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Bank systemic risk around COVID-19: A cross-country analysis

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ABSTRACT

Using 1,584 listed banks from 64 countries during the COVID-19 pandemic, we conduct the first broad-based international study of the effect of the pandemic on bank systemic risk. We find the pandemic has increased systemic risk across countries. The effect operates through government policy response and bank default risk channels. Additional analysis suggests that the adverse effect on systemic stability is more pronounced for large, highly leveraged, riskier, high loan-to-asset, undercapitalized, and low network centrality banks. However, this effect is moderated by formal bank regulation (e.g., deposit insurance), ownership structure (e.g., foreign and government ownership), and informal institutions (e.g., culture and trust).

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1. Introduction

As of December 10, 2020, there were more than 70 million confirmed COVID-19 cases worldwide and more than 1.5 million deaths, according to Johns Hopkins University Center for Systems Science and Engineering (CSSE). This pandemic has clearly caused havoc on countries around the world (e.g., [Fernandes 2020](#), [Ozili and Arun 2020](#)). Prior literature on bank systemic risk suggests that such shocks (e.g., the 2008 global financial crisis) lead to an increase in the tail comovements of banks, which may trigger the collapse of entire financial systems (e.g., [Adrian and Brunnermeier 2016](#), [Acharya et al. 2017](#)). However, the current pandemic is a serious health crisis, which is a key difference from past crises. Therefore, we cannot generalize prior results on bank systemic risk to this pandemic-induced crisis.

Extant research on the pandemic to date has focused on its economic effects (e.g., [Barro et al. 2020](#), [Barua 2020](#), [Chen et al. 2020](#), [Eichenbaum et al. 2020](#), [McKibbin and Fernando 2020](#)). While this unprecedented shock will likely leave its mark on banks, little is known yet about how it may impact the resilience of the banking

system as a whole.¹ In this paper, we attempt to close this gap by examining bank systemic risk during the COVID-19 pandemic in a large cross-country setting.

The spread of the virus compelled governments to instigate several containment measures such as social distancing, lockdowns, and business shutdowns. These in turn lead to negative economic effects on firms and households. As a result, firms have faced significant revenue drops and increases in costs, and households have faced job losses and declines in income. Thus, firms and households may not be able to service their debt, increasing the likelihood of default (e.g., [Ozili and Arun 2020](#), [Barua 2020](#), [Bartik et al. 2020](#)). These effects are likely to spread to banks, resulting in lost revenue and a surge in non-performing loans, which negatively affects banks' profits, solvency, and capital ([Beck and Keil, 2020](#)). Moreover, lower demand for bank services may result in lower non-interest revenues, which in turn reduces bank profitability (e.g., [Beck and Keil 2020](#), [Ozili and Arun 2020](#)). Con-

¹ There are a few notable exceptions. [Berger et al. \(2020\)](#) investigate whether relationship borrowers have obtained better loan terms than other borrowers during the COVID-19 crisis. [Beck and Keil \(2020\)](#) study the geographic variation in the exposure of U.S. banks to COVID-19 and lockdown policies. [Acharya and Steffen \(2020\)](#) use stress tests to assess how COVID-19 has affected U.S. banks' liquidity insurance function. [Li et al. \(2020\)](#) analyze the impact of the pandemic on bank liquidity supply. And [Demirgüç-Kunt et al. \(2020\)](#) examine its impact on the stock market performance of banks from 53 countries.

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sequently, banks may face higher credit risk, which can lead to an increase in systemic fragility.

Alternatively, the current pandemic shock may have only a trivial impact on bank systemic risk. The regulatory reforms implemented in the aftermath of the global financial crisis helped banks become more resilient to negative shocks (Carletti et al., 2020). In addition, businesses, households, and banks may have benefited from various forms of government support and access to central bank refinancing, reducing the potential negative effects on the banking system. Thus, the effect of the pandemic on systemic risk is ultimately an empirical question, which we address here.

Next, we exploit our cross-country setting to examine whether formal banking regulations and ownership structure mitigate the systemic risk arising from the pandemic shock. Countries with explicit deposit insurance schemes, as part of their financial system safety nets, are less likely to experience runs during an epidemic. This may mitigate systemic risk (e.g., Anginer et al. 2012). Foreign banks are also more likely to diversify their risks in the face of COVID-19 shocks because of different epidemic conditions and policies in various countries and regions. Therefore, foreign banks may contribute less to systemic risk than domestic banks (e.g., Faia et al. 2019). Government-owned banks may have the advantage of being able to withstand COVID-19 shocks due to their implicit guarantees (e.g., Iannotta et al. 2013, Boubakri et al., 2020).

Prior research shows that national culture and societal trust affect bank risk-taking and bank failures (e.g., Kanagaretnam et al. 2014, Boubakri et al. 2017, Kanagaretnam et al. 2019, Mourouzdou-Damtsa et al. 2019, Berger et al. 2021). Against this backdrop, we explore whether informal rules such as national culture and societal trust influence the effect of the pandemic on systemic risk.

To empirically examine the impact of the pandemic on bank systemic risk, we use a sample of 1,584 listed banks in 64 countries from February through December 2020. We use OLS regressions with bank and time fixed effects. To capture systemic risk, we use ΔCoVaR (Adrian and Brunnermeier, 2016). Similar to Ding et al. (2021), we also use the 14-day moving average log growth rate of confirmed COVID-19 cases from CSSE as a proxy for COVID-19 shocks. We find that the growth rate of confirmed cases is associated with higher systemic risk across countries. Additional analyses show that this evidence is driven mainly by two channels: the stringency of governments' responses to the pandemic and bank default risk. The results are robust to alternative dependent and independent measures and subsamples.

Prior studies have found that bank size, leverage, volatility, and other characteristics are the primary determinants of systemic risk (e.g., Adrian and Brunnermeier 2016, Billio et al. 2012, Black et al. 2016, Laeven et al. 2016). Therefore, we extend our main analysis to explore how pandemic-induced systemic risk is shaped by a series of bank characteristics. We find that the detrimental effect of the pandemic on systemic risk is more pronounced for large, highly leveraged, riskier, high loan-to-asset, undercapitalized, and low network centrality banks.

Next, we explore the roles of formal regulations, ownership structure, and informal rules in mitigating the impact of the pandemic. We use the Bank Regulation and Supervision Survey (BRSS) compiled by the World Bank to identify the formal regulation, competition, and ownership variables, including banking activity restrictions, capital regulations, supervisory authority, deposit insurance, bank concentration, and foreign- and government-owned bank assets. We also select Hofstede's (2001) cultural dimensions of power distance, collectivism, masculinity, uncertainty avoidance, and long-term orientation, as well as societal trust from the World Values Survey (WVS). The results show that deposit insurance and foreign- and government-owned banks help to mitigate the increase in bank systemic risk during the pandemic shock. Further-

more, informal institutions matter. Countries with higher power distance, collectivism, long-term orientation, and societal trust are better able to withstand the impact of the pandemic on systemic risk.

Our study contributes to two strands of the literature. First, there is substantial research on the determinants of systemic risk. These studies show it is driven by bank size (e.g., Adrian and Brunnermeier 2016), ownership structure (e.g., Acharya and Kulkarni 2012), and regulation (e.g., Anginer et al. 2014, Hoque et al. 2015). Closely related to our paper, other studies have examined systemic risk around the global financial crisis (e.g., Adrian and Brunnermeier 2016, Acharya et al. 2017).

Our study is the first to investigate whether and how a health crisis affects systemic risk in a cross-country setting. We find that the COVID-19 shock has significantly increased systemic risk. As such, our paper is related to recent studies on the effects of the pandemic on the banking sector. Berger et al. (2020) investigate whether relationship customers fare better or worse than other borrowers during the COVID-19 crisis, and document harsher loan contract terms for the former. Demirgüç-Kunt et al. (2020) find negative effects of the pandemic on bank stock returns. Beck and Keil (2020) find that banks that are geographically more exposed to the pandemic and to lockdowns saw increased loan-loss provisions and more non-performing loans.

Second, we complement the growing COVID-19 literature, which focuses mainly on the effects of the pandemic on valuation and corporate policies of non-financial firms (e.g., Fahlenbrach et al. 2020, Ramelli and Wagner 2020, Bae et al. 2021, Guedhami et al. 2021). These studies suggest that pre-pandemic corporate characteristics (e.g., profitability, cash, and corporate governance) shape corporate performance and resilience to the pandemic crisis. We focus instead on the resilience of the banking sector to the pandemic shock and the moderating roles of bank characteristics, as well as formal and informal institutions. These findings have important policy implications.

The remainder of the paper proceeds as follows. Section 2 gives an overview of the relevant literature and develops our hypothesis. Section 3 describes our variables and sample, and reports summary statistics. Our empirical results are in Section 4. Section 5 concludes.

2. Literature review and hypothesis development

2.1. COVID-19 and systemic risk

Several studies have attempted to describe the full impact of COVID-19 on the economy and the financial system. Fernandes (2020) notes that COVID-19 reduced global supply and demand. Barua (2020) provides a broad understanding of the likely macroeconomic effects of the pandemic. McKibbin and Fernando (2020) examine the impacts of different scenarios on macroeconomic outcomes and financial markets.

As historical evidence suggests, pandemics generally lead to economic recessions, which are likely to have significant repercussions on the stability of the banking sector. Barro et al. (2020) point out that the influenza pandemic of 1918–1920 caused a 6% decline in GDP. This is because consumption and investment are the main drivers of an economy, and pandemics affect both. Eichenbaum et al. (2020) model of the interaction between economic activity and epidemics implies that people's decisions to decrease consumption and work can reduce the severity of an epidemic, but with obviously devastating economic consequences. Chen et al. (2020) examine the impact of COVID-19 on consumption in China and come to similar conclusions.

In addition, investment is affected during a pandemic. Investment behavior, especially venture capital, tends to become

more cautious (Howell et al. 2020, Ozili and Arun 2020). The COVID-19 pandemic has also greatly damaged the financial system. Ding et al. (2021) and Ramelli and Wagner (2020) examine financial market reactions to COVID-19. They illustrate how the anticipated real effects from the health crisis are amplified through financial channels. Relatedly, Guedhami et al. (2021) find that multinational corporations suffer significantly higher stock price declines compared to domestic firms during pandemic crisis period. They also show that the strength of a country's financial system mitigates these adverse performance effects, while real factors (e.g., firm's supply chain, research and development) exacerbate the negative crisis returns. Cheema-Fox et al. (2020) and Fahlenbrach et al. (2020) find that firms differ significantly in how they are affected by the pandemic.

Several studies also show the importance of the government's response to the pandemic. Some policies, such as social distancing, were established to control the pandemic (e.g., Ozili and Arun 2020). Ding et al. (2020b) find that social distancing increases in response to higher case numbers and official orders in counties where residents contribute less to community activities or commit more to social goals. Hafiz et al. (2020) discuss various other policy responses to COVID-19 for managing systemic economic and financial risk, and outline the inherent conflicts and trade-offs among them.

After the 2008 financial crisis, a large body of literature analyzed the causes and consequences of bank systemic risk. Adrian and Brunnermeier (2016) propose a measurement of systemic risk for each bank, ΔCoVaR , that accounts for changes in the market value of assets. It represents "the change in the value at risk of the financial system conditional on an institution being under distress relative to its median state" (p. 1705). Several researchers have used this measure to distinguish between standalone and systemic risk (Laeven et al. 2016, Zedda and Cannas 2020).²

It is not clear yet how the pandemic has affected banking system stability. On the one hand, governments around the world implemented significant containment measures to mitigate the spread of the virus, causing a decline in economic activity and severe loss of revenue and income for businesses and households. This in turn impaired creditworthiness and ability to repay loans. It also lowered demand for banking services (e.g., Beck and Keil 2020, Ozili and Arun 2020, Barua 2020, Bartik et al. 2020).

The effects on businesses and households eventually spread to banks, negatively affecting their revenues, profits, solvency, and capital (Beck and Keil, 2020). Therefore, we expect the COVID-19 shock to increase the fragility of the banking system. However, as we noted earlier, banks may be more resilient to the current pandemic shock because of the regulatory reforms implemented following the global financial crisis (Carletti et al., 2020). In addition, businesses, households, and banks may have benefited from government support, reducing the potential negative effects.

2.2. Formal regulations and informal institutions

Prior studies delve into whether and how bank regulations mitigate systemic risk. Hoque et al. (2015) find that bank regulations can explain bank risk during the credit crisis and the sovereign debt crisis. In many countries, deposit insurance, which is part of the financial system safety net, also plays a role. Anginer et al. (2012) study the "moral hazard" and the "stabiliza-

tion" effects of deposit insurance and find that the former dominates during good times, while the latter dominates during turbulent times. However, Hoque et al. (2015) point out that deposit insurance performed poorly overall during the sovereign debt crisis.

Several other studies also explore the competition-fragility and competition-stability views of bank risk-taking (e.g., Beck et al. 2013, Anginer et al. 2014, Silva-Buston 2019). Furthermore, previous studies show that bank expansion overseas helps diversify risk, and that foreign banks contribute less to systemic risk than domestic banks (e.g., Faia et al. 2019). Foreign banks are also more likely to diversify their risks in the face of COVID-19 shocks due to the differing epidemic conditions and policies in different countries and regions. And government-owned banks have the advantage of being able to withstand COVID-19 shocks due to their implicit guarantees (e.g., Acharya and Kulkarni 2012, Iannotta et al. 2013, Boubakri et al. 2020).

Building on these studies, we examine how formal regulation measures affect the sensitivity of systemic risks to a pandemic. In particular, we investigate whether regulators may use traditional tools to mitigate the negative effects of the COVID-19 pandemic.

The influence of national culture and societal trust on bank risk has been widely studied (e.g., Kanagaretnam et al. 2014, Boubakri et al. 2017, Kanagaretnam et al. 2019, Mourouzdou-Damtsa et al. 2019, Berger et al. 2021). Hofstede's main national culture dimensions are commonly used to depict cultural attributes. Individualism, which rewards individual achievements and successes, and masculinity, which stresses competitiveness, achievements, and material success, are positively correlated with bank risk-taking or bank failure (e.g., Kanagaretnam et al. 2014, Boubakri et al. 2017, Kanagaretnam et al. 2019, Berger et al. 2021). Uncertainty avoidance, which pertains to a society's tolerance for uncertain, unknown, or unstructured situations, is negatively associated with bank risk-taking (e.g., Kanagaretnam et al. 2014, Mourouzdou-Damtsa et al. 2019). Moreover, bank managers in high-trust countries are more likely to exhibit pro-social behavior, thus reducing the likelihood of opportunistic risk-taking (e.g., Kanagaretnam et al. 2019).

However, existing research does not address how informal rules, such as culture and trust, influence the response of systemic risk during a pandemic. We address it by testing different dimensions to answer whether these informal rules can mitigate the adverse effects of the COVID-19 pandemic.

3. Variables and sample

3.1. Systemic risk

Following Adrian and Brunnermeier (2016), we construct the ΔCoVaR measure to assess systemic risk for each bank. ΔCoVaR represents the tail risk spillover of a single bank to the system, and it is measured by means of a bivariate DCC-GARCH model. As per Adrian and Brunnermeier (2009), we define the growth rate of the market value of assets for bank i from country j as $X_{i,j,t}$, as follows:

$$X_{i,j,t} = \frac{ME_{i,j,t} \cdot LEV_{i,j,t} - ME_{i,j,t-1} \cdot LEV_{i,j,t-1}}{ME_{i,j,t-1} \cdot LEV_{i,j,t-1}} = \frac{A_{i,j,t} - A_{i,j,t-1}}{A_{i,j,t-1}}, \quad (1)$$

where $LEV_{i,j,t} = BA_{i,j,t}/BE_{i,j,t}$ is the book value of total assets to the book value of equity ratio, and $ME_{i,j,t}$ is the market value of equity. $A_{i,j,t} = BA_{i,j,t} \times (ME_{i,j,t}/BE_{i,j,t})$ is the market-value total assets transformed by the market-to-book equity ratio, and $X_{i,j,t}$ includes claims not captured by the accounting value of assets (e.g., off-balance sheet items, exposures from derivative contracts). We also define the growth rate of the market value of assets for country j

² Acharya et al. (2012) and Acharya et al. (2017) explore the expected capital shortfall of banks during crises, which captures the characteristics of systemic risk. A large body of literature also measures systemic risk from various other perspectives (e.g., Allen et al. 2012, Black et al. 2016, Billio, Getmansky et al. 2012, Brownlees and Engle 2017, Kritzman et al. 2011, Van de Leur et al. 2017).

as $X_{j,t}$, as follows:

$$X_{j,t} = \sum_{i=1}^N X_{i,j,t} \cdot \left(A_{i,j,t-1} / \sum_{i=1}^N A_{i,j,t-1} \right). \quad (2)$$

Next, we assume that $X_{i,j,t}$ and $X_{j,t}$ follow a bivariate normal distribution:

$$(X_{i,j,t}, X_{j,t}) \sim N \left(0, \begin{pmatrix} (\sigma_{i,j,t})^2 & \rho_{i,j,t} \sigma_{i,j,t} \sigma_{j,t} \\ \rho_{i,j,t} \sigma_{i,j,t} \sigma_{j,t} & (\sigma_{j,t})^2 \end{pmatrix} \right), \quad (3)$$

where $\sigma_{i,j,t}$ is the standard deviation of $X_{i,j,t}$, $\sigma_{j,t}$ is the standard deviation of $X_{j,t}$, and $\rho_{i,j,t}$ is the dynamic correlation coefficient between $X_{i,j,t}$ and $X_{j,t}$. The above estimators can be estimated by DCC-GARCH (1,1). Following Adrian and Brunnermeier (2016), we derive our measure of systemic risk from the following equations:

$$VaR_{i,j,t}(q) = -\Phi^{-1}(q) \sigma_{i,j,t} \times 100, \quad (4)$$

$$\Delta CoVaR_{i,j,t}(q) = -\Phi^{-1}(q) \rho_{i,j,t} \sigma_{j,t} \times 100. \quad (5)$$

We assume that $q = 0.05$, so $\Phi^{-1}(0.05) = -1.96$. In addition, we multiply the right-hand side of both equations by -1 , so that higher values of $\Delta CoVaR$ imply higher systemic risk. To avoid using overly small numerical values, we multiply the right-hand side by 100.

3.2. COVID-19 cases

Dong et al. (2020) develop a dataset hosted by the CSSE at Johns Hopkins University to track reported cases of COVID-19 in real time. This dataset provides the location and number of confirmed COVID-19 cases, deaths, and recoveries for all affected countries. We obtain daily growth rates of COVID-19 cases from this dataset, and match the data by ISO country code and date. Note that confirmed COVID-19 cases often show an initial spike when they are first reported. Therefore, we exclude the first-day value of the growth rate of confirmed cases in each country when constructing the measures.

Following Ding et al. (2020a), and considering virus incubation and detection conditions that mean confirmed cases in a single day may fluctuate sharply, we use $COVID19_GR$, the 14-day moving average rate of confirmed cases as our main independent variable:

$$COVID19_GR_{j,t} = \sum_{t=13}^t \left[\ln(1 + Confirmed\ Cases_{j,t}) - \ln(1 + Confirmed\ Cases_{j,t-1}) \right] / 14, \quad (6)$$

where $Confirmed\ Cases_{j,t}$ represents the number of confirmed COVID-19 cases in country j on day t .

3.3. Sample selection

Stock returns for U.S. banks come from CRSP. Stock returns for non-U.S. banks and accounting data come from Compustat-Capital IQ. We exclude countries with no more than three banks, and banks with negative stock prices or missing returns. Our final sample consists of 1,584 banks in 64 countries over the February 6–December 10, 2020 period.

3.4. Descriptive statistics

Table 1 reports the variable definitions. The dependent variable is $\Delta CoVaR$, and the main independent variable is $COVID19_GR$, which is the log growth rate of confirmed COVID-19 cases. Table 2

Fig. 1. Bank Systemic Risk and COVID-19 Shocks. $\Delta CoVaR$ is the proxy for systemic risk; $COVID19_GR$ is the 14-day moving average log growth rate of confirmed COVID-19 cases. We obtain country-date-level $\Delta CoVaR$ by taking the market value-weighted averages, and country-level $\Delta CoVaR$ by taking the average over the sample period. $COVID19_GR$ is measured at the country level by taking the average. The line shows an upward-sloping trend.

shows the number of daily observations and averages of the main regression variables by country. The United States has the highest number of bank observations at 79,134, followed by India, Japan, and China. During the sample period, the average systemic risk of banks in Argentina is the highest at 3.786, followed by Spain, South Africa, and Sweden. The countries with the fastest average increase in COVID-19 cases are India and the United States, with an average increase of 0.049, followed by Ukraine, Argentina, and Russia.

Table 3 reports summary statistics for the variables used in the main analysis. $\Delta CoVaR$ has a mean of 1.371 and a standard deviation of 1.173. $COVID19_GR$ has a mean of 0.039 and a standard deviation of 0.063. Banks have a mean *Size* of -2.810 , which is the relative log market equity, indicating that most banks are smaller than average. The average bank has *Leverage* of 18.532, indicating that the sum of the market value of equity and book liabilities is about 18 times its market value of equity. In addition, *Return (Volatility)* has a mean of 0 (2.556) and a standard deviation of 0.03 (1.773).

Table 4 reports the correlation coefficients between the variables. The correlation coefficient of $\Delta CoVaR$ and $COVID19_GR$ is 0.352, which is significant at the 1% level. This indicates that the growth rate of confirmed cases is positively correlated with systemic risk. Systemic risk is positively correlated with *Size*, *Leverage*, and *Volatility*, while negatively correlated with *Return*.

Fig. 1 shows the simple relation between $\Delta CoVaR$ and $COVID19_GR$. We obtain country-date-level $\Delta CoVaR$ by taking the market value-weighted averages, and country-level $\Delta CoVaR$ by taking the average. $COVID19_GR$ is the country-level average over the sample period. The fitted line shows an upward-sloping trend, suggesting a positive relation between bank systemic risk and COVID-19 shocks. Fig. 2 shows bank systemic risk ($\Delta CoVaR$), bank size (*Size*), and the growth rate of confirmed cases ($COVID19_GR$) over time. We obtain date-level $\Delta CoVaR$, *Size*, and $COVID19_GR$ by taking the average. Note that, during the COVID-19 shock, the level of systemic risk has increased significantly, and the level of market capitalization has decreased sharply. The growth rate in COVID-19 cases moves in sync with changes in systemic risk.

Table 1

Variable definitions.

Variable Name	Definition	Source
Dependent Variables		
$\Delta CoVaR$	Change in conditional value at risk, following Adrian and Brunnermeier (2009, 2016) .	Compustat, CRSP
MES	Marginal expected shortfall of a bank, following Acharya et al. (2017) .	
SRISK	Capital shortfall of a bank on a severe market decline, following Brownlees and Engle (2017) .	
PC	First principal component of $\Delta CoVaR$, MES, and SRISK.	
VaR	Tail risk of a bank at the 5% confidence level.	
$\Delta CoVaR_ctry1$	Equal-weighted $\Delta CoVaR$ in a country.	
$\Delta CoVaR_ctry2$	Value-weighted $\Delta CoVaR$ in a country.	
Independent Variables		
COVID19_GR	Fourteen-day moving average log growth rate of confirmed COVID-19 cases.	CSSE (Johns Hopkins University Center for Systems Science and Engineering)
COVID19_GR_1D	Log growth rate of confirmed COVID-19 cases.	
COVID19_Death_1D	Log growth rate of COVID-19 death cases.	
COVID19_Death_Size	14-day moving average log growth rate of COVID-19 death cases.	Compustat, CRSP
SSize	Log of total market equity for each bank minus log of the cross-sectional average of market equity.	
Leverage	Equal-weighted market capitalization (\$ billions)	
Return	Sum of the market value of equity and book liabilities divided by the market value of equity.	
Volatility	Bank stock return.	
Network	Standard deviation of bank retruns over the previous 30 days.	
Size_ctry	Eigenvector centrality of each bank in a country, following Billio et al. (2012) . We use a 44-day rolling window to calculate the dynamic eigenvector centrality as our measure, following Brunetti et al. (2019) .	
Leverage_ctry	Average of Size in a country.	
Return_ctry	Average of Leverage in a country.	
Volatility_ctry	Average of Return in a country.	Oxford COVID-19 Government Response Tracker (OxCGRT)
Government Response	Average of Volatility in a country.	
log Z	Fourteen-day moving average growth rate of government response index.	
LtA	Log of $Z = \text{mean}(\text{ROA} + \text{Capital Ratio})/\text{volatility}(\text{ROA})$, where Capital Ratio is the capital-to-asset ratio and ROA is return on assets. Z is calculated using data from for the previous four quarters.	Wind
Capital Ratio	Loan-to-asset ratio.	
ROA	Capital-to-asset ratio.	
NPL	Return on assets ratio.	BankScope
Act_restrict	Non-performing loan ratio.	
Cap_reg	Overall restrictions on banking activities, including engaging in underwriting, brokering, dealing in securities, mutual funds, insurance, and real estate.	
Sup_power	Capital regulatory index, which combines the following two problems: 1) whether the capital requirement reflects certain risk elements and deducts certain market value losses from capital before minimum capital adequacy is determined; and 2) whether certain funds may be used to initially capitalize a bank and whether they are official.	BRSS (Bank Regulation and Supervision Survey)
No_dep	Whether the supervisory authorities have the authority to take specific actions to prevent and correct problems.	
Bank_con	No explicit deposit insurance scheme, and depositors were not fully compensated the last time a bank failed.	
For_bank	Bank concentration (assets). The degree of concentration of assets in the five largest banks in a country.	
Gov_bank	Extent to which the banking system's assets are foreign-owned (%).	
PDI	Extent to which the banking system's assets are government-owned (%).	
COL	Power distance (PDI). Hofstede's culture index for the extent to which the less powerful members of organizations and institutions expect and accept that power is distributed unequally.	Hofstede's cultural dimensions
MAS	Opposite of individualism (IDV). The degree to which a society stresses the role of the group versus that of the individual.	
UAI	Masculinity (MAS). Hofstede's culture index for the extent to which "male assertiveness" is promoted as a dominant value in a society.	
LTO	Uncertainty avoidance (UAI). Hofstede's culture index for a society's tolerance for uncertain, unknown, or unstructured situations.	
Trust	Long-term versus short-term (LTO). Hofstede's culture index for the extent to which long-term interests are valued more than short-term ones.	
GDP_growth	Country average of responses to "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?" The response is 1 if a participant reports most people can be trusted, and 0 otherwise.	
	GDP growth rate (annual %).	WVS (World Values Survey)
		World Development Indicators

Table 2
Sample and summary of key variables.

Country/Region	Obs.	ΔCoVaR	<i>COVID19_GR</i>	Size	Leverage	Return	Volatility
Argentina	1152	3.786	0.045	-1.701	9.633	0.003	3.843
Australia	5232	1.379	0.026	-2.508	9.321	0.000	3.208
Austria	985	1.717	0.036	-2.258	40.963	0.000	1.537
Bahrain	2132	0.498	0.028	-1.874	21.837	-0.001	1.367
Bangladesh	10032	0.813	0.039	-3.791	20.557	0.001	1.490
Botswana	692	0.648	0.031	-3.149	12.001	-0.001	0.527
Bulgaria	940	0.472	0.033	-4.161	20.161	0.000	1.745
Canada	7219	1.388	0.039	-3.043	8.310	0.000	2.849
Chile	1782	1.746	0.041	-0.720	11.946	0.000	1.588
China	11271	1.266	0.022	-0.155	31.488	0.000	1.587
Colombia	1323	1.435	0.043	-1.083	15.417	0.000	1.081
Côte d'Ivoire	930	0.705	0.031	-3.950	13.058	0.000	1.824
Croatia	1588	0.753	0.037	-4.578	39.494	0.000	1.845
Denmark	3869	1.022	0.029	-3.158	16.575	0.001	1.757
Egypt	3029	0.876	0.038	-2.708	20.447	0.000	1.468
Finland	864	1.836	0.031	-1.625	20.311	-0.001	2.723
France	3285	1.876	0.042	-1.932	87.161	-0.001	2.420
Germany	3052	1.093	0.039	-2.384	29.041	0.000	2.930
Ghana	1098	0.967	0.029	-3.471	11.491	-0.001	1.203
Greece	980	2.036	0.033	-1.719	59.064	0.001	4.319
India	37396	0.946	0.049	-5.809	10.591	0.000	2.080
Indonesia	10504	1.167	0.040	-2.645	7.633	0.000	2.670
Israel	2121	2.295	0.040	-1.305	27.236	0.000	2.082
Italy	4443	1.935	0.040	-1.428	32.428	0.000	2.721
Japan	23079	1.328	0.032	-1.833	50.252	0.000	2.312
Jordan	4215	0.288	0.041	-3.405	14.445	0.000	1.014
Kazakhstan	1104	1.043	0.033	-2.944	18.047	0.000	0.964
Kenya	1840	0.630	0.036	-2.819	18.293	0.000	1.900
Korea	3757	2.260	0.028	-1.885	31.844	0.001	2.357
Kuwait	3510	0.913	0.030	-1.541	7.061	0.000	1.991
Lebanon	1002	0.911	0.036	-2.873	50.534	-0.001	1.274
Malaysia	3270	1.327	0.029	-1.124	11.615	0.000	2.114
Malta	752	0.938	0.024	-2.763	15.437	0.000	1.866
Mexico	1938	2.017	0.044	-1.668	8.916	0.000	2.827
Morocco	1737	0.820	0.043	-1.612	8.564	0.000	1.505
New Zealand	776	0.999	0.023	-4.509	4.158	0.001	3.359
Nigeria	2910	1.306	0.038	-3.608	21.747	0.002	2.610
Norway	5292	1.983	0.025	-3.058	25.241	0.001	2.195
Oman	2796	0.542	0.035	-2.528	9.006	-0.001	1.129
Pakistan	7880	0.758	0.041	-5.515	16.350	0.001	3.041
Palestine	1440	0.378	0.031	-3.575	11.773	0.000	0.817
Peru	1134	0.888	0.039	-0.632	5.001	0.000	0.985
Philippines	4515	0.861	0.039	-2.785	9.608	0.000	2.367
Poland	4858	1.301	0.040	-4.268	14.485	0.001	3.956
Qatar	2300	0.861	0.032	-0.495	6.478	0.001	1.646
Russia	3210	1.766	0.045	-1.883	13.113	0.000	2.012
Saudi Arabia	2517	1.359	0.038	0.847	6.053	0.001	1.662
Singapore	1540	1.059	0.028	-2.223	9.265	0.000	2.181
South Africa	1782	2.701	0.043	-1.660	10.428	0.001	3.838
Spain	1491	3.327	0.043	0.382	53.096	-0.001	3.647
Sri Lanka	8284	0.898	0.031	-5.038	15.035	0.000	2.509
Sweden	852	2.538	0.038	0.467	17.081	0.000	2.674
Switzerland	3349	1.087	0.033	-1.393	22.595	0.000	1.427
Thailand	6630	1.453	0.019	-2.412	7.436	0.000	2.823
Trinidad and Tobago	732	0.562	0.022	-1.090	3.954	0.000	0.718
Tunisia	3438	0.524	0.036	-3.982	14.637	0.000	1.358
Turkey	3977	2.104	0.032	-2.249	13.589	0.004	3.184
Ukraine	1344	0.813	0.047	-3.810	12.832	0.000	0.218
United Arab Emirates	4750	0.669	0.034	-0.943	10.109	0.000	1.389
United Kingdom	5136	1.545	0.040	-1.923	23.767	-0.001	3.198
United States	79134	1.847	0.049	-2.322	13.357	0.000	3.574
Venezuela	1098	2.475	0.029	-4.390	25.209	0.011	4.492
Vietnam	2200	1.551	0.019	-1.224	11.796	0.001	2.315
Zimbabwe	890	2.238	0.030	-6.289	12.277	0.010	3.883

This table displays the number of observations and mean values of ΔCoVaR (%), growth rate of confirmed COVID-19 cases (*COVID19_GR*), and control variables for each country. The sample consists of 1,584 banks in 64 countries over the February 6–December 10, 2020 period. The data come from Compustat, CRSP, and CSSE. The sample banks are identified by SIC codes 60, 61, and 6712. ΔCoVaR is the proxy for systemic risk; *COVID19_GR* is the 14-day moving average log growth rate of confirmed COVID-19 cases; *Size* is the log of demeaned market capitalization; *Leverage* is the sum of the market value of equity and book liabilities divided by the market value of equity; *Return* is Bank stock return; *Volatility* is the standard deviation of bank retruns over the previous 30 days. All control variables are lagged.

Table 3
Summary statistics.

Variables	N	Mean	SD	P25	P50	P75
ΔCoVaR	328,378	1.371	1.173	0.454	1.109	1.897
COVID19_GR	328,378	0.039	0.063	0.006	0.014	0.038
<i>Size</i>	328,378	-2.810	2.720	-4.163	-2.632	-0.961
<i>Leverage</i>	328,378	18.532	23.254	5.016	10.662	19.487
<i>Return</i>	328,378	0.000	0.030	-0.009	0.000	0.008
<i>Volatility</i>	328,378	2.556	1.773	1.312	2.246	3.547

This table displays summary statistics for the variables used in the baseline regression. The sample consists of 1,584 banks in 64 countries over the February 6–December 10, 2020 period. ΔCoVaR is the proxy for systemic risk; COVID19_GR is the 14-day moving average log growth rate of confirmed COVID-19 cases; *Size* is the log of demeaned market capitalization; *Leverage* is the sum of the market value of equity and book liabilities divided by the market value of equity; *Return* is bank stock return; *Volatility* is the standard deviation of bank returns over the previous 30 days.

Fig. 2. Bank Systemic Risk, Bank Size, and COVID-19 Shocks Over Time. ΔCoVaR is the proxy for systemic risk; Size is the market capitalization (\$ billions); and COVID19_GR is the 14-day moving average log growth rate of confirmed COVID-19 cases. We obtain date-level ΔCoVaR , Size , and COVID19_GR by taking the averages.

4. Empirical results

4.1. COVID-19 pandemic and systemic risk

We empirically analyze the impact of COVID-19 on international systemic risk. The baseline model is shown in Eq. (7):

$$\Delta\text{CoVaR}_{i,j,t} = \beta \cdot \text{COVID19_GR}_{j,t-1} + \sum_{k=1}^K \gamma_k z_{i,j,t-1}^k + \delta_i + \tau_t + \varepsilon_{i,j,t}, \quad (7)$$

Table 4
Correlations.

Variables	ΔCoVaR	COVID19_GR	<i>Size</i>	<i>Leverage</i>	<i>Return</i>	<i>Volatility</i>
ΔCoVaR	1.000					
COVID19_GR	0.352***	1.000				
<i>Size</i>	0.493***	-0.045***	1.000			
<i>Leverage</i>	0.091***	-0.023***	0.063***	1.000		
<i>Return</i>	-0.025***	-0.074***	0.003*	-0.012***	1.000	
<i>Volatility</i>	0.458***	0.253***	0.055***	-0.015***	0.030***	1.000

This table displays the pairwise correlation coefficients for the variables used in the baseline regression. The sample consists of 1,584 banks in 64 countries over the February 6–December 10, 2020 period. ΔCoVaR is the proxy for systemic risk; COVID19_GR is the 14-day moving average log growth rate of confirmed COVID-19 cases; *Size* is the log of demeaned market capitalization; *Leverage* is the sum of the market value of equity and book liabilities divided by the market value of equity; *Return* is bank stock return; *Volatility* is the standard deviation of bank returns over the previous 30 days. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Main evidence.

	(1)	(2)	(3)	(4)
	Dependent Variable: ΔCoVaR			
COVID19_GR	2.320** (2.27)	2.125*** (2.80)	2.235*** (2.69)	3.193*** (2.78)
<i>Size</i>		-0.068* (-1.74)	0.248*** (5.98)	0.276*** (9.46)
<i>Leverage</i>		0.007*** (2.77)	0.005*** (3.55)	0.005*** (3.21)
<i>Return</i>		-0.479*** (-4.32)	-0.610*** (-3.40)	-0.862*** (-4.68)
<i>Volatility</i>		0.196*** (7.63)	0.124** (2.28)	0.209*** (6.44)
<i>LtA</i>				0.356 (1.62)
<i>Capital Ratio</i>				-0.003 (-1.34)
<i>ROA</i>				0.031 (1.20)
<i>NPL</i>				0.001 (0.10)
<i>NII</i>				10.921 (0.22)
<i>NDF</i>				0.024 (0.11)
Bank FE	Yes	Yes	No	No
Country FE	No	No	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Country Cluster	Yes	Yes	Yes	Yes
Observations	328,378	328,378	328,378	191,202
Adj. R ²	0.828	0.859	0.664	0.780

This table reports results on the effect of the pandemic on bank systemic risk. The sample consists of 1,584 banks in 64 countries over the February 6–December 10, 2020 period. ΔCoVaR is the proxy for systemic risk; COVID19_GR is the 14-day moving average log growth rate of confirmed COVID-19 cases; *Size* is the log of demeaned market capitalization; *Leverage* is the sum of the market value of equity and book liabilities divided by the market value of equity; *Return* is bank stock return; *Volatility* is the standard deviation of bank returns over the previous 30 days; *LtA* is loan-to-asset ratios; *Capital Ratio* is the capital ratio; *ROA* is return on assets; *NPL* is the non-performing loan ratio; *NII* is the ratio of non-interest income to total assets; and *NDF* is the share of non-deposit short-term funding in total deposits and short-term funding. All control variables are lagged. Columns (1)–(2) include bank and day fixed effects. Columns (3)–(4) include country and day fixed effects. Columns (2)–(3) include bank-level daily control variables. Column (4) adds bank-level control variables for 2019 from BankScope. Standard errors are adjusted for clustering at the country level. *t*-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

where $\Delta\text{CoVaR}_{i,j,t}$ represents the daily systemic risk of bank *i* in country *j* at day *t*; $\text{COVID19_GR}_{j,t-1}$ represents the average log growth rate of confirmed COVID-19 cases from days *t* – 14 to *t* – 1 in country *j*; and $z_{i,j,t-1}^k$ stands for the *k*th control variables, including *Size*, *Leverage*, *Return*, and *Volatility*. Because they are “too

big to fail," large bank failures cause greater economic losses than small bank failures, and thus large banks may exhibit higher systemic risk (Adrian and Brunnermeier, 2016). Higher bank leverage may also lead to greater systemic risk because contagious runs occur when creditors liquidate (Acharya and Thakor, 2016). In contrast, banks with higher returns may exhibit less systemic risk. We control for volatility because it is an important determinant of systemic risk (Brownlees and Engle, 2017). δ_i denote bank fixed effects, and τ_t denote daily fixed effects. Standard errors are clustered at the country level.

Table 5 shows the main results using ΔCoVaR as a proxy for systemic risk. In column (1), we include our key independent variable COVID19_GR , which is the lagged 14-day moving average log growth rate of confirmed COVID-19 cases, with bank and day fixed effects. Standard errors are clustered at the country level. The results show that the regression coefficient of the growth rate of confirmed cases is positive and significant at the 5% level, suggesting that the pandemic has deleterious effects on systemic risk. In column (2), we add control variables, and the coefficient on COVID19_GR continues to be positive and significant but at the 1% level. These results are also economically significant. A 1-standard deviation increase in COVID19_GR may cause a 9.76-percentage point increase in ΔCoVaR . In column (3), we replace bank fixed effects with country fixed effects. In column (4), we augment the specification of column (3) with bank annual control variables. The results in both columns continue to show adverse effects of the pandemic on systemic risk. For the controls, consistent with expectations, we find that systemic risk is positively related to size, leverage, and volatility, and negatively related to stock return.

4.2. Channels

We investigate two potential channels through which COVID-19 affects systemic risk. The first is the stringency of the government response, which includes workplace closings, travel restrictions, bans on public gatherings, stay-at-home orders, etc. More specifically, the increase in confirmed cases led governments around the world to adopt restrictive measures that caused a slowdown in economic activities and a decline in the creditworthiness of borrowing firms. The second channel is bank default risk, which is due to a combination of rising credit risk and declining bank profitability. Table 6 shows the results.

To test the first transmission channel, we use a two-step regression approach (e.g., Griffin et al. 2021). In the first step, we regress *Government Response*, the 14-day moving average growth rate of the government response index, on COVID19_GR and controls. In the second step, we test the impact of the predicted value of *Government Response* on systemic risk. The regression equation for testing the first channel is as follows:

$$\Delta\text{CoVaR}_{i,j,t} = \beta \cdot \widehat{\text{Government Response}}_{j,t-1} + \sum_{k=1}^K \gamma_k z_{i,j,t-1}^k + \delta_i + \tau_t + \varepsilon_{i,j,t}, \quad (8)$$

where $\Delta\text{CoVaR}_{i,j,t}$ represents the daily systemic risk of bank i in country j and $\widehat{\text{Government Response}}_{j,t-1}$ is the predicted value from the first-step regression.

The government response index, obtained from Hale (2020), includes all government responses to and policies regarding the pandemic (school and workplace closings, travel restrictions, bans on public gatherings, stay-at-home orders, emergency investments in healthcare facilities, income support, contact tracing, and other interventions to contain the spread of the virus, augment health sys-

tems, and manage the economic consequences).⁴ It ranges from 0 to 100. A higher index value indicates more policies and stronger responses. Columns (1) and (2) provide the first- and second-step regression results, respectively. Column (1) shows that the regression coefficient of COVID19_GR is positive and significant, suggesting that the growth in the number of cases led to stricter government responses to the pandemic. In column (2), we find that the effect of the predicted value of *Government Response* on systemic risk is positive and statistically significant. These results suggest that the intensity of the pandemic affected the government response, which in turn increased systemic risk.⁵

To test the bank default risk channel, we adopt the same two-step regression approach. In the first step, we examine the impact of COVID19_GR on bank default risk, which we measure using the distance to default of the bank ($\log Z$): the lower the value, the higher the bank default risk. In the second step, we test the impact of the predicted value of $\log Z$ on systemic risk. The regression equation for testing the second channel is as follows:

$$\Delta\text{CoVaR}_{i,t} = \beta \cdot \widehat{\log Z}_{i,t-1} + \sum_{k=1}^K \gamma_k z_{i,t-1}^k + \delta_i + \tau_t + \varepsilon_{i,t}, \quad (9)$$

where $\Delta\text{CoVaR}_{i,t}$ represents the daily systemic risk of bank i in China and $\widehat{\log Z}_{i,t-1}$ is the predicted value from the first-step regression.

Because banking data for 2020 in BankScope is incomplete, we test this channel using China's banking data from the Wind Economic Database. Columns (3) and (4) give the first- and second-step regression results, respectively. Column (3) shows that the regression coefficient of COVID19_GR is negative and significant, indicating that the growth in the number of cases increases bank default risk. In column (4), we find that the coefficient of the predicted value of $\log Z$ on systemic risk is negative and statistically significant, suggesting that bank default risk increases systemic risk. Collectively, these results suggest that an increase in confirmed cases has a positive impact on bank default risk, which in turn increases systemic risk.

4.3. Bank characteristics and systemic risk during the pandemic

We extend our main analysis by examining how bank characteristics affect the sensitivity of systemic risk to a pandemic. Our investigation builds on prior studies finding that bank size, leverage, volatility, loan-to-asset ratio, capital ratio, and network centrality have important effects on systemic risk. The "too big to fail" doctrine suggests that large bank failures cause greater economic losses than small bank failures, and therefore large banks involve higher systemic risk (Adrian and Brunnermeier, 2016). Higher bank leverage may lead to greater systemic risk because runs often occur when creditors liquidate (Acharya and Thakor, 2016). As noted earlier, volatility is also important to measuring systemic risk. Systemic risk highlights the correlation between idiosyncratic risk and system volatility (Brownlees and Engle, 2017). Several studies also find that the loan-to-asset ratio, capital ratio, and network centrality affect systemic risk (e.g., Mayordomo et al. 2014, Laeven et al. 2016, Billio et al. 2012).

⁴ In Online Appendix Table A1, we distinguish the differential effects of containment policies and economic support policies. We find that the government response channel is driven mainly by containment and health policies, with no significant effect from economic support policies.

⁵ In Online Appendix Table A2, we also test the existence of a sovereign risk channel using the two-step approach in Table 5. Our proxy for sovereign risk is sovereign CDS spread from Bloomberg. The results show that the increase in confirmed cases has a positive impact on the growth rate of daily sovereign CDS spreads, which in turn aggravates systemic risk. This risk channel is significant at a 5% level. Therefore, a sovereign risk channel is at work.

Table 6
Risk transmission channels.

	(1) Government Response	(2) ΔCoVaR	(3) Log Z	(4) ΔCoVaR
COVID19_GR	0.180*** (4.03)		-0.185*** (-18.94)	
Government Response		11.811*** (2.92)		
log Z				-9.078*** (-12.43)
Size	-0.002 (-1.03)	-0.047 (-1.00)	0.053*** (6.67)	-0.465*** (-4.04)
Leverage	-0.000 (-0.31)	0.008*** (2.77)	0.003*** (14.24)	0.007* (1.76)
Return	-0.003 (-0.66)	-0.451*** (-3.67)	0.061** (2.27)	-0.226 (-0.60)
Volatility	0.000 (0.33)	0.195*** (6.98)	0.002** (2.16)	0.452*** (45.62)
Bank FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	No	No
Country Cluster	Yes	Yes	No	No
Observations	327,623	327,623	3,173	3,173
Adj. R ²	0.677	0.084	0.958	0.425

This table reports results on the channels through which COVID-19 affects systemic risk. Columns (1) and (2) test the stringency of the government response channel, while columns (3) and (4) test the default risk channel. The sample in columns (1) and (2) consists of 1,584 banks in 64 countries over the February 6–December 10, 2020 period. The sample in columns (3) and (4) consists of 19 Chinese banks over the same period. We use a two-step regression approach. Columns (1) and (3) show the first-step regression results; columns (2) and (4) show the corresponding second-step regression results. ΔCoVaR is the proxy for systemic risk; *Government Response* is the 14-day moving average growth rate of the government response index; *log Z* is the log of $Z = \text{mean}(\text{ROA} + \text{Capital Ratio})/\text{volatility}(\text{ROA})$, where *Capital Ratio* is the capital-to-asset ratio and ROA is return on assets; *COVID19_GR* is the 14-day moving average log growth rate of confirmed COVID-19 cases; *Size* is the log of demeaned market capitalization; *Leverage* is the sum of the market value of equity and book liabilities divided by the market value of equity; *Return* is bank stock return; *Volatility* is the standard deviation of bank returns over the previous 30 days. All specifications include bank fixed effects and control variables. All control variables are lagged. Columns (1) and (2) also include day fixed effects, and standard errors are adjusted for clustering at the country level. *t*-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

To test how bank characteristics shape the impact of COVID-19 shocks on systemic risk, we estimate the following regression model:

$$\begin{aligned} \Delta\text{CoVaR}_{i,j,t} = & \alpha + \beta_1 \cdot \text{COVID19_GR}_{j,t-1} \\ & + \beta_2 \cdot \text{COVID19_GR}_{j,t-1} \\ & \times \text{Bank Characteristics}_{i,j,t-1} \\ & + \sum_{k=1}^K \gamma_k z_{i,j,t-1}^k + \delta_i + \tau_t + \varepsilon_{i,j,t}, \end{aligned} \quad (10)$$

where *Bank Characteristics* refer to *Size*, *Leverage*, *Volatility*, *LtA*, *Capital Ratio*, and *Network*. Our focus is on the interaction terms between *COVID19_GR* and bank characteristics.

Table 7 gives the results. We find that the coefficients on the interaction terms of *COVID19_GR* with *Size* and *Volatility* are positive and statistically significant at the 1% level. The interactions of *COVID19_GR* with *Leverage* and *LtA* load positively and significantly at the 10% level. Moreover, column (5) shows that the interaction term with the capital-to-asset ratio (*Capital Ratio*) has a negative and significant coefficient at the 5% level, and column (6) indicates that the interaction term with network centrality (*Network*) has a negative and significant coefficient at the 10% level. These findings suggest that the effect of the pandemic on systemic risk is exacerbated in large, highly leveraged, riskier, high loan-to-assets,⁶

⁶ We further analyze the impact of bank lending categories. We obtain data on mortgage loans, consumer loans, and corporate loans of banks for 2019 from Bank

undercapitalized, and low network centrality banks are associated with higher systemic risk during the COVID-19 crisis.

4.4. Moderating role of formal regulations

To examine how formal regulations affect the sensitivity of systemic risks to the pandemic, we estimate the following regression model:

$$\begin{aligned} \Delta\text{CoVaR}_{i,j,t} = & \beta_1 \cdot \text{COVID19_GR}_{j,t-1} \\ & + \beta_2 \cdot \text{COVID19_GR}_{j,t-1} \\ & \times \text{Formal Regulations}_{j,t-1} \\ & + \sum_{k=1}^K \gamma_k z_{i,j,t-1}^k + \delta_i + \tau_t + \varepsilon_{i,j,t}, \end{aligned} \quad (11)$$

where *Formal Regulations* includes a set of bank regulation variables related to banking activity restrictions (*Act_restrict*), capital regulations (*Cap_reg*), supervisory authority (*Sup_power*), deposit insurance (*No_dep*), bank concentration (*Bank_con*), and foreign- and government-owned bank assets (*For_bank* and *Gov_bank*, respectively). Bank regulation data come from the Bank Regulation and Supervision Survey (BRSS). We use the most recent survey

Focus, and construct the following four variables: “mortgage loans/total assets,” “consumer loans/total assets,” “corporate loans/total assets,” and “other loans/total assets.” The untabulated results suggest that higher proportions of mortgage loans and corporate loans contribute to increasing the effect of COVID-19 growth on systemic risk.

Table 7
Role of bank characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)
COVID19_GR	4.267*** (4.67)	2.059** (2.64)	1.315*** (2.67)	2.771** (2.56)	2.819*** (2.88)	3.080*** (3.45)
COVID19_GR × Size	0.830*** (6.36)					
COVID19_GR × Leverage		0.082* (1.67)				
COVID19_GR × Volatility			0.606*** (3.90)			
COVID19_GR × LtA				2.581* (1.82)		
COVID19_GR × Capital Ratio					-0.186** (-2.05)	
COVID19_GR × Network						-4.884* (-1.96)
Network						0.057 (1.40)
Size	-0.065 (-1.52)	-0.063 (-1.59)	-0.027 (-0.73)	-0.134* (-1.72)	-0.203* (-1.81)	-0.015 (-0.32)
Leverage	0.008*** (3.18)	0.007*** (2.67)	0.008*** (2.71)	0.007** (2.62)	0.006** (2.35)	0.009*** (3.49)
Return	-0.426*** (-3.55)	-0.457*** (-4.10)	-0.503*** (-3.89)	-0.608*** (-3.74)	-0.692*** (-4.33)	-0.432*** (-4.63)
Volatility	0.166*** (6.74)	0.193*** (7.02)	0.156*** (8.62)	0.241*** (7.12)	0.252*** (7.77)	0.192*** (8.49)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Country Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Observations	328,378	328,378	328,378	232,578	198,797	246,208
Adj. R ²	0.871	0.859	0.863	0.865	0.869	0.871

This table shows how banks with different characteristics respond to the COVID-19 pandemic. The sample consists of 1,584 banks in 64 countries over the February 6–December 10, 2020 period. ΔCoVaR is the proxy for systemic risk; *COVID19_GR* is the 14-day moving average log growth rate of confirmed COVID-19 cases; *Size* is the log of demeaned market capitalization; *Leverage* is the sum of the market value of equity and book liabilities divided by the market value of equity; *Return* is bank stock return; *Volatility* is the standard deviation of bank returns over the previous 30 days. *LtA* is loan-to-asset ratio; *Capital Ratio* is capital ratio; *Network* is the eigenvector centrality. *LtA* and *Capital Ratio* are measured as of 2019 and hence are excluded from the bank fixed effects models. Standard errors are adjusted for clustering at the country level. *t*-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

(survey 5), which covers 2017 through 2019. If data are missing, we use information from the previous survey. Our focus is on the interaction terms between *COVID19_GR* and bank regulation variables.

Table 8 presents the results. We do not find evidence that banking activity restrictions (column (1)), capital regulations (column (2)), supervisory authority (column (3)), or bank concentration (column (5)) shape the relation between pandemic and systemic risk. In contrast, in column (4) we find that the *COVID19_GR*×*No_dep* interaction term loads positively and significantly at the 1% level, suggesting that deposit insurance schemes help mitigate the increase in systemic risk caused by the pandemic. We also find that the *COVID19_GR*×*For_bank* (column (6)) and *COVID19_GR*×*Gov_bank* (column (7)) interaction terms exhibit negative and significant coefficients at the 1% and 10% levels, respectively. These findings suggest that higher proportions of foreign- and government-owned banks in the economy contribute to the stability of the banking system in the event of a pandemic.

4.5. Moderating role of informal institutions

To examine the role of informal institutions in influencing the sensitivity of systemic risks to a pandemic, we test the following regression model:

$$\begin{aligned} \Delta\text{CoVaR}_{i,j,t} = & \beta_1 \cdot \text{COVID19_GR}_{j,t-1} \\ & + \beta_2 \cdot \text{COVID19_GR}_{j,t-1} \\ & \times \text{Informal Institutions}_{j,t-1} \end{aligned}$$

$$+ \sum_{k=1}^K \gamma_k z_{i,j,t-1}^k + \delta_i + \tau_t + \varepsilon_{i,j,t}, \quad (12)$$

where *Informal Institutions* includes variables related to national culture and social trust. To capture national culture, we use Hofstede's five cultural dimensions: power distance (*PDI*), collectivism (*COL*), masculinity (*MAS*), uncertainty avoidance (*UAI*), and long-term orientation (*LTO*). Following Pevzner et al. (2015) and Brockman et al. (2020), we measure societal trust based on the following question from Wave 7 of the WVS: Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people? The response is 1 if a participant reports most people can be trusted, and 0 otherwise. We then calculate the mean of the response in each country in Wave 7 as our measure of societal trust. Our focus is on the interaction terms between *COVID19_GR* and these informal institution variables.

Table 9 reports the results. In column (1), we find that the coefficient on *COVID19_GR* × *PDI* is negative and statistically significant at the 1% level, implying that higher power distance helps mitigate the adverse effect of the pandemic on systemic risk. A greater power distance suggests higher subordinate obedience to superiors. Therefore, any mitigation efforts put forth by superiors can be implemented more efficiently. In column (2), we find that the coefficient on *COVID19_GR* × *COL* is negative and significant, suggesting that banking systems in collectivist societies are more resilient to pandemics than those in individualistic societies. This is because, under individualism, people value freedom more than following policies. Under collectivism, people tend to act as a group, which is more conducive to the successful implementation of policies.

Table 8
Systemic risk during the pandemic: the moderating role of the regulatory environment.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: ΔCoVaR							
<i>COVID19_GR</i>	2.336** (2.61)	1.425* (1.81)	2.294** (2.63)	1.951*** (3.14)	2.145*** (2.82)	2.130*** (2.69)	2.032** (2.62)
<i>COVID19_GR</i> $\times$ <i>Act_restrict</i>	0.309 (1.06)						
<i>COVID19_GR</i> $\times$ <i>Cap_reg</i>		-0.134 (-0.55)					
<i>COVID19_GR</i> $\times$ <i>Sup_power</i>			0.171 (0.74)				
<i>COVID19_GR</i> $\times$ <i>No_dep</i>				1.016*** (3.56)			
<i>COVID19_GR</i> $\times$ <i>Bank_con</i>					-0.513 (-1.38)		
<i>COVID19_GR</i> $\times$ <i>For_bank</i>						-0.907*** (-2.94)	
<i>COVID19_GR</i> $\times$ <i>Gov_bank</i>							-0.641* (-1.78)
<i>Size</i>	-0.051 (-1.17)	-0.028 (-0.69)	-0.045 (-0.99)	-0.064 (-1.35)	-0.060 (-1.36)	-0.050 (-1.20)	-0.048 (-1.04)
<i>Leverage</i>	0.007*** (2.80)	0.008** (2.26)	0.007*** (2.82)	0.007*** (2.73)	0.007*** (2.75)	0.008*** (2.92)	0.008*** (2.91)
<i>Return</i>	-0.401*** (-3.25)	-0.379*** (-2.91)	-0.405*** (-3.32)	-0.396*** (-3.34)	-0.398*** (-3.31)	-0.400*** (-3.29)	-0.401*** (-3.22)
<i>Volatility</i>	0.196*** (7.25)	0.197*** (7.70)	0.194*** (7.21)	0.192*** (7.84)	0.196*** (7.37)	0.192*** (7.46)	0.188*** (7.63)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	297,685	261,523	295,411	296,755	297,685	297,685	297,685
Adj. R ²	0.866	0.871	0.866	0.868	0.867	0.867	0.867

This table reports results on the moderating effects of banking regulation, competition, and ownership. ΔCoVaR is the proxy for systemic risk; *COVID19_GR* is the 14-day moving average log growth rate of confirmed COVID-19 cases; *Act_restrict* is the overall restrictions on banking activities; *Cap_reg* is the capital regulatory index; *Sup_power* captures whether the supervisory authority has the power to take specific actions to prevent and correct problems; *No_dep* means there is no explicit deposit insurance scheme; *Bank_con* is bank concentration; *For_bank* is the extent to which the banking system's assets are foreign-owned; *Gov_bank* is the extent to which the banking system's assets are government-owned. All control variables are lagged. All specifications include bank and day fixed effects and control variables. Standard errors are adjusted for clustering at the country level. *t*-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Analyzing the role of uncertainty avoidance, in column (4), we find that the coefficient on *COVID19_GR* $\times$ *UAI* is negative and significant at the 1% level. This suggests that the adverse effect of the pandemic on bank systemic risk is less pronounced in high uncertainty avoidance countries. Column (5) shows a negative and significant coefficient on *COVID19_GR* $\times$ *LTO*, suggesting the pandemic has a weaker effect on bank systemic risk in countries with higher long-term orientation.

We also note that high societal trust reduces the sensitivity of systemic risks to the pandemic. This is because, in economies with high societal trust, people tend to abide by public policy responses to pandemics (e.g., Barrios et al. 2020). This is more beneficial to the prevention and control of a pandemic. Overall, these findings suggest that countries with higher power distance, collectivism, uncertainty avoidance, long-term orientation, and societal trust are more able to withstand the impact of a pandemic on systemic risk.

4.6. Robustness tests

We conduct several sensitivity checks for our main evidence. First, we consider alternative proxies for COVID-19 shocks: *COVID19_GR_1D*, the log growth rate of confirmed COVID-19 cases; *COVID19_Death_1D*, the log growth rate of COVID-19 death cases; and *COVID19_Death*, the 14-day moving average log growth rate of COVID-19 death cases. The results in Online Appendix Table B1 show positive and highly significant coefficients on all of these proxies, reinforcing our main evidence.

In Online Appendix Table B2, we use alternative proxies for systemic risk (*MES* and *SRISK*) and the value at risk for individual banks (*Var*). *MES* is marginal expected shortfall, which measures how a bank's risk-taking adds to overall risk. *SRISK* represents the capital shortfall of a bank conditional on a severe market decline. *Var* represents individual banks' tail risk. The results suggest that the COVID-19 shock has positive effects on *MES*, *SRISK*, and *Var*. In addition to these proxies, we use the first principal component (*PC*) of ΔCoVaR , *MES*, and *SRISK* as our dependent variable. The results continue to show that the growth rate of confirmed cases positively impacts *PC*, suggesting an increase in systemic risk.

In Online Appendix Table B3, we evaluate the robustness of our main evidence to using different subsamples. Our main evidence continues to hold when we exclude countries with the fastest and slowest growth rates of confirmed COVID-19 cases and those with the highest or lowest GDP growth rates. Furthermore, Online Appendix Table B3 shows that the impact of COVID-19 on bank systemic risk is significant in both developed and developing countries. However, the test of the difference in coefficients of *COVID19_GR* between the two sample suggests that the difference is statistically insignificant.⁷

In Online Appendix Table B4, we use equal- and market value-weighted means of ΔCoVaR in each economy as dependent variables. The results show that the COVID-19 shock is associated with significantly greater systemic fragility.

⁷ Our main evidence is robust to excluding U.S. banks.

Table 9
Systemic risk during the pandemic, the moderating role of national culture and societal trust.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: $\Delta CoVaR$					
<i>COVID19_GR</i>	1.873** (2.59)	1.620** (2.51)	2.292** (2.60)	2.136*** (3.35)	1.751*** (3.00)	2.443** (2.62)
<i>COVID19_GR</i> × <i>PDI</i>	-0.949*** (-2.99)					
<i>COVID19_GR</i> × <i>COL</i>		-1.065*** (-5.03)				
<i>COVID19_GR</i> × <i>MAS</i>			0.441 (0.80)			
<i>COVID19_GR</i> × <i>UAI</i>				-1.142*** (-3.32)		
<i>COVID19_GR</i> × <i>LTO</i>					-1.217*** (-3.78)	
<i>COVID19_GR</i> × <i>Trust</i>						-0.973*** (-3.90)
<i>Size</i>	-0.041 (-1.06)	-0.049 (-1.21)	-0.048 (-1.30)	-0.057 (-1.36)	-0.054 (-1.22)	-0.041 (-0.76)
<i>Leverage</i>	0.008*** (3.17)	0.008*** (3.23)	0.008*** (3.02)	0.008*** (2.86)	0.008*** (2.92)	0.004 (1.40)
<i>Return</i>	-0.432*** (-4.12)	-0.422*** (-4.05)	-0.432*** (-4.11)	-0.413*** (-3.97)	-0.428*** (-4.18)	-0.426*** (-4.41)
<i>Volatility</i>	0.182*** (7.45)	0.181*** (7.54)	0.190*** (7.27)	0.191*** (7.71)	0.187*** (7.42)	0.199*** (7.75)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Country Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Observations	288,645	288,645	288,645	288,645	279,490	191,983
Adj. R ²	0.869	0.871	0.868	0.870	0.870	0.864

This table reports results on the moderating effects of national culture and societal trust. $\Delta CoVaR$ is the proxy for systemic risk; *COVID19_GR* is the 14-day moving average log growth rate of confirmed COVID-19 cases; *PDI* is the extent to which the less powerful expect and accept that power is distributed unequally; *COL* is the degree to which a society stresses the role of the group versus that of the individual; *MAS* is the extent to which “male assertiveness” is promoted as a dominant value in a society; *UAI* is a society's tolerance for uncertain, unknown, or unstructured situations; *LTO* is the extent to which long-term interests are valued more than short-term ones; *Trust* is societal trust. All control variables are lagged. All specifications include bank and day fixed effects and control variables. Standard errors are adjusted for clustering at the country level. *t*-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

In our channels analysis, one challenge is that government response and COVID-19 cases are endogenously to determined. Countries with stricter government responses were able to reduce the number of future COVID cases. To mitigate this concern, we run a regression using the initial government policy response. The results in Online Appendix Table B5 show that our main evidence remains unaffected.

5. Conclusion

In this paper, we conduct the first broad-based international study of the effects of COVID-19 on systemic risk. Our sample consists of 1,584 banks in 64 countries from February through December 2020. The results indicate that COVID-19 increases systemic fragility across countries, through both government policies and bank default risk channels. Our results are robust to alternative measures and hold across different subsamples. Focusing on the role of bank heterogeneity, we find that large, highly leveraged, riskier, high loan-to-assets, undercapitalized, and low network centrality banks exhibit higher systemic risk due to the COVID-19 shock.

We also examine whether and how regulatory and institutional environments moderate the adverse effect of the pandemic on bank systemic stability. We find that deposit insurance and foreign- and government-owned banks help mitigate the systemic risk of banks. In addition, countries with higher power distance, collectivism, uncertainty avoidance, long-term orientation, and societal trust are more able to withstand the impact of the pandemic on systemic risk. These findings have important policy implications.

To the extent that informal institutions are not under government control, improving the regulatory environment can help reduce the adverse effects of pandemic shocks on the systemic stability of the banking system. Our study also provides menu options for regulators to use to mitigate the effects of pandemics on the systemic stability of the banking system.

CRedit authorship contribution statement

Yuejiao Duan: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Sadok El Ghoul:** Conceptualization, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing. **Omrane Guedhami:** Conceptualization, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing. **Haoran Li:** Data curation, Formal analysis, Software, Writing – original draft. **Xinming Li:** Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing, Funding acquisition, Resources, Project administration.

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Supplementary materials

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