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Does macroprudential policy alleviate the adverse impact of COVID-19 on the resilience of banks?

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ABSTRACT

This paper examines the resilience of banks as perceived by market participants during the COVID-19 crisis. We analyse how bank stock returns during January–March 2020 relate to the pre-crisis activation of macroprudential policy across 52 countries in a cross-sectional dimension. We find that, overall, a tighter macroprudential policy stance is beneficial for bank systemic risk, as assessed by equity market investors. A robust finding is that a perceived decrease in bank risk stems primarily from the use of credit growth limits, reserve requirements, and dynamic provisioning. By contrast, a pre-crisis build-up of capital surcharges on systemically important financial institutions seems to lower bank stock returns. Alternative bank risk indicators suggest that the latter is likely to be driven by concerns about profits rather than the probability of default.

1. Introduction

COVID-19 and the public health measures taken to contain the pandemic have exerted unprecedented pressure on both consumption and production, which has been further exacerbated by increased uncertainty. The banking sector is believed to play a unique role in helping the corporate and household sectors cope with the COVID-19-induced downturn, although it is not certain that banks are sufficiently robust to rise to the challenge. As a step towards assessing bank resilience, this paper delves into the role of macroprudential policy in containing perceptions of bank risk during the crisis. One of the main aims of macroprudential policy is to prevent systemic risk in the banking sector. Yet, the literature directly examining its effect on bank risk remains sparse (Gaganis et al., 2020) and, despite the widespread implementation of macroprudential tools, our understanding of these policies and their efficacy is still evolving (e.g. Claessens 2015, Boar et al., 2017). Most research concentrates on analysing the impact of macroprudential tools on the intermediate target of credit growth, and not directly on the ultimate goal of containing risk (recent exceptions include Altunbas et al. 2018, Gaganis et al., 2020, and Meuleman and Vander Vennet 2020).

In this paper, we analyse whether bank risk, measured mainly by the severity of decline in bank stock returns experienced during the COVID-19 crisis, is alleviated by the macroprudential policies implemented in the years prior to the pandemic shock. We use data from 981 banks in 52 countries, and explore cross-bank as well as cross-country variations in stock-price responses. Changes in stock prices potentially reflect a multitude of factors. Nonetheless, if a bank is in a better position than others to weather this common shock, this should be captured in the relative stock price movement.[1] Our basic empirical strategy is thus to investigate whether the degree of bank stability, measured by the magnitude of changes in stock prices from December 31, 2019 to March 31, 2020, can be predicted by the pre-crisis strategies of macroprudential policy.

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[1] Similar arguments relying on the interpretation of differences in stock price movements have commonly been applied in the literature. For instance, Tong and Wei (2011) use firm stock price reactions to study whether pre-crisis international capital flows affected the scale of the credit crunch experienced during the 2007–09 crisis. As opposed to manufacturers, banks can much more readily alter their asset volatility. We provide robustness checks using alternative risk indicators in Section 4.3.

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There are many different macroprudential policy tools, and a subset of the literature investigates the potentially different effects of various tools for mitigating systemic risk in the banking sector. The findings diverge, with some tools being reported as more effective, with fewer side-effects, while other macroprudential tools raise doubts as to their relative stabilising properties (Gaganis et al., 2020). Hence, in addition to using a total index (where a higher value indicates a tightening of macroprudential policy), we conduct the estimation for each component of macroprudential policy.

Turning to measurement of risk, we use indicators at the bank level, rather than the aggregate level. We follow the argument that macroprudential policy tools are aimed at influencing bank behaviour, and that this, in turn, is captured in financial market information (Acharya et al., 2017). Hence, following Tong and Wei (2011), we estimate bank risk using changes in the log of stock prices during the COVID-19 period. The market data are expected to reflect a forward-looking assessment of firms' profits and losses together with any potential risks. That said, stock returns are an imperfect proxy for probability of default and financial stability. Therefore, as alternatives to bank stock returns, we also employ spreads on credit default swaps (CDS)—a more direct, market-based measure of probability of default—and other commonly-used, balance-sheet-based measures of risk such as the Z-score and the impaired loan ratio. An advantage of using stock returns and CDS spreads over balance-sheet-based measures is that a high frequency of market data allows us to detect unexpected changes in a bank's perceived risk. Moreover, it is possible that the market-based measure of bank risk is able to capture behaviour such as regulatory arbitrage, where banks may engage in less regulated activities, albeit potentially with the consequence of more risk (Meuleman and Vander Vennet 2020). This is relevant because, ideally, we would like to capture the contributions of individual banks to systemic risk. Acknowledging the limitations of stock returns as a proxy for systemic risk, we extend our analysis by calculating volatility and marginal expected shortfall (see details in Section 4.3).

In considering the main results, we find a statistically significant, positive association between the macroprudential policy index and stock returns. This provides supporting evidence of a sheltering effect of policy on banks. Furthermore, the components of macroprudential policy matter. Credit growth limits, reserve requirements, and dynamic provisioning (and, to a lesser extent, concentration limits) are the main contributors to an upward movement in bank stock returns. By contrast, the pre-crisis use of capital surcharges on systemically important financial institutions seems to be associated with poorer stock market performance, while other tools have no bearing on bank stock returns. Yet, these surcharges are not significantly associated with direct measures of default probability, suggesting that a concern about profits may be behind the negative relation between the pre-crisis use of surcharges and the movement of stock prices during the crisis.

Estimations of the impact of policy tools invariably encounter the problem of reverse causality. In our setting, even though COVID-19 was an unexpected, abrupt, exogenous shock, endogeneity may arise because policymakers may have undertaken macroprudential policy actions as a reflection of their assessment of a strong economy and a robust banking sector, so that countries with more macroprudential policy action may have simply been able to fend off the economic impact of the health crisis. It may also be the case that the active use of macroprudential policies could be associated with better policymaking more generally, allowing a more effective policy response to the pandemic itself, hence, limiting the impact on the economy and the banks. In order to mitigate the concern, we carry out the estimation with a view to minimising the issue of omitted variable bias by controlling for various country-specific variables, which may help isolate the effects of macroprudential policies from those of other potential factors (Galati and Moessner 2018). These other factors include vulnerability to a pandemic, the severity of COVID-19, and macroeconomic conditions. Moreover, we use the instrumental variable (IV) technique to mitigate the remaining concerns about endogeneity. This is in addition to other robustness tests conducted, such as an alternative computation of equity returns, altering the implementation timing of macroprudential policies, subsampling, and an alternative macroprudential database. Lastly, further analysis is executed by estimating models with other (both idiosyncratic and systemic) risk indicators including the Z-score, distance to default, probability of default, impaired loan ratio, volatility, marginal expected shortfall, and CDS spread as a dependant variable. All these sensitivity and complementary tests reinforce our main findings.

Our study is related to two different strands of literature. Firstly, it relates to studies that explain why some banks fare better during financial crises, especially during the 2008 global financial crisis. See Berger and Bouwman (2013), Demirgüç–Kunt et al. (2013) and Pelster et al. (2018) for a review on the impact of bank capital, Fahlenbrach et al. (2012) on the role of bank risk culture, Beltratti and Stulz (2012) on the effect of short-term financing, and Fahlenbrach and Stulz (2011) on the effect of corporate governance. The present study complements them by examining the impact of hitherto less studied macroprudential measures on the performance of banks during a crisis. Microprudential policy is concerned with the stability of individual financial institutions, whereas the stability of the whole financial system is the main focus of macroprudential policy, which aims to address externalities that would generate spillovers across banks. Given the overall objective of containing systemic risk, the latter may be more (or at least just as) important as the former in weathering the effects of an external shock on bank resilience. Secondly, our paper is linked to an emerging body of empirical studies on the effectiveness of macroprudential policy aimed at financial stability. See Galati and Moessner (2013), Claessens (2015), and Galati and Moessner (2018) for an overview. However, these studies usually employ either bank-level or country-level indicators of credit growth as the target variable, or utilise variables such as the Z-score or default rates as the indicators of bank risk during normal economic phases. In contrast to these existing studies, we use stock price performance as an indicator of bank resilience during a crisis. In other words, a forward-looking indicator is utilised when the banking sector is hit by a large exogenous shock.

In terms of its main contribution, this paper is, to the best of our knowledge, the first to explore the role of macroprudential policies (that were implemented prior to the COVID-19 crisis) in alleviating bank risk during this public health crisis. It appears that stock markets initially priced in the worst-case scenario and were then buoyed by the very substantial and rapid policy support, which has, however, dramatically increased volatility. Banks have been able to deal with the pandemic relatively well, being in a much stronger position than they were at the onset of the subprime crisis in 2008. Bank regulators across countries had already strengthened the frameworks for preventing a repeat of the global financial crisis, during which banks had been required to hold substantial buffers in terms of capital and liquidity in order to enable them to survive another dramatic downturn. At the same time, with the COVID-19 pandemic inflicting economic damage worldwide and its duration being highly uncertain, banks are one of the few industries considered essential to keep economies running. Our study is, therefore, of particular interest to a wide audience and exploits the pandemic as a momentous opportunity to investigate how macroprudential policy across countries is linked to bank resilience.

The remainder of the paper is organized as follows. Section 2 motivates the analysis with a discussion of the anticipated effect of macroprudential policy on bank risk. Section 3 introduces the methodology and the data, which is followed by the main empirical results and robustness tests in Section 4. Conclusions are drawn in Section 5.

2. Macroprudential policy and bank risk

Banks are intrinsically fragile, given their inevitable leverage and maturity transformation. Furthermore, common exposures to shocks and the procyclicality of bank risk-taking generates system-wide vulnerability. Macroprudential policy instruments are designed to mitigate balance sheet mismatches, reduce interlinkages across banks, and curb procyclicality in order to contain systemic risk and prevent financial instability (Claessens et al. 2013).

Macroprudential policy takes many forms. Demand-side measures such as loan-to-value ratios or debt-to-income ratios refer to credit-related tools that aim to enhance the quality of loans and reduce the probability of borrower default, which, in turn, improve bank resilience (Lim et al., 2011). Supply-side tools involve various restrictions imposed on banks in order to curb credit growth or strengthen loss-absorbing capacity. For instance, a tightening in capital requirements may lead banks to issue new equity, to deleverage, or to reduce risky loans. Certain exposure limits are also often introduced to reduce negative externalities stemming from interconnectedness (Meuleman and Vander Vennet 2020). Liquidity-related tools such as limits on maturity-mismatch and reserve requirements force banks to hold more liquid assets or decrease long-term risky loans in order to withstand unforeseen liquidity shocks. All these tools should, in principle, reduce individual bank risk, as well as their contributions to systemic risk.

There may, however, be unintended consequences. Risk-shifting could arise if banks substitute lending with unsecured exposures. Or, potentially detrimental effects on profitability could induce banks to undertake activities that are subject to a lower regulatory burden but carry higher risk (Meuleman and Vander Vennet 2020). Regulatory arbitrage can also manifest itself at the systemic level, whereby activity migrates to institutions beyond the macroprudential policy perimeter. Such leakages could occur due to cross-sector substitution, as credit provision shifts from banks to non-bank financial institutions (Cizel et al., 2016) or across borders, when foreign banks, which are not subject to the same macroprudential rules as the domestic ones in a given country, exploit this unlevel playing field and expand their lending (Aiyar et al. 2014, Reinhardt and Sowerbutts 2015, Cerutti et al. 2017).

In summary, there is a possibility that macroprudential policy incentivizes banks to engage in regulatory arbitrage and risk shifting, and such behaviour could ultimately induce unintended, adverse effects on bank risk. It then appears that the net effect of macroprudential policy measures becomes an empirical issue. On the whole, most empirical studies focus on the intermediate objectives of macroprudential policy, such as curbing credit and house price growth, and conclude that macroprudential policies achieve their targets with some variation (see, amongst many others, Lim et al., 2011, Akinci and Olmstead-Rumsey 2018). The strand of literature that examines the association between macroprudential policies and direct measures of bank risk is, by comparison, limited, but also tends to identify some success in macroprudential tools that improve bank resilience, and to provide important heterogeneity across banks (see Altunbas et al. 2018, Meuleman and Vander Vennet 2020).

3. Methodology and data

3.1. Empirical strategy

Our goal is to examine whether adopted macroprudential policies mitigate or intensify the adverse impact of the COVID-19 pandemic on bank risk. We do so by applying an empirical model similar to that in Tong and Wei (2011):

$$\Delta \mathrm{Risk}_{\mathrm{ic,\ Crisis}} = \beta_0 + \beta_1.\mathrm{MP}_{\mathrm{c,Pre}} + \gamma.\mathrm{X}_{\mathrm{ic,Pre}} + \mu.\mathrm{Z}_{\mathrm{c,Pre}} + \omega_{\mathrm{s}} + \omega_{\mathrm{R}} + \varepsilon_{\mathrm{ic,Crisis}} \tag{1}$$

where i and c denote bank i and country c. $\Delta \mathrm{Risk}_{\mathrm{ic,\ Crisis}}$ is a measure of the change in bank risk (resilience). In the baseline, this is computed as a change in the log stock price of bank i in country c from December 31, 2019 (pre-crisis) to March 31, 2020 (crisis), denoted as, StockReturn. $\mathrm{MP}_{\mathrm{c,Pre}}$ represents the sum of all macroprudential tools or the components activated in country c in 2017. $\mathrm{X}_{\mathrm{ic,Pre}}$ and $\mathrm{Z}_{\mathrm{c,Pre}}$ are a vector of bank-specific and country-specific variables in 2019, respectively. ω_{s} and ω_{R} denote the dummies for bank type s and region R to control for bank business models and regional differences in utilizing macroprudential policies. The regional dummies allow us to capture at least some unobserved country characteristics, in lieu of country fixed effects.

The main variable of interest is $\mathrm{MP}_{\mathrm{c,pre}}$. The coefficient β_1 measures the difference of bank stock prices in countries with high versus low utilization of macroprudential policies. This captures the contribution of ex-ante usage of macroprudential policies in explaining ex-post stock returns of banks domiciled in those countries, beyond that which is explained by standard bank and country factors ($\mathrm{X}_{\mathrm{ic,Pre}}$ and $\mathrm{Z}_{\mathrm{c,Pre}}$). Specifically, a positive and significant point estimate of β_1 would indicate that stock returns of banks located in countries with greater activation of macroprudential measures in the pre-crisis period were higher than those banks located in countries with lower activation of these tools. If we observe a negative and significant coefficient, this would imply that adoption of macroprudential policies in normal times might be associated with a higher level of bank risk during a crisis.

In our baseline regression, we add four idiosyncratic bank characteristics ($\mathrm{X}_{\mathrm{ic,Pre}}$) that are known to influence stock returns, according to the standard asset pricing models (Fama and French 1992). These are: (i) firm size (Size) measured by the natural log of total assets; (ii) the beta (Beta) measured by the correlation between the bank stock return and the market return over the past year; (iii) a measure of the momentum factor (Momentum) defined as the bank stock return from December 31, 2018 to December 31, 2019; and (iv) a proxy for Tobin's Q (Tobin Q) measured by the market value of common equity divided by the book value of assets. According to the literature, Size matters in identifying stock returns (Gandhi and Lusting 2015). Small firms tend to perform better than larger ones during a crisis (Aebi et al. 2012). Meanwhile, a high Beta suggests that we would observe a larger decline in the stock price of a given bank during a crisis (Pelster et al. 2018). Momentum indicates how well a stock performed in the recent past, so it allows us to ascertain whether banks with high stock returns in the pre-crisis period fare better during a crisis (Tong and Wei 2011). Tobin's Q is expected to have a positive impact on bank stock performance (Fahlenbrach et al. 2012).

Finally, we also consider twelve potential country-level control variables ($\mathrm{Z}_{\mathrm{c,Pre}}$). We classify these variables into four groups reflecting the relevant main factor they aim to capture, namely, crisis transmission channel, pandemic vulnerability, pandemic severity, and broad macroeconomic conditions (see, amongst others, Claessens et al. 2013; Cerutti et al. 2017; Gaganis et al., 2020):

A- Channels of transmission: Shocks spread through both real and financial channels. Typically, a crisis may propagate across countries via a collapse in international capital flows and/or in international trade (Claessens et al., 2010), which happened to be the case during the acute phase of COVID-19, given restrictions imposed on movement across and within borders, supply disruptions due to lockdowns, a sharp rise in uncertainty and drop in investor confidence. Thus, we consider two proxies: (i) Trade openness, computed as total exports and imports in% of GDP, to proxy for a country's economic integration with the rest of the world, and (ii) FDI, as a proxy for financial interconnectedness.

B- Pandemic vulnerability: In order to capture the vulnerability of countries to the pandemic, we utilize two indicators. The first one is the number of hospital beds per 1000 people (Bed/population), indicating healthcare system capacity in a country. The other indicator is a proxy for the share of employment prone to a pandemic (Share affected), which indicates the share of jobs that cannot be done at home in each sector. See Dingel and Neiman (2020) and the Online Supplement for the derivation.

C- Pandemic severity: In order to capture the severity of the pandemic shock across countries, we use two indicators. The first indicator captures the direct health impact: the number of COVID-19 deaths per 100,000 population (Death/population) as of March 31, 2020. The second one is the severity of the lockdown measures in response to the pandemic (Severity). This is a composite measure of school closures, workplace closures and travel bans, as of March 31, 2020, which is normalised to be from 0 to 100 with the score 100 being the strictest (Hale et al., 2020).

D- Macroeconomic conditions: General economic conditions have a bearing on how strongly an economic can bounce back as they not only reflect the underlying fundamentals but also determine the available space for policy response. Following existing literature, we consider six macroeconomic variables. (1) We use the exchange rate regime (*Foreign Exchange regime*) of a country based on the de facto classification by Ilzetzki et al. (2019) with the latest available year of 2016, which would indicate how much the economy could absorb a shock through the exchange rate adjustment. The classification ranges from 1 to 6, with 6 being the most freely floating regime. (2) We use the current account balance in the percentage of GDP (Current account), given its documented associations with risk of external sector and banking crises. (3) We use the ratio of government debt to GDP (Government debt), since high debt levels could limit the availability of fiscal policy space to deal with a crisis. (4) Foreign reserves as a percentage of GDP (Foreign reserve) is included to capture the degree to which international and domestic financial cycles are intertwined. Finally, (5) GDP growth and (6) Inflation are also included to control for precrisis general macroeconomic circumstances.

Eq. (1) is estimated with the ordinary least squares (OLS). Residuals from OLS estimations may be correlated across countries, resulting in biased standard errors. Thus, we cluster standard errors in all regressions at the country level. An advantage of our empirical strategy is that it incorporates information about heterogeneity across countries in the activation of macroprudential policies. The disadvantage is the classical problem of endogeneity, yet in the current setup, it is unlikely that the reaction of stock returns to an exogenous health shock would have an influence on the activation of macroprudential policy in the previous years. A more challenging concern is that any association may come about because of omitted variables. For instance, some countries may have stronger monitoring capacity and thus implement more macroprudential tools in preparation for a potential crisis, and stock markets of such countries could be more resilient to external shocks because of a lesser degree of uncertainty. Note that, since the main aim of our study is to use cross-country differences in utilization of macroprudential policies, we cannot include country dummies to fully address country-level, omitted variable bias. Hence, we directly control for observable characteristics in order to determine the possibility that our estimates are being driven by unobserved heterogeneity across countries (Altonji et al. 2005). In addition, we use other empirical strategies, including subsample analyses and instrumental variables approaches, to address the remaining concerns regarding endogeneity and omitted variable bias.

3.2. Data

Our empirical analysis focuses on publicly listed banks. We investigate the impact of macroprudential policies on individual banks' stock returns from December 31, 2019 to March 31, 2020.[2] The primary source of bank data is the OSIRIS database provided by Bureau van Dijk. We collect market and financial data on banks, including stock prices at market closing.

We start with all 1649 banks for which stock data at the end of March 2020 and the main bank control variables ($X_{ic,Pre}$) are available.[3] We then remove those banks labelled "investment bank" as well as those in countries where the data on macroprudential policy and other key variables are not available. This leaves us with a sample of 981 banks. Our sample contains bank holding companies (BHC) and commercial, cooperative, Islamic, real estate and savings banks from 52 countries. The sample is diverse in terms of income groups and geographical areas. On average, we have information on 19 banks per country.

Macroprudential data are retrieved from a comprehensive survey—Global Macroprudential Policy Instruments—originally carried out by the IMF's Monetary and Capital Markets Department during 2013–14. The information from the survey was organized and documented in a cross-country database by Cerutti et al. (2017). The database covers the period from 2000 to 2013, based on the original survey, and was updated up to 2017. Thus, the latest available year is 2017 covering 12 macroprudential instruments: (1) loan to value ratio (LTV), which constrains highly levered mortgage loans by requiring higher down payments; (2) debt to income ratio (DTI), which constrains household indebtedness; (3) limits on foreign currency loans (FC), which reduces vulnerability to movements in the foreign exchange rate; (4) limits on domestic currency loans (CG), which aims to curb rapid credit growth directly; (5) reserve requirement ratio (RR), which constrains a bank's capacity to extend loans; (6) limits on interbank exposures (INTER), which restrains the fraction of liabilities held by the banking sector or by individual banks; (7) countercyclical capital buffer requirement (CTC), which requires banks to hold more capital than they otherwise would during upturns; (8) dynamic loan loss provisioning (DP), which requires banks to hold more loan loss-provisions during upturns; (9) leverage ratio (LEV), which prevents bank liabilities from exceeding a certain level vis-à-vis the corresponding assets and equity; (10) capital surcharges on systematically important financial institutions (SIFI), which require "too-big-to-fail" institutions to adhere to a higher capital level than others; (11) concentration limits (CONC), which restricts the fraction of assets held by a limited number of borrowers; and (12) tax on financial institutions (TAX), which reduces revenues and retained earnings of financial institutions.

For each of these twelve policy measures, Cerutti et al. (2017) create a yearly, binary variable assigned a value of one if the measure was activated (or was in place), and zero otherwise. Note that this dummy variable does not capture the inten-

[2] The sharpest decline in stock prices due to the COVID-19 crisis occurred in March 2020. March 31, 2020 was the date the latest data were available at the time of commencing this research.

[3] In order to retain a reasonable sample size, when stock price data at the end of March 2020 are not available for a few banks, we use the last available data from the previous week. Also, for control variables, when the 2019 data are not available in some cases, we use the data for 2018 (or earlier years).

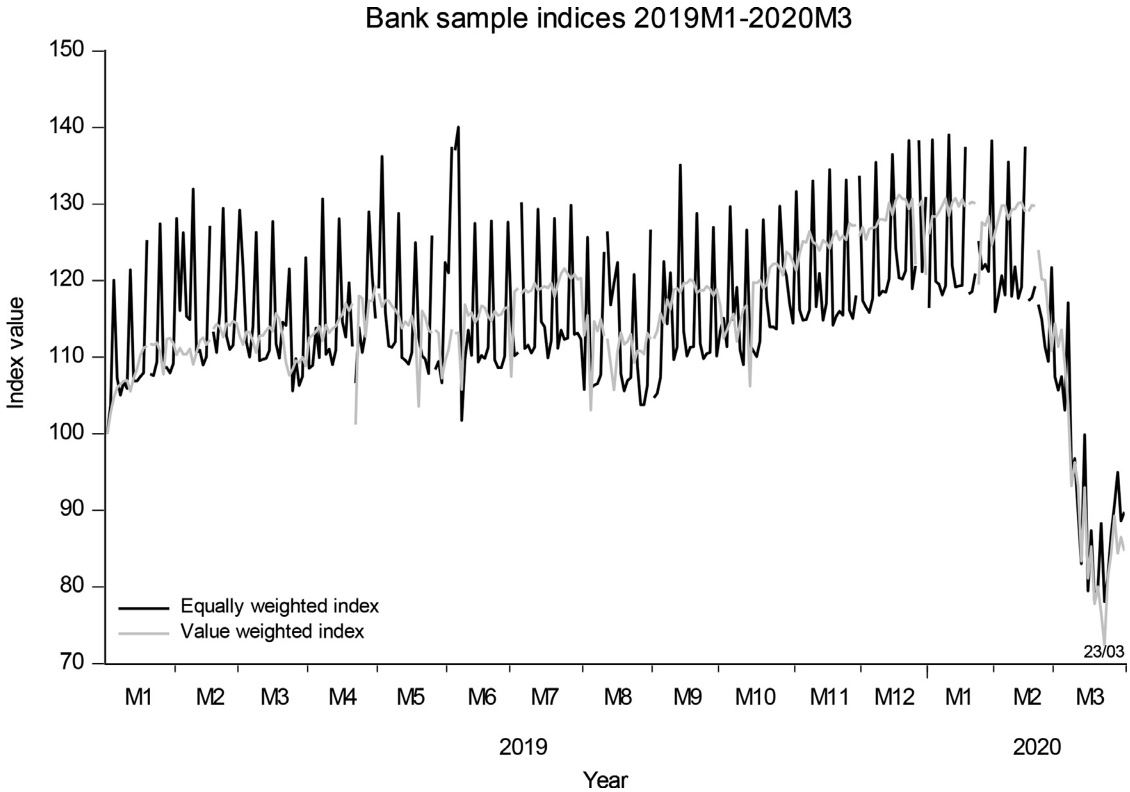

Fig. 1. Equally weighted and value-weighted indices of bank stock returns.

sity or the change of intensity of the instrument per se. Following Cerutti et al. (2017), we aggregate these measures according to the following two categories: (1) Demand, which is the sum of the scores on the two instruments LTV and DTI, aimed at strengthening borrowers' financial positions, and (2) Supply, which is the sum of the scores on the remaining ten instruments, which are more closely focused on the lenders. These aggregations reflect potential interactions within each category. For instance, as Claessens et al. (2013) point out, LTV and DTI could be substitutes in the sense that both can dampen borrowers' debt obligations, at the same time, they can complement each other. MP is an overall aggregate index of macroprudential policies, i.e., the sum of scores of all twelve instruments. For a given country, the value of Demand is between 0 and 2. Similarly, the value of Supply ranges from 0 to 10 and the value of MP from 0 to 12.

The data on other variables are retrieved from the World Bank and other sources and detailed in Appendix.

3.3. Descriptive evidence

As a preliminary way of exploring the data, in this section we provide some graphical and descriptive evidence on how the pandemic affected bank stock returns.

We look at the pattern of bank stock prices over time. Fig. 1 plots two series constructed for our sample of 981 banks from January 1, 2019 to March 31, 2020: equally-weighted index and value-weighted index using market capitalization as weights. The adverse impact of the crisis on bank stock prices emerged around mid-February 2020 and became more pronounced in March 2020. The lowest point is on the 23rd of March, when prices stood roughly 30% lower than their level in January 2019. We can also conjecture that the stock price movement for larger banks (indicated by the value-weighted index) is less volatile than that for their smaller counterparts.

The descriptive statistics for the variables used in the baseline analyses are presented in Table 1. As shown in Panel A, the mean change in log stock prices (StockReturn) is -36%, with a relatively high standard deviation of 25%. Regarding MP, countries activated, on average, 4.55 measures in 2017 with a standard deviation of 1.62 and a range running from 1 to 10. Examining the components of macroprudential policy reveals that countries used about 3.84 tools on the supply side (Supply) and 0.71 tools on the demand side (Demand). In Panel B, we present the mean values of the stock returns between countries at the bottom 25th percentile in terms of utilization of macroprudential policies and countries at the top 75th percentile. It is noteworthy that banks located in countries with greater usage of macroprudential tools perform relatively better in terms of stock returns. Specifically, StockReturn is 4.8% higher in banks domiciled in the top 75th percentile countries.

Next, we turn to formal regression analyses to understand the nexus between the activation of macroprudential measures prior to the pandemic and the severity of the increase in perceived bank risk during the crisis.

4. Regressions

In this section, we present the main results based on Eq. (1) together with those obtained in its variations, including those that employ a different bank risk indicator, and robustness tests.

4.1. Baseline results

Table 2 presents the baseline results for the specification with 4 bank-level control variables and 12 country-level control variables.[4] The dependant variable is ***StockReturn***. The coefficients of

[4] Note that multicollinearity among the independent variables is unlikely to be a problem. The variance inflation factor (VIF) ranges from 1 to about 6 for all variables

Table 1
Summary statistics.

Panel A: Summary statistics of all variables

Variable	N	Mean	S.D.	Min.	25 Perc.	Mdn.	75 Perc.	Max.
$\Delta Risk_{ic,Crisis}$								
StockReturn	981	-0.36	0.25	-1.47	-0.52	-0.37	-0.2	0.72
$MP_{c,Pre}$								
Total	52	4.55	1.62	1	4	4	5	10
Supply	52	3.84	1.32	0	3	4	4	8
CG	52	0.17	0.37	0	0	0	0	1
RR	52	0.14	0.35	0	0	0	0	1
DP	52	0.17	0.37	0	0	0	0	1
SIFI	52	0.82	0.39	0	1	1	1	1
CONC	52	0.96	0.19	0	1	1	1	1
FC	52	0.22	0.41	0	0	0	0	1
LEV	52	0.51	0.5	0	0	1	1	1
CTC	52	0.04	0.19	0	0	0	0	1
INTER	52	0.64	0.48	0	0	1	1	1
TAX	52	0.18	0.38	0	0	0	0	1
Demand	52	0.71	0.77	0	0	1	1	2
DTI	52	0.23	0.42	0	0	0	0	1
LTV	52	0.48	0.5	0	0	0	1	1
$X_{ic,Pre}$: BankControls (4)								
Size [log]	981	15.87	2.36	7.38	14.51	15.8	17.34	22.11
Beta	981	0.77	0.52	-2.81	0.38	0.82	1.11	3.17
Momentum	981	0.13	0.65	-0.92	-0.07	0.09	0.24	16.55
Tobin Q	981	0.24	0.89	0	0.06	0.12	0.2	21.6
$Z_{c,Pre}$: CountryControls (12)								
A-Channel of transmission								
Trade openness	52	57.71	43.3	27.54	27.54	43.02	66.57	326.2
FDI	52	1.62	2.7	-9.6	1.26	1.26	2.05	22.53
B- Pandemic vulnerability								
Bed / population	52	2.85	2.1	0.3	1.5	2.9	2.9	13.4
Share affected	52	0.71	0.05	0.47	0.69	0.71	0.73	0.87
C- Pandemic severity								
Death / population	52	1.35	3.46	0	0.05	0.27	1.18	20.57
Stringency	52	77.9	12.35	38.89	72.69	73.61	87.04	100
D- Broad macro conditions								
Foreign exchange regime	52	2.86	1.19	1	2	3	4	5
Current account	52	-1.01	4.51	-11.11	-2.65	-2.39	0.36	17.87
Government debt	52	66.59	34.26	13.11	35.82	72.33	92.57	201.39
Foreign reserve	52	13.92	19.39	0.66	0.66	7.87	17.18	120
GDP growth	52	3.53	1.88	-0.56	2.42	2.93	5.15	7.86
Inflation	52	3.54	4.07	0.34	2.07	2.44	3.24	29.5

Panel B: Univariate comparison of high vs. low macroprudential policies

Variable	Low MP (25th percentile) (1)	High MP (75th percentile) (2)	diff. (3)=(2)-(1)
StockReturn	-0.379	-0.331	0.048***

Panel A presents descriptive statistics for main variables used in our analysis. Panel B presents a univariate comparison of bank stock returns between countries with high usage of macroprudential measures (that is the top 75th percentile) versus countries with low usage (that is the bottom 25th percentile). ***StockReturn*** is change in log of stock prices from Dec. 31, 2019 to Mar. 31, 2020. $\boldsymbol{MP_{c,Pre}}$ represents sum of all (or components: ***Supply*** and ***Demand***) macroprudential tools activated in country ***c*** in year 2017. See Appendix for detailed definition of variables. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Our sample includes 981 banks in 52 countries.

aggregate MP for 'Total' in column [1], 'Supply'-side in column [2], and 'Demand'-side in column [13] are shown together with those of the individual tools. Column [1] indicates that there is a significant positive association between MP and bank stock returns. It implies that banks benefit from ex-ante macroprudential actions that are likely to contribute to stabilising the banking sector during the pandemic. This is in line with Altunbas et al. (2018) and Meuleman and Vander Vennet (2020). The estimated coefficient in column [1] suggests that the usage of one extra macroprudential measure is associated, on average, with an increase in stock returns of 2.1% during the crisis. However, the perceived impact differs between two types of policy actions. We find a highly significant effect of supply-side instruments on stock returns in column [2]. This is contrasted with column [13], where the coefficient on the demand-side, or borrower-targeted, policy is statistically insignificant.

In terms of individual macroprudential tools, the results are mixed. We observe benefits arising from the implementation of limits on domestic currency loans (CG): column [3] shows the significant coefficient at the 1% level and, at 0.246, the largest in magnitude. The result is in line with Meuleman and Vander Vennet (2020), who find that credit growth limits exert a downward effect on individual bank risk.[5] Reserve requirement ratio (RR) is

and for all regressions in baseline results of Table 2. This is much less than 10, a commonly suggested cut-off number for multicollinearity.

[5] Meuleman and Vander Vennet (2020) also report that credit growth limits are associated with a perceived increase in *systemic linkage* risk and attribute this result to risk-shifting behaviour by European banks. Similarly, Cizel et al. (2016) show that exposure limits are more prone to strong substitution effects in accordance with a risk-shifting explanation. Altunbas et al. (2018) also argue that lending-oriented tools force banks to shift their exposures to certain types of counterparties. Banks

Table 2
Did macroprudential policies alleviate the adverse impact of COVID-19 on bank stock returns? Baseline results.

	Total	Supply											Demand		
		Total	CG	RR	DP	SIFI	CONC	FC	LEV	CTC	INTER	TAX	Total	DTI	LTV
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]
MP	0.021**	0.034***	0.246***	0.109**	0.180***	-0.185**	0.223*	0.071	0.079	0.039	-0.048	-0.004	-0.002	0.016	-0.030
	(2.126)	(2.685)	(4.393)	(2.058)	(3.595)	(-2.399)	(1.960)	(1.281)	(1.475)	(0.394)	(-0.843)	(-0.080)	(-0.093)	(0.393)	(-0.619)
BankControls (4)															
Size	-0.016**	-0.016**	-0.013**	-0.014**	-0.015**	-0.014**	-0.015**	-0.015**	-0.016**	-0.015**	-0.013**	-0.015**	-0.015**	-0.015**	-0.015**
	(-2.587)	(-2.649)	(-2.668)	(-2.291)	(-2.572)	(-2.547)	(-2.397)	(-2.433)	(-2.474)	(-2.292)	(-2.219)	(-2.298)	(-2.294)	(-2.327)	(-2.280)
Beta	-0.125***	-0.126***	-0.125***	-0.128***	-0.129***	-0.115***	-0.129***	-0.130***	-0.124***	-0.125***	-0.131***	-0.125***	-0.125***	-0.124***	-0.124***
	(-4.771)	(-4.877)	(-4.958)	(-5.038)	(-5.001)	(-4.741)	(-4.884)	(-4.971)	(-4.616)	(-4.638)	(-4.603)	(-4.659)	(-4.645)	(-4.592)	(-4.673)
Momentum	-0.057**	-0.056**	-0.053*	-0.059**	-0.057**	-0.053*	-0.057**	-0.057**	-0.055**	-0.056*	-0.057**	-0.056*	-0.055*	-0.056*	-0.055*
	(-2.120)	(-2.122)	(-1.850)	(-2.381)	(-2.244)	(-1.874)	(-2.130)	(-2.116)	(-2.018)	(-1.998)	(-2.054)	(-2.005)	(-1.983)	(-2.003)	(-1.941)
Tobin Q	0.007	0.006	0.009**	0.007	0.007	0.008	0.006	0.007	0.007	0.007	0.008	0.007	0.007	0.007	0.007
	(1.153)	(1.137)	(2.484)	(1.257)	(1.127)	(1.528)	(1.028)	(1.374)	(1.124)	(1.153)	(1.519)	(1.191)	(1.189)	(1.171)	(1.168)
CountryControls (12)															
A-Channel of transmission															
Trade openness	0.001	0.001	0.001	0.001	0.001	-0.001	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000
	(0.984)	(1.265)	(1.139)	(1.047)	(0.863)	(-1.135)	(0.764)	(0.403)	(1.030)	(0.401)	(0.512)	(0.526)	(0.512)	(0.559)	(0.491)
FDI	-0.011	-0.012	-0.012*	-0.010	-0.011	0.003	-0.010	-0.009	-0.010	-0.007	-0.009	-0.009	-0.009	-0.009	-0.008
	(-1.587)	(-1.646)	(-1.695)	(-1.487)	(-1.609)	(0.396)	(-1.401)	(-1.231)	(-1.321)	(-0.821)	(-1.231)	(-1.201)	(-1.215)	(-1.301)	(-1.111)
B- Pandemic vulnerability															
Bed / population	0.020	0.020	0.022**	0.023*	0.022*	0.021*	0.029**	0.017	0.024	0.022	0.024	0.021	0.021	0.020	0.020
	(1.456)	(1.508)	(2.048)	(1.748)	(1.753)	(1.779)	(2.129)	(1.164)	(1.634)	(1.560)	(1.597)	(1.555)	(1.523)	(1.486)	(1.524)
Share affected	-0.796	-0.788	-0.362	-0.934**	-0.696*	-0.603	-0.846*	-0.699	-0.995*	-0.741	-0.774	-0.769	-0.761	-0.781	-0.771
	(-1.614)	(-1.639)	(-0.874)	(-2.108)	(-1.724)	(-1.497)	(-1.788)	(-1.386)	(-1.912)	(-1.518)	(-1.643)	(-1.618)	(-1.609)	(-1.654)	(-1.662)
C- Pandemic severity															
Death / population	0.001	0.002	0.004	0.002	0.003	-0.001	0.002	0.001	0.003	0.001	0.003	0.000	0.000	0.001	0.001
	(0.183)	(0.310)	(0.591)	(0.221)	(0.398)	(-0.170)	(0.266)	(0.143)	(0.424)	(0.091)	(0.322)	(0.044)	(0.041)	(0.093)	(0.148)
Stringency	-0.005*	-0.005**	-0.007***	-0.004	-0.006**	-0.005**	-0.004*	-0.004*	-0.005*	-0.004*	-0.004*	-0.004*	-0.004*	-0.004*	-0.005*
	(-1.983)	(-2.249)	(-3.180)	(-1.662)	(-2.245)	(-2.019)	(-1.913)	(-1.909)	(-1.983)	(-1.730)	(-1.772)	(-1.693)	(-1.746)	(-1.866)	(-1.817)
D- Broad macro conditions															
Foreign exchange regime	-0.054	-0.055	-0.036	-0.064*	-0.046	-0.065**	-0.069*	-0.059	-0.056	-0.064	-0.055	-0.063*	-0.063*	-0.061*	-0.065*
	(-1.433)	(-1.459)	(-1.179)	(-1.911)	(-1.310)	(-2.156)	(-1.804)	(-1.565)	(-1.450)	(-1.603)	(-1.483)	(-1.687)	(-1.736)	(-1.684)	(-1.780)
Current account	-0.012	-0.013	-0.007	-0.011	-0.007	-0.005	-0.013*	-0.010	-0.012	-0.012	-0.010	-0.011	-0.011	-0.011	-0.011
	(-1.542)	(-1.660)	(-1.192)	(-1.438)	(-1.263)	(-0.856)	(-1.684)	(-1.264)	(-1.550)	(-1.353)	(-1.375)	(-1.439)	(-1.446)	(-1.427)	(-1.432)
Government debt	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.030)	(-0.183)	(-0.185)	(-0.161)	(0.296)	(-0.535)	(-0.283)	(-0.105)	(-0.338)	(-0.204)	(-0.072)	(-0.170)	(-0.179)	(-0.162)	(-0.343)
Foreign reserve	0.003	0.003	0.002	0.003	0.002	0.004**	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	(1.537)	(1.605)	(1.253)	(1.538)	(1.233)	(2.068)	(1.603)	(1.648)	(1.506)	(1.358)	(1.497)	(1.517)	(1.540)	(1.523)	(1.498)
GDP growth	0.009	0.004	0.007	0.008	0.022	0.005	0.015	0.006	0.010	0.011	0.019	0.012	0.012	0.013	0.011
	(0.350)	(0.165)	(0.307)	(0.312)	(0.989)	(0.239)	(0.600)	(0.219)	(0.383)	(0.436)	(0.799)	(0.467)	(0.463)	(0.515)	(0.437)
Inflation	0.003	0.004	0.005	0.003	0.000	0.002	0.009	0.003	0.004	0.004	0.004	0.004	0.004	0.003	0.004
	(0.699)	(0.913)	(0.984)	(0.485)	(0.079)	(0.251)	(1.529)	(0.536)	(0.640)	(0.619)	(0.572)	(0.580)	(0.595)	(0.531)	(0.546)
Constant	0.733	0.745	0.455	0.860*	0.662	0.934**	0.602	0.772	0.951*	0.777	0.721	0.800	0.799	0.810	0.868
	(1.397)	(1.453)	(1.134)	(1.731)	(1.588)	(2.321)	(1.248)	(1.445)	(1.737)	(1.513)	(1.495)	(1.581)	(1.549)	(1.578)	(1.650)
Bank type FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	981	981	981	981	981	981	981	981	981	981	981	981	981	981	981
Adj. R^2	0.333	0.341	0.375	0.332	0.359	0.350	0.334	0.328	0.328	0.321	0.323	0.320	0.320	0.321	0.321

Table 3
Coefficient stability - test for omitted variable bias.

		Total	Supply				
			Total	CG	RR	DP	SIFI
		[1]	[2]	[3]	[4]	[5]	[6]
Full model	β_1	0.0207	0.0343	0.2465	0.1086	0.1797	-0.1854
(Table 2)	R^2	0.352	0.36	0.393	0.351	0.377	0.369
Restricted model	β_1	0.0185	0.0277	0.2275	0.0657	0.1759	-0.1456
(no country-level controls)	R^2	0.261	0.266	0.314	0.255	0.216	0.281
Oster Delta (R^{max}=1)		-1.3	-0.8	-1.7	-0.4	-12.2	-0.6
Oster Delta (R^{max}=1.3*R^{full})		-8.1	-4.5	-8.7	-2.3	-67.3	-3.7

This table reports the results of the coefficient stability test of Oster (2019). $\boldsymbol{\beta}_1$ is the coefficient of macroprudential variable, the one that is significant at the conventional level in Table 2, along with the associated R-squared, obtained by estimating Eq. (1) in a restricted version (omitting all country-level control variables) and in a full model (as presented in Table 2). The Oster Delta statistic represents the degree of selection on unobserved variables relative to that on observed variables, where we set $\boldsymbol{R^{max}} = 1.3 * \boldsymbol{R^{full}}$ or $\boldsymbol{R^{max}} = 1$. Note that $\boldsymbol{R^{max}}$ is described as the R-squared for a speculative regression that contains unobserved confounders.

positive and significant at the 5% level. Altunbas et al. (2018) also find a positive effect of a tightening of reserve requirements. Dynamic loan loss provisioning (DP) exhibits a positive effect at the 1% significance level. Concentration limits (CONC) also have a positive coefficient but this is only marginally significant at the 10% level.

Contrary to expectations, we find a negative significant association of capital surcharges on systematically important banks (SIFI) with bank returns, and an insignificant effect of other capital-related tools, such as leverage ratio and countercyclical buffer. This does not necessarily imply that capital regulation is not related to financial stability (see, e.g., Baker and Wurgler 2015). For instance, it is argued that SIFI is unlikely to bring new information to the market whereas countercyclical buffers may be anticipated by the market participants and, hence, have a limited effect, if any. Further, the tightening of these tools may come on top of already strong capital regulation under Basel III. Most banks hold capital buffers in excess of the regulatory minimum, hence the market may be less sensitive to additional capital buffers or may even interpret them as excessive regulatory burden and a potential threat to profitability. For example, Reinhardt and Sowerbutts (2015) find that, following tighter capital regulation, those banks that are not subject to new regulation increase their lending due to their competitive advantage. An excess of capital above the optimal level may also increase the social cost imposed on banks and jeopardise banks' profits. In line with these arguments, Moenninghoff et al. (2015) find a negative stock price reaction to new announcements of regulation on globally, systemically, important banks although the official designation of banks as "globally, systemically, important" itself has a partially offsetting positive effect. Meuleman and Vander Vennet (2020) also find a negative relationship between the bank systemic-linkage component of risk and unweighted capital ratios.

With respect to the control variables, the bank-level controls are relatively well-determined with similar signs and magnitudes across specifications. Larger banks, as well as those with higher Beta and higher stock returns in the pre-crisis period, are likely to experience lower returns. Tobin's Q is positive, as expected, but not statistically significant. Country-level control variables generally lack statistical significance, yet more or less consistently point to a larger decline in stock returns in countries that had less healthcare system capacity, greater share of employment in affected sectors, and more stringent lockdowns, and, to a lesser extent, a more flexible exchange rate regime.

4.2. Robustness checks

4.2.1. Omitted variables

We acknowledge that, although we control for a range of country-level variables, it might still be the case that some unobservables explain the relationship we document between (pre-crisis) macroprudential policy and bank stock returns during the COVID-19 crisis. Our findings may be biased due to omitted variables that may be correlated with macroprudential regulations and subsequently with stock price performance. For instance, in countries where supervisory quality is better or where fiscal space is available to respond to the pandemic or its repercussions for the banks, macroprudential policy stance might also be more stringent and, coincidentally, banks would be perceived to be more resilient.

In order to address this concern (and given the impossibility of controlling for every potential observable factor), we formally check for the stability of coefficients, applying the methodology introduced by Altonji et al. (2005), recently developed by Oster (2019), and also utilized by Claessens et al. (2021) with regard to macroprudential policies. Here, we rely on the changes that observables make to the coefficients of interest when moving from a restricted model (when we exclude all country-level covariates) to a full model. If these changes are substantial, it is likely that inclusion of more controls (i.e., unobservable factors) would reduce the estimated effect even further. If it is trivial, we can be more assured in proposing a causal interpretation to the estimated relationship. Oster (2019) argues that one should scale the coefficient movements by the observed increase in $\boldsymbol{R}^2$ in order for the change to be informative.

Table 3 reports the coefficients of macroprudential variables, those that are significant at the conventional level in Table 2, along with the associated R^2 obtained by estimating Eq. (1) in a restricted version (omitting all country-level control variables) and in a full model (as presented in Table 2). We find that the full model increases the magnitude of the coefficient, while R^2 increases from about 8% to 16%, depending on the proxy used for macroprudential policy. This result indicates that, holding other factors constant, unobservables bias our coefficient toward zero (similar to the case in Claessens et al. 2021). Therefore, the estimated effects are likely

may indeed avoid this type of macroprudential instruments by reallocating credit or increasing their exposure to other asset classes that are not subject to regulation.

Table 4
Sensitivity tests.

	Stock Return2	Stock Return3	MP (ave. 2016–17)	MP (ave. 2009–17)	Excluding advanced economies	Excluding BHC	Only commercial banks	Including other bank controls	Controlling for quality of regulation
# of regressions	6 [1]	6 [2]	6 [3]	6 [4]	6 [5]	6 [6]	6 [7]	6 [8]	6 [9]
MP (Total)	0.016**	0.032***	0.019**	0.019*	0.023**	0.027***	0.032***	0.036***	0.029**
	(2.254)	(4.026)	(2.131)	(1.732)	(2.662)	(2.940)	(3.558)	(4.897)	(2.084)
MP (Supply)	0.027***	0.048***	0.033***	0.014	0.035***	0.043***	0.046***	0.054***	0.037**
	(3.015)	(4.077)	(2.726)	(0.540)	(2.824)	(3.517)	(3.717)	(5.920)	(2.243)
CG	0.193***	0.296***	0.246***	0.156*	0.257***	0.247***	0.270***	0.257***	0.233***
	(4.736)	(6.957)	(4.267)	(1.743)	(5.292)	(4.757)	(5.615)	(7.862)	(4.503)
RR	0.093**	0.136**	0.088*	0.056	0.117**	0.115**	0.130***	0.117*	0.118*
	(2.636)	(2.116)	(1.727)	(0.972)	(2.125)	(2.273)	(2.703)	(1.722)	(1.981)
DP	0.160***	0.108**	0.180***	0.177***	0.165***	0.197***	0.202***	0.173***	0.006
	(4.277)	(2.494)	(3.595)	(3.435)	(2.826)	(4.619)	(5.080)	(4.638)	(0.096)
SIFI	-0.165***	0.081	-0.157*	-0.141	-0.152**	-0.188**	-0.201**	-0.062	-0.098
	(-2.817)	(0.952)	(-1.776)	(-0.812)	(-2.301)	(-2.573)	(-2.615)	(-1.049)	(-1.447)
Bank type FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
(per regression) Obs.	980	887	981	981	454	592	473	650	826
(average) Adj. R^2	0.371	0.389	0.345	0.331	0.430	0.377	0.369	0.418	0.294

This table reports the results estimating $\Delta \boldsymbol{Risk}_{ic,\ Crisis} = \beta_0 + \beta_1.\boldsymbol{MP}_{c,Pre} + \gamma.\boldsymbol{X}_{ic,Pre} + \mu.\boldsymbol{Z}_{c,Pre} + \omega_s + \omega_R + \varepsilon_{ic,Crisis}$ where $\boldsymbol{i}$ and $\boldsymbol{c}$ denote bank $\boldsymbol{i}$ and country $\boldsymbol{c}$. $\Delta \boldsymbol{Risk}_{ic,\ Crisis}$ is the change in bank risk, computed as a change in the log of stock prices in bank $\boldsymbol{i}$ in country $\boldsymbol{c}$ from Dec. 31, 2019 to Mar. 31, 2020, namely ***StockReturn*** (in columns [1] and [2] the dependant variable is computed alternatively: ***Stockreturn***2 and ***StockReturn***3 respectively, as defined in Appendix). $\boldsymbol{MP}_{c,Pre}$ represents sum of all (or components) macroprudential tools activated in country $\boldsymbol{c}$ in year 2017 (or average of 2016–17 in column [3] or average 2009–17 in column [4]). $\boldsymbol{X}_{ic,Pre}$ and $\boldsymbol{Z}_{c,Pre}$ are a vector of pre-crisis bank-specific and country-specific variables, respectively. Bank controls (4): Size, Beta, Momentum, and Tobin Q. Country controls (12): Trade openness, FDI, Bed / population, Share affected, Death / population, Stringency, Foreign exchange regime, Current account, Government debt, Foreign reserve, GDP growth, and Inflation. ω_s and ω_R denote the dummies for bank type $\boldsymbol{s}$ and region $\boldsymbol{R}$. See Appendix for detailed definition of variables. Regressions are estimated using OLS. The statistical inferences are based on robust standard errors (associated t-values reported in parentheses) clustered at the country-level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Our sample includes 981 banks in 52 countries. The main text contains a more detailed description.

to be conservative, resulting in negative figures for Oster delta as presented at the bottom of Table 3.

4.2.2. Sensitivity tests

We conduct a range of sensitivity tests by focusing on the macroprudential tools that are found to be significant at least at the conventional level of 5% in the baseline results in Table 2: namely, CG (limits on domestic currency loans), RR (reserve requirement), DP (dynamic provisioning) and SIFI (capital surcharges on large banks). For each sensitivity test in columns [1]–[9] in Table 4, we run 6 regressions covering MP (Total), MP(Supply), CG, RR, DP and SIFI. This makes a total of 54 regressions. For the sake of brevity, Table 4 only presents the coefficients on macroprudential policy variables.[6] The reported adjusted R-sq. is the average of 6 regressions.

A reasonable concern is that the results are driven by our choice for measurement of stock returns. Therefore, we check whether alternative measures corroborate our findings. We use two different time dimensions for stock returns as the dependant variable. The one in column [1] (***StockReturn***2) is the change in stock prices between the pre-crisis period average of November and December in 2019 and the crisis period average of February and March in 2020, and the other one in column [2] (***StockReturn***3) is the stock return based on the price on December 31, 2019 and that on March 23, 2020—the worst day in terms of stock price declines following the COVID-19 pandemic declaration. In terms of the macroprudential policy indices (MP), we alter the activation period: column [3] uses the annual average for 2016 and 2017, which reduces the impact of outliers, and column [4] the annual average between 2009 and 2017, which characterises the 2008 post-global-financial-crisis period. The findings broadly corroborate the baseline results. In particular, the coefficients on CG, RR and DP remain positive and significant whereas SIFI has a negative coefficient although its statistical significance is somewhat weaker. The results in columns [3] and [4] appears to indicate the persistent effect of CG and DP tools but a potentially more fleeting impact of SIFI.

Next, in order to check the presence of possible heterogeneity in the effectiveness of macroprudential tools, we estimate the model for subsamples of those banks and countries that may share certain common factors in columns [5], [6] and [7]. For emerging market economies, reactions to macroprudential policy instruments may diverge from those in advanced economies; the more widespread use of macroprudential policies in emerging market economies may be a key driver of the findings. Hence, we constrain the sample to banks operating only in emerging market economies in column [5]. Pooling information only from countries with similar experiences could also greatly reduce concerns about possible omitted variables (Demirgüç-Kunt et al. 2013). Further, if macroprudential tools are expected to limit a certain behaviour, then only banks currently engaging in such behaviour will be bound by the new restrictions and need to undertake curative action. This may then manifest itself as heterogeneous risk-reducing effects of the instruments across different bank business models. Column [6] excludes BHC (bank holding companies) and column [7] uses only commercial banks. The findings remain intact, and actually we observe statistically stronger results in terms of both magnitude and significance level of the coefficients as compared with those in Table 2. For instance, the coefficient of RR is 0.109 at the 5% significance level in Table 2 and 0.130 at the

[6] See the Online Supplement for detailed regression results regarding Table 4 and also the subsequent tables presented in this paper.

1% level in column [7]. This may, in part, reflect the fact that the emerging market economies have historically utilised macroprudential policies more frequently than advanced economies and that BHC are arguably less regulated than commercial banks. Therefore, the exclusion of advanced economies and BHC from the sample may have increased the sensitivity of stock returns to the activation of macroprudential policy tools.

We further elaborate on the issue of omitted variable bias by including more controls. Firstly, we consider the fact that the response to changes in macroprudential tools differs amongst banks depending on their balance sheet characteristics (Altunbas et al. 2018). We add to the model the bank-specific variables of capitalization, liquidity, efficiency and profitability—commonly used CAMEL components for bank health (see, e.g., Boubakri et al. 2017). When large, unpredictable, adverse shocks to equity markets occur—as was the case with the pandemic—investors would judge healthier banks as being better able to absorb shocks and thus the stock prices of these banks would not fall as much as fragile banks (Demirgüç-Kunt et al. 2013). The selected variables are computed as follows. Capitalization is proxied by the ratio of equity to total assets, where well-capitalized banks face lower risk of failure, have greater ability to cope with risks, and fare better during a crisis in terms of stock returns (Beltratti and Stulz 2012; Demirgüç-Kunt et al. 2013; Kapan and Minoiu 2018). Bank liquid assets to total assets ratio is used for ***Liquidity***. A rise in the holding of liquid assets lowers the volume of risky assets and reduces the risk of a run by investors (Demirgüç-Kunt et al. 2013; Igan and Mirzaei 2020). The degree of ***Efficiency*** is a measure of the quality of bank management.[7] If managers are capable of minimizing costs during normal times, they may also be better able to manage portfolios during crises. Therefore, efficient banks in pre-crisis periods are expected to be resilient during financial crises (Assaf et al., 2019). The return on equity is specified as Profitability, which is one of the factors to affect the level of stock returns at the firm level (Balvers et al. 2017). The data for these variables are collected from the OSIRIS database for the year 2019. Column [8] shows that the results remain the same except for the coefficient on SIFI, which is no longer statistically significant.[8]

Secondly, we augment the model with a control for the quality of regulation, using bank supervisor power as a proxy. We use the data from the latest survey on bank regulation and supervision of the World Bank. This indicator captures the extent to which the supervisory authorities are able to authorise their specific actions, taking values between 0 and 14. The higher values imply more supervisory power in preventing aggressive risk-taking behaviour and may influence the performance of banks, in particular when faced with external shocks. The estimation result with this additional control variable is reported in column [9], which is supportive of the main finding on credit growth limits but less so of the ones concerning the other macroprudential instruments.[9]

4.2.3. Instrumental variable (IV) strategy

We make an attempt to re-estimate the model with instrumental variables (IV), which enable us to account explicitly for possible endogeneity. This requires instruments that are correlated with macroprudential regulations but uncorrelated directly with stock price performance. We consider three instruments: credit-to-GDP gaps, central bank authority in activating macroprudential policy, and a proxy for the quality of the institutional environment.

Borio and Lowe (2002) describe the usefulness of credit-to-GDP gaps as an early warning indicator for banking crises. Drehmann and Tsatsaronis (2014) also point to the prominent role of the credit-to-GDP gap as a guide for policymakers, highlighting that the gap is a robust proxy for the build-up of financial vulnerabilities. Using the data series on domestic credit to GDP over the period 1990–2017 from the World Bank and the BIS, we apply the Hodrick-Prescott filter to calculate the deviation of the credit-to-GDP ratio from a long-term trend. We then use the values of the gap for 2017 as the instrument.[10]

Gadatsch et al. (2018) argue that a politically independent institution, such as a central bank, is more likely to adopt a politically sensitive macroprudential tool. Lim et al. (2013) also find that countries are likely to activate macroprudential policies in a timely manner if a strong authority is held by the central bank. In order to capture this concept, we utilise the following field in the IMF's 2017 Macroprudential Policy Survey Database: Institutional Aspects of Macroprudential Frameworks – Designated Macroprudential Authority. The score is 3 if the central bank is the designated authority, 2 if the central bank shares the power with another agency and 1 if the central bank is not involved. Beyond de jure designation of an authority, how well the designated authority can execute its responsibilities would depend on the overall institutional quality. Hence, we complement the information from the IMF survey with data on the institutional environment quality retrieved from the World Bank's World Governance Indicators Database, also as of 2017, based on the "voice and accountability" field.

We report the IV estimates in Table 5. Three tests for the relevancy and validity of the selected instruments are presented at the bottom of the table. Neither the first-stage F statistics nor the LM χ^2 indicate issues of under-identification or weak instruments in almost all cases. For the Hansen over-identification test, in which the null hypothesis implies the validity of the instruments, the J statistics tests do not reject the null in all but one. The estimated effect of macroprudential policy is consistent with the baseline result, with slightly larger coefficients than those obtained in Table 2.

4.3. Alternative risk indicators

The decline in the return of a particular stock (the dependant variable used so far) has the advantage of being forward looking, high frequency, and readily available in most cases. Yet, it may capture individual risk only under certain conditions and, hence, provide an imperfect proxy measure of probability of bank failure and financial stability. This is because changes in stock prices reflect a multitude of factors, and a negative equity return could indicate either that the value of the underlying asset has declined or that asset volatility has declined. While the former would be bad news for debtholders, the latter would be good news. Hence, it is important to look at other measures that could more directly capture the probability of default. Furthermore, one aim of activating macroprudential measures is to reduce the contribution of an individual bank to the risk of the banking system as a whole, thereby reducing the likelihood of a system-wide crisis. Bank stock returns are likely not suitable to capture such systemic risk.

To address the limitations of the dependant variable in our baseline and to demonstrate the relevance of our findings for probability of bank failure and financial stability, we employ a range

[7] Following Barth et al. (2013) and Chortareas et al. (2013), we derive the efficiency scores using non-parametric data envelopment analysis (DEA).

[8] We note a caveat in the interpretation of column [8]: the state of bank balance sheets in 2019 may have been affected by macroprudential policy actions undertaken in 2017.

[9] See the Online Supplement for the extension of the sensitivity tests together with additional robustness checks (including an alternative macroprudential policy dataset).

[10] The results remain unchanged if we use domestic credit to GDP or the change in domestic credit to GDP in 2017, instead of the credit-to-GDP gap.

Table 5
IV strategy (using gap of domestic credit/GDP in 2017, CB authority, and Voice in 2017 as instruments).

	Total	Supply				
		Total	CG	RR	DP	SIFI
	[1]	[2]	[3]	[4]	[5]	[6]
MP	0.051**	0.061**	0.377***	0.262***	0.260**	-0.387**
	(2.216)	(2.463)	(4.052)	(2.727)	(2.223)	(-2.196)
BankControls (4)						
Size	-0.019***	-0.018***	-0.012**	-0.012**	-0.015***	-0.012**
	(-2.902)	(-2.901)	(-2.537)	(-2.105)	(-2.672)	(-2.537)
Beta	-0.124***	-0.126***	-0.125***	-0.133***	-0.130***	-0.103***
	(-4.671)	(-4.930)	(-5.030)	(-5.252)	(-5.040)	(-4.368)
Momentum	-0.058**	-0.057**	-0.051*	-0.065***	-0.058**	-0.050*
	(-2.396)	(-2.290)	(-1.817)	(-2.928)	(-2.435)	(-1.789)
Tobin Q	0.006	0.006	0.010***	0.007	0.007	0.009*
	(1.120)	(1.116)	(3.193)	(1.377)	(1.122)	(1.939)
Constant	0.642	0.706	0.276	0.952*	0.603	1.084***
	(1.122)	(1.344)	(0.679)	(1.894)	(1.464)	(3.520)
Bank type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	981	981	981	981	981	981
F-value (first stage)	4.47***	8.88***	6.58***	18.28***	4.30***	2.81**
Instruments relevance (LM χ2)	6.36*	11.96***	8.14**	13.92***	6.29*	5.25
J-statistics (p-value)	0.160	0.190	0.226	0.312	0.115	0.039

This table reports the results estimating $\Delta \text{Risk}_{\text{ic, Crisis}} = \beta_0 + \beta_1.\text{MP}_{\text{c,Pre}} + \gamma.\text{X}_{\text{ic,Pre}} + \mu.\text{Z}_{\text{c,Pre}} + \omega_{\text{s}} + \omega_{\text{R}} + \varepsilon_{\text{ic,Crisis}}$ where i and c denote bank i and country c. $\Delta \text{Risk}_{\text{ic, Crisis}}$ is the change in bank risk, computed as a change in the log of stock prices in bank i in country c from Dec. 31, 2019 to Mar. 31, 2020, namely StockReturn. $\text{MP}_{\text{c,Pre}}$ represents sum of all (or components) macroprudential tools activated in country c in year 2017. $\text{X}_{\text{ic,Pre}}$ and $\text{Z}_{\text{c,Pre}}$ are a vector of pre-crisis bank-specific and country-specific variables, respectively. Country controls (12): Trade openness, FDI, Bed / population, Share affected, Death / population, Stringency, Foreign exchange regime, Current account, Government debt, Foreign reserve, GDP growth, and Inflation. ω_{s} and ω_{R} denote the dummies for bank type s and region R. Regressions are estimated using IV approach where instrument variables are the credit-to-GDP gap, bank authority in activating macroprudential measures, and voice and accountability. See Appendix for detailed definition of variables. The statistical inferences are based on robust standard errors (associated t-values reported in parentheses) clustered at the country-level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Our sample includes 981 banks in 52 countries.

of different measures to account for other dimensions of bank risk. Specifically, we construct five other idiosyncratic risk indicators (other than stock returns), following the literature on macroprudential policies, as well as two systemic risk indicators, as follows:

The Z-score is defined as the sum of equity-to-assets ratio and return on assets (ROA), divided by the standard deviation of ROA ($\boldsymbol{\sigma}(\boldsymbol{ROA})$). We estimate $\boldsymbol{\sigma}(\boldsymbol{ROA})$ over a 6-quarter rolling time window. Higher figures denote lower (insolvency) risk. We use the change in log Z-score between 2019Q1 and 2020Q1.

Distance-to-default (DTD) reveals how far away a firm is from default. It is a volatility adjusted leverage measure that accounts for differences in the capital structure of financial institutions through an adjustment method put forward by Duan (2010). Higher figures denote lower risk. We use the change in DTD between December 2019 and March 2020.

Probability of default (PD) reflects the default risk of publicly-listed firms by quantitatively analysing numerous covariates that cover market-based and accounting-based, firm-specific attributes, as well as macro-financial factors. The forward intensity model of Duan et al. (2012) is used for estimating the PD. We use predictions for a horizon of 12 months. Higher figures denote higher risk. We use the change in PD between December 2019 and March 2020.

Impaired loans as a percentage of total equity capital come directly from the balance sheets. Higher figures denote higher (credit) risk. We use the change in impaired loans as a share of equity between 2019Q1 and 2020Q1.

Bank stock return volatility is used as a proxy for total risk, to the extent that it reflects not only bank-specific factors but also systemic factors (e.g., Anginer et al. 2014). Higher figures denote higher (total) risk. We use the log standard deviation of daily stock returns in March 2020.

The marginal expected shortfall (MES) is used to gauge the contribution of each individual bank to the risk of the whole banking system (Anginer et al. 2014). MES is the expected loss an equity investor of a bank would experience if the larger market declined significantly. We compute MES as the average bank daily stock return when the corresponding country market return is less than 3%. Higher figures denote lower (systemic or tail) risk. We use the average for 2020Q1.

Finally, we use the CDS spreads, which mirror the spread between risky and riskless floating debt (Hasan et al. 2016; Acharya et al., 2017). CDS spread is the quarter-end CDS quote. Higher figures denote higher (insolvency) risk. We have to modify Eq. (1) as the data are available for only 98 banks. We discuss this shortly.

The sources of all these alternative risk indicators are reported in Appendix.

We now formally check the sensitivity of our baseline findings to using alternative risk indicators. Table 6 presents the results of Eq. (1) where the dependant variables are Δ(Z-score), Δ(DTD), Δ(PD), Δ(ImpLoan/Equity), Volatility, and MES, respectively, and

Table 6
Alternative risk indicators.

	Δ(Z-score)	Δ(DTD)	Δ(PD)	Δ(ImpLoan / Equity)	Volatility	MES
# of regressions	6	6	6	6	6	6
	[1]	[2]	[3]	[4]	[5]	[6]
MP (Total)	0.026***	0.112***	-0.001*	-0.006*	-0.059***	0.001
	(3.435)	(3.818)	(-1.756)	(-1.992)	(-2.677)	(0.482)
MP (Supply)	0.029***	0.160***	-0.001*	-0.007*	-0.072**	0.002
	(2.775)	(4.196)	(-1.850)	(-1.844)	(-2.588)	(1.326)
CG	0.056	0.316	-0.007***	-0.039*	-0.382***	0.014**
	(1.555)	(1.544)	(-3.921)	(-1.790)	(-3.434)	(2.482)
RR	0.149***	0.577***	0.001	-0.017	-0.163	0.020***
	(3.276)	(3.401)	(0.366)	(-1.067)	(-1.320)	(3.174)
DP	0.061	0.324	-0.001	-0.033**	-0.162	0.001
	(1.021)	(1.268)	(-0.579)	(-2.295)	(-1.577)	(0.161)
SIFI	0.022	0.367	0.003	0.040*	-0.030	-0.007
	(0.331)	(1.438)	(1.329)	(1.756)	(-0.273)	(-0.816)
Bank type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
(per regression) Obs.	782	703	711	551	975	934
(average) Adj. R^2	0.079	0.418	0.486	0.065	0.557	0.274

This table reports the results estimating $\Delta\text{Risk}_{\text{ic, Crisis}} = \beta_0 + \beta_1.\text{MP}_{\text{c,Pre}} + \gamma.\text{X}_{\text{ic,Pre}} + \mu.\text{Z}_{\text{c,Pre}} + \omega_\text{s} + \omega_\text{R} + \varepsilon_{\text{ic,Crisis}}$ where i and c denote bank i and country c. $\Delta\text{Risk}_{\text{ic, Crisis}}$ is a proxy for bank risk (or change in bank risk), an alternative to StockReturn. $\text{MP}_{\text{c,Pre}}$ represents sum of all (or components) macroprudential tools activated in country c in year 2017. $\text{X}_{\text{ic,Pre}}$ and $\text{Z}_{\text{c,Pre}}$ are a vector of pre-crisis bank-specific and country-specific variables, respectively. Bank controls (4): Size, Beta, Momentum, and Tobin Q. Country controls (12): Trade openness, FDI, Bed / population, Share affected, Death / population, Stringency, Foreign exchange regime, Current account, Government debt, Foreign reserve, GDP growth, and Inflation. ω_s and ω_R denote the dummies for bank type s and region R. See Appendix for detail definition of variables. Regressions are estimated using OLS. The statistical inferences are based on robust standard errors (associated t-values reported in parentheses) clustered at the country-level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Our sample includes 981 banks in 52 countries. Sample size reduces because not all alternative risk indicators are available for all banks.

the control variables are the same as in the baseline regressions. We find that the total MP index is associated with higher Z-score and DTD but lower PD and impaired loans as well as lower volatility. These findings are in line with the interpretation that higher stock returns for banks in countries with more active usage of macroprudential tools could reflect market-participants' perception that the risk profile of these banks is more favourable. As before, the individual, macroprudential component driving this finding appears to be credit growth limits (in particular, with regard to probability of default, impaired loans, and volatility) and reserve requirements (specifically, with regard to Z-score and distance to default). A noteworthy observation is that the coefficient on SIFI does not always have the expected sign and is only marginally significant in the specification with impaired loans as the dependant variable.

Interestingly, we do not find the overall MP index to have a significant relation with MES. Turning to the individual components, however, we detect a positive significant link with credit growth limits and reserve requirements. This suggests that the contribution of a bank to systemic risk is lower where these macroprudential tools are activated.

With regard to the CDS spread, we have data for only 98 banks in 26 countries (compared to 981 banks in 52 countries in the baseline regressions). Given the large number of regressors in the baseline Eq. (1), we cannot apply the same model by using the CDS spread as the dependant variable. Since we have quarterly data (from 2018Q1 to 2020Q3), we modify Eq. (1) to be more compatible with this risk indicator, as follows:

$$\begin{aligned}\boldsymbol{CDS\ Spread_{ict}} = {} & \beta_0 + \beta_1.\boldsymbol{Trend_t} + \beta_2.\boldsymbol{COVID_t} \\ & + \beta_3.\boldsymbol{COVID_t} \times \boldsymbol{MP_{c,2017}} \\ & + \boldsymbol{\gamma}.\boldsymbol{X_{ict-1}} + \boldsymbol{\mu}.\boldsymbol{COVID_t} \times \boldsymbol{Y_{c,2017}} + \boldsymbol{w_c} + \end{aligned} \quad (2)$$

where $\boldsymbol{i}$, $\boldsymbol{c}$ and $\boldsymbol{t}$ denote bank $\boldsymbol{i}$, country $\boldsymbol{c}$, and quarter $\boldsymbol{t}$. The dependant variable is the natural logarithm of (5-year) CDS spreads in basis points. $\boldsymbol{COVID_t}$ is a dummy that takes the value of 1 for quarters 2020Q1–Q3 and 0 otherwise. In order to isolate the impact of the COVID-19 event from long-term trends, we include a linear $\boldsymbol{Trend}$ variable in the model. $\boldsymbol{MP_{c,2017}}$ is a proxy for macroprudential tools activated in 2017, as in Eq. (1). $\boldsymbol{X_{ict-1}}$ is a vector of bank-level control variables that are lagged by one quarter. $\boldsymbol{Y_{c,2017}}$ is a vector of country-level control variables in 2017. In selecting controls, we follow Hasan et al. (2016), where we specify $\boldsymbol{w_c}$ to control for all country time-invariant factors. If $\boldsymbol{\beta_3}$ is negative and significant, we can interpret that the CDS spread for banks, located in countries which utilised more macroprudential measures, are affected less adversely by the pandemic.

Table 7 reports the results of this alternative specification, Eq. (2), while including bank-specific control variables in columns [1]–[6] and both bank- and country-level factors in columns [7]–[12]. We find that CDS spreads increase less when COVID strikes in countries where more macroprudential tools have been activated prior to the crisis. This corroborates our baseline findings. Notably, of the individual components with a statistically significant coefficient at conventional levels, all but SIFI retains the statistical significance. This suggests that the observed negative impact of SIFI on bank stock returns has to do with investors' expectations of profitability rather than the probability of default of these banks, as it would have otherwise been captured in the CDS spreads.[11]

[11] The findings reported in Table 7 remain unaltered when we use the Oxford stringency index as a proxy for the severity of the COVID-19 pandemic, instead of a *COVID* dummy.

Table 7
Alternative risk indicator - CDS spread.

	Total	Supply					Total	Supply				
		Total	CG	RR	DP	SIFI		Total	CG	RR	DP	SIFI
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
$Trend_t$	-0.032***	-0.031***	-0.032***	-0.032***	-0.032***	-0.031***	-0.032***	-0.032***	-0.032***	-0.032***	-0.032***	-0.031***
	(-4.346)	(-4.337)	(-4.360)	(-4.395)	(-4.402)	(-4.353)	(-4.289)	(-4.291)	(-4.320)	(-4.340)	(-4.325)	(-4.294)
$COVID_t$	0.489***	0.455***	0.331***	0.333***	0.346***	0.318***	1.230***	1.455***	1.282***	1.386***	1.114***	1.220***
	(5.867)	(5.454)	(7.326)	(7.941)	(7.899)	(3.468)	(4.459)	(4.703)	(3.884)	(5.003)	(3.842)	(4.002)
$COVID_t \times MP_{c,\ 2017}$	-0.035***	-0.035**	-0.193***	-0.184***	-0.143***	-0.004	-0.029	-0.049**	-0.269***	-0.543***	-0.129**	-0.090
	(-2.885)	(-2.692)	(-4.599)	(-3.309)	(-3.148)	(-0.042)	(-1.493)	(-2.363)	(-3.345)	(-3.265)	(-2.557)	(-0.818)
$COVID_t \times Y_{c,\ 2017}$	×	×	×	×	×	×	√	√	√	√	√	√
Constant	1.395**	1.401**	1.398**	1.371**	1.393**	1.414**	1.315**	1.300**	1.283**	1.268**	1.303**	1.303**
	(2.273)	(2.291)	(2.266)	(2.235)	(2.266)	(2.257)	(2.159)	(2.157)	(2.145)	(2.124)	(2.152)	(2.140)
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	634	634	634	634	634	634	634	634	634	634	634	634
Adj. R^2	0.751	0.751	0.751	0.751	0.751	0.750	0.750	0.751	0.751	0.751	0.750	0.750

This table reports the results estimating $\text{CDS Spread}_{ict} = \beta_0 + \beta_1.\text{Trend}_t + \beta_2.\text{COVID}_t + \beta_3.\text{COVID}_t \times \text{MP}_{c,2017} + \gamma.\text{X}_{ict-1} + \mu.\text{COVID}_t \times \text{Y}_{c,2017} + \text{w}_c + \varepsilon_{ict}$ where i, c and t denote bank i, country c and quarter t. The dependant variable is the natural logarithm of (5-year) CDS spreads in basis points. $COVID_t$ is a dummy that takes 1 for quarter 2020Q1-Q3 and 0 otherwise. Trend is a trend variable. MP is a proxy for macroprudential tools activated in 2017. X_{ict-1} is a vector of bank-level control variables (Size, NPL, Equity, ROA, Cost, Liquidity, Z-score, Fee income, Fund cost, Tier1, and Earning per share), with a one-quarter lag. $Y_{c,2017}$ is a vector of country-level control variables (Concentration, Activity restriction, Financial conglomerate restriction, Deposit insurance, Stock price volatility, Stock market return, GDP growth, and Inflation), measured in 2017. w_c represents country time-invariant fixed effects. Regressions are estimated using OLS. The statistical inferences are based on robust standard errors (associated t-values reported in parentheses) clustered at the country-level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Our sample includes 98 banks in 26 countries.

5. Conclusion

The global financial crisis in 2007–08 highlighted the importance of financial stability and the need for macroprudential policies to achieve that objective, as the critical priority. Our paper analyses their effectiveness in containing perceived bank risk, when faced with a new global crisis in the form of a pandemic. The empirical work exploits the cross-sectional variation in macroprudential policy usage before the crisis in a large panel of 981 banks operating in 52 economies.

We find that macroprudential policy tends to lower bank risk as assessed by stock market investors during COVID-19. This is consistent with existing literature which finds effectiveness of macroprudential policy in reducing the build-up of vulnerabilities in the upswing. We confirm that this is also true for pre-crisis activation of macroprudential instruments.

When we examine the effect of the individual instruments, a decrease in perceived bank risk seems to stem primarily from curbs on bank lending such as credit growth limits. This highlights the fact that the major risk banks face due to COVID is the potential for massive defaults by businesses and households. Those banks with less exposure to a rapid expansion of loans to the private sector due to macroprudential policy tightening may better withstand such a shock. This is contrasted with the insignificant or negative effect of the capital-related instruments on bank stock returns, in particular surcharges on systemically important institutions, though there is little evidence that this is directly related to an increase in the probability of default. Looking forward, our results call for a careful calibration of macroprudential regulations in order to avoid inadvertent consequences.

Appendix

Table A1: Definition and sources of all variables.

Variable	Definition	Source
$\Delta\text{Risk}_{ic,Crisis}$		
StockReturn	The change in log stock prices from December 31, 2019, to March 31, 2020. Higher figures denote lower risk.	Bureau van Dijk, OSIRIS, and own calculation.
StockReturn2	The change in log stock prices from average November and December, 2019, to average February and March, 2020.	"
StockReturn3	The change in log stock prices from December 31, 2019, to March 23, 2020.	"
$\text{MP}_{c,Pre}$		
(total)	Sum of macroprudential instruments activated (i.e. sum of 12 macroprudential tools: CG, RR, DP, SIFI, CONC, FC, LEV, CTC, INTER, TAX, DTI and LTV) in a country in year 2017. See the context for more information.	Cerutti et al. (2017) - 2018 updated dataset.
(Supply)	Sum of the following instruments (CG, RR, DP, SIFI, CONC, FC, LEV, CTC, INTER, and TAX), which capture financial institutions-based policies.	"
(Demand)	Sum of those instruments (DTI and LTV ratios) aimed at borrowers' leverage and financial positions.	"
$\text{X}_{ic,Pre}$: BankControls (4)		
Size	Natural logarithm of a bank total assets in year 2019.	Bureau van Dijk, OSIRIS.
Beta	Bank's equity beta from a market model of weekly returns in excess of three-month T-bills from January 20019 to December 2019, where the market is represented by the value-weighted CRSP index.	
Momentum	The stock return for each bank from December 31, 2018, to December 31th, 2019.	Bureau van Dijk, OSIRIS, and own calculation.
Tobin Q	Total market value of common equity divided by total book value of assets in year 2019.	Bureau van Dijk, OSIRIS.
$\text{Z}_{c,Pre}$: Country Controls (12)		
Trade openness	Total exports and imports as % of GDP in year 2019.	World Bank - WDI.
FDI	Foreign direct investment, which refers to direct investment equity flows in the reporting economy, as % of GDP in year 2019.	"
Bed / population	The number of hospital beds available for every 1000 inhabitants in a population in year 2019 or the most recent available year.	World Health Organisation.
Share affected	The share of employment prone to a pandemic, estimated by applying for each country the equation *Share affected_c=Sum(w_j*Employment_j) / sum(Employment_j)*, where *w_j* is Dingel and Neiman's (2020) share of jobs cannot be done at home in sector j, using NAICS classification at the 2-digit level. *Employment_j* is number of employees in sector *j*. We use the firm-level data for year 2019.	Bureau van Dijk, OSIRIS, and own estimation.
Death / population	Number of confirmed COVID death per 100,000 population in March 31st, 2020.	Johns Hopkins University.
Stringency	The country-level severity of the lockdown measures in response to the pandemic. This is a composite measure of the scale of school closures, workplace closures and travel bans based on the data on the 31st March 2020. The indicator is normalised to be from 0 to 100 with the score100 being the strictest.	Hale et al. (2020).
Foreign exchange regime	The de facto classification of a country foreign exchange regime for the latest available year of 2016. The classification ranges from 1-6 with 6 being the most freely floating regime.	Ilzetzki et al. (2019)
Current account	The ratio of the current account balance to GDP in year 2019.	World Bank - WDI.
Government debt	The ratio between a country's government debt and its gross domestic product in year 2019.	IMF Global Debt Database.
Foreign reserve	The foreign exchange reserves as % of GDP in year 2019.	World Bank - WDI.
GDP Growth	The real annual growth of GDP in year 2019.	"
Inflation	Inflation measured by consumer price index (CPI) is defined as the yearly change in the prices of a basket of goods and services in year 2019.	"
Other bank control variables: CAMEL		
Capitalization	Bank core capital (Tier 1) ratio in year 2019.	Bureau van Dijk, OSIRIS.
Liquidity	The natural log of bank liquid assets to total assets ratio in year 2019.	"
Efficiency	Bank efficiency score in year 2019, using DEA approach. See the context for more information.	"
Profitability	Return on equity, computed as net profits before tax as a percentage of total equity of a bank in year 2019.	"
Quality of regulation		
Bank supervisory power	Supervisory power captures whether the supervisory authorities have the authority to take specific actions to prevent and correct problems. It takes value between 0 and 14, with higher values indicating more power. The data are for the 2012 (latest) survey.	World Bank Surveys on Bank Regulation.
Alternative MP dataset (iMaPP) - See the Online Supplement		
LCG	Limits on growth or the volume of aggregate credit, the household-sector credit, or the corporate-sector credit by banks, and penalties for high credit growth.	The IMF's iMaPP database, constructed by Alam et al. (2019).
LOANR	Loan restrictions, that are more tailored than those captured in "LCG". They include loan limits and prohibitions, which may be conditioned on loan characteristics (e.g., the maturity, the size, the LTV ratio and the type of interest rate of loans), bank characteristics (e.g., mortgage banks), and other factors.	"
RR	Reserve requirements (domestic or foreign currency) for macroprudential purposes.	"
LFX	Limits on net or gross open foreign exchange (FX) positions, limits on FX exposures and FX funding, and currency mismatch regulations.	"

(*continued on next page*)

Appendix (*continued*)

Variable	Definition	Source
LTV	Limits to the loan-to-value ratios, including those mostly targeted at housing loans, but also includes those targeted at automobile loans, and commercial real estate loans.	"
SIFI	Measures taken to mitigate risks from global and domestic systemically important financial institutions (SIFIs), which includes capital and liquidity surcharges.	"
Alternative risk indicators		
Δ(Z-score)	Change in natural logarithm of Z-score between 2020Q1 and 2019Q1. The Z-score is defined as the summation of equity to assets ratio and return on assets (ROA) ratio, divided by the standard deviation of ROA (σ(ROA)). We estimate σ(ROA) over a 6-quarter rolling time window. Higher figures denote lower risk.	Authors' calculations using quarterly data from ORBIS database.
Δ(DTD)	Change in distance to default (DTD) indicator between Dec. 2019 and Mar. 2020. DTD reveals how far away a firm is from default. It is a volatility adjusted leverage measure based that accounts for differences in the capital structure of financial institutions through an adjustment method put forward by Duan (2010). Higher figures denote lower risk.	Credit Research Initiative – CRI, National University of Singapore.
Δ(PD)	Change in indicator of probability of default (PD) between Dec. 2019 and Mar. 2020. PD reflects the default risk of publicly listed firms by quantitatively analyzing numerous covariates that cover market-based and accounting-based firm-specific attributes, as well as macro-financial factors. We use a prediction for horizon of 12 months. Higher figures denote higher risk.	"
Δ(ImpLoan /Equity)	Change in bank impaired loans as a share of equity (which should be available to absorb losses) between 2020Q1 and 2019 Q1. Impaired loans are loans where it is unlikely that the full contractual principal and interest will be repaid. Higher figures denote higher risk.	ORBIS database.
Volatility	Natural logarithm of standard deviation of daily stock returns, using March 2020 stock data. Higher figures denote higher risk.	Bureau van Dijk, OSIRIS, and own calculation.
MES	Following Anginer et al. (2018), MES is the average bank daily stock return during the first quarter of year 2020 when market return decreases more than 3%. Higher figures denote lower risk.	Authors' calculations, using market stock data from Datastream, as constructed by the IMF researchers.
CDS Spread	Quarterly data using the natural logarithm of 5-year CDS spreads in basis points. CDS spread is the quarter-end CDS quote. Higher figures denote higher risk.	ORBIS database.

Declaration of Competing Interest

None.

CRediT authorship contribution statement

Deniz Igan: Visualization, Investigation, Writing – review & editing, Methodology, Data curation. **Ali Mirzaei:** Conceptualization, Methodology, Data curation, Investigation, Formal analysis, Writing – original draft. **Tomoe Moore:** Supervision, Visualization, Investigation, Writing – review & editing.

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The views expressed here are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or IMF Management. It also does not represent the position or opinions of the American University of Sharjah.

Supplementary materials

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