repeating the regression analysis with the new measure, the results are robust. We report them in Tables from C7 to C9 in the Appendix.

The results in Table C7 confirm our previous conclusion, namely that the efficacy of the policy interventions worldwide in reducing systemic risk is found to be mixed. The results for the developed countries hold almost identical in their coefficients' sign and significance. A few differences, especially for emerging countries are the following. For China, we find that now the COVID-19 variables (number of confirmed cases and lockdown restrictions) are significant and positively affecting systemic risk as well as the dummy for all policy interventions combined (significant at 10%). In this specification, fiscal and regulatory interventions are found not to reduce systemic risk in Italy, monetary policy is found now inefficient in Russia, while fiscal and regulatory policies are now found to increase systemic risk in Turkey. These results further confirm the conclusion drawn in section 5, namely a mixed effect in the policy efficacy worldwide on the country-specific systemic risk estimations, with, in some cases, policies leading to an increase in systemic risk.

When we study more traditional determinants on systemic risk conditional to the MSCI global stock index, we find an overall similar picture (see Table C8 in Appendix). When we interact the traditional channels of systemic risk with the COVID-19 related policy interventions as in subsection 5.3, we find the results are overall robust to the changing of the stock market index benchmark (see Table C9 in Appendix). We find that interactions among the policy interventions and, for instance, the leverage ratio among the financial variables and the CPI, among the economic variables, lose their significance in decreasing and increasing systemic risk, respectively. This might be justified by the fact that the global stock index benchmark averages out the financial and economic specific country conditions. In our results, this reflects in a significant role only for channels that are common to all the countries in the analysis (e.g., banks' balance sheets composition and low interest rates), but which misses country-specific characteristics.

[29] The correlation between the national stock market index based and the global stock market index based $\Delta CoVaR$s is, for example, very high and equal to 99.9% (United States), 97.9% (United Kingdom), 96.5% on average for the countries in the Euro Area, 89.6% (India), 88.2% (South Korea), while lower for emerging countries such as Brazil and China, 69.9% and 61.2%, respectively.

6.2 MES as a measure for systemic risk

As an additional robustness exercise, we adopt an alternative measure for systemic risk the MES proposed by Acharya et al. (2017). We define the MES as the expected shortfall of country i's financial sector in the tail of the aggregate sector's loss distribution. This measure can be interpreted as each country's financial sector losses when the entire system (benchmark equity index) is in a tail event. We estimate the MES as the average return of the financial sector portfolio during the 5% worst days for the market in each country included in our paper. This measure estimates the equal-weighted average return of any given country's financial sector (R^i) for the $q = 5\%$ worst days of the market returns (R^m):

$$MES^i_{q\%} = \frac{1}{\#days} \sum R^i_t \tag{11}$$

We report the MES time-series dynamics in Figure C1 in Appendix. The systemic risk trends are similar to the ones of the $\Delta CoVaR$ and reflect both global macroeconomic and country-specific events.[30] The level of systemic risk measured by the MES is also found to increase homogenously worldwide after the WHO declared COVID-19 a public health emergency (March 11, 2020). The ranking of country financial sectors' systemic risk based on the MES are materially the same of the $\Delta CoVaR$. Panel estimates of firm-specific, risk sentiment and macroeconomic variables and the effect of the policies are also found to be both quantitatively and qualitatively similar. For the sake of space, we do not report the results and they are available from the authors upon request.

We report the results of the main analysis of our study, namely the impact of traditional determinants and policy interventions (and their interaction factors) on systemic risk based on the MES in Table C10 in the Appendix. The results appear robust since we still detect significant and negative estimates with respect to main firm-specific variables such as leverage and NPL ratio when interacted with policy interventions (the exception holds for monetary policy) and the positive impact through the inflation channel, in line with the $\Delta CoVaR$ findings. T-Bill and volatility are still found to contribute to an increase in systemic risk, however when not interacted with policy interventions. Finally, we also uncover the price-to-book-ratio as a channel contributing to increase systemic risk based on MES when interacted with monetary and regulatory policies. This is in line with the market perception explanation we put forward in subsection 5.2.

[30] The correlation between the time-series of $\Delta Covar$ and MES is 0.91 which, when broken down into countries ranges from 0.84 for Turkey to a max of 0.95 for the United Kingdom. The Kendall's τ ranking correlation coefficient ranges between 0.81 for the dominance test of both systemic risk measures stressed at 5% and 0.83 over 2020.

6.3 Implied volatility measures

We also replace the realized volatility measures with implied volatility indices collected from Bloomberg at a daily frequency. The VIX-style implied volatility indices are extracted from the country stock index options and reflect the investors' expectations for uncertainty over the coming 30 days in the country stock market. Since these indices are only providing a partial coverage with respect to our sample period and selected countries, in the main analysis of the paper we adopt the measures of realized volatility.[31] The results are found to hold materially the same and, at times, with even greater significance. The whole set of results is available from the authors upon request.

7 Conclusion

We examine the impact of the COVID-19 crisis on global systemic risk and some of its main drivers through the lens of the mitigating or amplification effects of the large number of policy interventions implemented in response to the pandemic.

We first uncover evidence of a statistically significant common increase in systemic risk amid the COVID-19 outbreak. We then study the impact of the policy interventions on systemic risk worldwide, detecting mixed results. Fiscal and regulatory policies show a stronger reducing impact as opposed to monetary policies with, however, effects being country- and policy-dependent. Financial firm-specific variables do not have a significant impact on systemic risk during the COVID-19 crisis as opposed to the GFC. We can argue that the financial system has been a source of strength during the COVID-19 crisis, without being heavy on an already overheated economic scenario, opposite to the GFC. While the financial system has shown to be essential to containing economic distress and reducing systemic risk, inflation and interest rates are detected as the main channels through which the real economy drove higher systemic risk.

We shed new light on the *disconnect* between whole financial market and the real economy during the COVID-19 period, with the financial sector lying in between. This is possibly related to the still-high-risk perceptions of the financial system identified as a crucial actor for the containment of economic distress and future recovery. The decisive policy interventions aided the majority of sectors, households, and the economy in general, at the possible

[31] The implied volatility indices are namely the VIX, VSTOXX, FTSE100 IVI, CBOE Brazil ETF VIX, CBOE China ETF VIX, India NSE VIX, VKOSPI, and RUSSIATSVX Index for the United States, the Euro Area, the United Kingdom, Brazil, China, India, Korea and Russia respectively. These indices are not available for Turkey and Japan and start only in 2006 for Russia, 2008 for India and in 2011 for Brazil and China. For countries with no implied volatility data available, the realized volatility measures are kept in the regressions.

expense of a bigger burden for the financial system to carry.

Our results can potentially serve as guideposts for the assessment of market-based systemic risk going forward. We provide evidence for adopting market-based information for financial regulation and policy decisions. Our findings also suggest that central banks, regulators, fiscal authorities, and international organizations are required to carefully monitor and assess the health conditions of the financial system worldwide in the coming years given its fundamental role in the forefront of the economic recovery. Systemic risk is a key factor for financial stability, and regulatory frameworks and policy actions should aim at the financial stability objective while also promoting financial innovation and economic growth.

For future research avenues, it would be interesting to study whether the vast policy interventions driven by the pandemic had a different impact on financial risk across other (sub-) sectors to prepare regulators to better manage their systemic stability. Furthermore, the investigation of the impact of policy interventions related to the pandemic can be extended to understand whether financial and banking firms changed their business models and funding plans to financial sector risks previously unexplored. Future studies can also consider the systemic risk spillover across global and country stock markets at the sectoral level while accounting for the COVID-19 related policy interventions.

References

Abuzayed, B., E. Bouri, N. Al-Fayoumi, and N. Jalkh (2021). Systemic risk spillover across global and country stock markets during the COVID-19 pandemic. *Economic Analysis and Policy 71*, 180–197.

Acharya, V. V., R. Engle, and S. Steffen (2020). Why did bank stocks crash during COVID-19? *National Bureau of Economic Research Working Paper*.

Acharya, V. V. and N. Mora (2015). A crisis of banks as liquidity providers. *Journal of Finance 70*(1), 1–43.

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson (2017). Measuring systemic risk. *Review of Financial Studies 30*(1), 2–47.

Adrian, T. and M. K. Brunnermeier (2016). CoVaR. *American Economic Review 106*(7), 1705–41.

Allen, F., A. Babus, and E. Carletti (2012). Asset commonality, debt maturity and systemic risk. *Journal of Financial Economics 104*(3), 519–534.

Allen, F. and E. Carletti (2013). Systemic risk from real estate and macro-prudential regulation. *International Journal of Banking, Accounting and Finance 5*(1-2), 28–48.

Allen, F., I. Goldstein, J. Jagtiani, and W. W. Lang (2016). Enhancing prudential standards in financial regulations. *Journal of Financial Services Research 49*(2), 133–149.

Allen, F. and X. Gu (2018). The interplay between regulations and financial stability. *Journal of Financial Services Research 53*(2), 233–248.

Altunbas, Y., L. Gambacorta, and D. Marques-Ibanez (2014). Does monetary policy affect bank risk? *International Journal of Central Banking*.

Apostolakis, G. N., C. Floros, K. Gkillas, and M. Wohar (2021). Political uncertainty, COVID-19 pandemic and stock market volatility transmission. *Journal of International Financial Markets, Institutions and Money 74*, 101383.

Baker, S. R., N. Bloom, S. J. Davis, K. J. Kost, M. C. Sammon, and T. Viratyosin (2020). The unprecedented stock market impact of COVID-19. Technical report, National Bureau of Economic Research.

Beck, T., H. Degryse, R. De Haas, and N. Van Horen (2018). When arm's length is too far: Relationship banking over the credit cycle. *Journal of Financial Economics 127*(1), 174–196.

Beck, T., R. Levine, and N. Loayza (2000). Finance and the Sources of Growth. *Journal of Financial Economics 58*(1-2), 261–300.

Beltratti, A. and R. M. Stulz (2012). The credit crisis around the globe: Why did some banks perform better? *Journal of Financial Economics 105*(1), 1–17.

Benoit, S., J.-E. Colliard, C. Hurlin, and C. Pérignon (2017). Where the risks lie: A survey on systemic risk. *Review of Finance 21*(1), 109–152.

Bevilacqua, M., J. Danielsson, L. M. Ergun, A. Uthemann, and J.-P. Zigrand (2021). The calming of short-term market fears and its long-term consequences: The central banks' dilemma. *Available at SSRN 3774218*.

Bevilacqua, M., R. Tunaru, and D. Vioto (2023). Options-based systemic risk, financial distress, and macroeconomic downturns. *Journal of Financial Markets*, 100834.

Bisias, D., M. Flood, A. W. Lo, and S. Valavanis (2012). A survey of systemic risk analytics. *Annual Review of Financial Economics 4*(1), 255–296.

Bolton, P., X. Freixas, L. Gambacorta, and P. E. Mistrulli (2016). Relationship and transaction lending in a crisis. *Review of Financial Studies 29*(10), 2643–2676.

Borri, N. and G. Di Giorgio (2022). Systemic risk and the COVID challenge in the European banking sector. *Journal of Banking & Finance 140*, 106073.

Boyd, J. H. and A. Heitz (2016). The social costs and benefits of too-big-to-fail banks: A "bounding" exercise. *Journal of Banking & Finance 68*, 251–265.

Brownlees, C. and R. F. Engle (2016). SRISK: A conditional capital shortfall measure of systemic risk. *Review of Financial Studies 30*(1), 48–79.

Caballero, R. J. and A. Simsek (2020). Monetary policy and asset price overshooting: A rationale for the wall/main street disconnect. *National Bureau of Economic Research, Working Paper* (27712).

Caballero, R. J. and A. Simsek (2021). A model of endogenous risk intolerance and LSAPs: asset prices and aggregate demand in a "COVID-19" shock. *Review of Financial Studies 34*(11), 5522–5580.

Cai, J., F. Eidam, A. Saunders, and S. Steffen (2018). Syndication, interconnectedness, and systemic risk. *Journal of Financial Stability 34*, 105–120.

Capelle-Blancard, G. and A. Desroziers (2020). The stock market is not the economy? Insights from the COVID-19 crisis. *Insights from the COVID-19 Crisis (June 16, 2020). CEPR Covid Economics*.

Chen, Q., A. Filardo, D. He, and F. Zhu (2016). Financial crisis, US unconventional monetary policy and international spillovers. *Journal of International Money and Finance 67*, 62–81.

Corbet, S., D. J. Cumming, Y. G. Hou, Y. Hu, and L. Oxley (2022). Have crisis-induced banking supports influenced european bank performance, resilience and price discovery? *Journal of International Financial Markets, Institutions and Money 78*, 101566.

Correa, R., K.-H. Lee, H. Sapriza, and G. A. Suarez (2014). Sovereign credit risk, banks' government support, and bank stock returns around the world. *Journal of Money, Credit and Banking 46*(s1), 93–121.

Cox, J., D. L. Greenwald, and S. C. Ludvigson (2020). What explains the COVID-19 stock market? Technical report, National Bureau of Economic Research.

Darracq-Paries, M. and R. A. De Santis (2015). A non-standard monetary policy shock: The ECB's 3-year LTROs and the shift in credit supply. *Journal of International Money and Finance 54*, 1–34.

Davis, S. J., D. Liu, and X. S. Sheng (2021). Stock prices, lockdowns, and economic activity in the time of coronavirus. *National Bureau of Economic Research Working Paper*.

Demirgüç-Kunt, A. and H. Huizinga (2013). Are banks too big to fail or too big to save? International evidence from equity prices and CDS spreads. *Journal of Banking & Finance 37*(3), 875–894.

Demirgüç-Kunt, A., A. Pedraza, and C. Ruiz Ortega (2020). Banking sector performance during the Covid-19 crisis. *Demirguc-Kunt A, Pedraza A, Ruiz-Ortega C. Banking Sector Performance During the COVID-19 Crisis. World Bank Policy Research Working Paper 9363.*

Dombret, A. R., D. Foos, K. Pliszka, and A. Schulz (2019). What are the real effects of financial market liquidity? evidence on bank lending from the euro area. *Journal of International Financial Markets, Institutions and Money 62*, 152–183.

Duan, Y., S. El Ghoul, O. Guedhami, H. Li, and X. Li (2021). Bank systemic risk around COVID-19: A cross-country analysis. *Journal of Banking & Finance 133*, 106299.

Engle, R., E. Jondeau, and M. Rockinger (2015). Systemic risk in Europe. *Review of Finance 19*(1), 145–190.

Gambacorta, L., B. Hofmann, and G. Peersman (2014). The effectiveness of unconventional monetary policy at the zero lower bound: A cross-country analysis. *Journal of Money, Credit and Banking 46*(4), 615–642.

Gatev, E. and P. E. Strahan (2006). Banks' advantage in hedging liquidity risk: Theory and evidence from the commercial paper market. *Journal of Finance 61*(2), 867–892.

Goldstein, I., R. S. Koijen, and H. M. Mueller (2021). COVID-19 and its impact on financial markets and the real economy. *Review of Financial Studies 34*(11), 5135–5148.

Gormsen, N. J. and R. S. Koijen (2020). Coronavirus: Impact on stock prices and growth expectations. *Review of Asset Pricing Studies 10*(4), 574–597.

Igan, D., D. Kirti, and S. M. Peria (2020). The disconnect between financial markets and the real economy. *IMF Special Notes Series on COVID-19, August 26*, 2020.

Ilzetzki, E., C. M. Reinhart, and K. S. Rogoff (2020). Will the secular decline in exchange rate and inflation volatility survive COVID-19? *National Bureau of Economic Research*.

IMF (2019). World Economic Outlook, July 2019: Still Sluggish Global Growth. *World Economic Outlook Reports*.

IMF (2020). World Economic Outlook, October 2020: A Long and Difficult Ascent. *World Economic Outlook Reports*.

Ivashina, V. and D. Scharfstein (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics 97*(3), 319–338.

Jaravel, X. and M. O'Connell (2020). Real-time price indices: Inflation spike and falling product variety during the Great Lockdown. *Journal of Public Economics 191*, 104270.

Jokipii, T. and A. Milne (2011). Bank capital buffer and risk adjustment decisions. *Journal of Financial Stability 7*(3), 165–178.

Kashyap, A. K., R. Rajan, and J. C. Stein (2002). Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking. *Journal of Finance 57*(1), 33–73.

Koulischer, F., D. Pierret, and R. Steri (2020). The market value of public interventions in the corporate sector: Evidence from COVID-19. *Available at SSRN 3735052*.

Laeven, L., L. Ratnovski, and H. Tong (2016). Bank size, capital, and systemic risk: Some international evidence. *Journal of Banking & Finance 69*, S25–S34.

Lan, C., Z. Huang, and W. Huang (2020). Systemic risk in China's financial industry due to the COVID-19 pandemic. *Asian Economics Letters 1*(3).

Lehar, A. (2005). Measuring systemic risk: A risk management approach. *Journal of Banking & Finance 29*(10), 2577–2603.

Levine, R. (1997). Financial development and economic growth: views and agenda. *Journal of Economic Literature 35*(2), 688–726.

Levine, R. (1998). The legal environment, banks, and long-run economic growth. *Journal of Money, Credit and Banking*, 596–613.

Li, L., P. E. Strahan, and S. Zhang (2020). Banks as lenders of first resort: Evidence from the COVID-19 crisis. *Review of Corporate Finance Studies 9*(3), 472–500.

Linkov, I., J. M. Keenan, and B. D. Trump (2021). *COVID-19: systemic risk and resilience.* Springer.

López-Espinosa, G., A. Moreno, A. Rubia, and L. Valderrama (2012). Short-term wholesale funding and systemic risk: A global CoVaR approach. *Journal of Banking & Finance 36*(12), 3150–3162.

López-Espinosa, G., A. Rubia, L. Valderrama, and M. Antón (2013). Good for one, bad for all: Determinants of individual versus systemic risk. *Journal of Financial Stability 9*(3), 287–299.

Mayordomo, S., M. Rodriguez-Moreno, and J. I. Peña (2014). Derivatives holdings and systemic risk in the US banking sector. *Journal of Banking & Finance 45*, 84–104.

Morelli, D. and D. Vioto (2020). Assessing the contribution of china's financial sectors to systemic risk. *Journal of Financial Stability 50*, 100777.

Polyzos, S., A. Samitas, and I. Kampouris (2021). Economic stimulus through bank regulation: Government responses to the COVID-19 crisis. *Journal of International Financial Markets, Institutions and Money 75*, 101444.

Rajan, R. and L. Zingales (1998). Financial Dependence and Growth. *American Economic Review 88*(3), 559–86.

Reboredo, J. C. and A. Ugolini (2015). Systemic risk in European sovereign debt markets: A CoVaR-copula approach. *Journal of International Money and Finance 51*, 214–244.

Rizwan, M. S., G. Ahmad, and D. Ashraf (2020). Systemic risk: The impact of COVID-19. *Finance Research Letters 36*, 101682.

Rizwan, M. S., G. Ahmad, and D. Ashraf (2022). Systemic risk, Islamic banks, and the COVID-19 pandemic: An empirical investigation. *Emerging Markets Review 51*, 100890.

Schwert, G. W. (1989). Why does stock market volatility change over time? *Journal of Finance 44*(5), 1115–1153.

Suardi, S., C. Xu, and Z. I. Zhou (2022). COVID-19 pandemic and liquidity commonality. *Journal of International Financial Markets, Institutions and Money 78*, 101572.

Thanassoulis, J. and M. Tanaka (2018). Optimal pay regulation for too-big-to-fail banks. *Journal of Financial Intermediation 33*, 83–97.

Wu, D. D., D. L. Olson, D. D. Wu, and D. L. Olson (2020). The effect of COVID-19 on the banking sector. *Pandemic risk management in operations and finance: modeling the impact of COVID-19*, 89–99.

Zhang, D., M. Hu, and Q. Ji (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters 36*, 101528.

Zhang, Q., F. Vallascas, K. Keasey, and C. Cai (2015). Are Market-Based Rankings of Global Systemically Important Financial Institutions Useful for Regulators? *Journal of Money, Credit and Banking 47*(7), 1403–1442.

Appendices

A Data sources and description

This section documents in more details the data adopted in the paper and their sources.

A.1 Firm-specific and risk sentiment variables: descriptive statistics

Table A1 provides summary statistics.

A.2 Macroeconomic variables

Among the macroeconomic variables, we collect consumer price index (CPI), gross domestic product (GDP), industrial production (IP), T-Bill and unemployment rate for each country in our sample from the World Economic Outlook Database of the International Monetary Fund. The data can be collected from and more information can be found at https://www.imf.org/en/Data. Table A2 provides summary statistics.

A.3 COVID-19 data

Regarding the COVID-19 specific variables, we collect the number of confirmed cases in each of the selected countries from the Johns Hopkins Coronavirus Resource Center. The data is downloaded from https://github.com/CSSEGISandData/COVID-19 and can be visualized at https://coronavirus.jhu.edu/map.html. To measure governments' lockdown initiatives, we adopt the SIndex developed by the Oxford University, which tracks travel restrictions, trade patterns, school openings, social distancing and other such measures, by country and day. The index is computed as the average of nine sub-indexes, each ranging from 0 (the least stringent) to 100 (the most stringent) responses. The index takes into account external and internal movement restrictions, fiscal support, and even measures supporting the health care system. For more information and data about the SIndex, please see https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker. Table A3 provides summary statistics.

Table A1: Firm-specific and risk sentiment variables: descriptive statistics.

	Brazil	China	France	Germany	India	Italy	Japan	Russia	S. Korea	Spain	Turkey	UK	US
<u>Firm-specific variables</u>													
Basel leverage													
Mean	11.44	8.90	22.57	23.29	10.97	15.81	25.41	9.26	20.09	16.79	8.95	24.97	30.96
Median	11.67	9.15	22.13	24.67	10.44	15.39	21.36	8.98	19.85	16.03	9.32	24.51	29.75
Std. dev.	1.65	1.88	3.28	6.04	1.45	2.06	12.89	1.54	1.20	2.36	1.26	5.52	9.90
Min.	8.60	3.64	17.18	1.61	8.08	12.55	11.35	6.77	17.96	12.65	4.98	14.03	17.26
Max.	15.30	11.66	31.23	38.87	13.73	22.96	77.65	13.29	23.12	21.98	10.73	48.34	44.69
NPL ratio													
Mean	5.44	1.44	4.66	2.16	2.52	8.16	2.20	4.09	23.94	4.14	3.71	3.86	3.71
Median	5.85	1.37	4.73	2.01	2.41	7.32	2.42	3.83	13.74	3.98	3.36	3.18	0.68
Std. dev.	1.86	0.55	1.01	0.53	0.80	3.22	0.81	1.67	20.53	2.77	1.12	1.77	14.62
Min.	2.26	0.75	3.03	1.24	1.71	3.80	1.03	0.57	0.97	0.65	2.42	1.70	0.28
Max.	8.40	2.87	6.29	3.36	4.22	13.95	3.40	8.10	117.30	9.73	7.13	6.89	83.95
Price-to-book ratio													
Mean	2.12	3.77	0.90	1.39	3.53	1.23	1.41	0.76	0.64	1.36	1.30	1.98	1.56
Median	1.99	3.17	0.79	1.26	3.25	1.16	1.01	0.66	0.67	1.07	1.19	1.92	1.39
Std. dev.	0.56	1.97	0.33	0.38	1.05	0.51	0.79	0.48	0.14	0.69	0.52	0.68	0.51
Min.	1.07	1.26	0.36	0.73	1.34	0.35	0.48	-	0.24	0.36	0.50	0.94	0.49
Max.	4.18	15.64	1.81	2.85	7.83	2.85	3.84	2.35	1.05	2.98	3.02	8.48	3.32
Total assets (log)													
Mean	12.04	11.65	14.15	13.80	9.04	13.19	13.59	12.63	2.49	13.56	10.78	13.85	7.75
Median	12.41	12.54	14.40	13.78	9.41	13.36	13.90	12.74	2.45	13.77	11.10	14.12	7.72
Std. dev.	0.78	1.65	0.50	0.27	1.16	0.53	0.80	0.36	0.18	0.47	0.70	0.61	0.20
Min.	10.45	8.11	13.03	12.91	6.41	12.09	11.63	11.70	2.14	12.50	9.02	12.49	7.45
Max.	12.93	13.01	14.62	14.43	10.59	13.89	14.22	13.10	2.81	13.99	11.43	14.52	8.19
<u>Risk sentiment variable</u>													
Volatility													
Mean	13.78	11.61	10.91	11.20	10.45	11.73	11.28	13.52	10.21	11.20	14.74	8.86	8.81
Median	12.35	9.95	9.37	9.49	8.64	10.23	10.05	11.08	8.59	9.67	12.58	7.34	7.23
Std. dev.	6.74	5.94	6.19	6.30	6.16	6.43	5.72	9.12	5.80	6.10	7.39	5.38	6.14
Min.	4.62	2.10	2.16	2.36	2.92	2.58	3.12	3.23	2.78	3.07	4.67	1.85	1.89
Max.	69.87	36.65	46.66	44.67	47.37	50.80	61.97	86.25	48.85	46.36	61.69	43.98	52.40

Table A2: Macroeconomic variables: descriptive statistics.

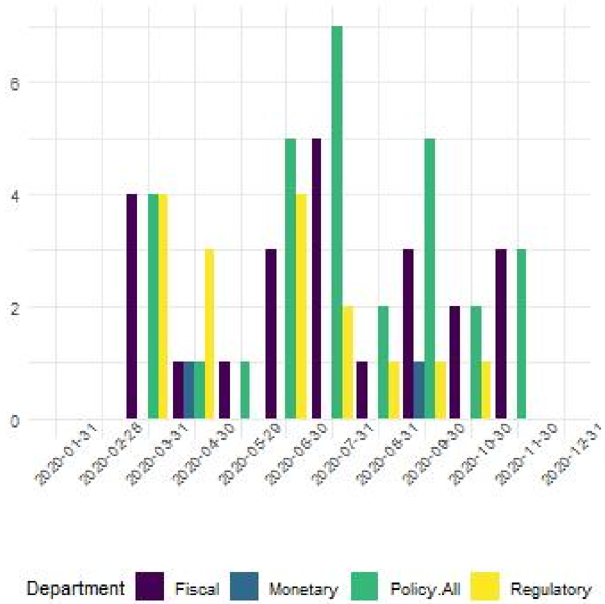
	Brazil	China	France	Germany	India	Italy	Japan	Russia	S. Korea	Spain	Turkey	UK	US
Macroeconomic variables													
CPI													
Mean	109.70	102.28	99.82	100.76	110.69	99.65	101.96	107.24	98.80	98.97	116.48	101.32	100.64
Median	101.91	101.90	100.43	100.48	103.84	100.58	101.24	102.70	100.92	101.60	102.13	101.05	100.63
Std. dev.	36.18	15.50	7.64	8.34	43.98	9.11	1.95	48.44	13.25	10.53	61.82	12.52	11.60
Min.	53.50	79.90	84.90	85.83	55.79	81.50	99.14	32.56	73.13	76.94	25.28	82.44	79.81
Max.	175.34	130.08	111.11	114.36	194.42	110.89	106.01	189.04	116.68	112.26	280.80	121.69	119.59
GDP													
Mean	347,209.84	3,166,232.60	396,415.85	562,603.85	438,632,946.70	353,241.03	135,336,811.90	2,474,291.36	185,216,011.00	185,769.90	73,832.01	289,321.85	2,710,845.48
Median	347,267.11	3,164,383.38	396,335.88	562,566.84	437,258,196.40	353,001.25	135,262,840.40	2,476,326.97	185,206,698.70	185,701.75	73,924.88	289,358.99	2,710,564.24
Std. dev.	347,438.60	3,158,739.99	396,091.41	562,451.07	433,151,259.90	352,272.03	135,037,925.90	2,482,466.22	185,177,413.30	185,494.11	74,205.03	289,469.99	2,709,716.92
Min.	347,495.68	3,156,828.02	396,008.44	562,410.94	431,788,042.50	352,025.76	134,961,984.50	2,484,523.20	185,167,225.40	185,423.88	74,298.91	289,506.85	2,709,433.42
Max.	347,552.73	3,154,901.17	395,924.76	562,370.06	430,427,700.90	351,777.95	134,885,573.20	2,486,585.34	185,156,836.40	185,353.15	74,393.05	289,543.65	2,709,149.47
IP													
Mean	88.67	110.97	104.16	102.69	93.62	102.94	99.92	102.89	92.47	105.31	113.35	103.08	106.15
Median	87.49	109.99	103.25	106.11	101.10	99.02	98.93	109.68	102.43	99.92	106.58	101.87	107.43
Std. dev.	8.33	9.16	6.23	8.97	26.12	11.07	7.01	22.22	21.06	12.63	35.87	5.39	6.09
Min.	61.40	92.43	66.58	77.10	49.46	55.12	76.59	-5.25	53.35	64.25	55.83	82.19	93.05
Max.	102.05	140.13	113.93	119.35	133.11	121.09	115.77	123.53	121.59	126.90	181.82	111.90	117.51
T-Bill													
Mean	12.88	1.02	1.78	1.61	3.01	1.66	0.08	3.76	5.40	1.78	16.34	2.23	1.40
Median	12.20	0.33	2.06	1.64	2.99	1.64	0.03	3.06	4.44	2.06	13.80	1.52	0.94
Std. dev.	5.39	1.24	1.75	1.52	1.62	1.55	0.20	3.23	2.03	1.75	19.75	1.94	1.54
Min.	2.10	-0.05	-0.57	-0.61	1.18	-0.61	-0.34	1.18	3.92	-0.57	0.14	0.09	0.01
Max.	28.15	5.70	5.71	4.52	9.30	4.58	0.60	13.55	11.32	5.71	76.49	5.72	5.36
Unempl. rate													
Mean	10.45	4.28	8.85	6.54	6.48	9.10	3.92	6.50	3.41	15.66	10.75	4.92	5.90
Median	11.60	4.11	8.84	5.81	6.55	8.66	3.96	5.89	3.44	14.64	10.15	4.18	5.41
Std. dev.	2.55	1.08	1.05	2.78	2.20	2.12	1.02	2.04	0.57	5.72	4.98	2.36	2.03
Min.	6.18	3.08	6.06	1.61	3.24	5.23	1.14	2.28	1.78	7.14	5.74	1.98	1.88
Max.	14.74	10.29	11.02	12.66	11.25	13.94	5.61	19.58	4.92	27.12	53.34	16.99	16.10

Table A3: COVID-19 variables: descriptive statistics.

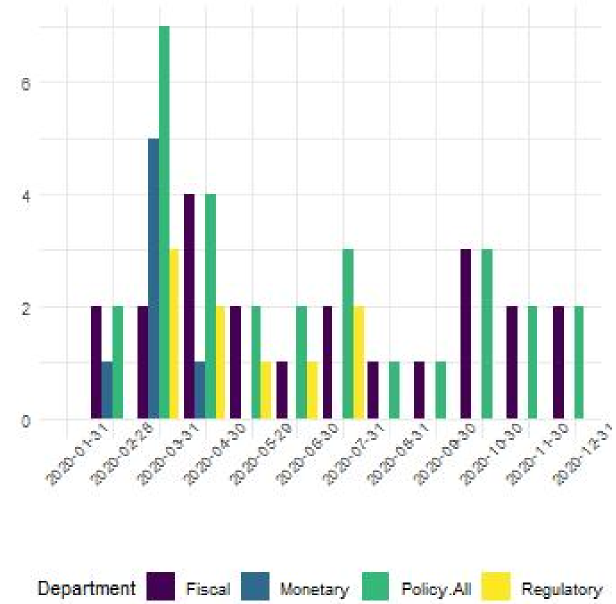
	Brazil	China	France	Germany	India	Italy	Japan	Russia	S. Korea	Spain	Turkey	UK	US
COVID-19 variables													
Conf. cases													
Mean	20,617.29	255.35	7,192.26	4,634.22	27,901.65	5,639.57	617.69	8,348.92	161.88	5,161.59	5,922.86	6,483.66	53,199.68
Median	23,941.79	34.21	1,272.57	1,167.79	18,631.00	1,277.07	414.79	6,057.21	71.00	3,237.86	1,369.21	1,636.36	36,282.29
Std. dev.	16,603.08	779.95	11,222.59	7,224.46	29,431.95	9,419.84	795.13	8,419.87	243.32	5,641.17	20,418.69	9,333.83	59,492.67
Min.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max.	49,826.71	4,606.86	56,225.29	25,757.00	93,198.57	35,072.57	3,577.43	28,349.57	1,047.43	21,129.29	145,043.71	43,012.43	220,056.29
SIndex													
Mean	66.32	68.29	54.76	51.97	63.27	58.32	33.63	50.72	46.83	56.23	53.56	56.84	56.18
Median	80.56	78.24	49.54	59.72	74.07	58.33	34.26	47.69	50.46	64.35	63.89	67.59	67.13
Std. dev.	31.47	18.97	26.08	23.40	29.30	25.26	12.71	26.36	17.83	26.00	23.78	26.14	25.93
Min.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max.	92.59	81.94	87.96	82.41	100.00	93.52	51.85	87.04	82.41	85.19	80.09	79.63	75.46

A.4 Policy interventions

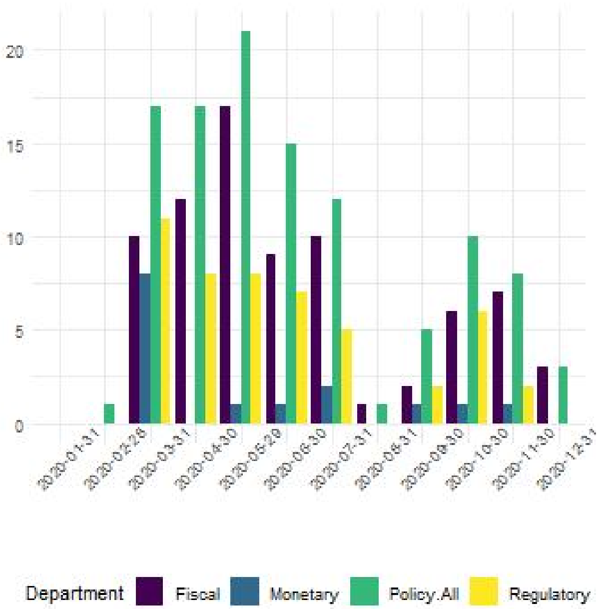
In order to gather the several policy interventions announced throughout the pandemic, we adopt the COVID-19 Financial Response Tracker (CFRT) developed by the Yale Program on Financial Stability (YPFS), which collects economic policy responses from official government websites around the world. The CFRT follows economic interventions by central banks, fiscal authorities, and international organizations aimed at combating the negative effects of the coronavirus pandemic and restoring financial stability. The tracker also highlights significant proposals from government representatives and institutions. Each tracker entry provides summary information and link to relevant press releases or articles about the intervention. For more information please see the Yale website: https://som.yale.edu/faculty-research-centers/centers-initiatives/program-on-financial-stability/COVID-19-crisis. We collect the dates of the press releases and meetings regarding government, central banks and regulators policy announcements and implementations across the countries in our sample from January to December 2020.



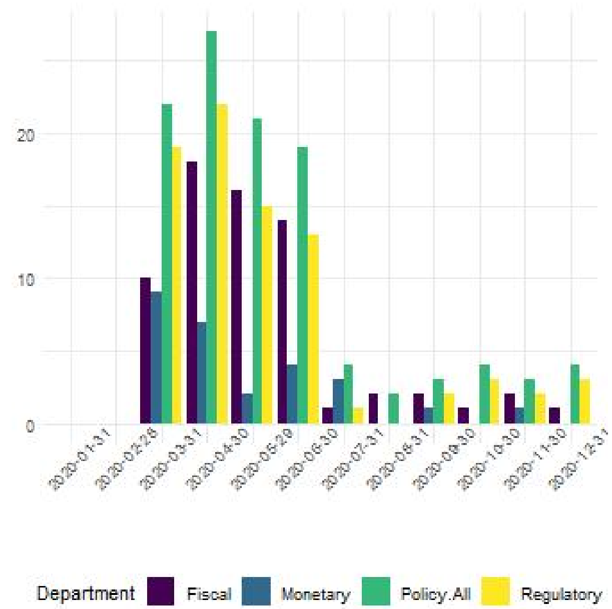
(a) Germany



(b) Italy



(c) United Kingdom



(d) United States

Figure A1: COVID-19 related policy interventions.
This bar chart reports the COVID-19 related policy interventions for four different countries, namely Germany, Italy, the U.K. and the U.S. as a illustration of the policy dynamics. The policies are divided into four categories which are Fiscal, Monetary, Regulatory and Policy All and aggregated for every month.

B Systemic risk measures: descriptive statistics and ranking

Table B1: $\Delta CoVaR_{95^{th}}$ of countries' financial system: descriptive statistics (%).

	Brazil	China	France	Germany	India	Italy	Japan	Russia	S. Korea	Spain	Turkey	UK	US
2001 – 2020													
Mean	4.8639	1.9689	4.7472	4.0339	3.2434	4.5196	2.8077	4.7904	3.9815	4.1609	6.5937	3.398	3.025
Median	4.6113	1.8133	3.1113	3.0176	2.9133	3.5202	2.3272	4.3145	3.5861	3.7382	6.1356	2.5708	2.3459
Std. dev.	1.8814	1.0906	3.4789	2.5726	1.6301	3.0799	1.4091	2.4116	2.3013	1.8987	1.7676	2.6457	2.2467
Min.	1.8921	0.147	0.9638	1.1176	0.7124	0.7493	0.8529	1.3891	1.445	1.2122	3.6175	0.5707	0.6035
Max.	11.5853	4.8305	14.187	12.8928	7.948	12.9461	6.2145	12.8649	12.6421	10.1473	12.4989	13.098	11.6397
Obs.	5219	5219	5219	5219	5219	5219	5219	5219	5219	5219	5219	5219	5219
2001 – 2007													
Mean	4.065	1.6245	2.8516	3.412	2.0208	1.8844	3.4802	3.1626	4.7535	2.9996	6.8574	2.0663	1.4441
Median	3.9892	1.7335	2.5746	2.6534	1.9619	1.8074	3.5024	2.7781	4.6915	2.563	6.6713	1.7499	1.2674
Std. dev.	1.197	0.9934	1.3703	1.6786	0.7963	0.7047	1.1325	1.4628	1.3518	1.2982	1.2092	0.9415	0.5638
Min.	2.2683	0.147	1.4535	1.5174	0.7124	0.7493	1.391	1.3891	2.4214	1.2122	4.5441	0.7663	0.6035
Max.	6.8057	3.4003	6.3418	7.6563	4.2348	3.2075	5.8471	9.0524	9.3444	5.6244	9.2183	3.7804	2.7524
Obs.	1826	1826	1826	1826	1826	1826	1826	1826	1826	1826	1826	1826	1826
2008 – 2013													
Mean	5.3175	2.5044	8.9294	6.4305	4.9186	8.0569	3.2972	6.6448	4.9752	6.1347	6.9413	6.2092	5.2307
Median	4.8487	1.8839	8.2841	5.8914	4.3877	8.2545	2.4361	5.842	3.9234	6.1769	6.1175	5.9431	4.3211
Std. dev.	2.5696	1.2476	3.3293	2.9409	1.3088	2.9459	1.5711	2.8118	3.0889	1.7566	2.5386	3.0291	2.4967
Min.	1.8921	0.8776	3.4789	2.6502	3.1246	2.8234	1.5808	2.6179	1.445	2.5235	3.6175	1.8338	2.2893
Max.	11.5853	4.8305	14.187	12.8928	7.948	12.9461	6.2145	12.8649	12.6421	10.1473	12.4989	13.098	11.6397
Obs.	1566	1566	1566	1566	1566	1566	1566	1566	1566	1566	1566	1566	1566
2014 – 2019													
Mean	5.1681	1.8499	2.7669	2.3501	2.8319	4.1097	1.7495	4.6856	2.0211	3.3994	6.0959	2.0667	2.2435
Median	5.1822	1.7596	2.5009	2.1798	2.5583	3.9677	1.8254	4.5195	1.986	3.1268	6.0012	1.7603	2.146
Std. dev.	1.4177	0.9027	1.0419	0.9588	1.1779	1.1944	0.6834	1.3969	0.2522	0.7462	1.2662	1.0693	0.518
Min.	2.3564	0.5657	0.9638	1.1176	1.6058	1.6222	0.8775	2.3989	1.5724	2.0971	3.9916	0.5707	1.1842
Max.	8.3415	3.9323	5.1623	4.9068	6.1817	6.6548	3.0194	7.8019	2.6416	5.3962	9.5368	4.8163	3.2742
Obs.	1565	1565	1565	1565	1565	1565	1565	1565	1565	1565	1565	1565	1565
2020													
Mean	5.9042	1.8791	4.7909	4.1025	4.2097	4.1907	1.5149	5.6777	4.3718	5.0057	5.652	3.8289	5.5267
Median	6.8181	1.8549	5.6209	4.6806	4.7652	4.6957	1.7506	6.4576	4.8784	5.7308	5.505	4.4107	6.6194
Std. dev.	1.3299	0.1315	1.5061	1.0359	0.9276	0.899	0.3644	1.4778	1.4888	1.2042	0.632	1.1121	1.757
Min.	3.3513	1.6608	1.8154	1.9871	2.4024	2.5469	0.8529	2.6266	1.7166	2.9553	4.8235	1.7144	1.9298
Max.	7.3148	2.1893	6.2942	4.8353	5.3175	5.1209	1.9137	6.7574	5.6753	6.2692	7.0359	4.8801	6.8095
Obs.	262	262	262	262	262	262	262	262	262	262	262	262	262

Table B2: Country financial sectors' systemic risk ranking in 2020.

H_0: $\Delta CoVaR^{i}_{95^{th}} \leq \Delta CoVaR^{j}_{95^{th}}$, with $i > j$, i=1,2,...,n and j=1,2,...,n-1

2020		$2020_{5\%}$	
1.	Brazil	1.	Brazil
	United States	2	Turkey
2.	Turkey	3.	United States
3.	Italy	4.	Russia
	Spain	5.	France
	Russia		Spain
4.	France	6.	South Korea
5.	Germany	7.	Italy
	India	8.	India
	South Korea	9	United Kingdom
6.	United Kingdom	10.	Germany
7.	China	11.	China
8.	Japan	12.	Japan

The ranking results from the bootstrap Kolmogorov-Smirnov test with 1% significance level. The hypothesis tested is $\Delta CoVaR^{i}_{95^{th}} \leq \Delta CoVaR^{j}_{95^{th}}$, with $i > j$, i=1,2,...,n and j=1,2,...,n-1. On the right-hand side, the $\Delta CoVaR^{i}_{95^{th}}$ is over 2020, while on the left-hand side only the 5% worst realizations are considered. The failure to reject this hypothesis means that the financial sector of country j is systemically riskier than that of country i, entailing a higher ranking position of j.

C Robustness checks

Table C1: COVID-19 related policies impact on global systemic risk: controlling for countries' volatility

Dependent variable	$\Delta CoVaR_{i,t}$						
Country	Brazil	China	Euro Area	France	Germany	India	Italy
$D_{i,t-1\|Mon}$	-0.185	-0.038	-0.141	-0.242	-0.677***	-0.151	-0.533*
$D_{i,t-1\|Fis}$	0.087	-0.022	0.302**	-0.583	-0.431**	-0.406**	-0.414
$D_{i,t-1\|Reg}$	0.042	0.016	-0.679***	-1.334***	-0.465***	-0.548***	-0.552*
$D_{i,t-1\|All}$	-0.065	0.008	0.277*	-0.208	0.698***	0.151	0.055*
$Conf.Cases_{i,t-1}$	0.007***	0.001*	0.005***	0.003***	0.001**	0.002***	0.003***
$SIndex_{i,t-1}$	0.010***	0.001**	0.029***	0.035***	0.037***	0.021***	0.005**
$Volatility_{i,t-1}$	-0.015	0.010	-0.027	0.131**	0.026	0.031*	0.055**
$adj.R^2$ (%)	84.4	21.3	59.5	52.2	70.4	77.4	21.8
Obs.	261	262	262	262	262	262	262
Country	Japan	Russia	South Korea	Spain	Turkey	UK	US
$D_{i,t-1\|Mon}$	0.077	-0.189	0.092	0.089	0.267	-0.032	-0.138
$D_{i,t-1\|Fis}$	-0.145	-0.059	2.696**	0.031	0.321**	-0.099	-0.227***
$D_{i,t-1\|Reg}$	-0.319***	-0.227	-0.732	-1.864***	0.218	-0.197**	-0.434***
$D_{i,t-1\|All}$	-0.035	-0.344*	-1.755**	-0.079	-0.090	-0.166	-0.173
$Conf.Cases_{i,t-1}$	0.002***	0.007***	0.001***	0.008***	0.001***	0.002***	0.001**
$SIndex_{i,t-1}$	0.007***	0.045***	0.038***	0.019***	0.001	0.037***	0.067***
$Volatility_{i,t-1}$	0.039**	0.011	0.085*	0.015	0.007	0.004	0.053**
$adj.R^2$ (%)	43.5	86.1	34.5	47.1	26.4	83.6	94.5
Obs.	261	261	261	261	261	261	261

The regression coefficients from model 8. The analysis is conducted for 2020 at a daily frequency. Intercept results are not reported for the sake of space. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table C2: COVID-19 related policies impact on global systemic risk.

Dependent variable	$\Delta CoVaR_{i,t}$						
Country	Brazil	China	Euro Area	France	Germany	India	Italy
$D_{i,t\|Mon}$	-0.188	-0.041	-0.154	-0.039	-0.734***	-0.112	-0.602*
$D_{i,t\|Fis}$	0.029	-0.022	0.328***	-0.681*	-0.440**	-0.428***	-0.464
$D_{i,t\|Reg}$	0.037	0.027	-0.676***	-1.382***	-0.512**	-0.588***	-0.653**
$D_{i,t\|All}$	-0.071	0.001	0.238	-0.071	0.726***	0.132	0.604*
$Conf.Cases_{i,t}$	0.006***	0.002*	0.004***	0.003***	0.001**	0.001***	0.003***
$SIndex_{i,t}$	0.010***	0.001**	0.029***	0.035***	0.039***	0.022***	0.005**
$adj.R^2$ (%)	84.6	21.2	59.7	51.1	69.7	77.4	20.6
Obs.	262	262	262	262	262	262	262
Country	Japan	Russia	South Korea	Spain	Turkey	UK	US
$D_{i,t\|Mon}$	0.047	-0.205	0.052	0.133	0.229	-0.033	-0.077
$D_{i,t\|Fis}$	-0.145	-0.099	2.733**	0.079	0.202	-0.099	-0.247***
$D_{i,t\|Reg}$	-0.318***	-0.239	-0.764	-1.894***	0.201	-0.186**	-0.425***
$D_{i,t\|All}$	-0.005	-0.348*	-1.776***	-0.149	-0.022	-0.176	-0.218*
$Conf.Cases_{i,t}$	0.001***	0.007***	0.001***	0.008***	0.001***	0.002***	0.001**
$SIndex_{i,t}$	0.008***	0.046***	0.038***	0.019***	0.001	0.037***	0.067***
$adj.R^2$ (%)	43.2	86.3	34.9	47.2	26.7	83.3	94.5
Obs.	262	262	262	262	262	262	262

The regression coefficients from model 8, where now the policy interventions and control variables are considered contemporaneously at time t. The analysis is conducted for 2020 at a daily frequency. Intercept results are not reported for the sake of space. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table C3: COVID-19 related policies impact on global systemic risk: controlling for countries' volatility.

Dependent variable				$\Delta CoVaR_{i,t}$			
Country	Brazil	China	Euro Area	France	Germany	India	Italy
$D_{i,t\|Mon}$	-0.187	-0.041	-0.139	-0.047	-0.751***	-0.129	-0.683*
$D_{i,t\|Fis}$	0.033	-0.017	0.318***	-0.545	-0.438**	-0.421**	-0.520
$D_{i,t\|Reg}$	0.034	0.029	-0.678***	-1.368***	-0.517**	-0.576***	-0.784***
$D_{i,t\|All}$	-0.070	0.004	0.236	-0.087	0.760***	0.139	0.072
$Conf.Cases_{i,t}$	0.006***	0.002*	0.004***	0.003***	0.001**	0.001***	0.003***
$SIndex_{i,t}$	0.010***	0.001*	0.028***	0.034***	0.039***	0.021***	0.004**
$Volatility_{i,t}$	-0.022	0.009	-0.036	0.072*	0.048**	0.040**	0.074***
$adj.R^2$ (%)	84.7	22.2	59.7	51.5	70.0	77.6	24.6
Obs.	262	262	262	262	262	262	262
Country	Japan	Russia	South Korea	Spain	Turkey	UK	US
$D_{i,t\|Mon}$	0.056	-0.203	0.081	0.013	0.228	-0.031	-0.092
$D_{i,t\|Fis}$	-0.141	-0.107	2.744**	0.057	0.202	-0.099	-0.251**
$D_{i,t\|Reg}$	-0.324***	-0.210	-0.674	-1.878***	0.202	-0.185**	-0.426***
$D_{i,t\|All}$	-0.012	-0.354*	-1.820**	-0.133	-0.029	-0.175	-0.220*
$Conf.Cases_{i,t}$	0.001***	0.007***	0.001***	0.008***	0.001***	0.002***	0.001**
$SIndex_{i,t}$	0.007***	0.045***	0.037***	0.018***	0.001	0.036***	0.068***
$Volatility_{i,t}$	0.042**	0.014	0.016**	0.035	0.012	0.022	0.043**
$adj.R^2$ (%)	44.6	86.6	34.9	47.8	28.5	83.4	94.8
Obs.	262	262	262	262	262	262	262

The regression coefficients from model 8, where now the policy interventions and control variables are considered contemporaneously at time t, and we also control for countries' volatility. The analysis is conducted for 2020 at a daily frequency. Intercept results are not reported for the sake of space. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table C4: COVID-19 related US policies on global systemic risk: Panel spillover analysis.

Dependent variable	$\Delta CoVaR_{i,t}$			
	(1)	(2)	(3)	(4)
$D_{i,t-1\|Mon,US}$	0.204***	0.085	0.079	0.019
$D_{i,t-1\|Fis,US}$	-0.038	-0.037	-0.129	-0.025
$D_{i,t-1\|Reg,US}$	0.204***	0.083	0.086	0.024
$D_{i,t-1\|All,US}$		0.195***	0.196***	0.154
$Conf.Cases_{i,t-1}$	0.005***	0.005***	0.005***	0.002***
$SIndex_{i,t-1}$	0.008***	0.007***	0.007***	0.001*
$Volatility_{i,t-1}$			0.374**	0.025*
$CoVaR_{i,t-1}$				0.982***
Time FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
$adj.R^2$ (%)	78.1	78.2	82.1	85.9
Obs.	3376	3376	3376	3376

The regression coefficients from model 7, where now the policies are considered to be only United States policy interventions. The analysis is conducted for 2020 at a daily frequency. All equations are estimated with country and time fixed effects. Intercept results are not reported for the sake of space. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table C5: COVID-19 related banks policies impact on global systemic risk: Panel analysis.

Dependent variable	$\Delta CoVaR_{i,t}$			
	(1)	(2)	(3)	(4)
$D_{i,t-1\|Banks}$	-0.163***	-0.101**	-0.102**	-0.003**
$D_{i,t-1\|All}$		0.102**	0.101**	0.004*
$Conf.Cases_{i,t-1}$	0.005***	0.005***	0.005***	0.171**
$SIndex_{i,t-1}$	0.007***	0.007***	0.007***	0.008*
$Volatility_{i,t-1}$			0.369**	0.025*
$CoVaR_{i,t-1}$				0.982***
Time FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
$adj.R^2$ (%)	81.3	81.5	82.4	82.7
Obs.	3376	3376	3376	3376

The regression coefficients from model 7, where now the policies of interest are the banks policies $D_{i,t-1|Banks}$. The analysis is conducted for 2020 at a daily frequency. All equations are estimated with country and time fixed effects. Intercept results are not reported for the sake of space. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table C6: COVID-19 related banks policies impact on global systemic risk.

Dependent variable				$\Delta CoVaR_{i,t}$			
Country	Brazil	China	Euro Area	France	Germany	India	Italy
$D_{i,t-1\|Banks}$	-0.073	0.023	-0.382***	-1.255***	-0.137	0.267	-0.503
$D_{i,t-1\|All}$	-0.014	0.019	0.392***	-0.320*	-0.039	-0.450***	0.028
$Conf.Cases_{i,t-1}$	0.006***	0.001*	0.007***	0.004***	0.001**	0.004***	0.003***
$SIndex_{i,t-1}$	0.011***	0.001**	0.023***	0.034***	0.037***	0.021***	0.005**
$Volatility_{i,t-1}$	0.015	0.008	0.037	0.111**	0.036*	0.037*	0.006*
$adj.R^2$ (%)	84.7	17.1	55.2	49.6	69.5	77.3	22.2
Obs.	261	261	261	261	261	261	261
Country	Japan	Russia	South Korea	Spain	Turkey	UK	US
$D_{i,t-1\|Banks}$	0.023	-0.183	-0.496	-1.991**	0.071	-0.446***	-0.262***
$D_{i,t-1\|All}$	-0.158***	-0.578***	-1.815***	0.023	0.212**	-0.247***	-0.528***
$Conf.Cases_{i,t-1}$	0.002***	0.007***	0.001**	0.008***	0.001***	0.002***	0.004***
$SIndex_{i,t-1}$	0.007***	0.045***	0.038***	0.018***	0.001	0.035***	0.067***
$Volatility_{i,t-1}$	0.035*	0.017	0.091	0.028	0.033	0.010	0.059***
$adj.R^2$ (%)	41.6	86.4	34.3	47.7	27.1	84.8	94.2
Obs.	261	261	261	261	261	261	261

The regression coefficients from model 7, where now the policies of interest are the contemporaneous banks policies $D_{i,t|Banks}$. The analysis is conducted for 2020 at a daily frequency. All equations are estimated with country and time fixed effects. Intercept results are not reported for the sake of space. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table C7: COVID-19 related policies impact on global systemic risk MSCI index based.

Dependent variable	$\Delta CoVaR_{i,t}^{MSCI}$						
Country	Brazil	China	Euro Area	France	Germany	India	Italy
$D_{i,t\|Mon}$	-0.209	-0.062	-0.147	0.087	-0.598***	-0.065	-0.454*
$D_{i,t\|Fis}$	0.182	-0.021	0.296***	-0.549*	-0.367**	-0.217**	-0.366
$D_{i,t\|Reg}$	0.094	0.006	-0.597***	-0.863**	-0.109	-0.322***	-0.480
$D_{i,t\|All}$	-0.071	0.095*	0.189	-0.129	0.567***	0.063	0.445*
$Conf.Cases_{i,t}$	0.006***	0.002***	0.004***	0.002***	0.007***	0.006***	0.003***
$SIndex_{i,t}$	0.034***	0.008***	0.021***	0.024***	0.027***	0.018***	0.003**
$adj.R^2$ (%)	91.11	63.41	54.52	44.13	58.11	82.68	18.90
Obs.	262	262	262	262	262	262	262
Country	Japan	Russia	South Korea	Spain	Turkey	UK	US
$D_{i,t\|Mon}$	0.057	-0.133*	-0.014	0.151	0.132	-0.016	-0.075
$D_{i,t\|Fis}$	-0.047	-0.071	0.870*	0.072	0.153*	-0.098	-0.242***
$D_{i,t\|Reg}$	-0.146***	-0.007	-0.243	NA	0.167*	-0.176**	-0.418***
$D_{i,t\|All}$	-0.012	-0.250**	-0.530**	-0.148	-0.038	-0.142	-0.217*
$Conf.Cases_{i,t}$	0.009***	0.003***	0.037***	0.005***	0.007***	0.001***	0.001**
$SIndex_{i,t}$	0.005***	0.015***	0.007***	0.017***	0.001	0.022***	0.066***
$adj.R^2$ (%)	46.56	79.15	27.95	42.71	25.43	74.50	94.42
Obs.	262	262	262	262	262	262	262

The regression coefficients from model 8. The analysis is conducted for 2020 at a daily frequency. Intercept results are not reported for the sake of space. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table C8: Firm-specific, risk sentiment and macroeconomic variables on systemic risk MSCI index based.

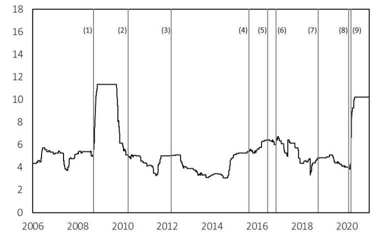
Dependent variable	$\Delta CoVaR_{i,t}^{MSCI}$				
	2001–2020	GFC	2016–2020	2016–2019	COVID-19
Firm-specific variables					
$Basel\ leverage_{i,t-1}$	-0.0109	0.0387	-0.0024	0.0330	-0.0220
$NPL\ ratio_{i,t-1}$	0.0225***	1.2701***	0.1757***	0.200***	-0.2180**
$Price\text{-}to\text{-}book\ ratio_{i,t-1}$	-0.1296**	-0.0702	-0.1479	-0.334**	-0.469
$Total\ assets\ (log)_{i,t-1}$	0.2943*	2.0620***	0.0342	1.602***	-0.189
Risk sentiment variable					
$Volatility_{i,t-1}$	2.2363***	0.5829**	0.9691***	0.634***	0.432**
Macroeconomic variables					
$CPI_{i,t-1}$	0.0227	0.9704**	0.2191**	0.204**	0.082
$GDP_{i,t-1}$	-0.1017***	0.1520**	-0.0607**	-0.057	-0.029
$IP_{i,t-1}$	-0.0013	0.216	0.0088	0.02	-0.002
$T\text{-}Bill_{i,t-1}$	0.2117***	-0.0932	0.1293***	0.184***	0.111***
$Unempl.\ rate_{i,t-1}$	0.0066*	-0.0127	0.0017	0.003	0.001
Time FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
$adj.R^2$ (%)	68.01	94.24	73.53	76.32	91.35
Obs.	3107	468	780	624	156

The panel regression coefficients from model 9. All the variables are taken at a monthly frequency. The panel regression is run for the whole sample (2001-2020) and four sub-samples, namely GFC, 2016-2020, 2016-2019 and the COVID-19 period. All equations are estimated with country and time fixed effects. Intercept results are not reported for the sake of space. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

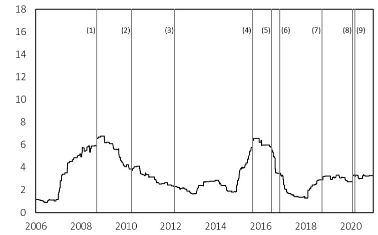
Table C9: Polices and COVID-19 related variables on systemic risk MSCI index based.

Dependent variable	$\Delta CoVaR_{i,t}^{MSCI}$				
	$D_{i,t\|Fis}$	$D_{i,t\|Mon}$	$D_{i,t\|Reg}$	$D_{i,t\|All}$	$D_{i,t\|Banks}$
	Firm-specific and macro variables				
$Basel\ leverage_{i,t-1}$	-0.040	-0.0284	-0.0185	-0.023	-0.029
$NPL\ ratio_{i,t-1}$	-0.223**	0.228**	-0.264**	-0.246**	-0.237**
$Price\text{-}to\text{-}book\ ratio_{i,t-1}$	-0.131	-0.123	-0.168	-0.148	-0.762
$Total\ assets\ (log)_{i,t-1}$	0.772	0.506	0.868	0.922	0.296
$Volatility_{i,t-1}$	0.357	0.221	0.294	0.279	0.301
$CPI_{i,t-1}$	-0.041	-0.052	0.016	-0.008	-0.026
$GDP_{i,t-1}$	-0.063*	-0.056*	-0.031	-0.052	-0.032
$IP_{i,t-1}$	0.008	-0.005	0.005	0.008	0.003
$T\text{-}Bill_{i,t-1}$	0.096***	0.081**	0.116***	0.103***	0.107***
$Unempl.\ rate_{i,t-1}$	0.004	0.002	0.002	0.005	0.002
	Interaction with policies				
$Basel\ leverage_{i,t-1}$	-0.002	-0.003	-0.002	-0.002	-0.005*
$NPL\ ratio_{i,t-1}$	-0.035**	-0.049***	-0.021**	-0.018***	-0.043***
$Price\text{-}to\text{-}book\ ratio_{i,t-1}$	0.036	0.031	0.022	0.018	0.017
$Total\ assets\ (log)_{i,t-1}$	0.004	0.001	0.003	0.002	0.002
$Volatility_{i,t-1}$	0.019	0.059	0.019	0.018	0.044
$CPI_{i,t-1}$	0.032	-0.022	0.020	0.013	0.073
$GDP_{i,t-1}$	0.008	0.017	0.003	0.004	0.001
$IP_{i,t-1}$	-0.003	-0.005	-0.002	-0.002	-0.006
$T\text{-}Bill_{i,t-1}$	0.029**	0.058**	0.014	0.014**	0.052**
$Unempl.\ rate_{i,t-1}$	-0.005	-0.007	-0.004	-0.004*	-0.004
	Policy Dummy				
$D_{i,t}$	0.199	0.335	0.167	0.127	0.298
	COVID-19 variables				
$Conf.\ cases_{i,t}$	0.000***	0.000***	0.000***	0.000***	0.000***
$SIndex_{i,t}$	0.017***	0.018***	0.019***	0.018***	0.015***
Time FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
$adj.R^2$ (%)	93.19	93.30	92.85	93.22	92.74
Obs.	156	156	156	156	156

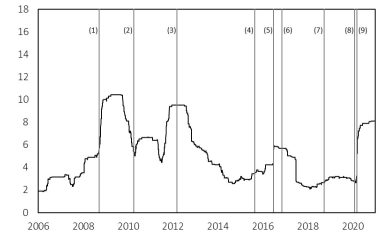
The panel regression coefficients from model 10. The interaction factors between the independent variables and each of the policy interventions dummy, namely ($D_{i,t|Fis}$), ($D_{i,t|Mon}$), ($D_{i,t|Reg}$), and ($D_{i,t|All}$) are included. The panel regression is run for the COVID-19 period. All equations are estimated with country and time fixed effects. All the variables are taken at a monthly frequency. Intercept results are not reported for the sake of space. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.



(a) Brazil



(b) China



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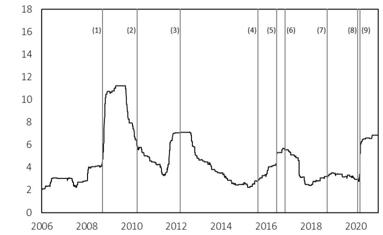

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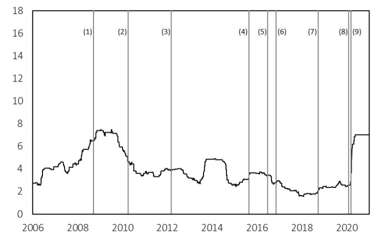
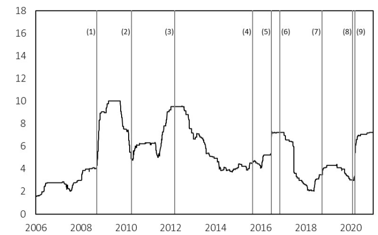
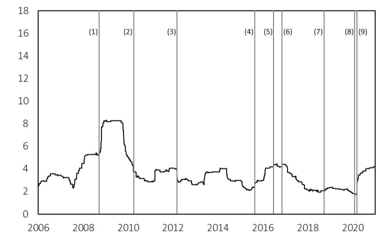


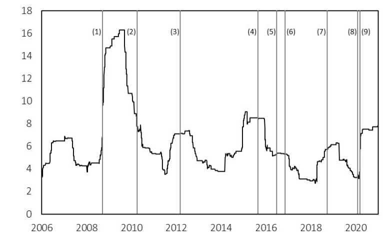
(e) India



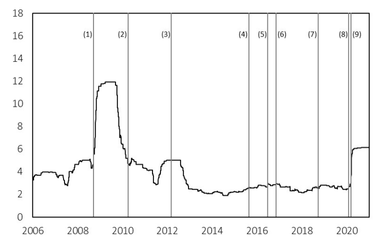
(f) Italy



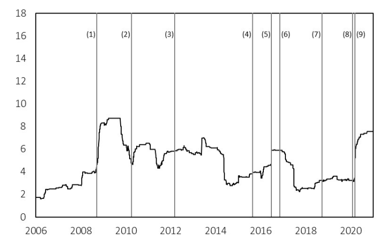
(g) Japan



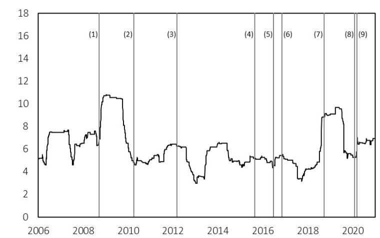
(h) Russia



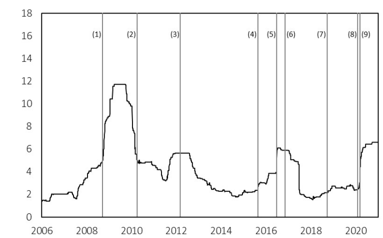
(i) South Korea



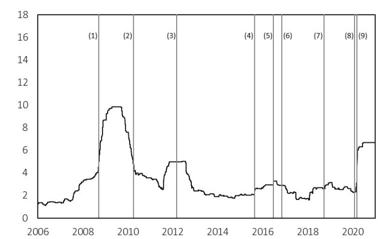
(j) Spain



(k) Turkey



(l) United Kingdom



(m) United States

Figure C1: Time series of MES.
Time series of MES at a daily-frequency from January 1, 2006 to December 31, 2020. The vertical axis reports values of MES in percentage – %. The horizontal axis reports the years. The solid vertical lines mark: (1) the Lehman Brothers bankruptcy; (2) the first bailout package for Greece; (3) the Greek 10-year bond yields peak; (4) the Chinese market crash; (5) the Brexit referendum result; (6) the US election 2016 results; (7) the tech crash; (8) the WHO declaring COVID-19 to be a public health emergency of international concern; and (9) the WHO characterizing COVID-19 as a pandemic.

Table C10: COVID-19 policies and traditional determinants on systemic risk (MES).

Dependent variable	$MES_{i,t}$				
	$D_{i,t\|Fis}$	$D_{i,t\|Mon}$	$D_{i,t\|Reg}$	$D_{i,t\|All}$	$D_{i,t\|Banks}$
	Firm-specific and macro variables				
$Basel\ leverage_{i,t-1}$	-0.001	0.001	-0.003	-0.004	-0.004
$NPL\ ratio_{i,t-1}$	-0.063	-0.157*	-0.114	-0.128	-0.122
$Price\text{-}to\text{-}book\ ratio_{i,t-1}$	0.335	0.287	0.381	0.348	0.292
$Total\ assets\ (log)_{i,t-1}$	0.137	0.301	0.162	0.357	0.209
$Volatility_{i,t-1}$	0.343*	0.328**	0.201	0.246	0.292*
$CPI_{i,t-1}$	0.192	0.139	0.081	0.132	0.041
$GDP_{i,t-1}$	-0.019	0.005	-0.006	-0.005	0.008
$IP_{i,t-1}$	0.007	0.007	0.006	0.008	0.004
$T\text{-}Bill_{i,t-1}$	0.146***	0.162***	0.168***	0.169***	0.163***
$Unempl.\ rate_{i,t-1}$	0.002	0.004	-0.009	-0.001	-0.001
	Interaction with policies				
$Basel\ leverage_{i,t-1}$	-0.002*	-0.002	-0.008	-0.008	-0.004**
$NPL\ ratio_{i,t-1}$	-0.044**	-0.009	-0.015**	-0.009**	-0.021*
$Price\text{-}to\text{-}book\ ratio_{i,t-1}$	0.016	0.066*	0.034**	0.022**	0.031*
$Total\ assets\ (log)_{i,t-1}$	0.012*	0.003	0.001	0.001	0.002
$Volatility_{i,t-1}$	0.011	-0.027	0.001	0.005	0.008*
$CPI_{i,t-1}$	0.102***	0.136***	0.080**	0.050***	0.090**
$GDP_{i,t-1}$	0.003	0.0001	0.002	0.002	0.005
$IP_{i,t-1}$	-0.002	-0.002	-0.004	-0.007	-0.006
$T\text{-}Bill_{i,t-1}$	0.005	0.008	0.005	0.001	0.011
$Unempl.\ rate_{i,t-1}$	0.000	0.001	0.002	0.001	0.002
	Policy Dummy				
$D_{i,t}$	0.082	0.521	0.105	0.131	0.317
	COVID-19 variables				
$Conf.\ cases_{i,t}$	0.000*	0.000*	0.000*	0.000*	0.000*
$SIndex_{i,t}$	0.018***	0.015***	0.022***	0.021***	0.017***
Time FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
$adj.R^2$ (%)	95.23	95.46	94.91	95.30	94.63
Obs.	156	156	156	156	156

Regression coefficients from model 10. The interaction factors between the independent variables and each of the policy interventions dummy, namely ($D_{i,t|Fis}$), ($D_{i,t|Mon}$), ($D_{i,t|Reg}$), and ($D_{i,t|All}$) are included. The panel regression is run for the COVID-19 period. All equations are estimated with country and time fixed effects. All the variables are taken at a monthly frequency. Intercept results are not reported for the sake of space. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.