Central Bank Independence and Systemic Risk*

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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 banks 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 institutional, country, and banking system indicators on these systemic measures. The results show that there might be trade-offs between central bank independence and a central bank's financial stability mandate and that central bank independence may exacerbate the effect of a crisis on the contribution of banks to systemic risk, hence the need for a coordinated interaction between central banks and the governments. We also find that an increase in central bank independence can ameliorate the effects of environments characterized by a low level of financial freedom or high market power that, by themselves, enhance the systemic risk contribution of banks.

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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 2007–09 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 (CBI) 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

[1]Greenspan (2007, pp. 110–11).

[2]The unconventional measures involved the purchasing of large amount of public debt in the secondary markets.

[3]Surveys are provided by Berger, de Haan, and Eijffinger (2001), Cukierman (2008), Fernández-Albertos (2015), and de Haan and Eijffinger (2016).

[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).

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,[5] and macroprudential policy, which, unlike 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. 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 United Kingdom and the euro zone 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, more specifically for containing banks' systemic risk. It also attempts to shed some light on the channels through which CBI could lessen this. Doumpos, Gaganis, and Pasiouras (2015) distinguish between a direct impact that CBI could have on the "well-functioning of banks" in cases where the central bank is involved in supervision and an indirect influence on bank soundness through monetary policy and price stability, regardless of "whether prudential supervision is assigned to

[5]Toniolo and White (2015) provide a historical perspective of the financial stability mandate.

the central bank or not." We add that a direct impact could work also through a financial stability mandate.

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 2007–08 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, Bostandzic, and Neumann (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 CBI and inflation, studies on the nexus of CBI 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 term and medium term there can be tradeoffs between these two mandates. Central banks also 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 on the conduct

[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, Qi, and Sun 2013).

of monetary policy or of capture by financial-sector players, and thereby allows timely actions 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, Khan, and Dewan (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, Gaganis, and Pasiouras (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, Sidiropoulos, and Spyromitros (2017) find that enhanced CBI increases stock market volatility. Using governor turnover as a proxy for limited actual independence, Moser and Dreher (2010) 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.

[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.

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.

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, Salsano, and Ferrari 2011) or is mainly cross-sectional (Crowe and Meade 2007). Our sample consists of 323 banks in 40 countries over a period of 14 years (2001–14). This period comprises the dot-com crisis, the recent global financial crisis (2007–09), and the sovereign debt crisis in Europe (2010–13).

We also analyze how central bank independence affects the impact of various institutional, country, and banking system indicators on systemic risk. The interaction with institutional variables such as the role of central bank in financial stability and the level of a country's development could shed light on potential channels though which CBI affects systemic risk.[9]

We document a negative and significant influence of central bank independence on major systemic and individual risk measures (ΔCoVaR, SRISK, MES, VaR, and Beta) computed for individual banks, i.e., central bank independence is desirable for containing systemic risk, hence for maintaining financial stability. Our findings are robust after controlling for nesting and potential endogeneity issues. At the same time, we find evidence of trade-offs between CBI and central banks having financial stability mandates that often involves coordination with the government. This indicates that CBI's effect on systemic risk works rather through the prudential supervision, especially when banking sector supervision is within the central

[9]We thank a reviewer for suggesting to analyze these potential channels.

bank, or through monetary policy preferences. An additional finding that a higher degree of central bank independence may exacerbate the effect of a crisis on the systemic risk contribution of banks adds to the evidence that central bank coordination with fiscal policy is needed for prevention of or in resolving a financial crisis. We further show that central bank independence mitigates the systemic risk contribution of banks in countries with a low level of financial freedom or where banks hold substantial market power. 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 (2001–14). 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 A.1 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."[10] We excluded banks that either failed to report daily market capitalization consistently throughout the observation period or had more than 25 percent of their quarterly balance sheets missing in the Worldscope data set.

[10]Ticker *G#LBANKSWD.*

2.2 Econometric Framework

Our data set has a clear hierarchical structure with individual banks nested in countries over a number of years. Similar to Doumpos, Gaganis, and Pasiouras (2015), we employ a hierarchical linear modeling (HLM) approach. This is one of the main empirical approaches that models clustered data, accounting for data having various levels of aggregation and controlling for potential dependency due to nesting effects. One of the main advantages of multilevel modeling comes with unbalanced data. In our sample, there are different sample sizes in different countries. Moreover, the HLM estimation does not require residuals to be independent (Mourouzidou-Damtsa, Milidonis, and Stathopoulos 2019).

The HLM approach has been recently applied in cross-country studies that examine firm performance (Kayo and Kimura 2011; Li et al. 2013; van Essen, Engelen, and Carney 2013; Marcato, Milcheva, and Zheng 2018), as well as bank risk-taking and stability (Doumpos, Gaganis, and Pasiouras 2015; Mourouzidou-Damtsa, Milidonis, and Stathopoulos 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 United States, 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 estimated model has the following form:

$$\begin{aligned} SR_{ij,t} = {} & \underbrace{\alpha_0 + \alpha_1 \times CBI_{j,t-1} + \gamma \times X_{ij,t-1} + \delta \times Z_{j,t-1}}_{fixed\ \ components} \\ & + \underbrace{u_{ij} + e_j + \varepsilon_{ij,t}}_{random\ \ components}, \end{aligned} \tag{1}$$

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.[11]

$X_{ij,t-1}$ is a $(k \times 1)$ vector of lagged bank-level control variables (bank size, credit risk ratio, profitability, capitalization, and the funding structure) associated with systemic risk in the literature (Beck, Demirgüç-Kunt, and Levine 2006; Berger, Klapper, and Turk-Ariss 2009; Farhi and Tirole 2012; Laeven, Ratnovski, and Tong 2016; Xu, Hu, and Das 2019).

$Z_{j,t-1}$ 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, De Nicolo, and Jalal 2006; Beck, De Jonghe, and Mulier 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, Gaganis, and Pasiouras (2015) show that central bank involvement in supervision has a positive impact on bank soundness.

Table A.2 in the appendix describes the variables and the sources of data. Table A.3 presents the summary statistics. Table A.4 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

[11]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.

likelihood (ML) estimation of the variance components of Hartley and Rao (1967). To mitigate the problem of outliers, we winsorize all variables within the 1 percent and 99 percent percentiles.

In our analysis of whether CBI affects the impact of selected variables on measures of systemic risk, we focus on the role of the central bank in financial stability, level of development (including financial development), crisis (the 2007–09 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:

$$\begin{aligned} SR_{ij,t} = & \underbrace{\begin{matrix}\alpha_0 + \alpha_1 \times CBI_{ij,t-1} + \alpha_2 \times CBI_{ij,t-1} \times W_{j,t-1} \\ + \gamma \times X_{ij,t-1} + \delta \times Z_{j,t-1}\end{matrix}}_{fixed\ \ components} \\ & + \underbrace{u_{ij} + e_j + \varepsilon_{ijw,t}}_{random\ \ components}, \end{aligned} \tag{2}$$

where $W_{j,t-1}$ is the vector of the selected variables.

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 several measures of systemic importance: (i) two measures of systemic risk contribution (ΔCoVaR and SRISK); (ii) two measures of systemic risk exposure (MES and Exposure-ΔCoVaR), and two measures of banks' individual (or stand-alone) risk (VaR and Beta) estimated for each bank over the 2001–14 period.[12]

[12] Bisias et al. (2012) provide an extensive survey of 31 measures of systemic risk.

2.3.1 Systemic Risk Contribution

ΔCoVaR. The first indicator considered for systemic risk contribution is the 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:[13]

$$q = \Pr\left(R^i_{Market\ \ Assets,t} \leq VaR^i_{q,t}\right), \tag{3}$$

where $R^i_{MarketAssets,t}$ is the bank's i market value of total 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. Similarly, the VaR of the system can be computed as follows:

$$q = \Pr\left(R^{System}_{Market\ \ Assets,t} \leq VaR^{System}_{q,t}\right). \tag{4}$$

VaR, which expresses the maximum possible loss (as a percent of the market value of total assets) that a bank or the system could register for a given confidence level over a specific period of time, is the loss that can be found in the left tail of the market value of total assets distribution function.

We focus on the daily change of the market value of total 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.[14] We eliminate banks that have missing total assets or equity data for two or more consecutive quarters.

VaR is an indicator that was used in the context of microprudential 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 value of total assets, we apply the CoVaR methodology. It implies the estimation

[13]Following Adrian and Brunnermeier (2016), all our systemic risk indicators are estimated for a 5 percent quantile.

[14]We perform cubic spline interpolations as a robustness check. The findings remain robust.

of the system's q^{th} quantile of the returns distribution over a given period of time conditional on the event that each bank registers its maximum possible loss. 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):

$$q = \Pr(R^{System}_{Market\ Assets,q} \\ \leq CoVaR^{System|R^{i}_{Market\ Assets,t}=VaR^{i}_{q,t}}_{q,t} | R^{i}_{Market\ Aseets,t} = VaR^{i}_{q,t}), \tag{5}$$

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 2020). 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 risk of 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 conditional 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 A.2 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 MI'_{t-1}):

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

where α^i is the constant (unobserved characteristics of bank i), β^i is a $(k \times 1)$ vector that captures the bank's i return dependence relationship with the market indices, and ε^i is an i.i.d. error term.

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

$$R^{System}_{Market\ Assets,t} = \alpha^{System|i} + \delta^{System|i} \times R^{i}_{Market\ Assets,t} + \beta^{System|i} \times MI'_{t-1}\varepsilon^{System|i}_{t}, \tag{7}$$

where $\alpha^{System|i}$ is the constant, capturing the banking system characteristics conditional on bank i, $\beta^{System|i}$ is a $(k \times 1)$ 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'si return, and $\varepsilon^{System|i}$ is the i.i.d. error term.

Running regressions from Equation (6) and Equation (7) for a quantile of 5 percent (distressed periods) and a quantile of 50 percent (median or tranquil state), we obtain the value of regressors to be used in VaR and CoVaR estimations:

$$\widehat{VaR}^{i}_{q,t} = \hat{\alpha}^{i}_{q} + \hat{\beta}^{i}_{q} \times MI'_{t-1} \tag{8}$$

$$\widehat{CoVaR}^{i}_{q,t} = \hat{\alpha}^{System|i}_{q} + \hat{\delta}^{System|i}_{q} \times \widehat{VaR}^{i}_{q,t} + \hat{\beta}^{System|i}_{q} MI'_{t-1}. \tag{9}$$

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

$$\Delta CoVaR^{System|i}_{q,t} = CoVaR^{System|R^{i}_{Market\ \ Assets}=VaR^{i}_{q,t}}_{q,t} - CoVaR^{System|R^{i}_{Market\ \ Assets=VaR^{i}_{50\%}}}_{q,t}. \tag{10}$$

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

SRISK. The second indicator considered for systemic risk contribution is based on the Systemic Risk Index (SRISK) introduced by Acharya, Engle, and Richardson (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, it is also close to capturing a bank's exposure to common shocks that affect the whole financial system (Laeven, Ratnovski, and Tong 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

$$CS_t^i = kA_t^i - E_t^i = k\left(L_t^i + E_t^i\right) - E_t^i. \tag{11}$$

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:

$$\begin{aligned} SRISK_t^i = E_t\left(CS_{t+h}^i | R_{t+1:t+h}^{System} < C\right) = kE_t\left(L_{t+h}^i | R_{t+1:t+h}^{System} < C\right) \\ - (1-k)\,E_t\left(E_{t+h}^i | R_{t+1:t+h}^{System} < C\right). \end{aligned} \tag{12}$$

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

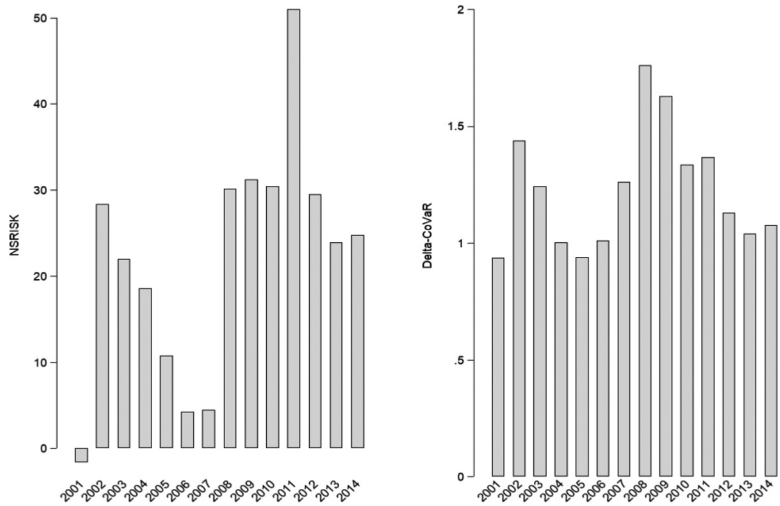
$$SRISK_t^i = kL_t^i - (1-k)E_t^i(1 - LRMES_t^i). \tag{13}$$

$LRMES_t^i$ 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 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 percent, and $beta$ is the bank's beta coefficient. The capital prudential ratio k is set at 8 percent 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, Roman, and Sedunov (2020), 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, Engle, and Richardson (2012) recommend setting negative SRISK values to zero because they imply a capital surplus and do not contribute to systemic risk, we follow Laeven, Ratnovski, and Tong (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 systemwide 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 2001–14 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 the onset of global financial crisis. For NSRISK, the peak is in 2011 when there was a sovereign

Figure 1. Evolution of Average Systemic Risk Contribution by Year



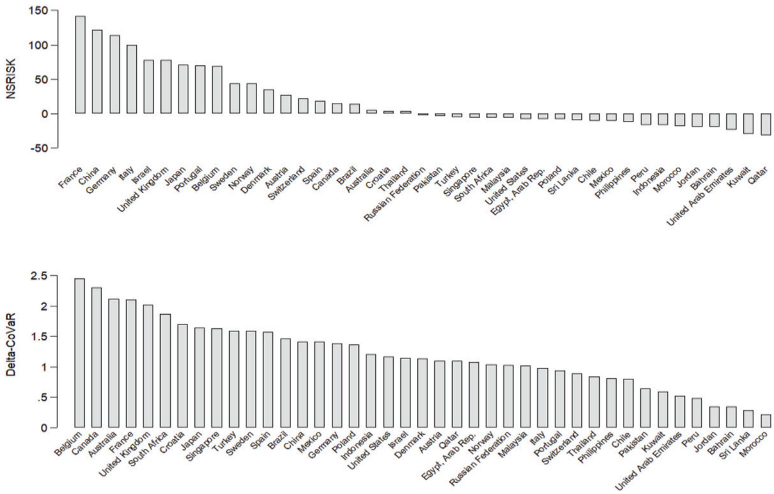
debt crisis in Europe characterized by high government debt and high yield spreads in government securities. Continent-wise, European banks had the largest average contribution to systemic risk over the whole period, defined by NSRISK. Asian banks were the second largest in terms of average contribution. However, Australian banks were the riskiest in terms of ΔCoVaR, followed by those from Europe.

In terms of average contribution to systemwide distress by country (Figure 2), French banks had the highest capital shortfall per unit of market capitalization in the 2001–14 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.

2.3.2 Measure of Systemic Risk Exposure

Systemic risk exposure is proxied by marginal expected shortfall (MES) of Acharya, Engle, and Richardson (2017) and

Figure 2. Average Systemic Risk Contribution by Country



Exposure-ΔCoVaR of Adrian and Brunnermeier (2016). 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.

$$MES^i_{t-1} = E_{t-1}\left(R^i_t | R^{System}_t < C\right), \tag{14}$$

where R^i_t is the return of bank i at time t and R^{System}_t 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:

$$R^{System}_t = \sigma^{System}_t \varepsilon^{System}_t \tag{15}$$

$$R^i_t = \sigma^i_t \varepsilon^i_t = \sigma^i_t \rho^i_t \varepsilon^{System}_t + \sigma^i_t \sqrt{1 - \rho^2_{i,t}} \xi_{i,t}. \tag{16}$$

σ^i_t and σ^{System}_t are the volatilities of bank i and the financial system, respectively; ρ^i_t is the correlation coefficient between the return of bank i and the return of the system; and ε^{System}_t, ε^i_t, and $\xi_{i,t}$ are the error terms which are assumed to be i.i.d. It follows that

$$
\begin{aligned}
MES_{t-1}^{i} &= E_{t-1}\left(R_t^i | R_t^{System} < C\right) \\
&= \sigma_t^i E_{t-1}\left(\varepsilon_t^i \middle| \varepsilon_t^{System} < \frac{C}{\sigma_t^{System}}\right) \\
&= \sigma_t^i \rho_{i,t} E_{t-1}\left(\varepsilon_t^i \middle| \varepsilon_t^{System} < \frac{C}{\sigma_t^{System}}\right) \\
&\quad + \sigma_t^i \sqrt{1-\rho_{i,t}^2} E_{t-1}\left(\xi_t^i \middle| \varepsilon_t^{System} < \frac{C}{\sigma_t^{System}}\right). \qquad (17)
\end{aligned}
$$

As in Benoit et al. (2013), we consider the threshold C equal to the conditional VaR of the system return, i.e., VaR (5 percent), 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.

Exposure-ΔCoVaR (eΔCoVaR) works in the opposite direction with ΔCoVaR, denoting the system's contribution to bank i or, alternatively, the exposure of bank i to the system. It is defined as the difference between VaR of the financial institution i conditional on the event that the system is in distress (5 percent worst outcomes), and VaR of the financial institution i conditional on the event that the system faces the median return (i.e., tranquil state):

$$
\begin{aligned}
e\Delta CoVaR_{q,t}^{i|System} &= CoVaR_{q,t}^{i|R_{Market\ Assets}^{System}=VaR_{q,t}^{System}} \\
&\quad - CoVaR_{q,t}^{i|R_{Market\ Assets=VaR_{50\%}^{System}}^{System}}. \qquad (18)
\end{aligned}
$$

2.3.3 Banks' Individual or Stand-Alone Risk

We also analyze how central bank independence influences individual risk of the banks (i.e., a microprudential approach). Before the global financial crisis, the microprudential 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 the 2007–09 recession. We define individual risk as the maximum possible loss as a percent of the total market equity a bank could register for a given confidence level (95 percent) 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. VaR is expressed as a positive number, higher values being associated with enhanced individual risk. In addition, we employ the dynamic conditional beta using the DCC framework of Engle (2002) to capture the conditional co-movement between each bank and the market (MSCI World Financials Index), where the GJR-GARCH process is employed to account for the conditional heteroskedasticity. Higher values of beta denote increased risk of bank i in comparison with the market.

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 with 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, Webb, and Neyapti (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 means perfect independence (see Cukierman, Webb, and Neyapti 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, Webb, and Neyapti (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:

- *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.
- *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.
- *Central Bank Objectives:* (viii) monetary stability as one of the primary policy objectives. The weight in the index is 0.15.
- *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.

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

Figure 3. Evolution of Average Weighted CBI Index and Its Subcomponents by Year

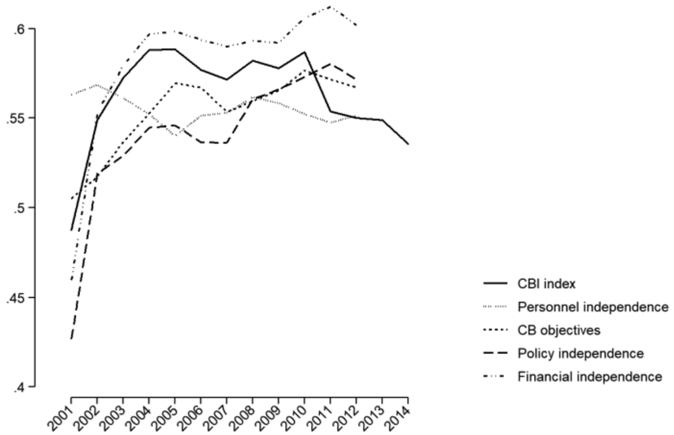
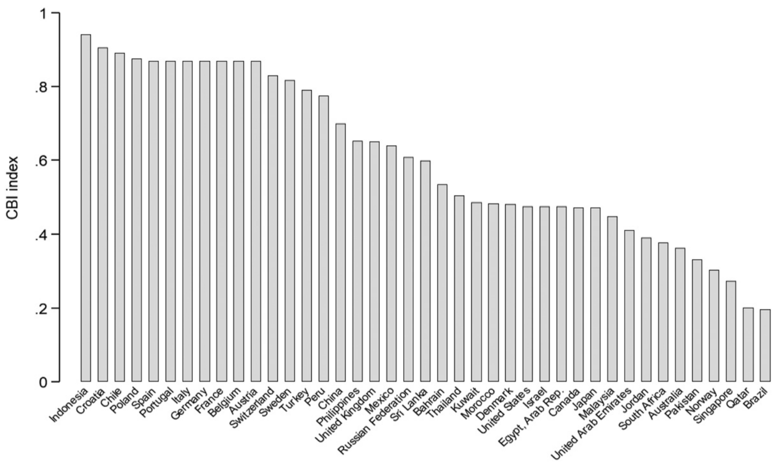


Figure 4. Average Weighted CBI Index by Country



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).[15] Each of these tables report the outcome of the estimations for the model described in Equation (1) corresponding to the five CBI measures. As the degree of central banks' independence increases, banks' contribution to systemwide 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 percent as measured by ΔCoVaR, and by 21.66 percent 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, Gaganis, and Pasiouras (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 ordinary least squares (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 a 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, Ratnovski, and Tong 2016). Hence, the negative sign in the NSRISK model could suggest that larger banks may diversify more efficiently and enjoy

[15]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.

easier access to capital markets, thereby putting them in a more solid position than smaller banks 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, Ratnovski, and Tong (2016).

As expected, deterioration in the quality of the loan portfolio enhances both measures of banks’ contribution to systemic risk. Better *profitability*, higher *capitalization*, and a funding structure that is mainly based on deposits reduce banks’ systemic distress. *Profitability*, however, 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, De Jonghe, and Mulier (2017) find concentration of bank assets to be a key contributor to accumulation of systemic risk in the banking sector. Boyd, De Nicolo, and Jalal (2006) claim probability of bank default is positively and significantly related to concentration. Beck, Demirgüç-Kunt, and Levine (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.[16]

[16] Previous studies (e.g., Reinhart and Rogoff 2009; Jordà, Schularick, and Taylor 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)
Profitability (t–1)	1.467	1.791	1.557	1.668	1.622
	(1.240)	(1.275)	(1.276)	(1.271)	(1.278)
Capitalization (t–1)	−1.076**	−1.047**	−1.068**	−0.949**	−1.152**
	(0.442)	(0.463)	(0.463)	(0.462)	(0.465)
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)

(continued)

Table 1. (Continued)

Dependent: ΔCoVaR	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
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)
Observations	3,327	3,233	3,233	3,233	3,233
Countries	40	43	43	43	43
Banks	323	329	329	329	329
LR Test Chi-Square	2,938.761***	2,748.187***	2,800.921***	2,825.238***	2,783.356***

Note: This table reports the results for the base model described in Equation (1). The dependent variable is ΔCoVaR, defined in Table A.2 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 the 1 percent, 5 percent, and 10 percent level, 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)
Profitability (t–1)	−3.167***	−3.471***	−3.760***	−3.631***	−3.600***
	(0.839)	(0.877)	(0.876)	(0.879)	(0.879)
Capitalization (t–1)	−2.449***	−2.593***	−2.593***	−2.545***	−2.731***
	(0.294)	(0.312)	(0.312)	(0.314)	(0.314)
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)

(*continued*)

Table 2. (Continued)

Dependent: NSRISK	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
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)
Observations	3,284	3,190	3,190	3,190	3,190
Countries	40	43	43	43	43
Banks	323	329	329	329	329
LR Test Chi-Square	2,188.474***	2,269.242***	2,307.954***	2,163.498***	2,296.290***

Note: This table reports the results for the base model described in Equation (1). The dependent variable is NSRISK, defined in Table A.2 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 the 1 percent, 5 percent, and 10 percent level, respectively.

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.

3.2 The Impact of Central Bank Independence on Systemic Risk Exposure and Stand-Alone Risk

Our findings for banks' exposure to systemwide distress are in line with those for banks' contribution to systemwide distress, but only in the case of MES (Table 3, column 1). Thus, a central bank that is politically independent is helpful to banks in reducing their exposure to systemic risk. A one-standard-deviation increase in the CBI index decreases systemic exposure of banks by 7.59 percent as measured by MES. In terms of stand-alone risk of individual banks measured by VaR and dynamic conditional beta, central bank independence reduces this in the case of both VaR and Beta estimations (Table 3, columns 3 and 4). A one-standard-deviation increase in the CBI index leads to a fall in banks' VaR by 11.94 percent, whereas a one-standard-deviation increase in the CBI index decreases Beta by 8.49 percent. Regarding the control variables, greater *size*, an increased *credit risk ratio* (MES, VaR, and Beta), *profitability* (eΔCoVaR), higher levels of *credit granted by financial sector* (MES, VaR, and Beta), and *inflation* (VaR) positively affect the risk measures. On the other hand, better *capitalization (*MES, eΔCoVaR, and VaR) *profitability* (Beta), a funding structure dominated by deposits, high *economic growth*, increased *bank concentration*, and a greater *involvement in supervision by the central bank* (MES, eΔCoVaR, and VaR) significantly reduce these measures of distress.

3.3 Further Evidence on the Role of Central Bank Independence on Systemic Risk Contribution

In this section, we analyze five hypotheses regarding how CBI affects the impact of selected institutional, macroeconomic, and banking system characteristics on the measures of the systemic risk of banks. The empirical analysis for each hypothesis includes the variable of interest and its interaction with CBI in addition to the control variables considered so far.

HYPOTHESIS 1. *Central banks' financial stability mandate is meant to manage banks' systemic risk contribution. A heightened central bank independence could reduce this effect because of a potentially lower collaboration with other agencies relevant for the financial stability.*

While central banks are thought to have a natural role in financial stability since monetary policy affects financial conditions and consequently financial stability, historically their de jure mandates have diverged widely (Haltom and Weinberg 2017). To achieve similar levels of performance as well as accountability as for the price stability mandate, an explicit goal for financial stability seems sensible but at the same time "more problematical than inflation targetry, because it is so much harder to monitor, and you cannot really tell whether the authorities are on the right track, or not" (Goodhart and Lastra 2018). At the same time, monetary and prudential policies have traditionally been designed and analyzed in isolation from one another (Collard et al. 2017). A more independent central bank could be more reluctant to share the financial stability responsibilities with other agencies and this could mitigate the beneficial effect of having an explicit mandate on the systemic risk.

To verify this hypothesis, we construct a variable for central bank's financial stability mandate (FSM). We collected data that describe the following three aspects: financial stability mandate or objective, publication of financial stability reports, and the role of central banks in macroprudential committees. For the sources, we used central bank's websites, the databases used in Cerutti, Claessens, and Laeven (2017) and Edge and Liang (2019), the International Monetary Fund's (IMF's) Central Bank Legislation Database, and IMF's Financial Sector Assessment Program reports database. We do not distinguish between whether FSM is a secondary or primary mandate. Out of 40 central banks, 5 have never had an FSM, 11 have had an FSM for the whole period, and 14 acquired an FSM after 2007.

In addition, we look at the effect of the quality of microprudential supervision, proxied by the index developed by Anginer, Demirgüç-Kunt, and Zhu (2014b) on banks' contribution to systemic risk and whether the CBI affects this relationship. This index assesses whether the supervisory authorities have the power and authority

Table 3. Estimation Results for Systemic Risk Exposure (MES and eΔCoVaR) and Individual Risk (VaR and Beta)

	(1)	(2)	(3)	(4)
Dependent Variables	**MES**	**eΔCoVaR**	**VaR**	**Beta**
Fixed-Effects Parameters				
CBI Index (t–1)	−0.550**	−0.039	−0.916***	−0.157**
	(0.275)	(0.209)	(0.350)	(0.075)
Size (t–1)	0.259***	0.080***	0.073**	0.064***
	(0.028)	(0.029)	(0.032)	(0.008)
Credit Risk Ratio (t–1)	2.623***	0.658	2.158***	0.269*
	(0.523)	(0.405)	(0.701)	(0.148)
Profitability (t–1)	−2.017	3.136**	−1.646	−2.705***
	(2.033)	(1.583)	(2.736)	(0.576)
Capitalization (t–1)	−2.113***	−0.951*	−3.185***	0.085
	(0.700)	(0.570)	(0.918)	(0.198)
Funding Structure (t–1)	−1.111***	−0.677***	−1.072***	−0.295***
	(0.202)	(0.169)	(0.259)	(0.057)
Real GDP Growth (t–1)	−2.891***	−1.390**	−3.850***	−0.483**
	(0.779)	(0.588)	(1.067)	(0.220)
Inflation (t–1)	−0.007	−0.019***	0.037***	0.002
	(0.007)	(0.005)	(0.009)	(0.002)

(*continued*)

Table 3. (Continued)

	(1)	(2)	(3)	(4)
Dependent Variables	**MES**	**eΔCoVaR**	**VaR**	**Beta**
Bank Concentration (t–1)	−0.009***	−0.007***	−0.010***	−0.001***
	(0.001)	(0.001)	(0.002)	(0.000)
Financial Intermediation (t–1)	0.009***	−0.002***	0.007***	0.001***
	(0.001)	(0.001)	(0.001)	(0.000)
CBIS Index (t–1)	−0.117***	−0.107***	−0.080*	−0.008
	(0.035)	(0.026)	(0.046)	(0.010)
Constant	−3.301***	0.738	2.395**	−0.815***
	(0.775)	(0.757)	(0.930)	(0.217)
Random-Effects Parameters				
Country-Level Variance	−0.109	−0.519***	−0.170	−1.573***
	(0.131)	(0.174)	(0.150)	(0.138)
Bank-Level Variance	−0.533***	−0.103**	−0.461***	−1.781***
	(0.049)	(0.044)	(0.053)	(0.049)
Residual Variance	−0.399***	−0.683***	−0.076***	−1.660***
	(0.013)	(0.013)	(0.013)	(0.013)
Observations	3,327	3,327	3,327	3,327
Countries	40	40	40	40
Banks	323	323	323	323
LR Test Chi-Square	1,967.876***	3,827.958***	970.073***	1,783.345***

Note: This table reports the results for other measures of bank risk. The dependent variables are MES, eΔCoVaR, VaR, and Beta, defined in Table A.2 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 the 1 percent, 5 percent, and 10 percent level, respectively.

to take specific preventive and corrective actions.[17] Better microprudential supervision should support the management of banks' contribution to systemic risk as it aims to enhance the resilience of individual financial institutions. Their health is a necessary, but not sufficient, condition for systemwide stability (Osiński, Seal, and Hoogduin 2013).

Hypothesis 2. *A country's level of development directly affects the implementation of financial regulation and hence could help lessen systemic risk. An independent central bank can enhance this effect.*

A country's development is largely associated with the overall level of institutional development and governance. Better governance further provides built-in mechanisms for the implementation of financial regulations, or at the least, it does not hinder this, and therefore could help mitigate the systemic risk. The relationship between development and CBI is not straightforward; countries from across the development spectrum have adopted policies to increase CBI, but their overall effectiveness often hinges on (the lack of) political constrains (Acemoglu et al. 2008). We are testing whether the overall level of development, level of financial freedom, or the level of financial market development neutralizes the effect of CBI documented so far in the analysis and, in addition, whether CBI affects the impact of the development variable on banks' contribution to systemic risk.

To capture this, we focus on two development variables (Real GDP/capita and Financial Freedom index) and three additional indexes that stand for the development of financial markets and institutions (Financial Markets index, Financial Institutions index, and Financial Development index). Table A.2 in the appendix describes these variables.

Hypothesis 3. *A crisis increases the contribution and exposure of banks to systemic risk. CBI can exacerbate this.*

[17]The index is based on World Bank's Bank Regulation and Supervision Surveys. It does not distinguish whether banking supervision is under the roof of the central bank.

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. CBI is important for preventing the accumulation of systemic risk.[18] But a heightened CBI could undermine necessary coordination of the central bank with other authorities *during* a financial crisis (Balls, Howar, and Stansbury 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.[19] During the first phase (July 2007 to the end of 2009), the effects of global financial crisis intensify in Europe (Brei, Gambacorta, and von Peter 2013). The second phase corresponds with the European sovereign debt crisis in Europe, spanning 2010 to 2013 (Cornille, Rycx, and Tojerow 2019). Samarakoon (2017) finds evidence of contagion effects from the European debt crisis to other emerging and developed markets around the world.

HYPOTHESIS 4. *High market power in the banking sector increases the systemic risk contribution of banks, but a higher level of CBI diminishes this effect.*

Banks with "high" market power[20] 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, Demirgüç-Kunt, and Zhu (2014a) 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,[21] increased bank competition erodes market power and decreases profit margins. This creates incentives

[18] Quintyn and Taylor (2003) find that in almost all systemic financial-sector crisis during 1990s, a major contributing factor was political interference in the supervisory process.

[19] We employ different definitions of crisis, including systemic banking crisis from Reinhart and Rogoff (2011) and Laeven and Valencia (2020). The interaction effect of crisis and CBI remains the same.

[20] We define "high" as values greater than or equal to the median of the sample.

[21] See Carletti and Hartmann (2003) for a review of the literature.

for banks to take on excessive risk as a way to increase their returns (Berger, Klapper, and Turk-Ariss 2009).

We measure market power in the banking system with the Lerner index.[22] 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.

HYPOTHESIS 5. *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, Laeven, and Marquez 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.

For Hypothesis 1 (results are presented in Table 4), the standalone coefficients of CBI as well as of FSM variables are negative (i.e., restraining, as expected, banks' systemic risk contribution), but the coefficients of their interactions are positive, indicating trade-offs between CBI and FSM. It also points out that, in terms of channels for CBI to affect systemic risk, the CBI has helped address systemic risk rather through monetary policy[23,24] or involvement in prudential supervision than through an explicit financial stability mandate. A closer look at the four corner solutions resulting from the coefficients of CBI and FSM (Table 4)—given that the CBI variable has a maximum value of 1 and a minimum of 0 and the FSM variable has a value of 1 when a FSM exists and 0 otherwise—reveals that the largest overall effects are obtained from combining the highest possible central bank independence with no financial stability

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

[23]See Adrian and Liang (2018) and Lamers et al. (2019) for channels through which monetary policy can affect financial stability.

[24]Levieuge, Lucotte, and Pradines-Jobet (2019) also find that differences in monetary policy preferences—relative preferences of central banks for the inflation stabilization—explain cross-country differences in banking vulnerabilities. Namely, if central banks were more preoccupied with output stabilization, they would focus more on financial stability objectives.

mandate.[25] This result is in line with the conclusion of Ueda and Valencia (2014), who find that having both price and financial stability mandates does not deliver social optimum due to a time-inconsistency problem.

A second-best solution points towards a less central bank independence with a financial stability mandate. Svensson (2013) considers that it may make sense to assign the objective of financial stability to the central bank, if the central bank is given control of the appropriate supervisory, regulatory, and crisis-management instruments. Bringing monetary and macroprudential policies under one central bank roof will tend to solve possible coordination problems that may arise from their interaction, but it may lead to incentive problems if failure of one policy domain affects the other policy domain (Smets 2014).

A caveat is in order here: while some central banks had financial stability mandates (albeit in most of the cases, secondary to the price stability mandate) before the financial crisis, their weight in the central banks' decisions and preferences has likely evolved after the crisis.[26] Similarly to Adrian and Liang (2018), our results emphasize that more research is needed to evaluate the efficacy of monetary and macroprudential policies framework to address systemic risk and to mitigate the consequences on the real economy.

Further, we do not find a significant impact on systemic risk measures from the proxies used for quality of microprudential supervision or quality of macroprudential supervision. Going forward, institutional arrangements for cooperation with other financial stability agencies for the implementation of macroprudential policies are needed and the governance of the current ones strengthened. Edge and Liang (2019) evaluated institutional structures and practices of macroprudential authorities in 58 countries as they continued to develop their frameworks and found that while most countries have established financial stability committees, many of these lack effectiveness.

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[25]We would like to thank an anonymous referee for suggesting the corner solution analysis.

[26]Central banks have started to communicate financial (in)stability issues more intensively (Horváth and Vaško 2016), but the degree to which financial stability considerations are taken into account in the monetary policy decision differs substantially across central banks (Friedrich, Hess, and Cunningham 2019).

Table 4. Interaction Regression Results: Financial Stability Mandate

Dependent: ΔCoVaR	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Fixed-Effects Parameters					
CBI Index (t–1)	−0.955***	−0.741***	−0.558***	−0.578***	−0.541***
	(0.160)	(0.163)	(0.146)	(0.164)	(0.145)
FS Mandate/Objective (t–1)	−0.655***				
	(0.108)				
FS Mandate/Objective (t–1) × CBI (t–1)	1.058***				
	(0.191)				
FS Report (t–1)		−0.269***			
		(0.064)			
FS Report (t–1) × CBI (t–1)		0.484***			
		(0.111)			
CB Role in MaPru Committee (t–1)			−0.454***		
			(0.075)		
CB Role in MaPru Committee (t–1) × CBI (t–1)			0.537***		
			(0.114)		
High MaPru Index (t–1)				−0.114	
				(0.089)	
High MaPru Index (t–1) × CBI (t–1)				0.104	
				(0.027)	
High-Quality MiPru Supervision Index (t–1)					−0.080
					(0.075)
High-Quality MiPru Supervision Index (t–1) × CBI (t–1)					0.026
					(0.123)
Size (t–1)	0.032	0.026	0.051**	0.037*	0.108***
	(0.021)	(0.021)	(0.020)	(0.020)	(0.020)

(continued)

Table 4. (Continued)

Dependent: ΔCoVaR	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Credit Risk Ratio (t–1)	0.442	0.308	0.483	0.382	0.293
	(0.314)	(0.316)	(0.313)	(0.315)	(0.283)
Profitability (t–1)	1.173	1.194	1.384	1.563	0.811
	(1.232)	(1.238)	(1.232)	(1.242)	(1.125)
Capitalization (t–1)	−0.931**	−0.950**	−0.970**	−0.920*	−0.333
	(0.440)	(0.441)	(0.440)	(0.441)	(0.404)
Funding Structure (t–1)	−0.405***	−0.455***	−0.362***	−0.446***	−0.195*
	(0.130)	(0.128)	(0.129)	(0.129)	(0.118)
Real GDP Growth (t–1)	−0.659	−0.940**	−1.051**	−0.932**	−0.752*
	(0.459)	(0.460)	(0.459)	(0.464)	(0.414)
Inflation (t–1)	0.001	0.002	0.000	0.001	−0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Bank Concentration (t–1)	−0.002**	−0.002**	−0.002**	−0.003***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Financial Intermediation (t–1)	0.001*	0.001**	0.001	0.001**	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
CBIS Index (t–1)	−0.092***	−0.075***	−0.062***	−0.078***	−0.061***
	(0.021)	(0.020)	(0.020)	(0.021)	(0.018)
Constant	1.039*	1.011*	0.297	0.769	−0.779
	(0.556)	(0.548)	(0.547)	(0.544)	(0.521)
Observations	3,313	3,313	3,313	3,313	3,181
Countries	40	40	40	40	40
Banks	322	322	322	322	322
LR Test Chi-Square	2,942.613***	2,865.342***	2,921.208***	2,867.126***	3,356.458***

Note: This table reports the results for the base model described in Equation (2). The dependent variable is ΔCoVaR, defined in Table A.2 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 the 1 percent, 5 percent, and 10 percent level, respectively. To conserve space, we suppressed the output for random-effects parameters.

Regarding institutional development (Hypothesis 2), results presented in Table 5 show that a low level of financial freedom increases banks' contribution to systemic risk, with this effect being ameliorated by an increase in CBI. We also see that countries with a higher-than-median level of the financial markets index that captures the development of financial markets (depth, access, and efficiency) are prone to an enhanced contribution to systemic risk. Our results are in line with Bostandzic and Weiß (2018), where their results reveal that the global importance of a country's stock market increases systemic risk. According to our results, the development in a country's material living standards is not associated with systemic risk. In line with the results of previous studies,[27] results from Models 4 and 5 show that financial institutions development and the overall financial development indices are not associated with systemic risk and neither augment nor mitigate the effect of CBI on systemic risk.

For Hypothesis 3, as anticipated, the sign of the interaction coefficient *Crisis* × *CBI (t–1)* is positive and significant in the case of the systemic interconnectedness measure (Table 6, Model 1). Thus, when crisis hits, a highly independent central bank could exacerbate delays in implementation of crisis measures when coordination with other institutions is involved. This suggests that there is need for a reassessment of the cooperation and collaboration between policymakers, especially in the context of the progress in institutional governance in the last two decades. Credibility and accountability of all players is pivotal.

Furthermore, if a banking sector is characterized by a high market power, the effect is an increase of systemic risk contribution of banks. 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 hypothesis, as the corresponding coefficients are insignificant.

[27] See, e.g., Brunnermeier and Oehmke (2012), who reveal that crises have occurred at all stages of financial system development: developed financial systems as well as emerging economies and developing financial systems.

Table 5. Interaction Regression Results: Institutional Development

Dependent: ΔCoVaR	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Fixed-Effects Parameters					
CBI Index (t–1)	−0.531**	−0.427***	−0.428***	−0.641***	−0.638***
	(0.258)	(0.165)	(0.163)	(0.160)	(0.159)
Low Real GDP/Capita (t–1)	0.027				
	(0.141)				
Low Real GDP/Capita (t–1) × CBI (t–1)	−0.069				
	(0.255)				
Low Financial Freedom Index (t–1)		0.322***			
		(0.097)			
Low Financial Freedom Index (t–1) × CBI (t–1)		−0.575***			
		(0.147)			
High Financial Markets Index (t–1)			0.343***		
			(0.092)		
High Financial Markets Index (t–1) × CBI (t–1)			−0.317*		
			(0.163)		
High Financial Institutions Index (t–1)				−0.021	
				(0.307)	
High Financial Institutions Index (t–1) × CBI (t–1)				0.183	
				(0.375)	
High Financial Development Index (t–1)					−0.132
					(0.118)
High Financial Development Index (t–1) × CBI (t–1)					0.326
					(0.200)
Size (t–1)	0.034*	0.035*	0.058***	0.034	0.033
	(0.021)	(0.021)	(0.020)	(0.020)	(0.021)

(continued)

Table 5. (Continued)

Dependent: ΔCoVaR	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Credit Risk Ratio (t–1)	0.403	0.499	0.582*	0.338	0.395
	(0.316)	(0.316)	(0.315)	(0.318)	(0.315)
Profitability (t–1)	1.604	1.726	1.401	1.530	1.637
	(1.238)	(1.236)	(1.232)	(1.237)	(1.237)
Capitalization (t–1)	−0.902**	−0.974**	−0.742*	−0.912**	−0.870**
	(0.442)	(0.441)	(0.441)	(0.441)	(0.442)
Funding Structure (t–1)	−0.441***	−0.445***	−0.404***	−0.440***	−0.447***
	(0.129)	(0.129)	(0.128)	(0.129)	(0.129)
Real GDP Growth (t–1)	−0.843*	−0.825*	−0.975**	−0.844*	−0.862*
	(0.461)	(0.460)	(0.459)	(0.461)	(0.462)
Inflation (t–1)	0.001	0.002	0.000	0.001	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Bank Concentration (t–1)	−0.003***	−0.003***	−0.003***	−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***	−0.076***	−0.069***	−0.079***	−0.078***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Constant	0.776	0.687	0.099	0.818	0.837
	(0.551)	(0.553)	(0.547)	(0.546)	(0.549)
Observations	3,313	3,131	3,313	3,313	3,313
Countries	40	40	40	40	40
Banks	322	322	322	322	322
LR Test Chi-Square	2,882.915***	2,918.253***	2,895.622***	2,898.157***	2,877.445***

Note: This table reports the results for the base model described in Equation (2). The dependent variable is ΔCoVaR, defined in Table A.2 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 the 1 percent, 5 percent, and 10 percent level, respectively. For the sake of conserving space, we do not present the output for random-effects parameters.

Table 6. Interaction Regression Results: Other Interactions

Dependent: ΔCoVaR	**(1)**	**(2)**	**(3)**
Fixed-Effect Parameters			
CBI Index (t–1)	−0.742***	−0.492***	−0.616***
	(0.160)	(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)
Profitability (t–1)	1.075	1.219	0.943
	(1.240)	(1.321)	(1.162)
Capitalization (t–1)	−0.873**	−0.904**	−0.475
	(0.441)	(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)
CBIS Index (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)
Observations	3,313	3,244	2,999
Countries	40	40	40
Banks	322	322	322
LR Test Chi-Square	2,929.444***	2,825.339***	3,200.578***

Note: This table reports the results for the model described in Equation (2). The dependent variable is ΔCoVaR, defined in Table A.2 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 the 1 percent, 5 percent, and 10 percent level, respectively. For the sake of conserving space, we do not present the output for random-effects parameters.

3.4 Robustness Assessment

3.4.1 Robustness Assessment Using Different Estimation Techniques

To test the consistency of the results, we run alternative estimation models. First, we reestimate the model described in Equation (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.

Second, we employ the fixed-effects estimator using both bank and year fixed effects to capture any unobserved heterogeneity across banks and the influence of aggregate time-series trends. Third, to account for potential endogeneity steaming from amendments to CBI as a result of financial crisis or further financial stability mandate being added to central banks' responsibilities, we estimate a dynamic panel model using the System GMM estimator.[28]

Fourth, we use the bias-corrected least square dummy variable (LSDVC) estimator proposed by Kiviet (1995) and subsequently Bun and Kiviet (2003), and extended to an unbalanced panel setting by Bruno (2005). It was shown in Monte Carlo simulations that the LSDVC outperforms the IV-GMM estimators in terms of bias and root mean squared error.

The findings are displayed in Table 7. The negative and significant effect of central bank independence on systemic risk contribution holds across all four models, in the case of both static and dynamic models. The LR test in the case of HLM REML compares the estimated model and the standard OLS estimation, with the null hypothesis that there are no significant differences between the two models. The results favor the multi-level specification.

3.4.2 Robustness Assessment Using Different Proxies for Systemic Risk Contribution

Further, we use alternative proxies for systemic risk contribution. Following the approach of Berger, Roman, and Sedunov (2020), we compute the principal-component factor using factor analysis based

[28]We thank a reviewer for suggesting this.

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 is 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).[29]

The results for Systemic Factor2 and Systemic Factor3 are shown in Table 8. 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. Concerning control variables, *credit risk ratio, inflation* (Systemic Factor3), and *financial intermediation* amplify banks' systemic relevance, whereas *profitability* (Systemic Factor3), better *capitalization,* a funding structure based on deposits, *economic growth*, and the *central bank involvement in supervision* index reduce banks' contribution to systemwide distress. Thus, assigning supervisory responsibilities to the central bank is beneficial for stability of the banking system and financial system as a whole. Doumpos, Gaganis, and Pasiouras (2015) reach similar conclusion in terms of bank soundness.

Finally, we test whether the findings are driven by sample selection. First, we exclude 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 A.1 from the appendix. Then, we look at whether the effect of CBI and the control variables differ substantially before and during/after the global financial crisis: (d) for the 2001–07 period and (e) for the 2008–14 period. The results are shown in Table 9. For the samples in (a), (b), and (c), the findings are in line with those from the benchmark model (Table 1). Regarding the estimations for sub-periods, the sign for the CBI's coefficients holds for

[29]A description of these variables and the computational methodological is provided in Table A.2 in the appendix.

Table 7. Robustness Analysis Using Different Estimation Techniques

Dependent: ΔCoVaR	(1) HLM REML	(2) FE	(3) System GMM	(4) LSDVC
CBI Index (t–1)	−0.580***	−0.716***	−0.460***	−0.314*
	(0.158)	(0.225)	(0.102)	(0.177)
Size (t–1)	0.027	−0.071	0.094***	0.057*
	(0.021)	(0.091)	(0.035)	(0.033)
Credit Risk Ratio (t–1)	0.383	0.554	0.023	0.326
	(0.317)	(0.950)	(0.344)	(0.306)
Profitability (t–1)	1.473	1.452	0.860	−0.453
	(1.245)	(1.764)	(1.067)	(1.203)
Capitalization (t–1)	−1.074**	−1.046	−0.099	−0.321
	(0.443)	(1.003)	(0.399)	(0.437)
Funding Structure (t–1)	−0.443***	−0.669**	−0.180	−0.053
	(0.130)	(0.277)	(0.119)	(0.130)
Real GDP Growth (t–1)	−0.830*	−0.771	−0.204	−0.289
	(0.464)	(0.832)	(0.392)	(0.404)
Inflation (t–1)	0.001	−0.000	−0.002	−0.002
	(0.004)	(0.010)	(0.004)	(0.003)
Bank Concentration (t–1)	−0.003***	−0.003	−0.002**	−0.000
	(0.001)	(0.002)	(0.001)	(0.001)
Financial Intermediation (t–1)	0.001**	0.001	0.001**	0.001**
	(0.001)	(0.002)	(0.001)	(0.001)
CBIS Index (t–1)	−0.078***	−0.072***	0.001	−0.042**
	(0.020)	(0.025)	(0.013)	(0.021)
ΔCoVaR (t–1)			0.914***	0.692***
			(0.100)	(0.018)
ΔCoVaR (t–2)			−0.628***	
			(0.075)	
Constant	0.985*	4.132*		
	(0.549)	(2.202)		
Observations	3,327	3,327	3,327	3,327
Countries	40	40	40	40
Banks	323	323	323	323
LR Test Chi-Square	2,933.362***			
R-Squared (Within)		0.328		
AR(1) Test			−6.107***	
AR(2) Test			0.406	
Hansen J Statistic			0.018	
No. of Instruments			27	

(*continued*)

Table 7. (Continued)

Note: This table reports the results using different estimation techniques. The dependent variable is ΔCoVaR, defined in Table A.2 in the appendix. The HML REML model is estimated using the restricted maximum likelihood estimation. The FE model is estimated using both bank and year fixed effects. The System GMM model follows the approach of Blundell and Bond (1998) and is estimated using the finite-sample correction to the two-step covariance matrix derived by Windmeijer (2005). To deal with serial correlation, we added the second lag of the dependent variable. The LSDVC model is the bias-corrected least square dummy variable developed by Kiviet (1995) and adopted to unbalanced panels by Bruno (2005), being initialized by the Blundell-Bond estimator. The LR test compares the estimated model with the standard OLS estimation with the null hypothesis that there are no significant differences between the two models. AR(1) and AR(2) are the Arellano-Bond test for first-order and second-order correlation, respectively, whereas the Hansen J statistic tests the validity of the overidentification restrictions with the null hypothesis that overidentification restrictions are valid. Standard errors are in parentheses for HLM REML. Cluster-robust standard errors at the country level are in parentheses for FE. Corrected standard errors are in parentheses for System GMM. Bootstrap standard errors are in parentheses based on 100 replications for LSDVC. ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively. For the sake of conserving space, we do not present the output for random-effects parameters for HLM REML.

both periods, but the significance is preserved only for the second period. While this can lend support for a more important role of CBI during/after the crisis, different sample sizes—the estimation for the second period includes four additional countries, with 22 additional banks—likely affects this as well.

Table 8. Robustness Analysis: Different Systemic Risk Measures

	(1)	(2)
Dependent: ΔCoVaR	**Systemic Factor2**	**Systemic Factor3**
Fixed-Effects Parameters		
CBI Index (t–1)	−0.996***	−2.544***
	(0.210)	(0.443)
Size (t–1)	−0.044*	−0.130**
	(0.026)	(0.052)
Credit Risk Ratio (t–1)	1.327***	2.831***
	(0.419)	(0.873)
Profitability (t–1)	−1.586	−8.216**
	(1.587)	(3.266)
Capitalization (t–1)	−3.896***	-11.233***
	(0.565)	(1.177)
Funding Structure (t–1)	−1.026***	−2.461***
	(0.165)	(0.343)
Real GDP Growth (t–1)	−1.416**	−2.674**
	(0.595)	(1.230)
Inflation (t–1)	0.008	0.022**
	(0.005)	(0.011)
Bank Concentration (t–1)	0.000	0.003
	(0.001)	(0.002)
Financial Intermediation (t–1)	0.007***	0.021***
	(0.001)	(0.002)
CBIS Index (t–1)	−0.072***	−0.108*
	(0.027)	(0.056)
Constant	0.700	0.486
	(0.690)	(1.431)
Random-Effects Parameters		
Country-Level Variance	−0.420***	0.536***
	(0.147)	(0.133)
Bank-Level Variance	−0.425***	0.253***
	(0.046)	(0.047)
Residual Variance	−0.678***	0.040***
	(0.013)	(0.013)
Observations	3,284	3,248
Countries	40	40
Banks	323	323
LR Test Chi-Square	2,541.686***	2,475.609***

Note: This table reports the results for alternative measures of systemic risk. The dependent variables are Systemic Factor2 and Systemic Factor3, defined in Table A.2 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 the 1 percent, 5 percent, and 10 percent level, respectively.

Table 9. Robustness Analysis Using Different Sample Structures

	(1)	(2)	(3)	(4)	(5)
Dependent: ΔCoVaR	**U.S. and Japan Excluded**	**No Countries with Fewer than Three Banks**	**(1) + (2)**	**Pre-crisis**	**Crisis/ Post-crisis**
Fixed-Effects Parameters					
CBI Index (t–1)	−0.596***	−0.570***	−0.577***	−0.465	−0.783***
	(0.146)	(0.161)	(0.149)	(0.292)	(0.237)
Size (t–1)	0.131***	0.029	0.137***	0.097***	−0.288***
	(0.025)	(0.021)	(0.026)	(0.024)	(0.027)
Credit Risk Ratio (t–1)	−0.148	0.347	−0.201	−1.040*	−1.697***
	(0.321)	(0.319)	(0.322)	(0.578)	(0.490)
Profitability (t–1)	2.284*	1.939	3.223**	2.518	1.579
	(1.311)	(1.253)	(1.316)	(2.225)	(1.530)
Capitalization (t–1)	0.383	−1.161***	0.292	1.271	−4.381***
	(0.498)	(0.447)	(0.503)	(0.810)	(0.551)
Funding Structure (t–1)	−0.199	−0.416***	−0.130	0.213	−1.508***
	(0.135)	(0.132)	(0.138)	(0.212)	(0.161)
Real GDP Growth (t–1)	−0.913*	−0.950**	−0.963**	−5.875***	0.750*
	(0.470)	(0.476)	(0.483)	(0.861)	(0.300)
Inflation (t–1)	−0.003	0.002	−0.002	0.002	0.005
	(0.004)	(0.004)	(0.004)	(0.008)	(0.004)
Bank Concentration (t–1)	−0.002*	−0.003***	−0.001*	−0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Financial Intermediation (t–1)	0.003***	0.001***	0.003***	−0.005***	−0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CBIS Index (t–1)	−0.067***	−0.084***	−0.069***	−0.162**	−0.145***
	(0.019)	(0.021)	(0.019)	(0.064)	(0.019)
Constant	−1.490**	0.922*	−1.628**	−0.011	11.199***
	(0.646)	(0.555)	(0.660)	(0.699)	(0.722)

(*continued*)

Table 9. (Continued)

	(1)	(2)	(3)	(4)	(5)
Dependent: ΔCoVaR	**U.S. and Japan Excluded**	**No Countries with Fewer than Three Banks**	**(1) + (2)**	**Pre-crisis**	**Crisis/ Post-crisis**
Random-Effects Parameters					
Country-Level Variance	-1.250^{***}	-1.083^{***}	-1.267^{***}	-0.841^{***}	0.037
	(0.216)	(0.203)	(0.221)	(0.195)	(0.132)
Bank-Level Variance	-0.552^{***}	-0.535^{***}	-0.559^{***}	-0.754^{***}	-0.261^{***}
	(0.055)	(0.045)	(0.056)	(0.055)	(0.049)
Residual Variance	-0.995^{***}	-0.916^{***}	-1.002^{***}	-0.767^{***}	-1.203^{***}
	(0.016)	(0.013)	(0.017)	(0.021)	(0.019)
Observations	2,080	3,201	1,954	1,490	1,837
Countries	38	34	32	36	40
Banks	224	310	211	280	320
LR Test Chi-Square	$1{,}947.811^{***}$	$2{,}787.773^{***}$	$1{,}818.790^{***}$	677.442^{***}	$2{,}255.892^{***}$

Note: This table reports the results for different sample structures. The dependent variable is ΔCoVaR, defined in Table A.2 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 the 1 percent, 5 percent, and 10 percent level, respectively.

4. Conclusion

The agreement around the concept of central bank independence has lessened in the wake of the global financial crisis of 2007–09. This shift reflects an increase in the range of powers central bank have acquired, with some of these powers involving coordination with fiscal policymaking. 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 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. In parallel, we find that an increase in CBI can ameliorate the effects of environments characterized by low level of financial freedom or high market power that, by themselves, enhance the systemic risk contribution of banks. However, the results also show trade-offs between CBI and central banks having financial stability mandates and that a heightened CBI can exacerbate the effect of a crisis on the contribution of banks to systemic risk.

Therefore, preserving central bank independence is important for financial stability but an emphasis on coordinated interaction with governments is also needed, or more elegantly in the words of former Federal Reserve chief Ben Bernanke: “The general principle of CBI does not preclude coordination of central bank policies with other parts of the government in certain situations” (Bernanke 2017). Better governance for the financial stability institutional structures would facilitate such needed collaboration.

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 findings are robust for different estimation models, controlling for both bank and year fixed effects and potential endogeneity issues of central bank independence, and for different sample structures.