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## Systemic risk: The impact of COVID-19<sup>☆</sup>

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### ABSTRACT

Banking sectors across the globe are under immense stress due to the evolving COVID-19 situation and policy responses thereto. This study investigates how COVID-19 impacted the systemic risk in the banking sectors of eight of the most COVID-19 affected countries. We find a significant increase in systemic risk among the sample countries initially, while stagnancy (at an elevated level) is observed during April 2020 except for China, which is showing some recovery. By using spillover measures, we also identify systemically important institutions. The findings of this study testify to the benefits of policy responses in containing systemic risk.

### 1. Introduction

The impact of the COVID-19 pandemic is felt beyond the health sector and exhibits severe economic consequences. The global economy is projected to decline by 3% in real GDP for 2020 (6.1% decline for developed economies).<sup>1</sup> Most governments responded immediately to manage economic and financial shocks by providing fiscal, monetary, and macro-financial stimuli. Globally, regulators responded by easing regulatory requirements, loan payment deferrals, and interim non-classification of non-performing loans (NPLs). However, extended lockdowns, loan payment deferrals, and an uncertain political outlook have increased the systemic vulnerability of the banking sector, and experts believe that “Vulnerabilities in credit markets, emerging countries and banks could even cause a new financial crisis”.<sup>2</sup> This study is motivated by this issue and provides an initial exploration of the systemic risk evolution in a sample of eight of the most COVID-19 affected countries.

The banking system's elevated systemic risk vulnerabilities are attributed to three reasons. First, liquidity risk due to economic slowdowns, financial forbearance and reduced access to capital markets due to potential credit rating downgrades.<sup>3</sup> Second, loss of intermediation income caused by regulatory and policy responses including loan payment reprieves and availability of government-guaranteed loans at ultra-low interest rates.<sup>4</sup> Although these measures help in curbing immediate default risk, a significant increase in

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<sup>1</sup> IMF, World Economic Outlook, April 2020.

<sup>2</sup> IMF Blog (Adrian, T., & Natalucci, F., 2020).

<sup>3</sup> How COVID-19 is Affecting Bank Ratings. (S&P Global Ratings, 22 Apr, 2020)

<sup>4</sup> IMF Policy Tracker: Policy Responses to COVID-19.

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NPLs is unavoidable (Ratnovski et al., 2020). Finally, a severe decline in intermediation business can adversely affect the ability to finance operations and funding costs of financial institutions. These risks may spread like a contagion through interconnected financial institutions.

In this study, we explore the probable contagion effect of the COVID-19 in the financial systems of eight of the most affected countries; Canada, China, France, Germany, Italy, Spain, the UK, and the USA. We include the Global Financial Crisis (GFC) of 2007–09 in the estimation for comparison purposes. The GFC was an endogenous shock, especially for the USA, and the regulatory frameworks, at the time, were micro-prudential. The current situation is exogenous with macro-prudential regulatory frameworks in place which have the ability to closely monitor and respond to such systemic shocks. For instance, on 20th March 2020, the Basel Committee on Banking Supervision (BCBS) coordinated policy and supervisory responses to COVID-19 advising a range of regulatory and supervisory measures to member jurisdictions.<sup>5</sup> Furthermore, the sample countries devised a range of policy responses to contain the systemic shock which we briefly reviewed in the next section.<sup>6</sup>

## 2. Policy responses

China promptly responded to the COVID-19 by injecting RMB3.33 trillion into the banking sector via open market operations, RMB1.8 trillion as an expansion to re-lending and re-discounting facilities, reducing the 7-day, and 14-day reverse repo rates by 30 and 10 bps, respectively, and decreasing the 1-year medium-term lending facility (MLF) rate and the targeted MLF rate by 30 and 20 bps, respectively.

The USA has taken several fiscal and monetary actions including USD484 billion Paycheck Protection Program and Health Care Enhancement Act, and around USD2.3 trillion Coronavirus Aid, Relief and Economic Security Act; to support the small and medium-sized businesses. The federal funds rate was lowered by 150 bps in March, and the current target rate is 0–0.25 bps. Furthermore, the regulators have encouraged lending depositories to use their capital and liquidity buffers and lowered the community bank leverage ratio to 8%.

In Europe, apart from the fiscal stimulus, the European Central Bank (ECB) provided monetary policy support to its member countries, including €120 billion additional asset purchases, for each country, until the end of 2020. A new liquidity facility (PELTRO) is introduced as a long-term refinancing operation with an interest rate of 25 bps lower than the average main refinancing operations (MRO) rate during the facility term. Systemically important institutions are temporarily allowed to operate below the Pillar 2 Guidance, the capital conservation buffer, and the liquidity coverage ratio. Furthermore, capitalization requirements for the Pillar-2 Requirement have been eased, and the ECB Banking Supervision has temporarily relaxed the classification requirements and expectations on loss provisioning for NPLs.

The Bank of Canada has reduced the overnight policy rate by 150 bps in March. The Domestic Stability Buffer of the systemically important banks has been lowered from 2.25% to 1% of the risk-weighted assets. The Canadian government has introduced a fiscal package of CAD193 billion and has planned to purchase insured mortgages of CAD150 billion to provide liquidity.

The aforementioned policy responses are intended to manage the economic and financial shocks. In the coming sections, we provide estimation methodology of systemic risk and analyze its evolution to see if these policy responses have provided the intended benefits.

## 3. Data and systemic risk measures

### 3.1. Data

USD denominated daily stock prices of the largest banks and Financial Services Providers (FSPs), based on the 2019 market capitalization, covering period from 2nd January 2006 to 27th April 2020 have been used. Table 1 shows the list of sample countries, market index for each country, and country-wise sample distribution of the number of banks and FSPs. A total sample of the 30 largest institutions for each country (20 banks and 10 FSPs) was used. However, if a country had less than 20 banks, available on the DataStream, we maintained the sample size by using more than 10 FSPs. For Spain, all of the banks and FSPs are used which are less than 30.

### 3.2. Systemic risk measures

An overview of systemic risk measures can be found in Bisias et al. (2012) and Giglio et al. (2012). Due to severe data limitations during the pandemic, we rely on CATFIN proposed by Allen et al. (2012). Allen et al. (2012) defined CATFIN as the arithmetic mean of value-at-risk (VaR) estimated using three different methodologies; the generalized Pareto Distribution (GPD) of Pickands (1975), the skewed generalized error distribution (SGED), and a non-parametric estimation. Using the closed-form solution of VaR for the GPD, provided by Bali (2003, 2007), the VaR threshold ( $VaR_{GPD}$ ) for the loss probability level  $\alpha$  can be calculated as:

<sup>5</sup> <https://www.bis.org/press/p200320.htm>

<sup>6</sup> The relevant information is extracted from the IMF Policy Tracker on Policy Responses to COVID-19.

**Table 1**  
Sample distribution and data detail.

Country	Market index (DataStream code)	Sample distribution		
		Banks	FSP	Total
Canada	Canada-DS Market (TOTMCN\$)	14	16	30
China	Shanghai SE B Share (CHSBSHR)	20	10	30
France	France-DS Market (TOTMFR\$)	18	12	30
Germany	Germany-DS Market (TOTMBD\$)	12	18	30
Italy	Italy-DS Market (TOTMIT\$)	16	14	30
Spain	Spain-DS Market (TOTMES\$)	8	4	12
UK	UK-DS Market (TOTMUK\$)	13	17	30
USA	S&P 500 Composite DS Calculated (S&PCOMZ)	20	10	30

$$VaR_{GPD} = \mu + \left(\frac{\sigma}{\varepsilon}\right) \left[ \left(\frac{\alpha N}{n}\right)^{-\varepsilon} - 1 \right] \quad (1)$$

where  $\mu$ ,  $\sigma$  and  $\varepsilon$  are the location, scale and shape parameters of the GPD, respectively, while  $n$  and  $N$  are the number of extremes, and the total number of observations, respectively.

Let  $f(R; \mu, \sigma, \kappa, \lambda)$  be the probability density function for the SGED where  $\mu$  and  $\sigma$  represent the mean and standard deviation of the excess stock return  $R$ , and the parameters  $\kappa$  and  $\lambda$  control the shape and skewness of the distribution, respectively. Then, the VaR threshold for the SGED ( $VaR_{SGED}$ ), at the loss probability level  $\alpha$ , is numerically calculated as:

$$\int_{-\infty}^{VaR_{SGED}} f(R; \mu, \sigma, \kappa, \lambda) dR = \alpha \quad (2)$$

The non-parametric estimation of VaR ( $VaR_{NP}$ ) is based on the cutoff point for the lower  $\alpha$  percentile of the excess return. Therefore, Allen et al. (2012) defined CATFIN as follows:

$$CATFIN = \frac{1}{3}(VaR_{GPD} + VaR_{SGED} + VaR_{NP}) \quad (3)$$

Giglio et al. (2012) shows that, among the individual systemic risk measures, CATFIN performs quite well in forecasting macroeconomic shocks. However, they define CATFIN as follows:

$$CATFIN = \frac{1}{2}(VaR_{GPD} + VaR_{NP}) \quad (4)$$

Therefore, following Giglio et al. (2012), we estimate CATFIN as defined in the Eq. (4).<sup>7</sup>

In addition to systemic risk, we also estimated the systemic importance of the financial institutions using the connectedness measures - "Spillover-To-Others" (STO) and "Spillover-From-Others" (SFO) - proposed by Diebold and Yilmaz (2014). These measures are based on the  $M$ -step variance decomposition. Let  $d_{ij}^M$  represent the  $ij$ th component of the  $M$ -step variance decomposition. The variance decomposition  $d_{ij}^M$  are calculated as  $d_{ij}^M = \frac{\tilde{d}_{ij}^M}{\sum_j \tilde{d}_{ij}^M}$  where  $\tilde{d}_{ij}^M$  is the generalized variance decomposition, introduced by Pesaran and Shin (1998), given as:

$$\tilde{d}_{ij}^M = \frac{\sigma_{jj}^{-1} \sum_{m=0}^{M-1} (e_i' A_m \Sigma e_j)^2}{\sum_{m=0}^{M-1} (e_i' A_m \Sigma A_m' e_i)} \quad (5)$$

where  $\sigma_{ii}$  is the  $i$ th diagonal element of  $\Sigma$ ,  $e_i$  is a selection vector with  $i$ th element as unity and other elements as zeros,  $A_m$  is the coefficient matrix for the  $m$ th lagged shock vector of the moving average representation of the vector autoregressive model, and  $\Sigma$  is the covariance matrix of the error term in the vector autoregressive model. Then,  $d_{ij}^M$  denotes the proportion of the forecast error variance in variable  $i$  due to the shocks in variable  $j$ . The STO and SFO measures, for an institution  $i$ , are defined as:

$$STO_i = \sum_{j \neq i} d_{ji}^M \quad (6)$$

$$SFO_i = \sum_{j \neq i} d_{ij}^M \quad (7)$$

Therefore,  $STO_i$  measures institution  $i$ 's total share of forecast error variance to other institutions while  $SFO_i$  measures institution  $i$ 's forecast error variance from other institutions.

<sup>7</sup> The required components of CATFIN were estimated using the Systemic Risk repository by Belluzzo (2020).

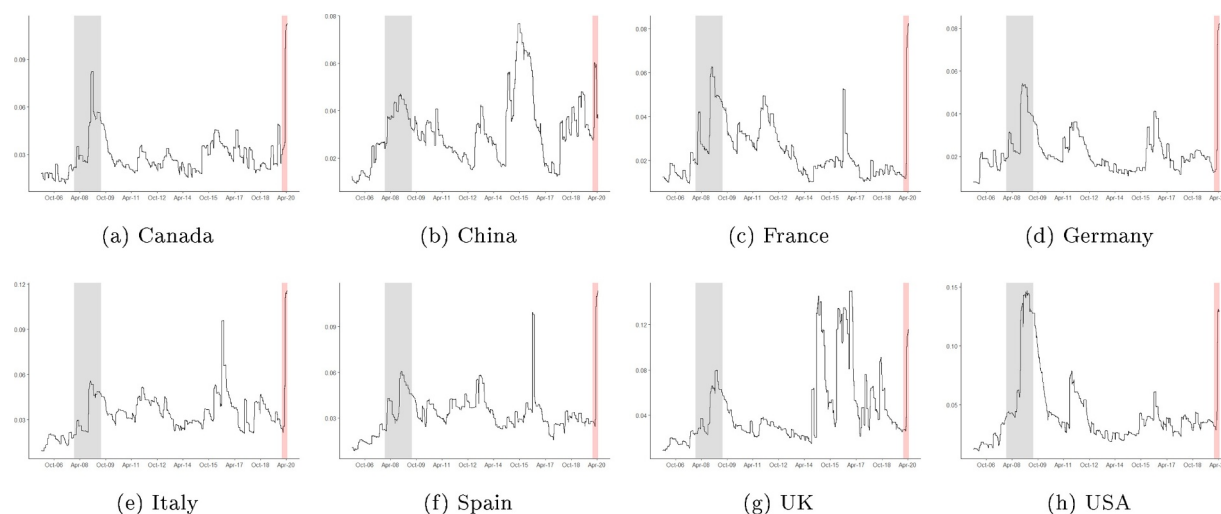


Fig. 1. Estimates of CATFIN from 2nd January 2006 to 27th April 2020.

## 4. Results and discussion

### 4.1. Systemic risk

Fig. 1 shows the evolution of CATFIN for the eight countries. The gray-shaded area represents the GFC (December 2007 to June 2009), and the red-shaded area corresponds to the COVID-19 period (27th December 2019 to 27th April 2020, end of sample period).

In Fig. 1, all of the countries exhibit a peak during the GFC followed by a recovery. As expected, for the USA, the peak during the GFC is the highest for the sample period. Peaks are also observed for all of the countries from 2010 to 2012 which corresponds with the European Sovereign Debt Crisis (ESDC). These peaks are more significant for France, Germany, Italy, and Spain. The USA also shows a significant amount of systemic risk during this period which is partly due to the supply chain disruptions caused by the Japanese earthquake, floods and tornadoes in the South and Midwest regions, and higher volatility in oil prices (Elwell, 2012).

All of the countries show elevated systemic risk from 2015 to 2016 especially China and the UK. The systemic risk of China and the UK, during this period, is at its highest for the sample period. This period corresponds with the Chinese stock market turbulence (Wang et al., 2018). Canada also exhibits relatively higher systemic risk during 2016 when the oil sector was hit by the wildfire in Fort McMurray, a decline of 4.5% in exports, and the largest decline in GDP since the second quarter of 2009.<sup>8</sup> The COVID-19 period marks the highest level of systemic risk for all of the countries except for China, the UK, and the USA. Better visualization of systemic risk during the pandemic is presented in Fig. 2.

Fig. 2 shows that systemic risk of all the countries, except for China, behaves very similarly for the COVID-19 period. The systemic risk is relatively stable until March after which there is a sharp increase. The systemic risk reaches its highest value mid-to-late March and then remains relatively stagnant, at the elevated level, till the end of the sample period.

Systemic risk behavior of China is markedly different which is rather unsurprising considering that COVID-19 affected it before the other countries. The estimate starts increasing at the end of January and reaches its peak in early February. It remains at the elevated level till the end of March after which there is some recovery. However, systemic risk in China is still at an elevated level compared to the pre-COVID-19 period.

Table 2 presents the average of CATFIN during the pre-COVID-19 and COVID-19 periods; the pre-COVID-19 period starts from 1st June 2019 till the date of the first reported case for each country. The two periods are also compared using the Kruskal-Wallis one-way analysis-of-variance test. The table shows that systemic risk is significantly higher in these countries during the pandemic.

In summary, all of the countries have experienced a rapid increase in their systemic risk during the pandemic, and the systemic risk became stagnant at higher levels. It is plausible that the current regulatory actions may have played a role in flattening the curves. However, these countries are still facing elevated systemic risk, and since the regulatory requirements have already been eased, increased scrutiny might be needed to achieve recovery to ensure the stability of the global financial system.

### 4.2. Systemically important financial institutions during COVID-19

To enable regulators to devise appropriate policies for managing the systemic risk, we use the methodology explained in Section 3.2, and identified Systemically Important Financial Institutions (SIFI) based on their ability to affect others (STO) and their

<sup>8</sup> The Daily: Statistics Canada.

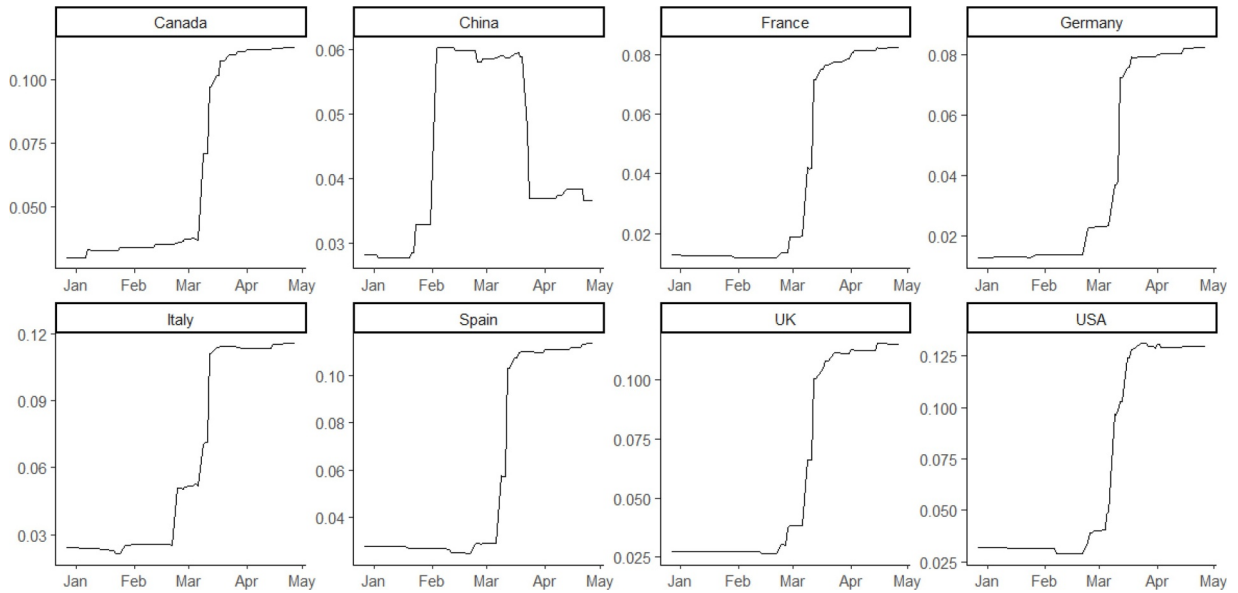


Fig. 2. Estimates of CATFIN from 27th December 2019 to 27th April 2020.

Table 2

Average CATFIN during COVID-19 and PreCOVID-19 period.

Country	Pre-COVID-19	COVID-19	Kruskal-Wallis test
Canada	0.03196	0.07429	79.32***
China	0.03336	0.04391	28.72***
France	0.01373	0.04718	11.98***
Germany	0.01664	0.04914	44.23***
Italy	0.02899	0.07906	50.54***
Spain	0.02779	0.07286	29.3***
UK	0.02896	0.07516	46.81***
USA	0.03524	0.07991	10.72***

vulnerability of being affected from others (*SFO*) during this pandemic. Fig. 3 provides heat diagrams of the SIFIs based on *STO*.<sup>9</sup> Fig. 3 shows that for China, Spain, the UK, and the USA, the majority of the financial institutions can have spillover on other institutions. However, for Canada, France, Germany, and Italy, the SIFIs are smaller in number which provides an opportunity for managing systemic risk by regulating these firms.

Fig. 4 provides a heat map based on *SFO*. Except for France and Germany, all the other countries have a large majority of the financial institutions exhibiting vulnerability to spillover from other institutions suggesting a high level of interconnectedness, in conjunction with the maps in Fig. 3, which is an important driver of systemic risk. Overall, the heat maps in Figs. 3 and 4 identify the SIFIs which could prove helpful for the regulators.

#### 4.3. Alternate systemic risk measure

As an alternative to CATFIN, we estimated Absorption Ratio (AR), proposed by Kritzman et al. (2011), as:

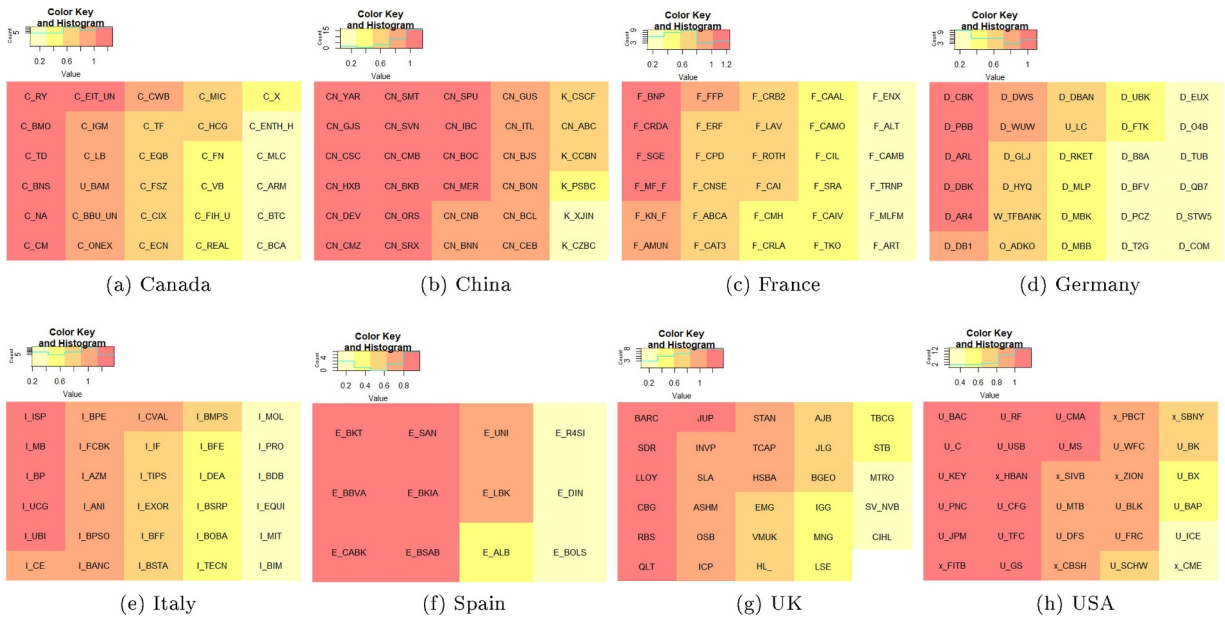
$$AR = \frac{\sum_k \sigma_{\gamma_k}^2}{\sum_i \sigma_{A_i}^2} \quad (8)$$

where  $\sigma_{\gamma_k}^2$  is the variance of the  $k$ th eigenvector of the covariance matrix of asset returns, and  $\sigma_{A_i}^2$  is the variance of the  $i$ th asset. So, higher values of AR indicate that the risk sources are more unified compared to lower values.

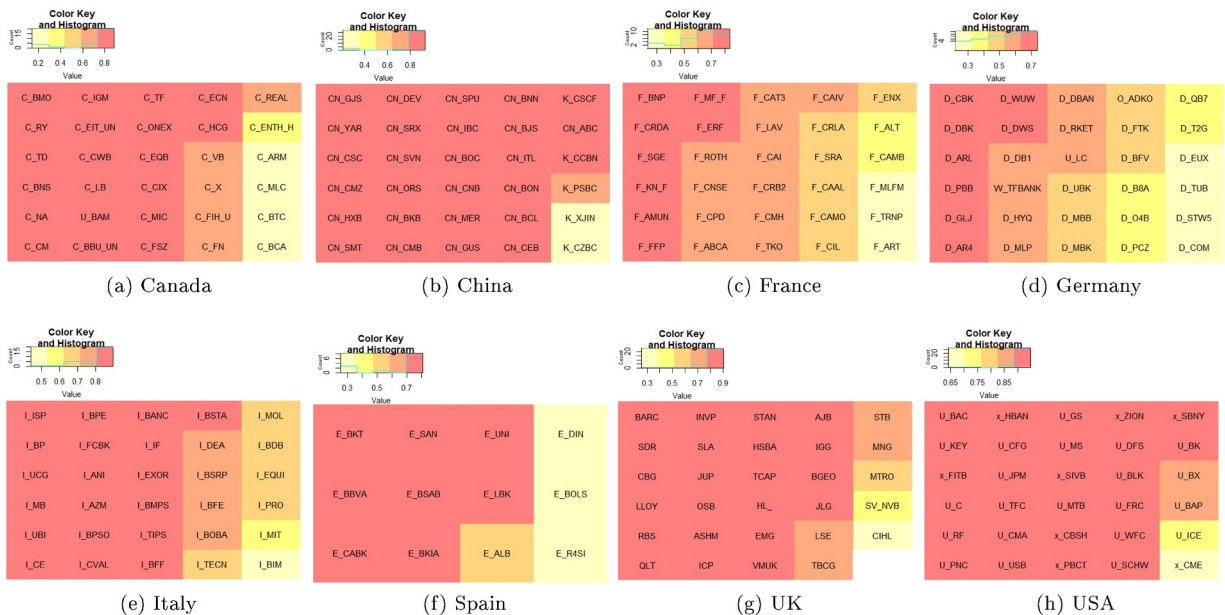
Fig. 5 shows the AR during the pandemic. Overall, we observe similar results for all countries except for Canada where we observed a recovery in systemic risk starting from mid-March. Fig. 5 shows recovery for China in mid-February which is short-lived and the systemic risk increases during March.

<sup>9</sup> Due to space limitations, only codes are provided here. Institution names are available on request.





**Fig. 3.** Country-wise heat maps of *STO*. Color Key above each figure shows the range of systemic importance of the institutions; dark red (most important) to light yellow (least important). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



**Fig. 4.** Country-wise heat maps of *SFO*. Color Key above each figure shows the range of systemic importance of the institutions; dark red (most important) to light yellow (least important). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

**5. Conclusion**

COVID-19 has slowed down the global economy. Consequently, financial institutions are facing elevated levels of liquidity risk, loan defaults, and loss of intermediation revenues. Interconnectedness among financial institutions can spread individual issues to the network of institutions resulting in an overall heating-up of the financial system. Our results show a sharp increase in systemic risk, for countries included in this study, during the COVID-19 period. However, by the end of April 2020, the sample countries exhibit flattened systemic risk curves which may be attributed to policy responses. The findings of this paper has certain policy implications for regulators. First, the findings testify to the positive response of systemic risk towards policy responses, discussed in Section 2, as

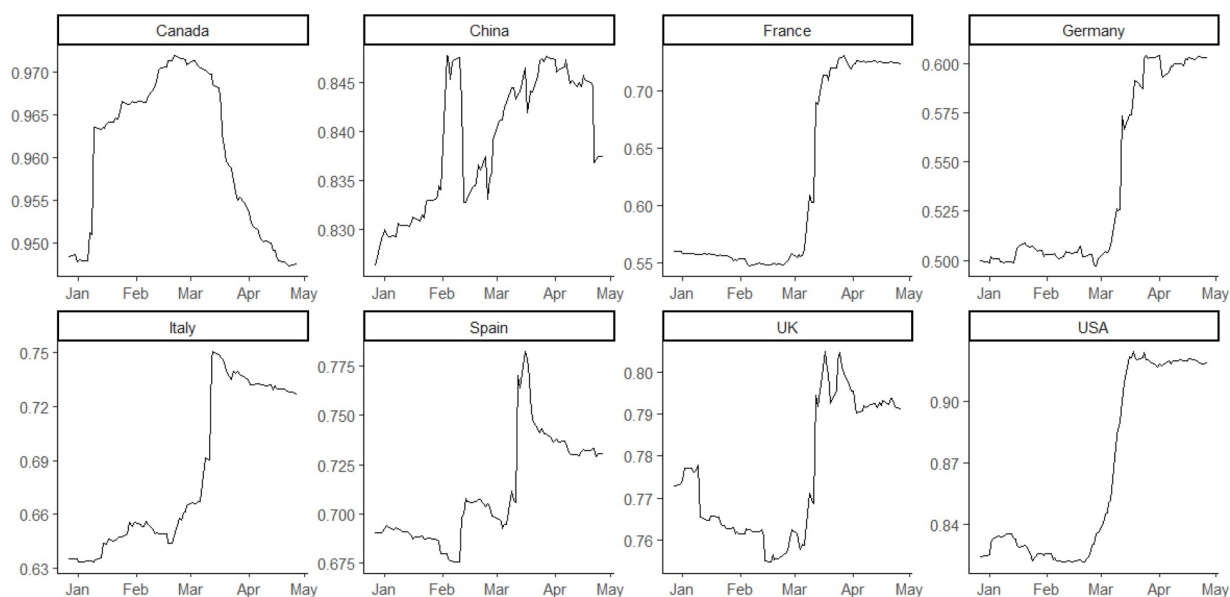


Fig. 5. AR during the COVID-19 period.

shown by the flattening of the systemic risk curves, albeit at an elevated level. Second, regulators can better manage systemic risk through focusing on those institutions which are highlighted by this study as being systemically important during the COVID-19 period. However, there is a need to analyze the causal relationship between systemic risk and the policy responses which can be an avenue for future research.

#### CRediT authorship contribution statement

**Muhammad Suhail Rizwan:** Conceptualization, Data curation, Formal analysis, Investigation, Writing - original draft. **Ghufuran Ahmad:** Methodology, Visualization, Software, Investigation, Writing - original draft. **Dawood Ashraf:** Project administration, Supervision, Validation, Writing - review & editing.

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