BOFIT Discussion Papers
13 • 2020

Alin Marius Andrieș, Anca Maria Podpiera and Nicu Sprincean

Central bank independence and systemic risk

BOFIT
THE BANK OF FINLAND INSTITUTE FOR ECONOMIES IN TRANSITION

BOFIT Discussion Papers
Editor-in-Chief Zuzana Fungáčová

BOFIT Discussion Papers 13/2020
12.6.2020

Alin Marius Andrieș, Anca Maria Podpiera and Nicu Sprincean: Central bank independence and systemic risk

ISBN 978-952-323-333-1, online
ISSN 1456-5889, online

Suomen Pankki
Helsinki 2020

Contents

Alin Marius Andrieș, Anca Maria Podpiera and Nicu Sprincean

Central bank independence and systemic risk

Abstract

We investigate the relationship of central bank independence and banks' systemic risk measures. Our results support the case for central bank independence, revealing that central bank independence has a robust, negative, and significant impact on the contribution and exposure of a bank to systemic risk. Moreover, the impact of central bank independence is similar for the stand-alone risk of individual banks. Secondarily, we study how the central bank independence affects the impact of selected country and banking system indicators on these systemic measures. The results show that central bank independence may exacerbate the effect of a crisis on the contribution of banks to systemic risk. However, central bank independence seems to mitigate the harmful effect of a bank's high market power on its systemic risk contribution.

Keywords: systemic risk; central bank independence; supervisory framework
JEL classification: G21; E58; G28

Alin Marius Andrieș, orcid.org/0000-0002-4415-4197. Alexandru Ioan Cuza University of Iasi.
E-mail: alin.andries@uaic.ro

Anca Maria Podpiera, orcid.org/0000-0002-6136-2385. World Bank. E-mail: apodpiera@worldbank.org

Nicu Sprincean, orcid.org/0000-0001-6815-0003. Alexandru Ioan Cuza University of Iasi.
E-mail: sprincean.nicu@uaic.ro

Acknowledgments
We thank Zuzana Fungacova and Razvan Vlahu for helpful comments on earlier drafts of the paper. The views expressed in this paper are those of the authors and do not reflect the views of Alexandru Ioan Cuza University of Iasi, the World Bank or its affiliated organizations. Part of this research was completed while Andrieș was a visiting researcher at the Bank of Finland Institute for Economies in Transition (BOFIT). The kind hospitality was greatly appreciated. Sprincean acknowledges financial support from the Romanian National Authority for Scientific Research and Innovation, *CNCS – UEFISCDI – Project PN-III-P1-1.1-TE-2016-1855.*

1 Introduction

> *No wonder politicians often find the Fed a hindrance. Their better selves may want to focus on America's long-term prosperity, but they are far more subject to constituents' immediate demands. That's inevitably reflected in their economic policy preferences. If the economy is expanding, they want it to expand faster; if they see an interest rate, they want it to be lower – and the Fed's monetary discipline interferes.*
>
> Alan Greenspan, 2007[1]

The 2007–2009 global financial crisis was followed by a low-inflation environment, aggressive use of unconventional monetary measures by central banks and an increased number of central bank responsibilities. These stirred up the debate about the importance of maintaining central bank independence (De Haan et al., 2018). Allegations of distributional effects across different segments of population generated by the unconventional measures[2] employed by the central banks and of central banks over-stretching their mandates in their response to the financial crisis escalated this debate (Mersch, 2017). We ask whether these new and revised mandates, particularly the financial stability mandate, are justifications for undermining the independence of central banks.

Central bank independence has been credited with maintaining price stability, and more recently, with helping in recovery from the financial crisis.[3] Indeed, independence is one of the three institutional underpinnings[4] to which the success of inflation targeting in delivering low and stable inflation rates has been attributed (Mishkin, 2004). A large empirical literature shows that inflation and central bank independence are negatively related in both developed and developing countries (Cukierman, 2008). Central bank independence is also recognized as a key factor for lower volatility of output (Bernanke, 2004). It is usually measured along two dimensions: political and economic independence.

Political independence refers to the central bank's discretion in designing and implementing policies consistent with the monetary stability goal. It shields the central bank from short-term political pressures. *Economic independence* relates to the freedom of the central bank for choosing the set of instruments consistent with monetary policy (Masciandaro and Romelli, 2015).

Recently, a significant number of reforms increased the range of powers of central banks in the areas of prudential supervision, financial stability and macroprudential policy, which, unlike

[1] Greenspan, A. (2007, pp. 110-111).
[2] The unconventional measures involved the purchasing of large amount of public debt in the secondary markets.
[3] Recent surveys are provided by Berger et al. (2001), Cukierman (2008), De Haan and Eijffinger (2016) and Fernández-Albertos (2015).
[4] The other two institutional underpinnings are: (i) clear mandate to maintain price stability and commitment to achieve that goal; (ii) central bank accountability (Mishkin, 2004).

monetary policy, can require the central bank to coordinate with the government and other regulatory institutions. This increases the challenge of preserving central bank independence.[5] In 2013, for example, the Bank of Japan agreed to coordinate policy with the government (Condon, 2019). Issing (2018) considers that "a permanent threat for independence relates to the coordination with fiscal policies." More than half of respondents in an expert survey agreed with the statement that there will be significant changes in the independence of monetary policy in the UK and the Eurozone in the foreseeable future (De Haan et al., 2017). Goodhart and Lastra (2018) add the rise in populism to the sources that dented the consensus for central bank independence.

This paper aims to contribute to the policy debate about the importance of maintaining central bank independence by analyzing empirically its significance for financial stability. The financial stability mandate for containing potential systemic risk returned to prominence after public authorities, both national and supranational, intervened during the financial crisis (Goodhart (2011); Capie and Wood, 2013).[6] While financial stability was already an element of most central bank mandates before the crisis, it was secondary to the prime objective of delivering price stability (Bolton et al, 2019). As an example, the Federal Reserve's role in financial system stability started in the late 1960s. Despite the stepping up of "unprecedented actions" during the 2007–2008 financial crisis, questions remained as to the proper scope and design of the mandate (Haltom and Weinberg, 2017).

Systemic financial risk measures developed in the wake of the crisis made it possible to quantify the contribution and exposure of banks to systemic risk, as well as improve the regulatory framework. In parallel, there has been major interest in assessing the determinants of systemic risk. Weiß et al. (2014) find little empirical evidence in favor of commonly identified factors such as bank size, leverage, non-interest income, and the quality of a bank's credit portfolio as determinants of systemic risk across financial crises. Instead, institutional structures and characteristics of the regulatory regimes seem to be the important factors.

While there is a substantial literature on the relationship of central bank independence (CBI) and inflation, studies on the nexus of financial stability and systemic risk are scarce. Cihak (2010) attributes this to the complex relationship of price stability and financial stability: while in the long run the price stability can be seen as an important component of the financial stability, in the short- and medium-term there can be trade-offs between these two mandates. Central banks also

[5] Toniolo and White (2015) provide a historical perspective of the financial stability mandate.
[6] It has been argued that systemic risk is a particular feature of financial systems (De Bandt and Hartmann, 2000). It emerges when all parts of the financial system, including multiple markets and institutions, are simultaneously distressed (Patro et al., 2013).

have less control over policy outcomes with respect to financial stability as they must share responsibilities with other agencies, hence it is unclear how more CBI affects financial stability. At the same time, greater CBI reduces the likelihood of political constraints or capture by financial sector players, and thereby confers time to take action to prevent a financial crisis. Restraining the influence of politicians on central bank policy removes the danger that a financial crisis can be used as an issue in the reelection campaign of the incumbent government (Keefer, 2001).

The theoretical work also presents mixed conclusions. In making the case for greater CBI, Ueda and Valencia (2014) find that if a central bank or macroprudential regulators are not politically independent, a social optimum is unachievable.[7] In contrast, Berger and Kißmer (2013) find that central bankers with greater independence are more likely to refrain from implementing preemptive monetary tightening to maintain financial stability.

There is a small body of empirical work analyzing the effect of CBI on financial stability, and more generally on the functioning of financial markets. Most of this literature supports a positive effect of the CBI. Khan et al. (2013) suggest that an increase in the autonomy of the central bank lowers the probability of a banking crisis.[8] In the same vein, Garcia-Herrero and Del Rio Lopez (2003) and Klomp and de Haan (2009) observe a positive relationship between the degree of central bank independence and financial stability. Doumpos et al. (2015) find that central bank independence exercises a positive impact on bank soundness. Empirical papers in this area offer mixed findings as to the impact of CBI on stock market performance. Förch and Sunde's (2012) results indicate a positive effect of CBI over stock market returns, while Papadamou et al. (2017) find that enhanced CBI increases stock market volatility. Using governor turnover as a proxy for limited actual independence, Moser and Dreher (2010) use governor turnover as a proxy for limited actual independence and show that higher turnover affects financial markets negatively. Kuttner and Posen (2010) also observe that the lack of independence of the central bank enhances the disruptive impact of the frequent appointments of central bank governors on exchange rates and bond yields.

To examine how the CBI affects banks' systemic risk, our approach looks at systemic risk from three angles: the contribution of banks to systemic risk, the exposure of banks to systemic risk, and the stand-alone risk of banks. Every central bank has its own set of objectives such as price stability, financial stability, or full employment. Such objectives may conflict on occasion (e.g. activist policy, countercyclical monetary policy). Our intuition is that a more independent central bank is better at pursuing its full palette of objectives.

[7] The "social optimum" described in the paper requires separating price and financial stability objectives.
[8] Arnone et al. (2009) argue that there is a difference between central bank independence (lack of institutional constraints) and central bank autonomy (operational freedom). These terms, however, are used interchangeably in the literature.

In addition, we contribute to the extant literature concerned with the determinants of the systemic risk by analyzing a global sample of banks which includes banks from both emerging and developed countries over an extensive period of time, thus enriching the current literature that tends to concentrate on developed countries (Broz, 2002; Pistoresi et al., 2011) or is mainly cross-sectional (Crowe and Meade, 2007). We also analyze how the central bank independence affects the impact of various country and banking system indicators on systemic risk. Our sample consists of 323 banks in 40 countries over a period of 14 years (2001–2014). This period comprises the dot-com crisis, the recent global financial crisis (2007–2009), and the sovereign debt crisis in Europe (2010–2013).

We document a negative and significant influence of central bank independence on major systemic risk measures (ΔCoVaR, SRISK, MES and VaR) computed for individual banks, i.e. central bank independence is desirable for maintaining financial stability. Our findings are robust after controlling for nesting and potential endogeneity issues. We further establish that central bank independence mitigates the systemic risk contribution of banks in environments where banks hold substantial market power. At the same time, the degree of central bank independence may exacerbate the effect of a crisis on the systemic risk exposure and contribution of banks. Hence, central bank coordination with fiscal policy is needed in resolving a financial crisis.

The remainder of our paper is structured as follows. In Section 2, we describe the methodology, sample and data employed. In Section 3, we discuss the empirical findings. Section 4 presents the concluding remarks.

2 Data, sample, and methodology

This section presents the data used and the econometric model. We explain the framework employed to estimate the impact of CBI on how much banks contribute to systemic risk and their exposure to systemic risk. We also describe our measures of CBI and systemic risk.

2.1 Sample and data

We analyze the potential impact of CBI on systemic risk in a panel framework using bank-level data for 14 years (2001–2014). The final sample in the regression analysis is composed of 323 publicly-listed banks with the mean size of USD 220 billion at the end of 2014. All banks are active at the international or national level, and represent 40 countries (Table A1 in the Appendix). The final sample is a refinement of an original sample comprising the 560 banks in 66 countries identified in Thomson Reuters Datastream as “global banks.”[9] We excluded banks that either failed to report

[9] Ticker G#LBANKSWD.

daily market capitalization consistently throughout the observation period or had more than 25% of their quarterly balance sheets missing in the Worldscope dataset.

2.2 Econometric framework

Our dataset clearly shows a hierarchical structure with individual banks nested in countries over a number of years. Similar to Doumpos et al. (2015), we employ a Hierarchical Linear Modeling (HLM) approach that considers the fact that the data have various levels of aggregation and control for potential dependency due to nesting effects. The HLM approach has been recently applied in cross-country studies that examine firm performance (Kayo and Kimura, 2011; Essen et al., 2013; Li et al., 2013; Marcato et al., 2018), as well as bank risk-taking and stability (Doumpos et al., 2015; Mourouzidou-Damtsa et al., 2019). It is appropriate for explaining the variance at all levels of aggregation and deals with the fact that there are inherent differences in banking systems in different countries. The practices of banks in Islamic countries that comply with Sharia law and business models may differ only nominally from conventional banking in some instances, and quite substantially in others. Financial markets provide the bulk of financing in the US, while in Europe and many Asian countries, the banking system plays a dominant role, so banks tend to be preferred by companies in raising project financing. Langfield and Pagano (2016) show that Europe is more prone to systemic risk because of its dependence on bank-based financial structure.

The model estimated has the following form:

$$SR_{ij,t} = \underbrace{\alpha_0 + \alpha_1 \times CBI_{j,t-1} + \gamma \times \boldsymbol{X}_{ij,t-1} + \delta \times \boldsymbol{Z}_{j,t-1}}_{fixed\ components} + \underbrace{u_{ij} + e_j + \varepsilon_{ij,t}}_{random\ components} \quad (1)$$

where $SR_{ij,t}$ is the systemic risk measure of bank *i* from country *j* in year *t* and $CBI_{j,t-1}$ is the main variable of interest that quantifies the degree of central bank independence, i.e. CBI index and its subcomponents (*personnel independence*, *central bank objectives*, *policy independence*, and *financial independence*), from country *j* in year *t-1.* For all banks, including the international banks, country *j* is the country where the bank is incorporated.[10]

$\boldsymbol{X}_{ij,t-1}$ is a $(k \times 1)$ vector of lagged bank-level control variables (bank size, credit risk ratio, capitalization, profitability and the funding structure) associated to systemic risk in the literature (Beck et al., 2006; Berger et al., 2009; Farhi and Tirole, 2012; Laeven et al., 2016; Xu et al., 2019).

[10] For international banks, we capture only the effect of the CBI index in the country where the banks are incorporated. We acknowledge that the CBI indices from the countries where they operate would have an effect on their SR measures, but we cannot account for this here.

$\boldsymbol{Z}_{j,t-1}$ is a $(k \times 1)$ vector that includes banking system variables (bank concentration and level of financial intermediation) associated with systemic risk in the banking sector (Boyd et al., 2006; Beck et al., 2017), standard country-level control variables (real GDP growth and inflation) and a variable that captures the degree of central bank involvement in microprudential supervision (with the maximum value assigned when all supervisory responsibilities are consolidated under the roof of the central bank). Melecky and Podpiera (2015) show that having banking supervision in the central bank can help prevent systemic banking crises, while Doumpos et al. (2015) show that central bank involvement in supervision has a positive impact on bank soundness.

Table A2 in the Appendix describes the variables and the sources of data. Table A3 presents the summary statistics. Table A4 shows the correlation matrix of the regressors.

We use lagged independent variables (except for crisis dummy variables) to control for the speed of adjustment of systemic risk indicators and to account for potential endogeneity issues (Melecky and Podpiera, 2013). The random variables u_{ij} and e_j allow the intercept $(\alpha_0 + u_{ij} + e_j)$ to be random and unique to every bank and country. $\varepsilon_{ij,t}$ is the error term. The model assumes the intercept is random and slopes are fixed. The model is fit using the maximum likelihood estimation (ML) of the variance components of Hartley and Rao (1967). To mitigate the problem of outliers, we winsorize all variables within the 1% and 99% percentiles.

In our analysis of whether CBI affects the impact of selected variables on measures of systemic risk, we focus on the effect of crisis (the 2007–2009 global financial crisis and sovereign debt crisis in Europe) and two relevant macroeconomic and banking system characteristics (market power in the banking system and exchange rate regime) by including these variables and their interaction with CBI in the benchmark regression. The model has the following specification:

$$SR_{ij,t} = \underbrace{\beta_0 + + \alpha_1 \times CBI_{ij,t-1} + \beta_1 \times CBI_{ij,t-1} \times \boldsymbol{W}_{j,t-1} + \delta \times \boldsymbol{Z}_{j,t-1} + \gamma \times \boldsymbol{X}_{ij,t-1}}_{fixed\ components} + \underbrace{u_{ij} + e_j + \varepsilon_{ijw,t}}_{random\ components} \quad (2)$$

where $\boldsymbol{W}_{j,t-1}$ is the vector of the three selected variable.

2.3 Measures of banks' systemic risk

It is recognized that all systemic risk measures fall short in capturing the multifaceted nature of systemic risk, and further that different measures of systemic relevance can lead to conflicting results in identification of systemically important financial institutions (Benoit et al., 2013). We therefore employ three measures of systemic importance estimated for each bank: (1) two measures of systemic risk contribution (ΔCoVaR and NSRISK); (2) a measure of systemic risk exposure, and (3) a measure of banks' individual (or stand-alone) risk.[11]

2.3.1 Systemic risk contribution

i) ΔCoVaR

The first indicator considered for systemic risk contribution is Conditional Value at Risk (CoVaR) of Adrian and Brunnermeier (2016). It is based on the well-known Value at Risk (VaR) measure that involves the estimation of each bank's q^{th} quantile of the following loss function:[12]

$$q = \Pr(R^{i}_{Market\ Assets,t}) \leq VaR^{i}_{q,t} , \tag{3}$$

where $R^{i}_{Market\ Assets,t}$ is the bank's i market value of assets at time t determined by adjusting the book value of total assets by the ratio between market capitalization (market value of equity) and the book value of equity:

We focus on the daily change of the market assets of institution i from t-1 to t. Because total assets and book equity have quarterly frequencies while market equity has a daily frequency, we transform the first two accounting measures into daily frequencies through linear interpolation between two consecutive quarters.[13] We eliminate banks that have missing total assets or equity data for two or more consecutive quarters.

VaR is the tail risk measure of individual risk of a bank used in the context of micro-prudential supervision. It therefore fails to capture the risk of the whole system. To assess contagion spillovers from a bank to the whole system in the case of a severe reduction of the market assets, we apply the CoVaR methodology. It implies the estimation of the system's q^{th} quantile of the returns distribution over a given period of time ($R^{System}_{Market\ Assets,t}$), conditioned on the event that each bank registers its maximum possible loss of returns for the same significance level. More precisely, we focus on the loss generated by the reduction of banks' market value of total assets under extreme events as in Adrian and Brunnermeier (2016):

$$q = \Pr(R^{System}_{Market\ Assets,q} \leq CoVaR_{q,t}^{System|R^{i}_{Market\ Assets,t}=VaR^{i}_{q,t}} | R^{i}_{Market\ Aseets,t} = VaR^{i}_{q,t}), \tag{4}$$

[11] Bisias et al. (2012) provide an extensive survey of 31 measures of systemic risk.
[12] Following Adrian and Brunnermeier (2016), all our systemic risk indicators are estimated for a 5% quantile.
[13] We perform cubic spline interpolations as a robustness check. The findings remain robust.

where system is defined by the market value of total assets of the sample. Thus, CoVaR is the VaR of the banking system when banks are in distress and thus a good indicator of tail-event linkages between financial institutions (Diebold and Yılmaz, 2014).

To compute VaR and CoVaR, we use the Quintile Regression (QR) developed by Koenker and Bassett (1978). This method allows us to estimate the dependent variable's quantiles conditioned on the explanatory variables. It is more robust in the presence of extreme market conditions (Nistor and Ongena, 2019). We use the method of Machado and Santos Silva (2013), which permits standard errors to be asymptotically valid in the presence of heteroskedasticity and misspecification.

The individual and systemic risks of the banks have a time-varying component, depending on different risk factors that affect the banking sector. Adrian and Brunnermeier (2016) propose the estimation of VaR and CoVaR to be conditioned on several market indices that incorporate information representative for the global financial markets. These indices are lagged one period to control for the speed of adjustment. The market indices we use are presented in Table A2 in the Appendix.

Each bank's VaR is computed using a linear model that captures the dependence of a bank's asset returns on lagged market indices (i.e. vector $\boldsymbol{MI}'_{t-1}$):

$$R^{i}_{Market\ Assets,t} = \alpha^{i} + \beta^{i} \times \boldsymbol{MI}'_{t-1} + \varepsilon^{i}\ , \tag{5}$$

where α^{i} is the constant (unobserved characteristics of bank *i*), β^{i} is a *(k × 1)* vector that captures the bank's *i* return dependence relationship with the market indices, and ε^{i} is an *iid* error term.

The return of the system can vary with each bank's return and with the lagged market indices as well:

$$R^{System}_{Market\ Assets,t} = \alpha^{System|i} + \delta^{System|i} \times R^{i}_{Market\ Assets,t} + \boldsymbol{MI}'_{t-1} \times \beta^{System|i} + \varepsilon^{System|i}_{t}, \tag{6}$$

where $\alpha^{System|i}$ is the constant, capturing the banking system characteristics conditioned on bank *i*, $\beta^{System|i}$ is a *(k × 1)* vector of coefficients that captures the system's return dependence relationship with the lagged market indices, $\delta^{System|i}$ reflects the conditional dependence of the system's return on bank's *i* return, and $\varepsilon^{System|i}$ is the *iid* error term.

Running regressions from Eq. (5) and Eq. (6) for a quantile of 5% (distressed periods) and a quantile of 50% (median or tranquil state), we obtain the value of regressors to be used in VaR and CoVaR estimations:

$$\widehat{VaR^{i}_{q,t}} = \widehat{\alpha^{i}_{q,}} + \boldsymbol{MI}'_{t-1} \times \widehat{\beta^{i}_{q}} \tag{7}$$

$$\widehat{CoVaR^{i}_{q,t}} = \alpha_{q}^{\widehat{System|i}} + \delta_{q}^{\widehat{System|i}} \times \widehat{VaR^{i}_{q,t}} + \boldsymbol{MI}'_{t-1} \times \beta_{q}^{\widehat{System|i}}. \tag{8}$$

In the end, each financial institution's contribution to systemic risk (ΔCoVaR) is defined as the difference between VaR of the whole system conditioned on the event that the financial institution registers the lowest return at a given confidence level and VaR of the whole system conditioned on the event that the financial institution faces the median return:

$$\Delta CoVaR_{q,t}^{System|i} = CoVaR_{q,t}^{System|R^i_{Market\ Assets}=VaR^i_{q,t}} - CoVaR_{q,t}^{System|R^i_{Market\ Assets}=VaR^i_{50\%}}. \quad (9)$$

A greater value of ΔCoVaR is associated with an enhanced contribution to overall systemic risk, and thus increased interconnectedness.

ii) SRISK

The second indicator considered for systemic risk contribution is based on the Systemic Risk Index (SRISK) introduced by Acharya et al. (2012) and extended to a conditional framework by Brownlees and Engle (2017). SRISK measures the contribution of a bank to wide systemic risk, defined as the loss of a specific bank in terms of capital shortfall, conditioned by the financial system being in distress. To the extent that SRISK captures a bank's performance conditional on the left tail of system returns is also close to capturing a bank's exposure to common shocks that affect the whole financial system (Laeven et al., 2016). However, as emphasized by Brownlees and Engle (2017), "when the economy is in a downturn, the bankruptcy of a firm cannot be absorbed by a stronger competitor," hence the obligations will extend to the financial and further to the real sector. The size of the capital shortfall of a bank during a systemic crisis determines how risky it is systemically.

We define the market as the MSCI World Financials index as in Bostandzic and Weiß (2018). SRISK is conveniently expressed in monetary units, thereby making it reliable in monitoring systemic risk contribution. It also accounts for differences in volatility between individual banks. The capital shortfall of bank *i* at time *t* is defined as:

$$CS_t^i = kA_t^i - E_t^i = k\left(L_t^i + E_t^i\right) - E_t^i \quad (10)$$

E_t^i is the market capitalization of the bank (market value of equity), L_t^i is the book value of total liabilities, A_t^i is the implied value of total assets, and *k* is the prudential capital ratio. As specified above, SRISK is the capital shortfall conditioned by a systemic event, which is the decline of the system below threshold *C* over time horizon *h*. Putting these altogether, we have the following expression:

$$SRISK_t^i = E_t\left(CS_{t+h}^i \middle| R_{t+1:t+h}^{System} < C\right) = kE_t\left(L_{t+h}^i \middle| R_{t+1:t+h}^{System} < C\right) - (1-k)E_t\left(E_{t+h}^i \middle| R_{t+1:t+h}^{System} < C\right). \quad (11)$$

Further, we assume that when a crisis defined by C hits the financial system, the debt cannot be renegotiated. It follows that:

$$SRISK_t^i = kL_t^i - (1-k)E_t^i(1 - LRMES_t^i) \tag{12}$$

$LRMES_t^i$ is the long-run marginal expected shortfall, i.e. the expectation of the bank equity multi-period return conditional on the systemic event. Following Brownlees and Engle (2017), we compute LRMES without (Monte Carlo) simulation as $1 - \exp(\log\ (1-d) \times beta)$, where d is the six-month crisis threshold for the market capitalization of the sample decline when set at 40%, and *beta* is the bank's beta coefficient. The capital prudential ratio *k* is set at 8% in accordance with the Basel Accords. SRISK is estimated using the GJR-GARCH framework with a two-step quasi-maximum likelihood estimation (QMLE). The SRISK indicator of a distressed institution is positive, thereby indicating insufficient working capital. A negative value, in contrast, indicates a capital surplus (no distress).

As in Berger et al. (2019), we normalize the SRISK of bank *i* from country *j* by its market capitalization and call the new measure NSRISK (Normalized SRISK), denoting the proportional capital shortfall per unit of market capitalization. This normalization ensures that the value of the systemic risk indicator is not driven by the market size (market capitalization) of individual banks. Although Acharya et al. (2012) recommend setting negative SRISK values to zero because they imply a capital surplus and do not contribute to systemic risk, we follow Laeven et al. (2016) and choose not to do so because this would result in a series with many zeroes that econometrically would be hardly to explain and result in biased estimations. Moreover, negative NSRISK values are useful in measuring the relative contribution of the banks to system-wide distress. Thus, our next approach is to construct two synthetic systemic risk measures using factor analysis that include NSRISK (see section 3.4), and the series that contain only zeroes (capital surplus only) will be discarded because they have zero variance.

Figure 1 shows the evolution of average banks' systemic risk contribution, defined by ΔCoVaR and NSRISK during the 2001–2014 period. One can observe that both ΔCoVaR and NSRISK increased during periods of distress such as the dot-com crisis and global financial crisis. However, the peaks differ for the two indicators, perhaps reflecting the differences between the two measures, with the ΔCoVaR closer to capturing contagion risks and NSRISK closer to capturing the exposure to common shocks affecting the whole financial sector. For ΔCoVaR, the peak is in 2008, the year associated with the Lehman Brothers default and onset of global financial crisis. For NSRISK, the peak is in 2011 when there was a sovereign debt crisis in Europe characterized by high government debt and high yield spreads in government securities. Continent-wise, European banks had the largest average contribution to systemic risk over the whole period, defined by NSRISK. Asian banks were the second largest in terms of average contribution. However, Australian banks were the most risky in terms of ΔCoVaR, followed by those from Europe.

In terms of average contribution to systemic wide-distress by country (Figure 2), French banks had the highest capital shortfall per unit of market capitalization in the 2001–2014 period, following by bank based in China and Germany. Banks based in the United Arab Emirates, Kuwait, and Qatar had the highest capital surplus per unit of market capitalization. As for ΔCoVaR, Belgian, Canadian and Australian banks were the main contributors, on average, to systemic risk, whereas the banks from Bahrain, Sri Lanka and Morocco contributed least to systemic risk.

Figure 1 Evolution of average systemic risk contribution by year

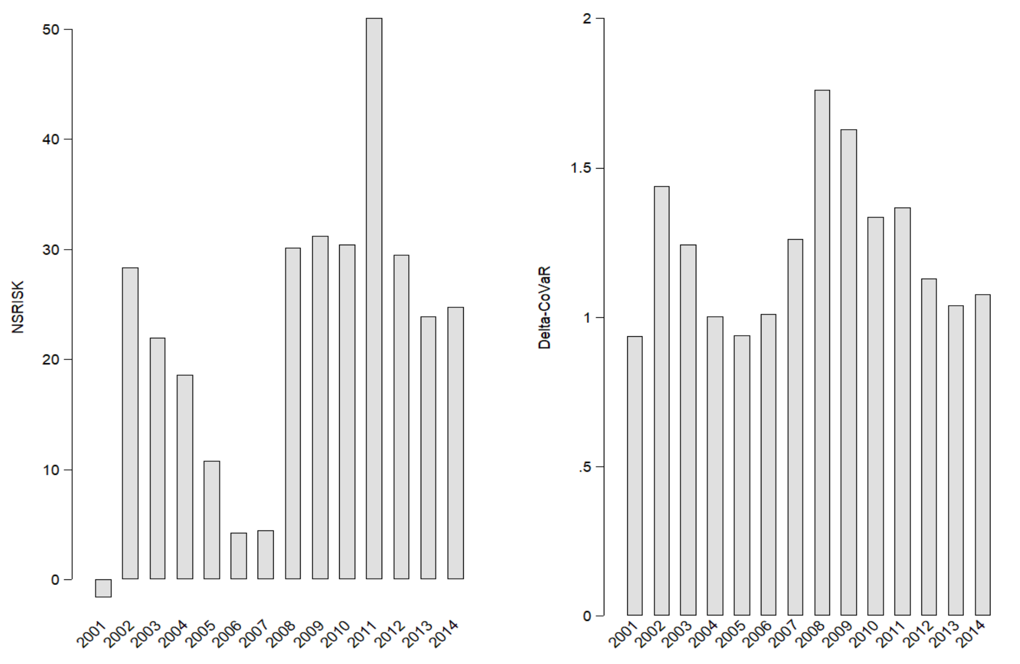
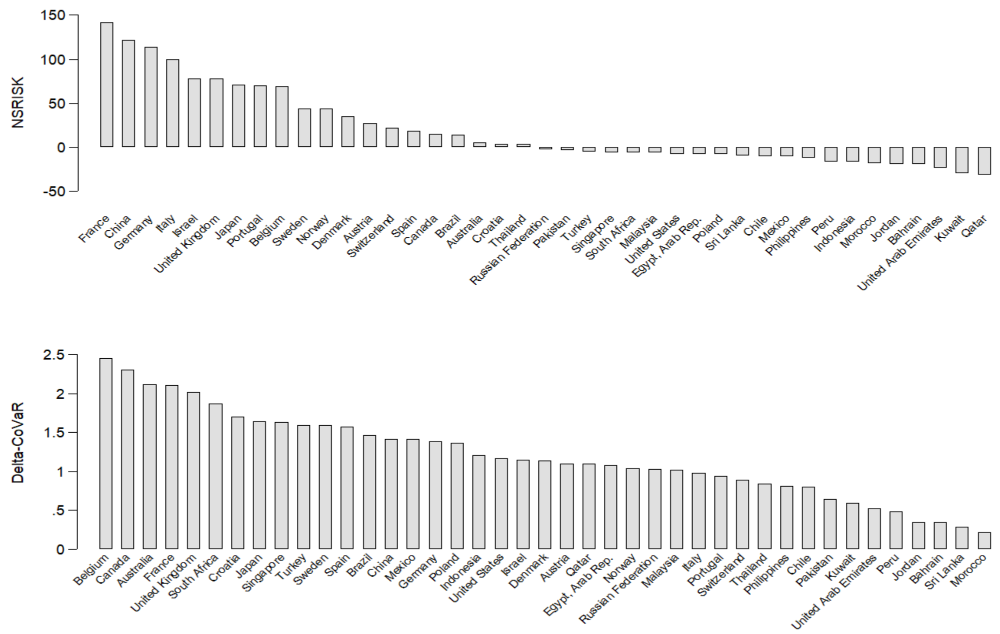


Figure 2 Average systemic risk contribution by country



2.3.2 Measure of systemic risk exposure

Systemic risk exposure is proxied here by Marginal Expected Shortfall (MES) of Acharya et al. (2017). MES is defined as the average return on an individual bank's stock on days when the market (MSCI World Financials index) experiences a loss greater than a specified threshold *C* indicative of market distress.

$$MES_{t-1}^{i} = E_{t-1}(R_t^i | R_t^{system} < C) \,, \tag{13}$$

where R_t^i is the return of bank *i* at time *t* and R_t^{system} is the return of the financial system, defined as MSCI World Financials index. We model the bivariate process of bank and market returns as follows:

$$R_t^{system} = \sigma_t^{system} \varepsilon_t^{system} \tag{14}$$

$$R_t^i = \sigma_t^i \varepsilon_t^i = \sigma_t^i \rho_t^i \varepsilon_t^{system} + \sigma_t^i \sqrt{1 - \rho_{i,t}^2 \xi_{i,t}} \tag{15}$$

σ_t^i and σ_t^{system} are the volatilities of bank *i* and financial system, respectively, ρ_t^i is the correlation coefficient between the return of bank *i* and the return of the system, and ε_t^{system}, ε_t^i and $\xi_{i,t}$are the error terms which are assumed to be *iid.* It follows that:

$$MES_{t-1}^{i} = E_{t-1}\left(R_t^i \middle| R_t^{system} < C\right) = \sigma_t^i E_{t-1}(\varepsilon_t^i | \varepsilon_t^{system} < \frac{C}{\sigma_t^{system}}) = \sigma_t^i \rho_{i,t} E_{t-1}(\varepsilon_t^i | \varepsilon_t^{system} < \frac{C}{\sigma_t^{system}}) + \sigma_t^i \sqrt{1-\rho_{i,t}^2} E_{t-1}(\xi_t^i | \varepsilon_t^{system} < \frac{C}{\sigma_t^{system}}) \; . \quad (16)$$

As in Benoit et al. (2013), we consider the threshold *C* equal to the conditional VaR of the system return, i.e. VaR (5%), which is common for all institutions. Conditional volatilities of the equity returns are modeled using asymmetric GJR-GARCH models with a two-step Quasi Maximum Likelihood estimation. The time-varying conditional correlation is modeled using the Dynamic Conditional Correlation (DCC) framework of Engle (2002). The higher the MES, the higher the exposure of the bank to systemic risk.

2.3.3 Banks' individual or stand-alone risk

We also analyze how the central bank independence influences individual risk of the banks (i.e. a micro-prudential approach). Before the global financial crisis, the micro-prudential paradigm (Basel I and Basel II approaches) was used to describe financial stability. It assumed that financial instability is exogenous to the financial system and that risk should be assessed on an individual basis. Its main drawback was the fact that it ignored spillover effects between institutions – a cause often cited as the main driver of 2007–2009 recession. We define individual risk as the maximum possible loss a bank could register for a given confidence level $\alpha = 95\%$ over a specific period of time, i.e. its VaR. We compute VaR using the same methodological approach employed for MES, modeling conditional volatilities of the equity returns with the asymmetric GJR-GARCH model.

2.4 Central bank independence measures

In general, measures of the degree of central bank independence are built using de facto and de jure measures of independence. *De facto indices* associate the independence of central banks to the autonomy of its governor. Thus, a high rate of governor turnover is associated with low central bank independence. *De jure indices* capture central bank legislative requirements such as the objective function of the central bank, the procedures for the appointment of the governor and other board members, designation of the authority responsible for monetary policy, as well as procedures for resolving conflicts between the central bank and the government. The de jure index of CBI proposed by Cukierman et al. (1992) has been widely embraced by researchers. The authors compute the CBI index for 21 developed and 51 developing countries. The index takes values between zero and one, where zero means no independence and one perfect independence (see Cukierman et al., 1992 for a detailed description of the index).

Here, we use the CBI index computed by Bodea and Hicks (2015). It expands the CBI index of Cukierman et al. (1992) to comprise 80 countries covering a period from 1972 to 2015. Similar to this approach, Garriga (2016) codes the central bank legislation for more countries, (182 countries), but a slightly shorter period (1970 to 2012). We opted for using Bodea and Hicks's (2015) index because it covers the longest period (more observations for after Lehman Brothers period), and has a fair overlap of countries with our database. We also employ Garriga's (2016) index for robustness check.

The aggregated CBI index of these both databases is a weighted index of four components and 16 criteria in total:

1. *Governor characteristics (Personnel independence)*: (i) length of governor's term; (ii) entity delegated to appoint him / her; (iii) provisions for dismissal; and (iv) ability to hold another office in the government. The weight in the index is 0.2.
2. *Policy formulation attributions (Policy independence)*: (v) whether the central bank is responsible for monetary policy formulation; (vi) rules concerning resolution of conflicts between the central bank and government and (vii) the degree of central bank participation in the formulation of the government's budget. The weight in the index is 0.15.
3. *Central bank objectives*: (viii) monetary stability as one of the primary policy objectives. The weight in the index is 0.15.
4. *Limitations on central bank lending to the public sector (Financial independence)*: (ix) advances and (x) securitized lending; (xi) authority having control over the terms (maturity, interest rate, and amount) of lending; (xii) width of circle of potential borrowers from the central bank; (xiii) types of limitations on loans, where such limits exist; (xiv) maturity of possible loans; (xv) limitations on interest rates applicable to lending, and (xvi) prohibitions on central bank participation in the primary market for government securities. The weight in the index is 0.5.

Figure 3 Evolution of average weighted CBI index and its subcomponents by year

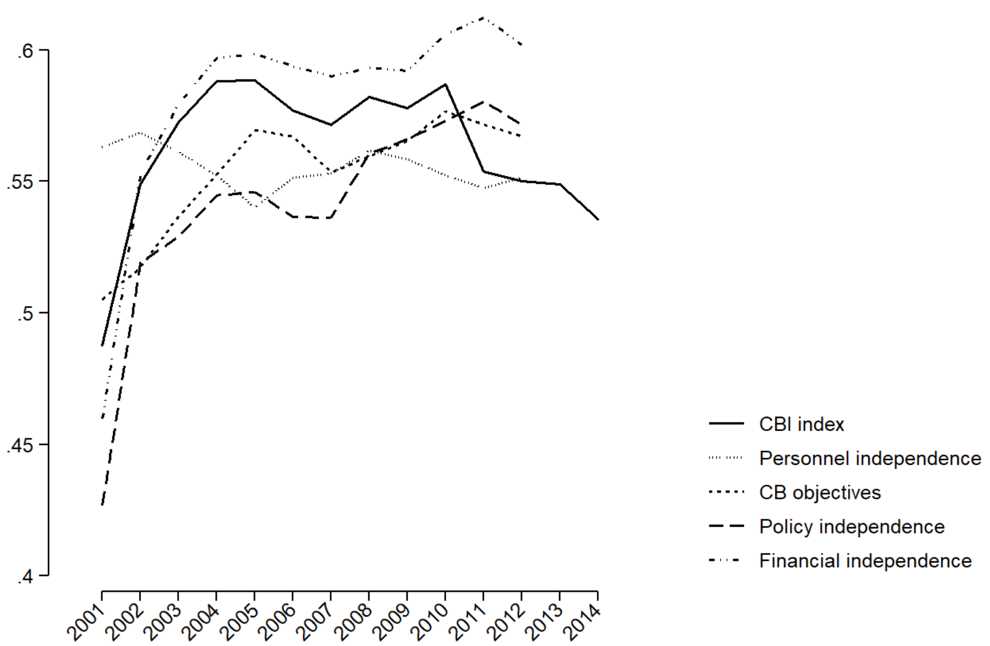
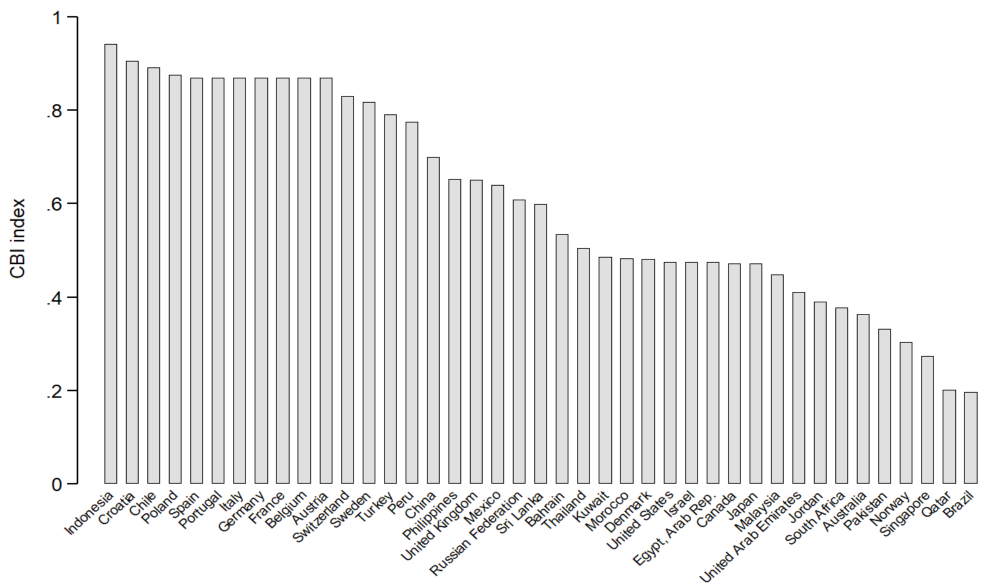


Figure 4 Average weighted CBI index by country



The CBI index and its subcomponents represented in Figure 3 begin a remarkable increase in 2001. The main difference is in terms of *Personnel independence*, where the index showed a downward trend until 2006. Note the sharp drop in value of CBI index starting in 2011. This is likely due to the fact that the values for European Central Bank (ECB) that we substitute for countries within the euro zone were only available through 2010. The most independent central banks are, on average, the central banks of Indonesia, Croatia, and Chile. The least independent central banks are those of Singapore, Qatar, and Brazil (Figure 4).

3 Main empirical results

3.1 Base results

The benchmark results presented in Tables 1 and 2 show the negative impact of CBI measures on the measures of banks' contribution to systemic risk (ΔCoVaR and NSRISK).[14] Each of these tables report the outcome of the estimations for the model described in Eq. (1) corresponding to the five CBI measures. As the degree of central bank's independence increases, banks' contribution to system wide-distress decreases. This is strongly valid for all subcomponents of the CBI index and for the weighted index, except for *financial independence* in the case of ΔCoVaR where its coefficient, although with a negative sign, lacks statistical significance. A one standard deviation increase in the CBI index leads to decline in the systemic contribution of the banks by 13.23% as measured by ΔCoVaR, and by 21.66% as measured by NSRISK. Our results are in line with those of Klomp and de Haan (2009), suggesting a positive link between central bank independence and financial stability, as well as with those of Doumpos et al. (2015), who find that central bank independence exercises a positive impact on bank soundness. The LR test is statistically significant for all models, meaning that the estimated model through HLM is different from the standard OLS regression, favoring the multi-level specification.

The estimated coefficients for control variables yield some noteworthy results. The impact of *size*, while significant, has opposite signs in the two models, i.e. a negative value in the NSRISK model and positive value in the ΔCoVaR model (only in two models out of five the coefficient of the *size* variable is statistically significant). As discussed earlier, NSRISK is closer to the exposure to common shocks that affect the whole financial system, whereas ΔCoVaR is linked to contagion risks (Laeven et al., 2016). Hence, the negative sign in the NSRISK model could suggest that larger banks may diversify more efficiently and enjoy easier access to capital markets, thereby putting them in a more solid position than smaller bank in the event of a downturn. This assessment is in line with Shim (2013). On the other hand, size seems to increase contribution to systemic risk contagion. This comports with the "too-big-to-fail" hypothesis, whereby large banks confident of being bailed out by government in the event of financial distress having greater incentive to engage in excessive risk-taking behavior and thereby increase the overall systemic risk in the financial sector (Farhi and Tirole, 2012). This finding is consistent with that of Laeven et al. (2016).

[14] Note that the number of the banks and countries differs in concordance with the central bank independence measure employed. The time span of the CBI index is from 2001 to 2014, whereas for its subcomponents the availability of the data is from 2001 to 2012.

As expected, deterioration in the quality of the loan portfolio enhances both measures of banks' contribution to systemic risk. Higher *capitalization*, better *profitability* and a funding structure that is mainly based on deposits reduce banks' systemic distress. *Profitability* is significant only in explaining NSRISK; it decreases exposure to common shocks but does not prevent systemic risk contagion. In terms of macroeconomic and banking-system control variables, higher economic growth helps banks reduce their systemic importance, whereas *inflation* amplifies exposure to common shocks.

Bank concentration's coefficient is significant but has opposite signs in the two models: negative for explaining systemic risk contagion and positive for explaining the exposure to common shocks. Intuitively, this makes sense. Fewer banks in the system make them more prone to exposure to common shocks but have less impact on contagion. This also mimics the mixed results in the literature. Beck et al. (2017) find concentration of bank assets to be a key contributor to accumulation of systemic risk in the banking sector. Boyd et al. (2006) claim probability of bank default is positively and significantly related to concentration. Beck et al. (2006) find that the likelihood of a banking crisis is reduced in countries with concentrated banking sectors.

Elevated levels of financial intermediation amplify the risk banks pose to the whole financial system, consistent with the literature.[15] *CBIS index* does not influence exposure to common shocks but negatively affects the systemic risk contagion, i.e. greater central bank involvement in supervision of the financial sector helps reduce tail-event linkages between banks.

[15] Previous studies (e.g., Reinhart and Rogoff, 2009; Jordà et al., 2013) emphasize that the credit boom is a first-order factor in explaining banking crises.

Table 1 Results for the base model: ΔCoVaR

Dependent: ΔCoVaR	(1)	(2)	(3)	(4)	(5)
Fixed-effects parameters					
CBI index (t-1)	-0.575***				
	(0.157)				
Personnel indep. (t-1)		–0.678***			
		(0.179)			
CB objectives (t-1)			–0.343***		
			(0.105)		
Policy indep. (t-1)				–0.699***	
				(0.117)	
Financial indep. (t-1)					–0.214
					(0.142)
Size (t-1)	0.029	0.035	0.040*	0.030	0.044**
	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)
Credit risk ratio (t-1)	0.380	0.769**	0.755**	0.667**	0.854***
	(0.316)	(0.320)	(0.320)	(0.319)	(0.318)
Capitalization (t-1)	–1.076**	–1.047**	–1.068**	–0.949**	–1.152**
	(0.442)	(0.463)	(0.463)	(0.462)	(0.465)
Profitability (t-1)	1.467	1.791	1.557	1.668	1.622
	(1.240)	(1.275)	(1.276)	(1.271)	(1.278)
Funding structure (t-1)	–0.441***	–0.336**	–0.275**	–0.340**	–0.287**
	(0.129)	(0.135)	(0.134)	(0.134)	(0.134)
Real GDP growth (t-1)	–0.831*	–1.128**	–1.011**	–1.338***	–1.044**
	(0.462)	(0.484)	(0.483)	(0.483)	(0.484)
Inflation (t-1)	0.001	–0.001	–0.001	–0.002	–0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Bank concentration (t-1)	–0.003***	–0.002***	–0.002***	–0.002***	–0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Financial intermediation (t-1)	0.001**	0.001**	0.001**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CBIS index (t-1)	–0.079***	–0.086***	–0.087***	–0.078***	–0.086***
	(0.020)	(0.024)	(0.024)	(0.024)	(0.024)
Constant	0.947*	0.784	0.424	0.946*	0.310
	(0.546)	(0.569)	(0.555)	(0.564)	(0.555)
Random-effects parameters					
Country-level variance	–1.052***	–0.945***	–1.043***	–1.013***	–1.090***
	(0.194)	(0.175)	(0.191)	(0.186)	(0.197)
Bank-level variance	–0.534***	–0.527***	–0.527***	–0.525***	–0.526***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Residual variance	–0.919***	–0.904***	–0.902***	–0.907***	–0.901***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Yearly observation	3327	3233	3233	3233	3233
Countries	40	43	43	43	43
Banks	323	329	329	329	329
LR test chi-square	2938.761***	2748.187***	2800.921***	2825.238***	2783.356***

Note: This table reports the results for the base model described in Eq. (1). The dependent variable is ΔCoVaR, defined in Table A2 from the Appendix. The HML model is estimated using the maximum likelihood estimation. The LR test compares the estimated model with the standard OLS regression, and the null hypothesis is that there are no significant differences between the two models. Standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

Table 2 Results for the base model: NSRISK

Dependent: NSRISK	(1)	(2)	(3)	(4)	(5)
Fixed-effects parameters					
CBI index (t-1)	–0.628***				
	(0.114)				
Personnel indep. (t-1)		–0.723***			
		(0.131)			
CB objectives (t-1)			–0.459***		
			(0.076)		
Policy indep. (t-1)				–0.344***	
				(0.096)	
Financial indep. (t-1)					–0.363***
					(0.115)
Size (t-1)	–0.036***	–0.040***	–0.039***	–0.040***	–0.038***
	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)
Credit risk ratio (t-1)	0.426*	0.949***	0.923***	0.921***	1.082***
	(0.222)	(0.229)	(0.229)	(0.232)	(0.229)
Capitalization (t-1)	–2.449***	–2.593***	–2.593***	–2.545***	–2.731***
	(0.294)	(0.312)	(0.312)	(0.314)	(0.314)
Profitability (t-1)	–3.167***	–3.471***	–3.760***	–3.631***	–3.600***
	(0.839)	(0.877)	(0.876)	(0.879)	(0.879)
Funding structure (t-1)	–0.678***	–0.689***	–0.642***	–0.647***	–0.642***
	(0.086)	(0.091)	(0.090)	(0.091)	(0.090)
Real GDP growth (t-1)	–0.954***	–0.610*	–0.475	–0.653*	–0.487
	(0.318)	(0.340)	(0.340)	(0.342)	(0.342)
Inflation (t-1)	0.011***	0.010***	0.010***	0.009***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Bank concentration (t-1)	0.002***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Financial intermediation (t-1)	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CBIS index (t-1)	0.003	0.028	0.028	0.030*	0.028
	(0.014)	(0.018)	(0.018)	(0.018)	(0.018)
Constant	1.188***	1.278***	1.070***	1.069***	1.052***
	(0.342)	(0.360)	(0.353)	(0.358)	(0.359)
Random-effects parameters					
Country-level variance	–0.870***	–0.550***	–0.565***	–0.518***	–0.517***
	(0.130)	(0.125)	(0.125)	(0.128)	(0.129)
Bank-level variance	–1.275***	–1.285***	–1.284***	–1.284***	–1.288***
	(0.047)	(0.048)	(0.048)	(0.048)	(0.048)
Residual variance	–1.305***	–1.270***	–1.271***	–1.267***	–1.266***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Yearly observation	3284	3190	3190	3190	3190
Countries	40	43	43	43	43
Banks	323	329	329	329	329
LR test chi-square	2188.474***	2269.242***	2307.954***	2163.498***	2296.290***

Note: This table reports the results for the base model described in Eq. (1). The dependent variable is NSRISK, defined in Table A2 of the Appendix. The HML model is estimated using the maximum likelihood estimation. The LR test compares the estimated model with the standard OLS regression, and the null hypothesis is that there are no significant differences between the two models. Standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

3.2 The impact of central bank independence on systemic risk exposure and stand-alone risk

Our findings for banks' exposure to system-wide distress and the stand-alone risk of individual banks (Table 3, columns 1 and 2, respectively) are in line with those for banks' contribution to system-wide distress. Thus, a central bank that is independent in terms of *personnel selection*, *policy setting* and *pursuit of its core objectives* is helpful to banks in reducing their exposure to systemic risk and their own stand-alone risk. A one standard deviation increase in the CBI index decreases systemic exposure of banks by 7.59% as measured by MES, and a one standard deviation increase in CBI index leads to a fall in the banks' individual risk by 11.94% as measured by VaR. Regarding the control variables, greater *size*, an increased *credit risk ratio*, and higher levels of *credit granted by financial sector* positively impact the risk measures. *Inflation* has a positive impact on VaR. On the other hand, better *capitalization*, a *funding structure dominated by deposits*, high *economic growth*, increased *bank concentration* and a greater *involvement in supervision by the central bank* significantly reduce these measures of distress.

Table 3 Estimation results for systemic risk exposure (MES) and individual risk (VaR)

	MES	VaR
Fixed-effects parameters		
CBI index (t–1)	–0.550**	–0.916***
	(0.275)	(0.350)
Size (t-1)	0.259***	0.073**
	(0.028)	(0.032)
Credit risk ratio (t-1)	2.623***	2.158***
	(0.523)	(0.701)
Capitalization (t-1)	–2.113***	–3.185***
	(0.700)	(0.918)
Profitability (t-1)	–2.017	–1.646
	(2.033)	(2.736)
Funding structure (t-1)	–1.111***	–1.072***
	(0.202)	(0.259)
Real GDP growth (t-1)	–2.891***	–3.850***
	(0.779)	(1.067)
Inflation (t-1)	–0.007	0.037***
	(0.007)	(0.009)
Bank concentration (t-1)	–0.009***	–0.010***
	(0.001)	(0.002)
Financial intermediation (t-1)	0.009***	0.007***
	(0.001)	(0.001)
CBIS index (t-1)	–0.117***	–0.080*
	(0.035)	(0.046)
Constant	–3.301***	2.395**
	(0.775)	(0.930)
Random-effects parameters		
Country-level variance	–0.109	–0.170
	(0.131)	(0.150)
Bank-level variance	–0.533***	–0.461***
	(0.049)	(0.053)
Residual variance	–0.399***	–0.076***
	(0.013)	(0.013)
Yearly observation	3327	3327
Countries	40	40
Banks	323	323
LR test chi-square	1967.876***	970.073***

Note: This table reports the results for the model described in Eq. (1). The dependent variables are MES and VaR, defined in Table A2 from the Appendix. The HML model is estimated using the maximum likelihood estimation. The LR test compares the estimated model with the standard OLS regression, and the null hypothesis is that there are no significant differences between the two models. Standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

To conserve space, we only present the results for the weighted CBI index. The findings for subcomponents are similar with ΔCoVaR estimations.

3.3 Further evidence on the role of central bank independence on systemic risk contribution

In this section, we analyze three propositions regarding how CBI affects the impact of selected macroeconomic and banking system characteristics on the measures of the systemic risk of banks.

Proposition 1. *A crisis increases the contribution and exposure of banks to systemic risk. CBI can exacerbate this.*

While we expect a financial crisis to increase the level of the systemic risk measures, the extent of the impact may depend on several factors, including CBI. Heightened CBI could undermine necessary coordination of the central bank with other authorities during a financial crisis (Balls et al., 2018). For example, *the lender of last resort* function of central banks was insufficient during the global financial crisis. Governments had to bail out distressed financial institutions to prevent financial contagion. The crisis period had two phases.[16] During the first phase (July 2007 to the end of 2009), the effects of global financial crisis intensify in Europe (Brei et al., 2013). The second phase corresponds with the European sovereign debt crisis in Europe, spanning 2010 to 2013 (Cornille et al., 2019). Samarakoon (2017) find evidence of contagion effects from the European debt crisis to other emerging and developed markets around the world.

Proposition 2. *High market power in the banking sector increases the systemic risk contribution of banks, but the effect is diminished by a higher level of CBI.*

Banks with "high" market power[17] can charge higher interest rates to firms that can further engage in risky activities, and thereby increase the fragility of the financial system (Boyd and De Nicolo, 2005). Anginer et al. (2014) find that the systemic risk of banks and competition are negatively related. High market power indicates the erosion of competition in the banking sector. We should note the existence of different, competing thoughts on the nexus competition-fragility/stability. Under *competition-fragility* theory,[18] increased bank competition erodes market power and decreases profit margins. This creates incentives for banks to take on excessive risk as a way to increase their returns (Berger et al., 2009).

[16] We employ different definitions of crisis, including systemic banking crisis from Reinhart and Rogoff (2011) and Laeven and Valencia (2018). The interaction effect of crisis and CBI remains the same.
[17] We define "high" as values greater or equal to the median of the sample.
[18] See Carletti and Hartmann (2003) for a review of the literature.

We measure market power in the banking system with the Lerner index.[19] Heightened CBI can discourage risky behavior caused by high market power as the central bank authorities can evade capture by financial participants and strengthen the supervisory functions of the central bank.

Proposition 3. *Rigid exchange rate regimes positively contribute to systemic risk, but a higher level of CBI alleviates the effect.*

Rigid exchange rates are associated with greater foreign currency borrowing that exposes the economy to systemic risk (Dell'Ariccia et al., 2020). An independent monetary policy authority may be able to avoid this problem, however, through mitigating the effects of foreign currency borrowing and mitigating the effects from systemic risk contagion.

The results (Tables 4 and 5) suggest several interesting insights. As expected, the sign of the interaction coefficient *Crisis* × *CBI (t-1)* is positive and significant, but only in the case of the systemic interconnectedness measure. Thus, when crisis hits, an independent central bank could exacerbate delays in implementation of crisis measures when coordination with other institutions is involved. The sign of the interaction coefficient maintains its statistical significance for the alternative systemic relevance measures we discuss in section 3.4 (see Tables A6 and A7 in the Appendix for results).

Furthermore, if a banking sector is characterized by a high market power, the effect is an increase of systemic risk contribution of banks (although the coefficient of *High Lerner index (t-1)* is not significant in the case of NSRISK, it is significant for ΔCoVaR). This negative effect is diminished if the central bank acts independently without any external interference. Regarding the effect of the exchange rate regime and CBI influence on it, we did not find backing for our proposition as the corresponding coefficients are insignificant. Nevertheless, we do find evidence supporting Proposition 3 for the two alternative systemic risk measures discussed in the next section, which are constructed based on both ΔCoVaR and NSRISK. Thus, an increased degree of CBI could help circumvent the effect of rigid exchange rate regimes on the contribution of banks to system-wide distress.

[19] The Lerner index is defined as the difference between output prices and marginal costs relative to prices.

Table 4 Interaction regression results: ΔCoVaR

Dependent: ΔCoVaR	(1)	(2)	(3)
Fixed-effects parameters			
CBI index (t-1)	–0.782***	–0.492***	–0.616***
	(0.159)	(0.163)	(0.146)
Crisis	0.135**		
	(0.067)		
Crisis × CBI (t-1)	0.336***		
	(0.079)		
High Lerner index (t-1)		0.226***	
		(0.067)	
High Lerner index (t-1) × CBI (t-1)		–0.313***	
		(0.114)	
Rigid exchange rate (t-1)			0.036
			(0.092)
Rigid exchange rate (t-1) × CBI (t-1)			–0.196
			(0.125)
Size (t-1)	0.031	0.036*	0.092***
	(0.021)	(0.021)	(0.020)
Credit risk ratio (t-1)	0.366	0.338	0.488*
	(0.314)	(0.322)	(0.293)
Capitalization (t-1)	–0.873**	1.219	0.943
	(0.441)	(1.321)	(1.162)
Profitability (t-1)	1.075	–0.904**	–0.475
	(1.240)	(0.450)	(0.416)
Funding structure (t-1)	–0.471***	–0.507***	–0.329***
	(0.129)	(0.137)	(0.120)
Real GDP growth (t-1)	–0.874*	–1.026**	–1.014**
	(0.459)	(0.470)	(0.421)
Inflation (t-1)	0.003	0.001	–0.005
	(0.004)	(0.004)	(0.004)
Bank concentration (t-1)	–0.002**	–0.003***	–0.002***
	(0.001)	(0.001)	(0.001)
Financial intermediation (t-1)	0.001*	0.001**	0.003***
	(0.001)	(0.001)	(0.001)
CBISI (t-1)	–0.084***	–0.081***	–0.065***
	(0.020)	(0.021)	(0.018)
Constant	0.958*	0.803	–0.377
	(0.547)	(0.560)	(0.542)
Yearly observations	3313	3244	2999
Countries	40	40	40
Banks	322	322	322
LR test chi-square	2929***	2825***	3201***

Note: This table reports the results for the model described in Eq. (2). The dependent variable is ΔCoVaR, defined in Table A2 in the Appendix. The HML model is estimated using the maximum likelihood estimation. The LR test compares the estimated model with the standard OLS regression, and the null hypothesis is that there are no significant differences between the two models. Standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively. To conserve space, we suppressed the output for random-effects parameters.

Table 5 Interaction regression results: NSRISK

Dependent: NSRISK	(1)	(2)	(3)
Fixed-effects parameters			
CBI index (t-1)	–0.683***	–0.563***	–0.549***
	(0.116)	(0.117)	(0.117)
Crisis	0.232***		
	(0.046)		
Crisis × CBI (t-1)	0.061		
	(0.055)		
High Lerner index (t-1)		0.051	
		(0.047)	
High Lerner index (t-1) × CBI (t-1)		–0.200**	
		(0.079)	
Rigid exchange rate (t-1)			–0.062
			(0.072)
Rigid exchange rate (t–1) × CBI (t–1)			–0.135
			(0.096)
Size (t-1)	–0.036***	–0.040***	–0.013
	(0.012)	(0.013)	(0.013)
Credit risk ratio (t-1)	0.431*	0.415*	0.045
	(0.223)	(0.227)	(0.228)
Capitalization (t-1)	–2.424***	–3.930***	–3.344***
	(0.296)	(0.894)	(0.869)
Profitability (t-1)	–3.230***	–2.291***	–2.079***
	(0.845)	(0.301)	(0.306)
Funding structure (t-1)	–0.687***	–0.799***	–0.631***
	(0.086)	(0.091)	(0.088)
Real GDP growth (t-1)	–0.976***	–0.920***	–1.038***
	(0.319)	(0.324)	(0.323)
Inflation (t-1)	0.011***	0.010***	0.011***
	(0.003)	(0.003)	(0.003)
Bank concentration (t-1)	0.003***	0.002***	0.003***
	(0.001)	(0.001)	(0.001)
Financial intermediation (t-1)	0.005***	0.005***	0.006***
	(0.000)	(0.000)	(0.000)
CBISI (t-1)	0.002	–0.005	0.006
	(0.014)	(0.015)	(0.014)
Constant	1.207***	1.357***	0.665*
	(0.344)	(0.351)	(0.364)
Yearly observations	3270	3201	2967
Countries	40	40	40
Banks	322	322	322
LR test chi-square	2179***	2114***	2254***

Note: This table reports the results for the model described in Eq. (2). The dependent variable is NSRISK, defined in Table A2 in the Appendix. The HML model is estimated using the maximum likelihood estimation. The LR test compares the estimated model with the standard OLS regression, and the null hypothesis is that there are no significant differences between the two models. Standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively. To conserve space, we suppressed the output for random-effects parameters.

3.4 Robustness assessment using different proxies for systemic risk contribution

To test the consistency of the results, we run alternative specifications and models. First, we re-estimate the model described in Eq. (1) fitting a restricted or residual maximum likelihood estimator (REML). Unlike ML, REML portions the likelihood function into two parts, one independent from the fixed effects (Corbeil and Searle, 1976). The maximization of this part gives the REML. The findings are similar to our baseline analysis and available upon request.

Second, we use alternative proxies for systemic risk contribution. Following the approach of Berger et al. (2019), we compute the principal-component factor using factor analysis based on our two systemic risk indicators, NSRISK and ΔCoVaR. We call the new measure Systemic Factor2. Employing factor analysis to construct new indicators of systemic risk, we synthesize the main information conveyed by NSRISK and ΔCoVaR. Additionally, we employ the same technique and compute Systemic Factor3, which based on NSRISK, ΔCoVaR, and the Systemic Expected Shortfall (SES). According to Acharya et al. (2017), SES denotes a firm's "propensity to be undercapitalized when the system as a whole is undercapitalized," and it is a function of two variables: Marginal Expected Shortfall (MES) and Leverage (LVG).[20]

The results for Systemic Factor2 are shown in Table 6. We obtain the same negative and strongly significant relationship between this measure of systemic relevance and central bank independence, which is consistent with the main findings. Moreover, all components of the CBI measure, including *financial independence,* are significant. Concerning control variables, *size, inflation, profitability, and bank concentration* are not statistically significant. However, the coefficient of *central bank involvement in supervision index* is negative and significant in four models out of five: assigning central bank with many supervisory responsibilities is beneficial for stability of the banking system and financial system as a whole. Doumpos et al. (2015) reach the same conclusion in terms of bank soundness.

The results for Systemic Factor3 are shown in Table A5 in the Appendix. Overall, our findings remain robust. The five measures that capture the degree of central bank independence are all negative and highly statistically significant. Comparing to Systemic Factor2, this time *profitability* is significant, with a negative impact on systemic risk, being in line with the findings for NSRISK, presented in Table 2. The impact of *size* is negative and significant for all models. *Inflation* and *central bank involvement in supervision index* are statistically significant only in the case of weighted CBI index.

[20] A description of these variables and the computational methodological is provided in Table A2 in the Appendix.

Finally, we test whether the findings are not driven by the sample selection by excluding from the analysis a) the countries with the highest number of banks (the United States and Japan), b) the countries with no more than three banks, and c) both groups of countries. A detailed list with the number of banks by country is given in Table A1 from the Appendix. To conserve space, the results for this robustness assessment are showcased in Table 7, but only for the weighted CBI index. Note that our findings are in line with those from the benchmark models (Table 1 and Table 2), and the coefficients of the CBI index across all six models preserve their negative sign and statistical significance.

Table 6 Robustness assessment using a different SR measure: Systemic Factor2

Dependent: SF2	(1)	(2)	(3)	(4)	(5)
Fixed-effects parameters					
CBI index (t-1)	–0.996*** (0.210)				
Personnel indep. (t-1)		–1.248*** (0.238)			
CB objectives (t-1)			–0.691*** (0.139)		
Policy indep. (t-1)				–0.673*** (0.168)	
Financial indep. (t-1)					–0.448** (0.201)
Size (t-1)	–0.044* (0.026)	–0.042 (0.026)	–0.036 (0.026)	–0.042 (0.026)	–0.034 (0.026)
Credit risk ratio (t-1)	1.327*** (0.419)	2.218*** (0.428)	2.200*** (0.428)	2.157*** (0.432)	2.444*** (0.427)
Capitalization (t-1)	–3.896*** (0.565)	–4.110*** (0.598)	–4.136*** (0.598)	–4.024*** (0.601)	–4.334*** (0.603)
Profitability (t-1)	–1.586 (1.587)	–1.467 (1.651)	–1.938 (1.652)	–1.755 (1.654)	–1.725 (1.657)
Funding structure (t-1)	–1.026*** (0.165)	–0.983*** (0.175)	–0.885*** (0.173)	–0.925*** (0.174)	–0.896*** (0.174)
Real GDP growth (t-1)	–1.416** (0.595)	–1.382** (0.631)	–1.159* (0.631)	–1.502** (0.634)	–1.206* (0.634)
Inflation (t-1)	0.008 (0.005)	0.005 (0.005)	0.005 (0.005)	0.004 (0.005)	0.005 (0.005)
Bank concentration (t-1)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)
Financial intermediation (t-1)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
CBIS index (t-1)	–0.072*** (0.027)	–0.054* (0.033)	–0.054* (0.032)	–0.049 (0.033)	–0.054* (0.033)
Constant	0.700 (0.690)	0.700 (0.720)	0.202 (0.705)	0.407 (0.716)	0.094 (0.712)
Random-effects parameters					
Country-level variance	–0.420*** (0.147)	–0.327** (0.140)	–0.373*** (0.142)	–0.359** (0.147)	–0.375** (0.148)
Bank-level variance	–0.425*** (0.046)	–0.418*** (0.046)	–0.420*** (0.046)	–0.416*** (0.047)	–0.419*** (0.046)
Residual variance	–0.678*** (0.013)	–0.650*** (0.013)	–0.649*** (0.013)	–0.648*** (0.013)	–0.645*** (0.013)
Yearly observation	3284	3190	3190	3190	3190
Countries	40	43	43	43	43
Banks	323	329	329	329	329
LR test chi-square	2541.686***	2352.671***	2432.430***	2391.663***	2421.616***

Note: This table reports the results for the base model described in Eq. (1). The dependent variable is Systemic Factor2, defined in Table A2 in the Appendix. The HML model is estimated using the maximum likelihood estimation. The LR test compares the estimated model with the standard OLS regression, and the null hypothesis is that there are no significant differences between the two models. Standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 7 Robustness assessment using different sample structures

	(1) US and Japan excluded		(2) No countries with fewer than 4 banks		(1) + (2)	
Dependent variables	ΔCoVaR	NSRISK	ΔCoVaR	NSRISK	ΔCoVaR	NSRISK
Fixed-effects parameters						
CBI index (t-1)	–0.596***	–0.356***	–0.570***	–0.674***	–0.577***	–0.370***
	(0.146)	(0.114)	(0.161)	(0.113)	(0.149)	(0.111)
Size (t-1)	0.131***	0.047***	0.029	–0.040***	0.137***	0.054***
	(0.025)	(0.017)	(0.021)	(0.012)	(0.026)	(0.018)
Credit risk ratio (t-1)	–0.148	1.284***	0.347	0.319	–0.201	1.170***
	(0.321)	(0.246)	(0.319)	(0.217)	(0.322)	(0.235)
Capitalization (t-1)	0.383	–1.389***	–1.161***	–2.396***	0.292	–1.214***
	(0.498)	(0.363)	(0.447)	(0.288)	(0.503)	(0.351)
Profitability (t-1)	2.284*	–2.404**	1.939	–3.013***	3.223**	–2.096**
	(1.311)	(0.961)	(1.253)	(0.817)	(1.316)	(0.916)
Funding structure (t-1)	–0.199	–0.622***	–0.416***	–0.641***	–0.130	–0.555***
	(0.135)	(0.098)	(0.132)	(0.085)	(0.138)	(0.096)
Real GDP growth (t-1)	–0.913*	–0.863**	–0.950**	–1.160***	–0.963**	–1.061***
	(0.470)	(0.350)	(0.476)	(0.316)	(0.483)	(0.342)
Inflation (t-1)	–0.003	0.011***	0.002	0.012***	–0.002	0.012***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Bank concentration (t-1)	–0.002*	0.000	–0.003***	0.002***	–0.001*	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Financial intermediation (t-1)	0.003***	0.006***	0.001***	0.005***	0.003***	0.005***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
CBIS index (t-1)	–0.067***	0.003	–0.084***	0.004	–0.069***	0.006
	(0.019)	(0.014)	(0.021)	(0.014)	(0.019)	(0.014)
Constant	–1.490**	–0.705	0.922*	1.282***	–1.628**	–0.905**
	(0.646)	(0.454)	(0.555)	(0.342)	(0.660)	(0.461)
Random-effects parameters						
Country-level variance	–1.250***	–1.075***	–1.083***	–0.821***	–1.267***	–1.018***
	(0.216)	(0.144)	(0.203)	(0.136)	(0.221)	(0.151)
Bank-level variance	–0.552***	–1.155***	–0.535***	–1.280***	–0.559***	–1.143***
	(0.055)	(0.057)	(0.045)	(0.048)	(0.056)	(0.058)
Residual variance	–0.995***	–1.300***	–0.916***	–1.340***	–1.002***	–1.363***
	(0.016)	(0.017)	(0.013)	(0.013)	(0.017)	(0.017)
Yearly observations	2080	2041	3201	3158	1954	1915
Countries	38	38	34	34	32	32
Banks	224	224	310	310	211	211
LR-test chi-square	1948***	1475***	2788***	2464***	1819***	1553***

Note: This table reports the results for the base model described in Eq. (1). The dependent variables are ΔCoVaR and NSRISK, defined in Table A2 in the Appendix. The HML model is estimated using the maximum likelihood estimation. The LR test compares the estimated model with the standard OLS regression, and the null hypothesis is that there are no significant differences between the two models. Standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

4 Conclusion

The agreement around the concept of central bank independence has lessened in the wake of the global financial crisis of 2007–2009. This shift reflects an increase in the range of powers central bank have acquired, with some of these powers involving coordination with fiscal policy-making. Some evidence of distributional effects across different segments of population resulting from unconventional monetary policy has increased calls for reining in central bank independence. However, a core issue is how the financial stability that has been fastened stronger than before to central banks in many countries relates to the central bank independence.

We find a robust, negative and significant impact of central bank independence on the contribution and exposure of banks to systemic risk, as well as a similar impact of central bank independence on stand-alone bank risk. These results lend support for central bank independence as it helps banks reduce the risk they pose to the banking system as a whole as well as the risk individual banks face. However, the results also show that the too much central bank independence can exacerbate the effect of a crisis on the contribution of banks to systemic risk. In parallel, in environments where banks enjoy above median or "high" market power, the systemic risk contribution of banks is enhanced. In such case, the effect is reduced if the central bank acts independently.

Therefore, preserving central bank independence is important for financial stability even at times when coordinated interaction with governments is needed. A memorandum of understanding between a country's independent central bank and government might facilitate such needed collaboration, or more elegantly in the words of former Fed chief Ben Bernake: "The general principle of CBI does not preclude coordination of central bank policies with other parts of the government in certain situations" (Bernanke, 2017).

We confirm a significant effect on the measure of the systemic relevance of bank characteristics (size, credit risk ratio, capitalization, profitability, funding structure), banking sector characteristics (concentration, level of financial intermediation), macroeconomic variables (GDP growth and inflation) and the degree of central bank involvement in microprudential supervision. The impact of some variables such as bank size, profitability, and concentration of the banking sector on different measures of systemic distress varies in terms of sign and significance.

References

Acharya, V., Engle, R., Richardson, M. (2012). Capital Shortfall: A new approach to ranking and regulating systemic risks. American Economic Review 102(3), 59–64.

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

Adrian, T., Brunnermeier, M.K. (2016). CoVaR. American Economic Review 106(7), 1705–1741.

Anginer, D., Demirguc-Kunt, A., Zhu, M. (2014). How does competition affect bank systemic risk? Journal of Financial Intermediation 23, 1–26.

Arnone, M., Laurens, B.J., Segalotto, J.-F., Sommer, M. (2009). Central bank autonomy: lessons from global trends. IMF Staff Papers 56(2), 263–296.

Balls, E., Howar, J., Stansbury, A. (2018). Central Bank Independence Revisited: After the financial crisis, what should a model central bank look like? M-RCBG Associate Working Paper No. 87.

Bank for International Settlements (2009). Issues in the governance of central banks: a report from the Central Bank Governance Group. Available online at: https://www.bis.org/publ/othp04.htm.

Beck, T., De Jonghe, O., Mulier, K. (2017). Bank sectoral concentration and (systemic) risk: Evidence from a worldwide sample of banks. CEPR Discussion Paper 12009.

Beck, T., Demirgüç-Kunt, A., Levine, R. (2006). Bank concentration, competition, and crises: First results. Journal of Banking & Finance 30, 1581–1603.

Benoit, S., Colletaz, G., Hurlin, C., Pérignon, C. (2013). A theoretical and empirical comparison of systemic risk measures. HEC Paris Research Paper No. FIN-2014-1030.

Berger, A.N., Klapper, L.F., Turk-Ariss, R. (2009). Bank Competition and Financial Stability. Journal of Financial Services Research 35, 99–118.

Berger, A.N., Roman, R.A., Sedunov, J. (2019). Did TARP reduce or increase systemic risk? The effects of government aid on financial system stability. Journal of Financial Intermediation 100810.

Berger, H., De Haan, J., Eijffinger, S.C.W. (2001). Central Bank Independence: An Update of Theory and Evidence. Journal of Economic Surveys 15, 3–40.

Berger, W., Kißmer, F. (2013). Central bank independence and financial stability: A tale of perfect harmony? European Journal of Political Economy 31, 109–118.

Bernanke, B. (2004). The Great Moderation, Remarks at meeting of the Eastern Economic Association. Available online at: https://www.federalreserve.gov/boarddocs/speeches/2004/20040220/.

Bernanke, B. (2017). Monetary policy in a new era. Paper prepared for Conference on Rethinking Macroeconomic Policy, Peterson Institute, Washington DC, October 12–13 (2017).

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

Bodea, C., and R. Hicks. 2015. Price stability and central bank independence: Discipline, credibility and democratic institutions. International Organization 69(1), 35–61.

Bolton, P., Cecchetti S., Danthine J.P. and X. Vives. 2019. Sound at Last? Assessing a Decade of Financial Regulation. The Future of Banking 1. 2019 Centre for Economic Policy Research, London, UK.

Bostandzic, D., Weiß, G.N.F. (2018). Why do some banks contribute more to global systemic risk? Journal of Financial Intermediation 35, 17–40.

Boyd, J. H., De Nicolo, G. 2005. The Theory of Bank Risk Taking and Competition Revisited. The Journal of Finance 60, 1329–1343.

Boyd, J. H., De Nicolo, G., Jalal, A. M., 2006. Bank risk-taking and competition revisited: New theory and new evidence. IMF Working Paper, WP/06/297.

Brei, M., Gambacorta, L., von Peter, G. (2013). Rescue packages and bank lending. Journal of Banking & Finance 37(2), 490–505.

Brownlees, C., Engle, R. (2017). SRISK: A Conditional Capital Shortfall Measure of Systemic Risk. Review of Financial Studies 30(1), 48–79.

Broz, L. (2002). Political system transparency and monetary commitment regimes. International Organization 56(4), 861–887.

Capie, F., Wood, G. (2013). Central Bank Independence: A Victim of the Crisis? Economic Affairs 33(3), 379–385.

Carletti, E., Hartmann, P. (2003). Competition and financial stability: what's special about banking? In: Monetary history, exchange rates and financial markets: Essays in honour of Charles Goodhart, Mizen, P. (ed.), vol. 2. Edward Elgar, Cheltenham, UK.

Cihak M. (2010). Price Stability, Financial Stability, and Central Bank Independence. Oesterreichische Nationalbank 38th Economic Conference. Wien, 45–55.

Corbeil R.R., Searle, S.R. (1976). Restricted Maximum Likelihood (REML) Estimation of Variance Components in the Mixed Model. Technometrics 18, 31–38.

Cornille, D., Rycx, F., Tojerow, I. (2019). Heterogeneous effects of credit constraints on SMEs' employment: Evidence from the European sovereign debt crisis. Journal of Financial Stability 41, 1–13.

Crowe, C., Meade, E.E. (2007). The Evolution of Central Bank Governance around the World. Journal of Economic Perspectives 21, 69–90.

Cukierman, A. (2008). Central bank independence and monetary policymaking institutions – Past, present and future. European Journal of Political Economy 24, 722–736.

Cukierman, A., Webb, S.B., Neyapti, B. (1992). Measuring the independence of central banks and its effect on policy outcomes. World Bank Economic Review 6, 353–398.

Dell'Ariccia, G., Laeven L., Marquez, R. (2020). Financial Frictions, Foreign Currency Borrowing, and Systemic Risk, IMF, Manuscript.

De Bandt, O., Hartmann, P. (2000). Systemic Risk: A Survey. European Central Bank Working Paper Series, No. 35.

De Haan, J., Bodea, C., Hicks, R., Eijffinger, S. (2018). Central Bank Independence Before and After the Crisis. Comparative Economic Studies 60(2), 183–202.

De Haan, J., Eijffinger, S.C. (2016). The politics of central bank independence. DNB Working Paper 539.

De Haan, W., Ellison, M., Ilzetzki, E., McMahon, M. Reis, R. (2017). The future of central bank independence: results of the CFM-CEPR survey, VoxEU, 10 January, Available online at: https://voxeu.org/article/future-central-bank-independence.

Diebold, F.X., Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics 182, 119–134.

Doumpos, M., Gaganis, C., Pasiouras, F. (2015). Central bank independence, financial supervision structure and bank soundness: An empirical analysis around the crisis. Journal of Banking & Finance 61, S69–S83.

Draghi, M. (2018). Central bank independence. First Lamfalussy Lecture. Available online at: https://www.ecb.europa.eu/press/key/date/2018/html/ecb.sp181026.en.html

Engle, R., 2002. Dynamic Conditional Correlation. Journal of Business & Economic Statistics 20, 339–350.

Essen, M., Engelen, P., Carney, M. (2013). Does "Good" Corporate Governance Help in a Crisis? Corporate Governance: An International Review 21: 201–224.

Farhi, E., Tirole, J. (2012). Collective Moral Hazard, Maturity Mismatch, and Systemic Bailouts. American Economic Review 102, 60–93.

Fernández-Albertos, J. (2015). The Politics of Central Bank Independence. Annual Review of Political Science 18:1, 217–237.

Förch, T., Sunde, U. (2012). Central bank independence and stock market returns in emerging economies. Economics Letters 115, 77–80.

García-Herrero, A., Del Rio Lopez, P. (2003). Financial stability and the design of monetary policy. Banco De España Working Paper 0315.

Garriga, A.C. (2016). Central Bank Independence in the World: A New Data Set. International Interactions 42, 849–868.

Goodhart, C. (2011). The changing role of central banks. Financial History Review 18(2), 135–154.

Goodhart, C., Lastra, R. (2018). Populism and Central Bank Independence. Open Economies Review 29(1): 49–68.

Greenspan, A. (2007). The Age of Turbulence. Adventures in a New World. Penguin Press, New York.

Haltom, R., Weinberg, A.J. (2017). Does the FED have a Financial Stability mandate? Economic Brief 17–06, Federal Reserve Bank of Richmond.

Hartley, H. O., Rao, J. N. K., 1967. Maximum likelihood estimation for the mixed analysis of variance model. Biometrika 54(1–2), 93–108.

Issing, O. (2018). The uncertain future of central bank independence. VoxEU, 2 April. Available online at: https://voxeu.org/article/uncertain-future-central-bank-independence.

Jordà, Ò., Schularick, M., Taylor, A.M. (2013). When Credit Bites Back. Journal of Money, Credit and Banking 45, 3–28.

Kayo, E.K., Kimura, H. (2011). Hierarchical determinants of capital structure. Journal of Banking & Finance 35, 358–371.

Keefer, P., 2001. When do special interests run rampant? Disentangling the role of elections, incomplete information and checks and balances in banking crises. World Bank Policy Research Working Paper No. 2543.

Khan, A.H., Khan, H.A., Dewan, H. (2013). Central Bank Autonomy, Legal Institutions and Banking Crisis Incidence: Central Bank Autonomy, Legal Institutions and Banking Crisis Incidence. International Journal of Finance & Economics 18, 51–73.

Klomp, J., de Haan, J.(2009). Central bank independence and financial instability. Journal of Financial Stability 5, 321–338.

Koenker, R., Bassett, G.S. (1978). Regression quantiles. Econometrica 46, 33–50.

Kuttner, K.N., Posen, A.S. (2010). Do Markets Care Who Chairs the Central Bank? Journal of Money, Credit and Banking 42, 347–371.

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

Laeven, L., Valencia, F. (2018). Systemic Banking Crises Revisited. IMF Working Papers 18/206.

Langfield, S., Pagano, M. (2016). Bank bias in Europe: effects on systemic risk and growth. Economic Policy 31, 51–106.

Li, K., Griffin, D., Yue, H., Zhao, L. (2013). How does culture influence corporate risk-taking? Journal of Corporate Finance 23, 1–22.

Machado, J.A.F., Santos Silva, J.M.C. (2013). Quantile regression and heteroskedasticity. University of Surrey Working paper. Available online at: https://jmcss.som.surrey.ac.uk/JM_JSS.pdf.

Marcato, G., Milcheva, S., Zheng, C. (2018). Market integration, country institutions and IPO underpricing. Journal of Corporate Finance 53, 87–105.

Masciandaro, D., Romelli, D. (2013). Ups and downs of central bank independence from the Great Inflation to the Great Recession: theory, institutions and empirics. Financial History Review 22, 259–289.

Melecky, M., Podpiera, A.M. (2013). Institutional structures of financial sector supervision, their drivers and historical benchmarks. Journal of Financial Stability 9, 428–444.

Melecky, M., Podpiera, A.M. (2015). Placing Bank Supervision in the Central Bank. Implications for Financial Stability Based on Evidence from the Global Crisis. Policy Research Working Paper 7320, World Bank.

Mersch, Y. (2017). Central bank independence revisited. Keynote address at "Symposium on building the financial system of the 21st century: an agenda for Europe and the United States," Frankfurt, 30 March, Available online at:

https://www.ecb.europa.eu/press/key/date/2017/html/sp170330.en.html.

Mishkin, F.S. (2004). Can Inflation Targeting Work in Emerging Market Countries? NBER Working Paper No. 10646. Available online at: https://www.nber.org/papers/w10646.

Moser, C., Dreher, A. (2010). Do Markets Care about Central Bank Governor Changes? Evidence from Emerging Markets. Journal of Money, Credit and Banking 42, 1589–1612.

Mourouzidou-Damtsa, S., Milidonis, A., Stathopoulos, K. (2019). National culture and bank risk-taking. Journal of Financial Stability, 40, 132–143.

Nistor, S., Ongena, S. (2019). The Impact of Policy Interventions on Systemic Risk across Banks. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2580791.

Papadamou, S., Sidiropoulos, M., Spyromitros, E. (2017). Does central bank independence affect stock market volatility? Research in International Business and Finance 42, 855–864.

Patro, D., Qi, M., Sun, X. 2013. A simple indicator of systemic risk. Journal of Financial Stability 9, 105–116.

Pistoresi, B., Salsano, F., Ferrari, D. (2011). Political institutions and central bank independence revisited. Applied Economics Letters 18, 679–682.

Reinhart, C. M.,. Rogoff, K.S. (2009). The aftermath of financial crises. American Economic Review 99, 466–72.

Reinhart, C.M., Rogoff, K.S. (2011). From Financial Crash to Debt Crisis. American Economic Review 101, 1676–1706.

Restoy, F. 2018. The European banking union: what are the missing pieces? Public lecture at the International Center for Monetary and Banking Studies, Geneva, Switzerland, 16 October 2018, Available online at: https://www.bis.org/speeches/sp181018a.pdf.

Samarakoon, L.P. (2017). Contagion of the eurozone debt crisis. Journal of International Financial Markets, Institutions and Money 49, 115–128.

Shim, J. (2013). Bank capital buffer and portfolio risk: The influence of business cycle and revenue diversification. Journal of Banking & Finance 37, 761–772.

Toniolo, G.,White, E.N. (2015). The evolution of financial stability mandate: from origins to its present day. NBER Working Paper No. 20844.

Ueda, K., Valencia, F. (2014). Central bank independence and macro-prudential regulation. Economics Letters 125, 327–330.

Weiß, G.N.F., Bostandzic, D., Neumann, S. (2014). What factors drive systemic risk during international financial crises? Journal of Banking & Finance 41, 78–96.

Appendix

Table A1 Distribution of the banks by country

Country	Number of banks	Percent	Cumulative percent
Australia	5	1.55	1.55
Austria	5	1.55	3.10
Bahrain	6	1.86	4.95
Belgium	1	0.31	5.26
Brazil	4	1.24	6.50
Canada	8	2.48	8.98
Chile	6	1.86	10.84
China	7	2.17	13.00
Croatia	1	0.31	13.31
Denmark	5	1.55	14.86
Egypt, Arab Rep.	6	1.86	16.72
France	6	1.86	18.58
Germany	3	0.93	19.50
Indonesia	8	2.48	21.98
Israel	6	1.86	23.84
Italy	13	4.02	27.86
Japan	48	14.86	42.72
Jordan	9	2.79	45.51
Kuwait	7	2.17	47.68
Malaysia	8	2.48	50.15
Mexico	4	1.24	51.39
Morocco	3	0.93	52.32
Norway	3	0.93	53.25
Pakistan	8	2.48	55.73
Peru	4	1.24	56.97
Philippines	8	2.48	59.44
Poland	8	2.48	61.92
Portugal	2	0.62	62.54
Qatar	8	2.48	65.02
Singapore	3	0.93	65.94
South Africa	5	1.55	67.49
Spain	5	1.55	69.04
Sri Lanka	5	1.55	70.59
Sweden	4	1.24	71.83
Switzerland	14	4.33	76.16
Thailand	4	1.24	77.40
Turkey	9	2.79	80.19
United Arab Emirates	8	2.48	82.66
United Kingdom	5	1.55	84.21
United States	51	15.79	100.00
Total	323	100	

Table 2 Description of variables

Variable name	Definition	Source
Dependent variables (bank level)		
Normalized SRISK (NSRISK)	The loss of the bank i within a year conditioned by the whole system in distress (5% worst outcomes of market capitalization) per unit of market capitalization. SRISK is determined using the DCC-GJR GARCH method with a two-step Quasi Maximum Likelihood (QML) estimation as in Acharya et al. (2012) and Brownlees and Engle (2017). We divide SRISK by bank i's market capitalization to get NSRISK. SRISK is expressed in USD as well as market capitalization. System is defined by the MSCI World Financials Index.	Own calculations
ΔCoVaR	Bank i's yearly contribution to systemic risk as defined by Adrian and Brunnermeier (2016). It is measured as the difference of the value-at-risk (VaR) of the system's market value of total assets conditional on the distress of a particular bank (5% worst outcomes) and the VaR of the system's market value of total assets conditional on the median state of the bank (median outcomes). ΔCoVaR is estimated using the Quantile Regression method for an empirical specification. The system's market value of total assets is regressed on each bank's market value of total assets and on a set of market indices that captures the exposure of financial institutions to common factors. The common factors are: (i) the daily return of the MSCI World Index, (ii) the CBOE Volatility Index (VIX), (iii) the daily real estate sector return (MSCI World Real Estate) in excess of the banking sector return (MSCI World Banks), (iv) the change in the three-month T-bill rate, (v) the spread between three-month repo rate and three-month T-bill rate, (vi) the spread of change in 10-year bond yield and three-month T-bill rate, and (vii) the change in the spread of Moody's Baa corporate bond yield and 10-year bond yield. System is defined as the market value of total assets of the sample.	Own calculations
Marginal Expected Shortfall (MES)	Yearly Marginal Expected Shortfall as defined by Acharya et al. (2017), i.e. the average return on an individual bank's stock on the days the MSCI World Financials Index experienced a 5% worst outcome. Conditional volatilities of the equity returns are modeled using asymmetric GJR-GARCH models with a two-step Quasi Maximum Likelihood (QML) estimation. The time-varying conditional correlation is modeled using the Dynamic Conditional Correlation (DCC) framework of Engle (2002).	Own calculations
Leverage (LVG, market leverage)	Market leverage computed as the ratio of the quasi-market value of assets divided by market value of common equity, where the quasi-market value of assets is book value of assets minus book value of common equity plus market value of common equity as in Acharya et al. (2017).	Own calculation
Systemic Expected Shortfall (SES)	A bank's propensity to be undercapitalized when the system as a whole is undercapitalized increases in its leverage, volatility, correlation, and tail dependence. SES is computed as in Acharya et al. (2017), based on MES and LVG for each bank i in year t: $SES_{i,t} = 0.02 - 0.15 \times MES_{i,t-1} - 0.04 \times LVG_{i,t-1}$.	Own calculation
Systemic Factor2	Principal-component factor computed using factor analysis based on NSRISK and ΔCoVaR similar to Berger et al. (2019).	Own calculations
Systemic Factor3	Principal-component factor computed using factor analysis based on NSRISK, ΔCoVaR and SES similar to Berger et al. (2019).	Own calculation
Value-at-Risk (VaR)	The maximum possible loss as a percent of returns that a bank could register for a given confidence level (95%). The loss is found in the left tail corresponding to the 95% confidence level of the returns distribution function.	Own calculation
Data used for systemic risk (bank level)		
Market equity	Market capitalization	Datastream
Total assets	Book value of Total assets	Worldscope
Book equity	The book value of Common equity	Worldscope
Market assets	Total assets × (Market equity/Book equity)	Own calculations
MSCI World Financials index (market)	Log-returns of MSCI World Financials Index	Datastream

Variable name	Definition	Source
Bank level variables		
Size	Natural logarithm of Total assets in US dollars	Worldscope
Credit risk ratio	Non-performing loans/Total loans	Worldscope
Capitalization	Common equity/Total assets	Worldscope
Profitability (ROA)	Net income/Total assets	Worldscope
Funding structure	Total deposits/Total liabilities	Worldscope
Macro/banking system level variables		
Central Bank Independence index	Updated version of Cukierman et al.'s (1992) index by Bodea and Hicks (2015). The index has four components that we use in our analysis relating to (i) appointment, dismissal, and term of office for the head of the central bank (Personnel independence), (ii) the resolution of conflicts between the executive branch and the central bank (Policy independence), (iii) the objectives of the central bank (Central bank objectives), and (iv) the rules limiting lending to the government (Financial independence). The indexes range between 0 and 1, higher values express greater independence.	Bodea and Hicks (2015) and Garriga (2016)
Real GDP growth	Annual percentage growth rate of Gross Domestic Product based on constant local currency. Aggregates are based on constant 2010 U.S. dollars.	WDI
Inflation	Inflation as measured by the change in consumer price index, reflecting the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly.	WDI
Bank concentration	Assets of three largest banks as a share of total commercial banking assets. Total assets include total earning assets, cash and due from banks, foreclosed real estate, fixed assets, goodwill, other intangibles, current tax assets, deferred tax, discontinued operations and other assets.	WDI
Financial intermediation	Domestic credit provided by financial sector/GDP.	WDI
Central bank involvement in supervision index (CBIS index)	An index that captures the roles of the central bank in supervising all, some, or none of the various financial sector actors. The CBIS Index takes a maximum score of 6 in countries where all supervisory responsibilities are assigned to the central bank and the minimum score of 1 in countries where the central bank is not involved in supervision.	Masciandaro and Romelli (2017)
Variables used in interaction regressions		
Crisis	Dummy variable: takes a value of 1 if the period is between 2007 and 2013, and 0 otherwise.	Own calculations
High market power	Lerner index values greater or equal to the sample median. The Lerner index is defined as the difference between output prices and marginal costs (relative to prices). An increase in the Lerner index indicates a deterioration of the competitive conduct of financial intermediaries.	Own calculations; WDI
Rigid exchange rate regime	Dummy variable: takes the value of 0 if the exchange regime in a country is either floating or free-floating, and 1 otherwise.	Own calculations; IMF

World Development Indicators (WDI); International Monetary Fund (IMF)

Table A3 Summary statistics

	Mean	Std. dev.	p25	Median	p75	Min	Max	Obs.
ΔCoVaR	1.247	0.892	0.591	1.178	1.804	–2.39	5.484	3327
NSRISK	23.350	87.948	–14.675	0.316	36.879	–70.019	2841.164	23.350
CBI index	0.565	0.194	0.472	0.475	0.775	0.173	0.954	3293
Personnel independence	0.553	0.159	0.438	0.582	0.707	0.063	0.832	2936
CB objectives	0.559	0.227	0.400	0.600	0.600	0.000	1.000	2936
Policy independence	0.549	0.328	0.268	0.668	0.750	0.000	1.000	2936
Financial independence	0.587	0.290	0.329	0.626	0.891	0.013	1.000	2936
Size	24.204	1.716	23.148	24.011	25.06	18.568	29.011	3327
Credit risk ratio	3.600	3.900	1.000	2.600	4.800	0.000	53.500	3270
Capitalization	1.300	1.400	0.500	1.200	1.800	–25.800	12.800	3226
Profitability	8.400	4.300	5.500	7.600	10.100	1.100	61.000	3263
Funding structure	74.900	19.300	63.800	79.900	90.900	0.000	100.400	3327
Real GDP growth	2.800	3.400	1.400	2.400	4.200	–5.700	26.200	3327
Inflation	2.846	3.823	0.803	2.27	3.393	–4.863	54.4	3327
Bank concentration	55.41	21.283	36.97	46.319	74.84	23.113	100	3318
Financial intermediation	165.619	90.878	85.909	156.385	227.188	15.171	346.489	3321
CBIS index	2.009	1.109	1.000	2.000	3.000	1.000	6.000	3105

Note: These figures correspond to the actual number of observations, i.e. not winsorized. A complete description of variables is given in Table A2 in the Appendix.

Table A4 Correlation matrix of the regressors

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) CBI index	1.000														
(2) Personnel indep.	0.187*	1.000													
(3) CB objectives	0.592*	0.223*	1.000												
(4) Policy indep.	0.563*	0.357*	0.420*	1.000											
(5) Financial indep.	0.719*	–0.140*	0.324*	0.274*	1.000										
(6) Size	0.093*	–0.001	–0.065*	–0.090*	0.085*	1.000									
(7) Credit risk	–0.066*	0.102*	0.011	0.267*	–0.154*	–0.215*	1.000								
(8) Capitalization	–0.071*	–0.084*	–0.001	–0.073*	0.124*	–0.427*	0.067*	1.000							
(9) Profitability	0.093*	–0.092*	0.138*	0.019	0.204*	–0.148*	–0.165*	0.457*	1.000						
(10) Funding structure	–0.312*	0.197*	0.096*	–0.145*	–0.470*	–0.395*	0.138*	0.063*	–0.219*	1.000					
(11) Real GDP growth	–0.036*	–0.048*	0.062*	–0.047*	0.115*	–0.150*	0.005	0.279*	0.334*	0.021	1.000				
(12) Inflation	0.066*	–0.082*	0.036*	0.167*	0.178*	–0.211*	0.091*	0.249*	0.332*	–0.121*	0.279*	1.000			
(13) Bank concentration	0.069*	–0.084*	0.077*	0.188*	0.107*	–0.027	0.083*	–0.034*	0.117*	–0.343*	0.206*	0.121*	1.000		
(14) Financial intermed.	–0.306*	0.089*	–0.065*	–0.261*	–0.456*	0.208*	–0.144*	–0.350*	–0.436*	0.340*	–0.477*	–0.488*	–0.446*	1.000	
(15) CBIS index	–0.100*	–0.218*	–0.239*	0.088*	0.182*	–0.137*	0.190*	0.314*	0.093*	–0.159*	0.227*	0.205*	0.182*	–0.471*	1.000

Note: * denotes statistical significance at the maximum level of 10%.

Table A5 Robustness assessment using a different SR measure: Systemic Factor3

Dependent: SF3	(1)	(2)	(3)	(4)	(5)
Fixed-effects parameters					
CBI index (t-1)	–2.544***				
	(0.443)				
Personnel indep. (t-1)		–3.040***			
		(0.506)			
CB objectives (t-1)			–1.810***		
			(0.294)		
Policy indep. (t-1)				–1.575***	
				(0.370)	
Financial indep. (t-1)					–1.116**
					(0.439)
Size (t-1)	–0.130**	–0.119**	–0.111**	–0.120**	–0.108**
	(0.052)	(0.054)	(0.054)	(0.055)	(0.054)
Credit risk ratio (t-1)	2.831***	5.275***	5.201***	5.129***	5.860***
	(0.873)	(0.904)	(0.904)	(0.916)	(0.904)
Capitalization (t-1)	–11.233***	–11.750***	–11.788***	–11.518***	–12.300***
	(1.177)	(1.258)	(1.258)	(1.265)	(1.269)
Profitability (t-1)	–8.216**	–9.555***	–10.770***	–10.245***	–10.140***
	(3.266)	(3.439)	(3.439)	(3.448)	(3.455)
Funding structure (t-1)	–2.461***	–2.365***	–2.141***	–2.201***	–2.137***
	(0.343)	(0.366)	(0.363)	(0.365)	(0.365)
Real GDP growth (t-1)	–2.674**	–2.904**	–2.344*	–3.115**	–2.450*
	(1.230)	(1.322)	(1.322)	(1.330)	(1.330)
Inflation (t-1)	0.022**	0.018	0.018	0.016	0.018
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Bank concentration (t-1)	0.003	0.004*	0.004	0.004*	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Financial intermediation (t-1)	0.021***	0.021***	0.021***	0.021***	0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
CBIS index (t-1)	–0.108*	0.040	0.040	0.049	0.039
	(0.056)	(0.069)	(0.069)	(0.069)	(0.069)
Constant	0.486	0.107	–0.913	–0.660	–1.193
	(1.431)	(1.499)	(1.470)	(1.493)	(1.489)
Random-effects parameters					
Country-level variance	0.536***	0.676***	0.648***	0.683***	0.659***
	(0.133)	(0.128)	(0.129)	(0.133)	(0.134)
Bank-level variance	0.253***	0.248***	0.248***	0.250***	0.247***
	(0.047)	(0.048)	(0.048)	(0.048)	(0.048)
Residual variance	0.040***	0.082***	0.082***	0.084***	0.087***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Yearly observation	3248	3154	3154	3154	3154
Countries	40	43	43	43	43
Banks	323	329	329	329	329
LR test chi-square	2475.609***	2342.727***	2416.620***	2350.032***	2396.280***

Note: This table reports the results for the base model described in Eq. (1). The dependent variable is Systemic Facor3, defined in Table A2 in the Appendix. The HML model is estimated using the maximum likelihood estimation. The LR test compares the estimated model with the standard OLS regression, and the null hypothesis is that there are no significant differences between the two models. Standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table A6 Interaction regression results: Systemic Factor2

Dependent: SF2	(1)	(2)	(3)
Fixed-effects parameters			
CBI index (t-1)	–1.224***	–0.865***	–1.022***
	(0.212)	(0.216)	(0.197)
Crisis	0.397***		
	(0.087)		
Crisis × CBI (t-1)	0.330***		
	(0.102)		
High Lerner index (t-1)		0.253***	
		(0.087)	
High Lerner index (t-1) × CBI (t-1)		–0.496***	
		(0.148)	
Rigid exchange rate (t-1)			0.002
			(0.120)
Rigid exchange rate (t-1) × CBI (t-1)			–0.297*
			(0.162)
Size (t-1)	–0.041	–0.040	0.033
	(0.026)	(0.026)	(0.026)
Credit risk ratio (t-1)	1.323***	1.281***	1.088***
	(0.416)	(0.427)	(0.389)
Capitalization (t-1)	–3.673***	–2.468	–2.035
	(0.563)	(1.686)	(1.484)
Profitability (t-1)	–1.939	–3.534***	–3.033***
	(1.587)	(0.575)	(0.533)
Funding structure (t-1)	–1.055***	–1.197***	–0.855***
	(0.164)	(0.175)	(0.155)
Real GDP growth (t-1)	–1.467**	–1.558***	–1.836***
	(0.591)	(0.604)	(0.543)
Inflation (t-1)	0.009*	0.007	0.002
	(0.005)	(0.005)	(0.005)
Bank concentration (t-1)	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)
Financial intermediation (t-1)	0.006***	0.006***	0.010***
	(0.001)	(0.001)	(0.001)
CBISI (t-1)	–0.077***	–0.082***	–0.061***
	(0.027)	(0.027)	(0.023)
Constant	0.677	0.682	–0.960
	(0.689)	(0.705)	(0.691)
Yearly observations	3270	3201	2967
Countries	40	40	40
Banks	322	322	322
LR test chi-square	2533***	2450***	2885***

Note: This table reports the results for the model described in Eq. (2). The dependent variable is Systemic Factor2, defined in Table A2 in the Appendix. The HML model is estimated using the maximum likelihood estimation. The LR test compares the estimated model with the standard OLS regression, and the null hypothesis is that there are no significant differences between the two models. Standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively. To conserve space, we suppressed the output for random-effects parameters.

Table A7 Interaction regression results: Systemic Factor3

Dependent: SF3	(1)	(2)	(3)
Fixed-effects parameters			
CBI index (t-1)	–2.853***	–2.233***	–2.565***
	(0.444)	(0.453)	(0.426)
Crisis	1.006***		
	(0.178)		
Crisis × CBI (t-1)	0.374*		
	(0.212)		
High Lerner index (t-1)		0.451**	
		(0.180)	
High Lerner index (t-1) × CBI (t-1)		–1.027***	
		(0.305)	
Rigid exchange rate (t-1)			–0.016
			(0.256)
Rigid exchange rate (t-1) × CBI (t-1)			–0.613*
			(0.346)
Size (t-1)	–0.124**	–0.124**	–0.001
	(0.052)	(0.053)	(0.053)
Credit risk ratio (t-1)	2.905***	2.719***	2.183***
	(0.864)	(0.884)	(0.832)
Capitalization (t-1)	–10.866***	–10.448***	–9.772***
	(1.168)	(3.449)	(3.140)
Profitability (t-1)	–8.345**	–10.431***	–9.442***
	(3.253)	(1.190)	(1.140)
Funding structure (t-1)	–2.458***	–2.805***	–2.030***
	(0.339)	(0.361)	(0.328)
Real GDP growth (t-1)	–2.719**	–2.807**	–3.491***
	(1.218)	(1.241)	(1.156)
Inflation (t-1)	0.023**	0.019*	0.013
	(0.011)	(0.011)	(0.010)
Bank concentration (t-1)	0.004*	0.003	0.006***
	(0.002)	(0.002)	(0.002)
Financial intermediation (t-1)	0.020***	0.020***	0.027***
	(0.002)	(0.002)	(0.002)
CBISI (t-1)	–0.113**	–0.132**	–0.093*
	(0.055)	(0.056)	(0.050)
Constant	0.364	0.516	–2.453*
	(1.419)	(1.447)	(1.454)
Yearly observations	3234	3166	2932
Countries	40	40	40
Banks	322	322	322
LR test chi-square	2454***	2373***	2725***

Note: This table reports the results for the model described in Eq. (2). The dependent variable is Systemic Factor3, defined in Table A2 in the Appendix. The HML model is estimated using the maximum likelihood estimation. The LR test compares the estimated model with the standard OLS regression, and the null hypothesis is that there are no significant differences between the two models. Standard errors in parentheses.***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively. To conserve space, we suppressed the output for random-effects parameters.

BOFIT Discussion Papers

A series devoted to academic studies by BOFIT economists and guest researchers. The focus is on works relevant for economic policy and economic developments in transition / emerging economies.

2019	No 1	Çağatay Bircan and Orkun Saka: Lending cycles and real outcomes: Costs of political misalignment
	No 2	Lucy Chernykh, Denis Davydov and Jukka Sihvonen: Financial stability and public confidence in banks
	No 3	Yin-Wong Cheung and Shi He: Truths and myths about RMB misalignment: A meta-analysis
	No 4	Yuping Deng, Yanrui Wu, Helian Xu: Political connections and firm pollution behaviour: An empirical study
	No 5	Sophia Chen, Lev Ratnovski and Pi-Han Tsai: Credit and fiscal multipliers in China
	No 6	Alexander Kostrov and Mikhail Mamonov: The formation of hidden negative capital in banking: A product mismatch hypothesis
	No 7	Ning Cai, Jinlu Feng, Yong Liu, Hong Ru and Endong Yang: Government credit and trade war
	No 8	Michael Funke and Andrew Tsang: The direction and intensity of China's monetary policy conduct: A dynamic factor modelling approach
	No 9	Hamza Bennani: Does People's Bank of China communication matter? Evidence from stock market reaction
	No 10	Alexei Karas, William Pyle and Koen Schoors: Deposit insurance, market discipline and bank risk
	No 11	Gerard Roland and David Y. Yang: China's lost generation: Changes in beliefs and their intergenerational transmission
	No 12	Abel François, Sophie Panel and Laurent Weill: Are some dictators more attractive to foreign investors?
	No 13	Anna Pestova and Mikhail Mamonov: Should we care? The economic effects of financial sanctions on the Russian economy
	No 14	Haiyue Yu, Jin Cao and Shulong Kang: Fertility cost, intergenerational labor division, and female employment
	No 15	Max Breitenlechner and Riikka Nuutilainen: China's monetary policy and the loan market: How strong is the credit channel in China?
	No 16	Yiping Huang, Xiang Li and Chu Wang: What does peer-to-peer lending evidence say about the risk-taking channel of monetary policy?
	No 17	Heli Simola: Evaluating international impacts of China-specific shocks in an input-output framework
	No 18	Sris Chatterjee, Xian Gu, Iftekhar Hasan and Haitian Lu: Ownership structure and the cost of debt: Evidence from the Chinese corporate bond market
	No 19	Ke Song and Le Xia: Bilateral swap agreement and Renminbi settlement in cross-border trade
	No 20	Aaron Mehrotra, Richhild Moessner and Chang Shu: Interest rate spillovers from the United States: expectations, term premia and macro-financial vulnerabilities
	No 21	Zuzana Fungáčová, Eeva Kerola and Laurent Weill: Does experience of banking crises affect trust in banks?
	No 22	Mustafa Caglayan, Oleksandr Talavera and Wei Zhang: Herding behaviour in P2P lending markets
	No 23	Michael Funke, Xiang Li and Andrew Tsang: Monetary policy shocks and peer-to-peer lending in China
	No 24	Gayane Barseghyan: Sanctions and counter-sanctions: What did they do?
	No 25	Karlo Kauko: Benford's law and Chinese banks' non-performing loans
2020	No 1	Chang Ma, John Rogers and Sili Zhou: The effect of the China connect
	No 2	Karlo Kauko: The vanishing interest income of Chinese banks
	No 3	Mariya Hake and Philipp Poyntner: Keeping up with the Novaks? Income distribution as a determinant of household debt in CESEE
	No 4	Risto Herrala and Fabrice Orlandi: Win-Win? Assessing the global impact of the Chinese economy
	No 5	Weijia Li, Gérard Roland and Yang Xie: Erosion of state power, corruption control, and political stability
	No 6	Ryan Banerjee, Boris Hofmann and Aaron Mehrotra: Corporate investment and the exchange rate: The financial channel
	No 7	Amanda Gregg and Steven Nafziger: Financing nascent industry: Leverage, politics, and performance in Imperial Russia
	No 8	Zuzana Fungáčová, Koen Schoors, Laura Solanko and Laurent Weill: Political cycles and bank lending in Russia
	No 9	Francis Osei-Tutu and Laurent Weill: Sex, language, and financial inclusion
	No 10	Josef C. Brada, Chunda Chen, Jingyi Jia and Ali M. Kutan: Does bilateral investment treaty arbitration have any value for multinational corporations?
	No 11	Cristiano Perugini: Patterns and drivers of household income dynamics in Russia: The role of access to credit
	No 12	Michael Funke and Andrew Tsang: The People's Bank of China's response to the coronavirus pandemic – A quantitative assessment
	No 13	Alin Marius Andrieș, Anca Maria Podpiera and Nicu Sprincean: Central bank independence and systemic risk

BOFIT Discussion Papers
http://www.bofit.fi/en • email: bofit@bof.fi
ISSN 1456-4564 (print) // ISSN 1456-5889 (online)