Bank systemic risk: An analysis of the sovereign rating ceiling policy and rating downgrades[*]

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Abstract

We investigate the impact that the sovereign ceiling policy has on financial stability. In the event of a sovereign rating downgrade, we find that the rating agencies' sovereign ceiling policy leads to a disproportionate downgrade of the most creditworthy financial institutions in the economy and results in increased systemic risk. This asymmetric variation in bank ratings also impairs equity growth which further exacerbates bank insolvency. Our results are robust to several matching techniques, such as propensity score matching and entropy balancing, falsification tests, subsample analyses, and alternative empirical proxies and model specifications.

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Keywords: Sovereign ceiling policy, systemic risk, financial system stability.

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1. Introduction

Credit rating agencies tend to follow a sovereign ceiling rule, whereby domestic banks are not assigned a higher rating than their sovereign, even if the banks themselves are not deserving of a downgrade. As an example, on June 14, 2019, Moody's Investor Services downgraded Turkey's sovereign credit rating based on an elevated risk of a balance of payments crisis. Within four days, the agency subsequently downgraded 18 Turkish banks to ensure their ratings were not above the sovereign credit rating, even though the banks' fundamentals remained unchanged with 50% higher capital ratios than the global benchmark.[5]

The sovereign ceiling policy can, therefore, have a direct impact on the stability of the financial system by also subsequently affecting the ratings of multiple banks within the domestic banking sector. While Manso (2013) documents that even a small rating downgrade can deteriorate investor's perception about the credit quality of a borrower and raise its default probability in the first place, our research objective is to examine whether widespread downgrade actions, due to the sovereign ceiling rule, can induce systemic risks.[6] Investigating this phenomenon is important because it sheds light on how the ceiling rule can have a first-order effect of exacerbating the system-wide risk, which can subsequently lead to decreases in banking activities such as lending (Adelino and Ferreira, 2016).

In particular, we examine whether banks with credit ratings similar to the sovereign are more affected by a sovereign rating downgrade due to the application of the sovereign ceiling rule. On the one hand, ceteris paribus, the higher rated banks should be better-capitalized and have

[5] As reported by the local Turkish news agency, Anadolu Agency, on June 17, 2019 when interviewing the president of the Bank Association of Turkey (TBB).
[6] Following Billio et al. (2012) we define systemic risk as the propagation of illiquidity, insolvency, and losses among the interconnected financial institutions during periods of financial distress.

stronger loss absorption capacity (i.e., more capital enables these banks to better absorb unexpected losses). This implies that, during a crisis, the equity value of these banks in the market should be less affected and thereby their contribution to systemic risk should be lower than the other lower rated (and possibly lower-capitalized) banks (Laeven, Ratnovski and Tong, 2016). On the other hand, the sovereign ceiling policy is also likely to lead to these banks experiencing a larger rating downgrade. This can then result in a more negative stock price reaction for these banks, leading to increased systemic risk throughout the banking sector, even if the banks' fundamentals are sound. As an argument can be posited that these banks will be either more or less affected by the sovereign rating downgrade than other banks, we proceed to empirically investigate the issue.

To examine the above-mentioned issue, we adopt an identification strategy similar to Borensztein, Cowan and Valenzuela (2013) who show that ratings of bound firms (entities with the same or better ratings than the sovereign) are downgraded disproportionately more than non-bound firms (entities with lower ratings than the sovereign) during a sovereign downgrade event. The authors emphasize that this asymmetry in ratings can be attributed to the application of the sovereign ceiling policy, as, otherwise, the bound firm ratings would be less affected by the prevailing macroeconomic decline, given that these firms possess stronger credit quality.

By utilizing the above framework we can establish a causal effect of the sovereign ceiling rule on the discontinuous variation in bank ratings and the subsequent impact on bank systemic risk. To elaborate, the bound banks are higher rated financial institutions than the non-bound banks. Therefore, during a macroeconomic shock imposed by a sovereign downgrade, the bound banks' fundamentals (which have higher financial strength) should be less affected than those of the non-bound banks. This notion makes it hard to make the case that the asymmetric change in bank ratings (i.e., a larger downgrade of the bound banks) is driven by the deteriorating bank fundamentals caused by the economic slowdown. Hence, we argue that this discontinuous effect on bank ratings can be ascribed to the application of the sovereign ceiling rule that can consequently raise systemic risk.

Notably, Millon and Thakor (1985) highlight that a negative rating action can decrease the equity (or firm) value of the financial intermediary. Similarly, Acharya et al. (2016) show that this can impair a firm's ability to financially intermediate and amplify its overall contribution to system-wide failure, i.e., systemic risk, especially during aggregate economic shocks such as a sovereign downgrade. Therefore, as bound banks, relative to non-bound banks, are likely to undergo a greater decline in ratings and experience capital constraints during a sovereign downgrade event, they will consequently experience larger systemic risk changes due to the application of the sovereign ceiling policy. This leads us to hypothesize that the growth in bound banks' systemic risk will be higher compared to non-bound banks following a sovereign downgrade event.

To test our hypothesis, we use a sample of banks from around the world. We obtain their ratings and stock market data from Refinitiv Eikon database from 1996 to 2016. Following Adelino and Ferreira (2016), we use Standard and Poor's (S&P) ratings to convert them into a numerical scale where a decline in the value denotes a downgrade action. Furthermore, we designate banks as bound when their ratings are equal to or above their sovereign in the pre-sovereign downgrade year. Following Acharya et al. (2012), we measure systemic risk by estimating the marginal expected shortfall (MES) of banks given by their average stock returns during the 5% worst days for the country's banking sector. Our baseline panel ordinary least squares (OLS) regressions use an interaction term of bound banks and sovereign downgrades to predict the growth in systemic risk (MES) induced by the sovereign ceiling rule.

Our empirical results show strong support for our hypothesis. Specifically, our main results indicate that bound banks, relative to non-bound banks, experience three times larger growth in systemic risk following a sovereign downgrade action. To further support our analysis, we conduct a difference-in-difference (DiD) estimation based on a matched sample of bound (treated) and non-bound (control) banks employing sovereign downgrades as the treatment effect. To obtain well-matched samples, we utilize a propensity score matching (PSM) technique and several bank-specific measures as covariates. Although our identification strategy aids us to develop the sovereign ceiling rule's causal impact on systemic risk, our DiD test further strengthens our initial findings as we conduct the analysis on banks with similar pre-downgrade characteristics. This test, therefore, helps us to reduce concerns that the pre-existing variation in fundamentals between banks can lead to a discontinuous effect on systemic risk. Our results from the DiD test remain consistent with our main findings, in that bound banks, compared to non-bound banks, exhibit around 3.9 times larger growth in systemic risk in post sovereign downgrade conditions. Furthermore, these outcomes also remain similar upon running a weighted OLS regression on a matched sample of banks obtained from entropy balancing on 3 moments of the covariates.

We employ several other empirical strategies to deal with some other alternative explanations. Specifically, we conduct falsification tests to verify whether other macroeconomic shocks, barring the sovereign downgrade, can lead to a difference in the growth in systemic risk between the bound and non-bound banks. In particular, we run our baseline tests in the presence of a currency crisis, banking crisis, and stock market crisis, excluding the years of a sovereign downgrade. In doing these tests, we find no evidence to support that these crises impact our results, confirming our finding of the sovereign ceiling rule's causal effect on systemic risk.

We also conduct other robustness checks to address further identification challenges. Specifically, we execute our baseline regression excluding the too-big-to-fail banks as they can rely more on international funding, and, therefore, face higher costs due to their sovereign debt rating downgrade and, consequently, experience a larger growth in systemic risk. Furthermore, we run our baseline specification when removing banks with large holdings of government debt as its impairment can directly deteriorate these banks' asset quality and exacerbate their systemic risk. Collectively, these analyses produce consistent results with our baseline findings, further substantiating our hypothesis.

Additionally, we also show that our baseline results are similar when utilizing another prominent measure of systemic risk, Δ CoVaR (conditional value at risk), suggested by Adrian and Brunnermeier (2016). We focus on Δ CoVaR as it enables us to measure the externality a bank has on the system, whereas the growth in MES shows the increase in a bank's exposure to a potential systemic crisis. At the same time, we also investigate the effect of exercising the sovereign ceiling rule on bank capitalization as this impact can be the underlying economic mechanism for exacerbating the systemic risk. We find that following sovereign downgrades, bound banks, compared to non-bound banks, undergo a twice-fold larger decline in equity growth, suggesting that the sovereign ceiling rule can lead to a bank capital shortfall inducing a larger rise in systemic risk.

Finally, we find that although the banking sector's overall profitability declines following a sovereign downgrade, bound banks undergo a smaller decline than the non-bound banks. Therefore, this finding challenges the validity of applying the sovereign ceiling rule as we find that it leads to a larger downgrade of the more creditworthy bound banks whose profits, after the downgrade, are affected the least.

Our study makes several contributions. First, our work adds novel findings to the literature on credit ratings by examining the impact of the sovereign ceiling rule on financial stability. Most existing studies have focused on firm-level implications of the sovereign ceiling rule, such as the reduction in corporate investments (Almeida et al., 2017), a decrease in bank lending (Adelino and Ferreira, 2016) and lower bond yields (Durbin and Ng, 2005). However, there is a dearth of evidence on how the application of the rule can induce a system-wide risk within the country and decline its macro financial stability. Our study fills this gap. Moreover, supporting Manso's (2013) theory that a downgrade creates pressure for downgrades of other entities in a form of feedback effects and triggers systemic risks, we advocate a stickier rating regime that can prevent such aggravation of systemic risks and the subsequent decline of banking activities.

Second, our findings add to the literature on systemic risk. Previous work has established that reliance on non-traditional income (Brunnermeier, Dong and Palia, 2020) and sovereign debt crises (Black et al., 2016) are major contributors to global systemic risk. Some studies have also suggested that bank size and valuation are the main drivers of systemic risk within the developed economies (O'Hara and Shaw, 1990; Acharya and Yorulmazer, 2008). We contribute to this stream of literature by concentrating on the asymmetric impact that the sovereign ceiling policy has on systemic risk.

Finally, our findings contribute to the discussion on incorporating macro-prudential elements to the latest Basel III regulatory framework, particularly in the area that focuses on mitigating systemic risks (BIS, 2018). We show that the application of the sovereign ceiling rule by the rating agencies can exacerbate systemic risk, especially for banks with the highest credit quality within an economy. Therefore, as per the framework's Pillars 1 and 2, which deal with bank risk coverage and supervision, respectively, these more creditworthy banks may be subject to more stringent loss absorbency requirements (such as increased capital buffer) to safeguard the financial stability of the country during a sovereign downgrade event. Moreover, given that the revised Basel Core Principles for effective banking supervision (BCP) caters to international regulators and takes a macro perspective to identify and analyze systemic risk, the framework should consider the impact that exercising this de facto ceiling policy has on increasing the systemic risk of a country.

The remainder of the paper is organized as follows. Section 2 provides a literature review and hypothesis development. Section 3 discusses the data and the empirical framework. Section 4 provides the empirical analysis and Section 5 concludes our study.

2. Literature review and hypothesis development

A wide body of literature discusses the justification for a sovereign ceiling rule and highlights the economic rationale behind it. For example, Borensztein, Cowan and Valenzuela (2013) suggest that sovereign stress can incite the government to impose capital controls (i.e., prevent the flow of funds between countries) which can endorse the sovereign ceiling rule. Prati, Schindler and Valenzuela (2012) highlight that capital controls can raise the credit risk of publicly traded firms and negatively impact their ratings. As a result, these capital account restrictions can lead to a concurrent rating revision at both the firm and the sovereign levels, which can therefore support the application of the sovereign ceiling rule.

In addition, Borensztein, Cowan and Valenzuela (2013) also hint that a country-specific macro-level vulnerability can simultaneously lead to a rise in corporate and government insolvency risk. In particular, they argue that an external shock to the economy can result in a higher variation in the revenue stream of both firms and government, which raises their default risks. At the same time, Durbin and Ng (2005) indicate that during economic stress, the government may take several measures that can transfer risk onto the private sector. For instance, as Cagan (1956) notes, the government may impose additional taxes on labor income and produced commodities, triggering surprise inflation, while Barro (1983) highlights that the government may exercise an inflationary financing policy, resulting in an excessive tax burden on firms. These government interventions can evoke a positively correlated rating variation between corporates and the sovereign simultaneously, thereby supporting the application of the sovereign ceiling rule.

However, in contrast to the above studies that support the sovereign ceiling rule application, some papers oppose it, particularly where the rule is based on the use of capital controls as an underlying economic rationale for it. For example, Forbes (2007), Magud, Reinhart and Rogoff (2011), and Klein (2012) emphasize that capital controls can be unsuccessful in reducing real exchange rate pressures, while Neely (1999) suggests that it can contribute to a balance of payments crisis. Furthermore, a more recent study of Fernández, Rebucci and Uribe (2015) also shows that capital controls can be ineffective macroeconomic stabilizers as they have previously been applied in a pro-cyclical manner, contrary to the established theory on financial stability. Therefore, applying the sovereign ceiling rule based on capital account restrictions can be deemed an inappropriate exercise, since there is, at best, inconclusive evidence that these restrictions can impact the broader economy (Blanchard, Dell'Ariccia and Mauro, 2013).

In considering the argument for not imposing the sovereign ceiling rule, it is also worth noting that a firm's bonds can trade at a lower risk premium than their sovereign bonds (Durbin and Ng, 2005). This would suggest that the market sometimes assesses corporates to have a lower default risk than its host government, and therefore challenges the correlated ratings argument of

Borensztein, Cowan and Valenzuela (2013). Additionally, some recent studies also highlight the negative consequences of the sovereign ceiling rule on real economic activities, especially at the firm-level. In particular, Almeida et al. (2017) suggest that corporate investments can reduce due to the application of the sovereign ceiling rule, while Adelino and Ferreira (2016) show similar adverse consequences for financial institutions, whereby bank funding and lending supply can decrease significantly following the imposition of the rule. Taken together, these papers show that the application of the sovereign ceiling rule is not necessarily justified from an economic perspective but can also be harmful to the financial environment.

Based on the above discussion, the sovereign ceiling rule would seem to impact the banks' systemic risk, especially if there are widespread rating revisions. Although, the extant literature (Anginer, Demirgüç-Kunt and Mare, 2018) emphasizes that sufficient bank capital is associated with a reduction in systemic risk, the seminal work by Millon and Thakor (1985) highlights that a rating downgrade can impair a financial intermediary's ability to access the capital markets. This adverse effect on bank capitalization can subsequently lead to a drop in equity values for the banks and raise economy-wide systemic risk (Eichberger and Summer, 2005).

Moreover, systemic risk can increase when banks experience a decline in stock returns caused by rating downgrades, especially during the market's worst performing days. Specifically, Acharya et al. (2016) suggest that systemic risk captures a bank's overall contribution to a system-wide failure, measured through a marginal expected shortfall (MES) that estimates a bank's average equity returns during the five percent worst days of the market. Hand, Holthausen and Leftwich (1992) show that the stock returns of publicly listed firms decline when faced with a rating downgrade, while Correa et al. (2014) indicate similar outcomes when a firm's home country sustains a sovereign downgrade. Similarly, when there is a rating downgrade of the banks, alongside the sovereign, there would be a general expectation that their equity returns would also decline along with the market returns and consequently lead to an increase in systemic risk.

This motivates our study to examine the impact of concurrent sovereign and bank rating changes on systemic risk, which to our knowledge, has not been analyzed before. More precisely, studies examining credit rating revisions have explored their effect on the financial markets across other countries (Kaminsky and Schmukler, 2002), as well as their impact on several bank characteristics (Drago and Gallo, 2017). At the same time, the literature investigating systemic risk has primarily concentrated on financial institutions' size, leverage, non-core activities, as some of the main drivers of this risk (Bostandzic and Weiß, 2018). There is, however, limited evidence on the impact that simultaneous sovereign and bank rating revisions can have on systemic risk, which is what we address.

This leads us to our hypothesis. We follow Almeida et al. (2017) and Adelino and Ferreira (2016), who show that a downward adjustment of the sovereign credit rating can impose an exogenous shock on the firm and the bank ratings due to the sovereign ceiling doctrine. In particular, these papers highlight that following a sovereign downgrade, the bound firms (firms with the same or better ratings than the sovereign) are downgraded disproportionately more than the non-bound firms (firms with lower ratings than the sovereign). They attribute this asymmetric rating variation to the sovereign ceiling rule, as, alternatively, firm ratings should be uniformly affected in a sovereign downgrade event. Similarly, we also expect that the bound banks will undergo a larger downgrade relative to the non-bound banks in the post sovereign downgrade period and therefore exhibit increased systemic risk. Accordingly, as a consequence of this, we hypothesize that the growth in systemic risk of bound banks will be greater, compared to non-bound banks, following a sovereign downgrade event.

3. Data and empirical framework

To construct our sample, we focus on all publicly traded banks worldwide from 1996 to 2016 in Refinitiv Eikon database and use this platform to retrieve all our credit ratings and other related market data. Following Adelino and Ferreira (2016), we obtain long-term foreign-currency issuer ratings for our banks and the countries from Standard and Poor's (S&P). We focus on ratings provided by S&P as they make more frequent rating revisions compared to other leading agencies (Kaminsky and Schmukler, 2002). We convert these ratings into a numerical scale of 22 points, where the highest rating of AAA is assigned the maximum of 22, the second highest rating of AA+ is assigned 21, and so forth until the lowest (default) rating is assigned the minimum of 1. We then compare these rating points of our banks and the countries on an annual basis and denote a decline in the current year relative to the previous year as a downgrade action (Almeida et al. 2017).

In filtering our data, we check for countries that have experienced a sovereign downgrade event, as our analysis considers the impact of the sovereign ceiling rule that is exercised in a post sovereign downgrade environment. Furthermore, we exclude the countries where the commercial bank index was unavailable and those with no publicly traded bound banks, as we need the market data to estimate our systemic risk measure. In addition, we exclude development banks and also state-owned banks as government ownership can influence bank ratings (Almeida et al., 2017). This leads to our final sample consisting of 162 banks from 12 countries around the world.

Overall, our sample is similar in size to Almeida et al. (2017), who also investigate the effects of the sovereign ceiling doctrine in 13 countries. Furthermore, our sample consists of a wide range of countries that captures the sovereign downgrade events in both the emerging and developed markets. In particular, we observe that emerging countries, such as Argentina and Brazil, have faced multiple downgrades, while some developed countries like Spain, Greece and

Italy, have also experienced multiple downgrade events during our sample period. We have listed the countries in our sample, along with their year of downgrade, and the number of bound bank observations in Appendix I.

Next, to compute our systemic risk measure, we collect the banks' stock prices in our sample and the bank sector index of the market where each bank has the primary listing of its shares (Weiß, Neumann and Bostandzic, 2014; Bostandzic and Weiß, 2018). Our choice to use this index lets us measure a bank's reaction to systemic events, such as a sovereign downgrade, in its own country (Altunbas, Manganelli and Marques-Ibanez, 2017) and can, therefore, be considered a suitable benchmark for our systemic risk estimation. More specifically, following Acharya et al. (2016), we designate the ex-ante marginal expected shortfall (MES) as our primary measure of systemic risk where MES is the average return of a bank conditional on the market experiencing the 5% lowest returns in a given year:

$$MES_{i,t} = E[R_{i,t} | R_{m,t} \leq VaR_{m,t}^{5\%}], \quad (1)$$

where $R_{i,t}$ denotes the daily stock returns of bank *i* at time *t*, $R_{m,t}$ is the return on the bank sector index at time *t*, and $VaR_{m,t}^{5\%}$ stands for value at risk, which is a threshold value for the 5% tail return for the bank sector index of the country. Following common practice in the literature, we multiply MES with negative 1 to compute MES (transformed), where a higher positive value implies larger systemic risk (De Jonghe, Diepstraten and Schepens, 2015). We then proceed to calculate the growth in MES (transformed), which is its relative spread between the previous and the current year (i.e., Δ *MES*). We focus on the growth in systemic risk, rather than in levels, as this helps us to assess the extent to which systemic risk increases during the crisis, compared to the pre-crisis, period (Weiß, Neumann and Bostandzic, 2014; van Bekkum, 2016).

Our analysis uses an identification strategy that relies on a quasi-natural experiment where the expectation is that the sovereign downgrade event will lead to a disproportionate larger downgrade of bound banks, relative to non-bound banks, potentially causing increased growth in their systemic risk. This leads us to test our hypothesis through panel ordinary least squares (OLS) regressions using the following baseline model:

$$\Delta\, MES_{it} = \alpha + \beta_1\, (Bound_{i,t\text{-}1}) + \beta_2\, (Downgrade_{i,t}) + \beta_3\, (Bound_{i,t\text{-}1})^*(Downgrade_{i,t})$$
$$+ \gamma X_{i,t\text{-}1} + \mu_t + \mu_{bc} + \varepsilon_{i,t}. \qquad (2)$$

In Equation (2), $\Delta\, MES_{it}$ is the annual growth in systemic risk for bank *i* in year *t*. Also, $Bound_{i,t\text{-}1}$ is a dummy variable that represents bound banks and takes a value of one if bank *i* has a rating equal to or above the sovereign rating in year t – 1, and otherwise it is equal to zero. Furthermore, $Downgrade_{i,t}$ is another dummy variable that indicates the sovereign downgrade event and takes a value of one if the country of bank *i* is downgraded in year *t*, and 0 otherwise. Our main variable of interest is the interaction term of these dummy variables (i.e., $(Bound_{i,t\text{-}1})^*(Downgrade_{i,t})$), which encapsulates the impact on the growth in systemic risk ($\Delta\, MES$) of bound banks relative to non-bound banks, following a sovereign downgrade event. A positive (negative) β_3 indicates that systemic risk grows at a larger (lower) rate for bound banks, as opposed to non-bound banks, in the post sovereign downgrade period.

Although utilizing quarterly observations can better capture the changes in the bank balance sheet, our empirical design focuses on an annual measure of *MES* because it considers the aggregate effects of changes in bank characteristics and ratings over a year. Particularly, Acharya et al. (2016) hint that the *MES*, calculated using a benchmark of 5% lowest returns in a year, has natural additivity properties and scales naturally in response to variations in bank characteristics. Furthermore, utilizing the annual ratings data also enables us to perform a more complete analysis which considers all rating revisions due to the feedback effect following the initial rating action (Manso, 2013), and the time lags between the sovereign and bank rating actions.

Moreover, in equation (2), $X_{i,t-1}$ represents our set of bank-specific and country-specific control variables lagged by one year. Based on Adelino and Ferreira (2016), we use bank size, profitability, capital, liquidity and deposits to account for bank specific characteristics. Specifically, we include bank size to control for the diversification of a bank's assets. We also use profitability to control for a bank's debt servicing ability while we include capital ratios to account for the banks' financial position (Santos, 2010). Furthermore, we incorporate liquidity and deposit ratios to control for bank funding costs (Acharya and Mora, 2015). Additionally, we include the non-interest income ratio to control for a bank's business model choices (Schepens, 2016) and loan loss provisions to account for the quality of a bank's loan portfolio (Laeven and Majnoni, 2003). We collect the data for these bank-specific controls from Refinitiv Eikon database and provide their definitions in Appendix II.

Following Laeven, Ratnovski and Tong (2016), we employ a standard set of country-specific controls that includes the GDP growth rate, to account for economic growth, and a deposit insurance indicator to adjust for the overall risk-taking in the banking system (Keeley, 1990). As additional country controls, we also incorporate stock market turnover to account for the equity market's depth and liquidity (Bostandzic and Weiß, 2018) and the monetary policy rate to account for the monetary policy stance of a country (Morais et al., 2019). We provide a detailed description of these country-specific control variables and the data sources in Appendix II.

Finally, we include year fixed effects, μ_t, and either country or bank fixed effects, μ_{bc}, in our regressions. We cluster the standard errors by bank type (Bostandzic and Weiß, 2018).[7]

4. Empirical results

4.1 Descriptive statistics

Table 1 reports the descriptive statistics and the correlation matrix for the sample of banks included in the baseline regressions. On average, our banks exhibit systemic risk of 2.8% (i.e. the mean *MES (transformed)* is 0.028), which is similar to Acharya et al. (2016), who show that MES for banks can range from 0.39% to 3.6% during financial crisis periods. The mean growth in systemic risk (Δ *MES*) is about 0.5 times suggesting that the spread in systemic risk is moderate over the whole sample period.[8] In addition, the banks also have a mean asset size of about $14.5bn (computed from the natural log of bank size of 23.398). According to Laeven, Ratnovski and Tong (2016), this would indicate that the average bank in our sample is relatively large and systemically important (>$10bn in asset size). At the same time, our banks are, on average, profitable with a mean profitability ratio of 7.7% and are also reasonably liquid with a mean liquidity ratio of 8.1%. Moreover, they are also sufficiently capitalized with an average capital ratio of 5.5%, safely meeting the minimum tier 1 regulatory capital requirements of 4% (BIS, 2010). Therefore, on average, the banks in our sample possess sound fundamentals.

[7] Following Laeven, Ratnovski and Tong (2016), we classify bank type as being either 'large' (systemically important) banks if they have an asset base of greater than $10bn, and otherwise as 'small' banks. This can correct for the residual correlation in the growth in systemic risk within our sample of large and small banks.
[8] It is worth mentioning that the standard deviation in Δ *MES* is about 6.7 times, which hints that in some cases (for instance, during the sovereign downgrade years) the banks in our sample undergo large rises in systemic risk. Furthermore, in the absence of the sovereign downgrade phases, we find that the mean and the standard deviation in Δ *MES* of our banks are 0.28 times and 1.94 times, respectively. Thus, this preliminary analysis implies that there are large increases in systemic risk during the sovereign downgrade years.

Furthermore, *size* and *MES (transformed)* are positively correlated in our sample, suggesting that larger banks tend to have more systemic risk, as shown by O'Hara and Shaw (1990). On the other hand, both *capital* and *liquidity* are negatively correlated with *MES (transformed)*. This indicates that a stronger financial position, given by higher capital as well as greater liquidity, can be associated with a lower systemic risk for banks (BIS, 2010). Also, the negative correlation between *GDP growth* and *MES (transformed)* is not surprising given that lower economic growth is related to increased risk within the banking system (Männasoo and Mayes, 2009).

< Insert Table 1 >

4.2 Univariate analysis

Figure 1 shows the evolution of the change in systemic risk (Δ *MES*) for the bound and the non-bound banks around sovereign downgrade events (with $t = 0$ signifying the downgrade year). We find Δ *MES* displays a similar trend for both groups of bound and non-bound banks in the pre-sovereign downgrade period. However, while the non-bound banks maintain their trend, the bound banks show a steep increase in Δ *MES* in the sovereign downgrade year. This indicates that, relative to the non-bound banks, Δ *MES* of the bound banks increases more due to the sovereign downgrade action.

< Insert Figure 1 >

Table 2 presents univariate analysis where we compare the means and the medians of the main dependent variable and the bank-specific characteristics concerning the bound and non-bound banks. On average, the bound banks exhibit significantly higher *MES transformed* (i.e. systemic risk) than non-bound banks ($p<0.01$). This provides preliminary support for our expectation whereby bound banks exhibit greater systemic risk than the non-bound banks, especially as the banks have experienced multiple sovereign downgrade events within our sample period. Additionally, we find that, compared to the non-bound banks, the mean in Δ *MES* for the bound banks is significantly larger ($p<0.01$). This again suggests that, on average, the bound banks experience larger rises in systemic risk than the non-bound banks.

Furthermore, compared to non-bound banks, the bound banks are significantly larger ($p < 0.01$) in terms of their mean and median sizes. This suggests that, relative to non-bound banks, the bound banks have a more extensive asset base and, thereby, are likely to experience increased growth in systemic risk (Bostandzic and Weiß, 2018). It is also worth highlighting that the median of *profitability* is significantly larger for the bound banks compared to the non-bound banks ($p < 0.01$). This potentially indicates that these bound banks remain more profitable than non-bound banks, despite undergoing multiple downgrades at both the firm and the sovereign levels.

< Insert Table 2 >

4.3 Baseline regression analysis

Table 3 reports our baseline results from the panel OLS regressions, which analyze the impact on the growth in systemic risk (Δ *MES*) of the bound banks, relative to non-bound banks, around the sovereign downgrade event. In all the columns, we employ Δ *MES* as our primary dependent variable to measure systemic risk growth. Supporting our hypothesis, the coefficient of our main variable of interest (i.e., *Bound*Downgrade*) is positive and significant at the 1% level in column (1). With a coefficient value of 3.3, it indicates that the bound banks, as opposed to the non-bound banks, experience approximately 3 times larger growth in systemic risk following a sovereign downgrade action.

Similarly, our key variable of interest remains positive and significant when we include bank-specific as well as country-specific control variables, alongside year and country fixed effects in column (2). Furthermore, as shown in columns (3) and (4), our main results remain qualitatively consistent when we execute the regressions using bank, instead of country, fixed effects. Collectively, these results support the view that the sovereign ceiling rule leads to a larger growth in systemic risk within the banking network of a country, which can exacerbate its overall financial system stability.

It is also worth noting that the control variables displayed in columns (2) and (4) behave as expected when they are significant in our baseline analysis. For instance, in column (2) we find that *Bank size*, *Deposits* and *Non-interest income* are positive and significant at the 5% level (or better). This outcome is consistent with De Jonghe, Diepstraten and Schepens (2015) who suggest that larger banks that are likely to have more deposits and more non-traditional banking activities have larger MES (i.e. systemic risk). At the same time, columns (2) and (4) show that greater stock market turnover induces a larger growth in systemic risk due to enhanced stock market activity, in line with Bostandzic and Weiß (2018).

< Insert Table 3 >

4.4 Difference-in-differences (DiD) analysis

Our baseline analysis includes bound and non-bound banks, which are likely to have dissimilar bank-specific attributes due to different credit qualities. Therefore, as an alternative explanation, one could argue that the differential growth in systemic risk, shown in our baseline results, is driven by these differences in the characteristics between the bound and the non-bound banks. To help mitigate this concern, we conduct a difference-in-differences (DiD) estimation of the growth in systemic risk (Δ *MES*) of comparable bound and non-bound banks, around each sovereign downgrade event.

We start by running matching regressions, in which we use a propensity score matching (PSM) process where the sovereign downgrade is the treatment effect. To obtain propensity scores for each bank in our sample, we run a probit regression where the dependent variable is Δ MES_{it} and, following Adelino and Ferreira (2016), the covariates are our pre-treatment set of bank characteristics (i.e., *Size, Capital, Profitability, Liquidity, Deposits, Non-interest income, Loan loss provisions* and *MES*). Using the generated propensity scores, we then proceed to match bound banks (our treatment group) with non-bound banks (our control group), on a year and country basis.[9]

We obtain 95 treated bank-year observations from the above matching process and report their summary statistics in Panel A of Table 4. In particular, this panel shows the mean of the bank-specific covariates of our bound and non-bound bank observations in the period before the sovereign downgrade. Our results indicate no statistically significant difference in the mean values between these covariates, suggesting that our two cohorts of banks are comparable in terms of their bank-specific attributes after the matching procedure.

We then execute a DiD estimation using this sample and present the results in Panel B of Table 4. While we do not find a significant difference in the pre-sovereign downgrade period, the bound banks experience around 3.978 times larger ($p < 0.05$) growth in systemic risk (Δ *MES*) than the non-bound banks in the post sovereign downgrade period. Taken together, in contrast to the non-bound banks, the bound banks exhibit around 3.909 times larger ($p < 0.05$) growth in

[9] In line with González-Uribe and Reyes (2020), the matching algorithm we use is a kernel matching technique. Over other traditional pairwise matching techniques, this process has an advantage that the variance in the information used is lower (see Smith and Todd (2005) for further details). Specifically, to obtain good matches we impose a common support condition of the propensity scores on our bank observations. We also apply a bandwidth of 0.06 which is set by default.

systemic risk (Δ *MES*) around the sovereign downgrade event.[10] This signifies that, as opposed to comparable non-bound banks, the bound banks experience a considerably larger growth in systemic risk when faced with a sovereign downgrade phenomenon. Therefore, this outcome allows us to rule out the alternative explanation that the observed disproportionate growth in systemic risk is due to differing bank-specific characteristics

< Insert Table 4 >

4.5 Falsification tests

Another key concern is that, in addition to sovereign downgrades, there may be other concurrent macroeconomic shocks that can lead to bound banks experiencing a larger growth in their systemic risk than non-bound banks. Therefore, to exclude this alternative possibility, we conduct a series of falsification tests. Particularly, we consider the impact of three different macroeconomic crises (a currency crisis, a banking crisis, and a stock market crisis) on the growth in systemic risk of the bound banks, compared to the non-bound banks, in the absence of a sovereign downgrade.

We collect the data on crisis periods from Reinhart and Rogoff's (2011) database and conduct falsification tests by replicating our baseline analysis using these crisis events as placebo shocks instead of the sovereign downgrade events. Specifically, following Adelino and Ferreira (2016), we create *Placebo shock* indicators by assigning a value of one if a country experiences a given crisis (as shown in the database) when not accompanied by a sovereign downgrade in the same year and zero otherwise. To perform the falsification tests, we use the following model:

[10] Given that King and Nielsen (2019) suggest that the PSM method can entail certain biases, we also run a weighted OLS regression using a matched sample of banks obtained through the entropy balancing procedure. In particular, we find well-matched treated (i.e., bound) and control (i.e., non-bound) bank observations by employing 3 moments of the same covariates as those included in our PSM methodology. As reported in Table IA.1 of the Internet Appendix, our inferences from the weighted OLS regression remain consistent with the baseline and the DiD analyses.

$$\Delta\ MES_{it} = \alpha + \beta_1\ (Bound_{i,t\text{-}1}) + \beta_2\ (Placebo\ shock_{i,t}) + \beta_3\ (Bound_{i,t\text{-}1})*(Placebo\ shock_{i,t}) + \gamma\ X_{i,t\text{-}1} + \mu_t + \mu_{bc} + \varepsilon_{i,t}. \quad (3)$$

Our main variable of interest in Equation (3) is *Bound*Placebo shock,* which captures the impact of a given economic crisis on the growth in systemic risk of the bound banks, relative to the non-bound banks, barring the sovereign downgrade phenomena. All other variables are as described in Equation (2).

We present the results of our falsification tests in Table 5 where the main variable of interest (i.e., *Bound*Placebo shock*) is insignificant for all crisis indicators shown in columns (1) to (6). This suggests that in the absence of a sovereign downgrade, none of the alternative macroeconomic shocks result in a larger growth in systemic risk for the bound banks as opposed to the non-bound banks. In other words, without a sovereign downgrade, these crisis periods alone do not cause a differential growth in systemic risk between the bound and the non-bound banks. This suggests that the sovereign downgrade event we examine is the key factor that leads to a larger growth in the bound bank systemic risk as shown in our baseline analysis, which therefore also speaks to the role of the sovereign ceiling rule in causing this asymmetric effect. Finally, as expected, we find that banking crises lead to more substantial growth in systemic risk (columns 3 to 4), indicating the effect that this type of macroeconomic crisis is likely to have on the whole banking system.

< Insert Table 5 >

4.6. Equity as a transmission mechanism

Brownlees and Engle (2016) show that large financial institutions' under-capitalization can impose significant negative externalities on the real economy. At the same time, Acharya et al. (2016) suggest that banks can experience capital shortfalls when the overall financial system is undercapitalized, such as during a sovereign downgrade period, leading to greater systemic risk.

Similarly, we consider a bank's access to capital as an underlying mechanism that can be affected by applying the sovereign ceiling rule, causing the differential growth in systemic risk between the bound and non-bound banks. Particularly, we expect the bound banks' equity to be more affected, relative to the non-bound banks, around a sovereign downgrade event. To examine this phenomenon, we follow Gambacorta and Shin (2018) and utilize the growth in equity to assess bank capitalization and estimate the following panel OLS specification:

$$\Delta\, ln\ (Equity)_{it} = \alpha + \beta_1\, (Bound_{i,t\text{-}1}) + \beta_2\, (Downgrade_{i,t}) + \beta_3\, (Bound_{i,t\text{-}1})^*(Downgrade_{i,t}) + \gamma X_{i,t\text{-}1} + \mu_t + \mu_{bc} + \varepsilon_{i,t}, \quad (4)$$

where Δ *ln (Equity)* denotes the natural logarithm of the annual growth rate of common equity of bank *i* in year *t*, while the other variables are used as described in Equation (2). Moreover, to account for the impact of systemic risk on equity, we also include the growth in systemic risk (lagged by one year) in this regression alongside all the other bank-specific control variables.

We report the results of this test in Table 6. Specifically, in columns (1) and (2) of panel A we find that the interaction term (i.e., *Bound*Downgrade*) is negative and significant, suggesting that, in contrast to the non-bound banks, the bound banks experience a lower growth in equity in the post sovereign downgrade period. Moreover, for further robustness checks, we also conduct a difference-in-differences (DiD) analysis on the growth rate of equity of matched groups of bound banks (treated sample) and non-bound banks (control sample) employing sovereign downgrades as the treatment effect.[11] As shown in column (1) of panel B, our DiD analysis indicates a similar outcome to our OLS findings, whereby the bound banks, compared to the non-bound banks,

[11] To identify matched treated and control samples, we employ a propensity score matching procedure which uses the pre-sovereign downgrade bank-specific covariates of *Size, Capital, Profitability, Liquidity, Deposits, Non-interest income, Loan loss provisions* and Δ *MES*. We also use exact matching of the year and the country of the banks.

experience a lower growth in equity by about 2.35 times[12] ($p < 0.05$) in the post sovereign downgrade period. Taken together, these results signify that a sovereign downgrade event can impair a bound bank's ability to raise capital considerably more than the non-bound banks, and can consequently result in a larger growth in its systemic risk.

< Insert Table 6 >

4.7 The impact on profitability

We now consider whether the application of the sovereign ceiling rule can affect a bank's performance channel, proxied by profitability. This analysis can be important because the extant literature suggests that profitability can be a significant factor for determining bank ratings (Poon and Firth, 2005). Furthermore, the literature also hints that while profitability can help predict firms' creditworthiness and financial distress (Altman, 1993), lower profitability can also be associated with lower credit ratings (Bouzouita and Young, 1998). Therefore, based on this line of reasoning, we aim to test whether the banks' profitability also undergoes an asymmetric decline alongside their ratings due to the application of the sovereign ceiling doctrine. Particularly, we expect that, due to a larger downgrade, the bound banks' profitability will decline significantly more than the non-bound banks around the sovereign downgrade event. More formally, we investigate this phenomenon through a panel OLS regression as shown below:

$$Profitability_{it} = \alpha + \beta_1 (Bound_{i,t\text{-}1}) + \beta_2 (Downgrade_{i,t}) + \beta_3 (Bound_{i,t\text{-}1})^*(Downgrade_{i,t})$$
$$+ \gamma X_{i,t\text{-}1} + \mu_t + \mu_{bc} + \varepsilon_{i,t}, \quad (5)$$

where, following Poon and Firth (2005), we measure *Profitability* as the return (total bank revenue) scaled by total assets of bank i in year t, while the other variables are as described in Equation (2).

[12] Computed as the absolute value of the natural logarithm of equity growth of 0.856, as presented in column (1) of panel B in Table 6.

We present the results of this test in Table 6 as well. Notably, in columns (3) and (4) of panel A, we find that the interaction term (*Bound*Downgrade*) is positive and statistically significant. This implies that the bound banks remain more profitable than the non-bound banks in the post sovereign downgrade period. As an additional robustness test, we perform a DiD analysis of the profitability of matched samples of bound banks (treated group) and non-bound banks (control group), using the sovereign downgrades as the treatment effect.[13] As presented in column (2) of panel B, in this test we find qualitatively similar results to our OLS specification, whereby, compared to the non-bound banks, the bound banks exhibit greater profitability of 2.6% ($p < 0.05$) in the post sovereign downgrade period.

Furthermore, in our DiD analysis, we find that while both groups show a decrease in profitability, the bound banks, as opposed to the non-bound banks, undergo a smaller decline in the profitability when faced with a sovereign downgrade phenomenon. This indicates that, relative to the non-bound banks, the bound banks' performance is less affected during a sovereign downgrade period. These findings support Berger (1995) as well as Coccorese and Girardone (2021) and show that due to the pre-existing robust capital buffers and high creditworthiness, the profitability of the bound banks may experience a lower impact of a sovereign downgrade. Therefore, these results further question the validity of the sovereign ceiling doctrine as its application leads to a larger downgrade of those banks which continue to exhibit superior performance than others. [14]

[13] To obtain matched treated and control groups, we employ a propensity score matching procedure which uses the pre-sovereign downgrade bank specific covariates of *Size, Capital, Profitability, Liquidity, Deposits, Non-interest income and Loan loss provisions*. We also use exact matching of the year and the country of the banks.

[14] While the existing literature (Durbin and Ng (2005); Borensztein, Cowan and Valenzuela (2013); Adelino and Ferreira (2016); and Almeida et al. (2017)) have shown considerable evidence of the sovereign ceiling rule's asymmetric effect on ratings, we also reconfirm this phenomenon and report the results in Table IA.2 of the Internet Appendix. Specifically, in a DiD analysis of a matched sample of banks, we find that the bound banks undergo a larger decline in ratings than the non-bound banks after a sovereign downgrade event.

4.8 Robustness checks

4.8.1 Alternative specifications and sub-sample tests of the baseline analysis

Although our empirical design follows the prior literature (Almeida et al., 2017), employing unit fixed effects can also lead to a bias as our sovereign downgrade events are staggered over time (Athey and Imbens, 2021, among others). Therefore, in line with Adelino and Ferreira (2016), we estimate our baseline specification by including country-year fixed effects that help absorb the time-variant country-specific unobserved factors and reduce such bias. As presented in columns (1) and (2) of Table IA.3 of the Internet Appendix, our results remain qualitatively similar to our baseline findings and further confirm that the impact on systemic risk is driven by the downgrade events within a given country in a particular year.

Moreover, to further address the above-mentioned issue of a possible bias, we follow Baker, Larcker and Wang (2021) and Cengiz et al. (2019), and employ a stacked regression approach. In particular, we create series of bound and non-bound banks by first filtering the sample to only include observations with full data over a seven-year window centered on the sovereign downgrade event. Then we stack each of these series together to form a stacked sample. Finally, we estimate our baseline specification utilizing this stacked sample and the coefficient of our key interaction parameter, *Bound*Downgrade*, presented in column (3) of Table IA.3, is positive and significant ($p < 0.05$). This shows that the bias due to the staggered treatment timing is unlikely to drive our findings. Additionally, as shown in columns (4) and (5) of Table IA.3, our baseline analysis holds when we incorporate additional control variables (i.e., square of bank size, natural log of the GDP per capita, square of the GDP growth, inflation and the current account balance).

In Table IA.4 of the Internet Appendix, we show results when we segregate banks from countries that are part of the Organisation for Economic Cooperation and Development (OECD) and those that come from emerging countries, as classified by the United Nations (2019). As indicated in columns (1) – (4), we see that in the post sovereign downgrade phase the bound banks exhibit a larger growth in systemic risk for the OECD countries relative to the non-OECD countries. Furthermore, in columns (5) – (6), a positive value for the coefficient of the interaction term of *Bound*Downgrade*OECD* further supports these findings. Altogether, these outcomes highlight that the sovereign ceiling rule can lead to a larger growth in systemic risk in the more developed and interconnected banking systems, as noted by Laeven, Ratnovski and Tong (2016).

In Table IA.5, we also find that our results remain unaffected when we exclude the banks with a rating above the sovereign, as they can be systematically different from the banks which have the same rating as the sovereign. Additionally, Table IA.6 shows that the baseline outcomes remain unaffected when we exclude banks that are downgraded before the sovereign downgrade. This test helps us to mitigate the reverse causality concern whereby the sovereign downgrade can be partially caused by the downgrade of those banks leading to increased systemic risk.

Furthermore, we also conduct a further test of our baseline model by splitting our sample into pre- and post- Global Financial Crisis (GFC) periods. We present the results of this test in Table IA.7, where we find similar outcomes as our baseline specification in both the periods. Also, as one would expect, the growth in systemic risk is much larger in magnitude in the post GFC period. Therefore, this finding suggests that the application of the sovereign ceiling rule not only affects systemic risk regardless of the GFC, but exacerbates the risk further in the post GFC period.

Finally, given that our baseline empirical design utilizes few groups for clustering the standard errors, we employ a bootstrap-t procedure to obtain more accurate cluster-robust inference of our analysis (Cameron, Gelbach and Miller, 2008). In particular, after running our linear regressions as per Equation (2), we test the hypotheses, $H_0 : \beta_3 = 0$ and $H_a : \beta_3 \neq 0$, using the wild cluster resampling approach with 999 replications and Mammen weights. This process yields a *p*-value of 0.000 when we use both bank and country fixed effects alternately and thus further confirms our baseline findings.

4.8.2 Alternative explanations

In line with Acharya et al. (2015), banks can experience financial distress due to a macroeconomic downturn, especially when they have a large exposure to government bond debt. Specifically, during a sovereign downgrade, this distress condition can worsen for a bank as it will face a deterioration in the quality of its government bond investments, leading to higher systemic risk. Therefore, to address this alternative explanation, we test our baseline specification excluding the banks that have large government bond holdings. To conduct the test, we rely on Refinitiv Eikon database to retrieve the data on treasury securities, which captures a banks' investment in domestic government debt.

Following Adelino and Ferreira (2016), to remove the effect of a bank's government bond holdings on our baseline analysis, we exclude the banks that hold greater than the median ratio of treasury securities to total assets of the distribution. As presented in columns (1) and (2) of Table 7, a positive coefficient of *Bound*Downgrade* indicates that the bound banks, compared to non-bound banks, show a larger growth in systemic risk in the post sovereign downgrade environment, even when we exclude banks with large government bond holdings.

We also investigate the impact of a sovereign downgrade on bound banks, as opposed to non-bound banks, when we exclude the banks that are considered to be the too-big-to-fail financial institutions. In particular, this test helps us examine whether our baseline results hold when we exclude those large banks that are likely to be more affected by the international markets and exhibit higher systemic risk. To conduct the test, we follow Adelino and Ferreira (2016) and first categorize the too-big-to-fail financial institutions as banks above the 75th percentile of the distribution of total liabilities to GDP ratio. Then we estimate our baseline specification excluding these banks and report the main outcomes in columns (3) and (4) of Table 7. Our results show a positive coefficient for *Bound*Downgrade*, suggesting that following a sovereign downgrade, the bound banks exhibit higher growth in systemic risk even in the absence of the too-big-to-fail banks.[15] Furthermore, as shown in columns (5) and (6), these results remain qualitatively similar when we also exclude the banks which are considered Globally Systemically Important Banks (G-SIBs) and can have a high contribution to systemic risk (Financial Stability Board, 2020).[16] Therefore, this finding gives us confidence to exclude the possibility that these large banks, with presumably high systemic risk, are driving our baseline results.

< Insert Table 7 >

4.8.3 Systemic risk surrounding sovereign downgrades using ratings by other rating providers

While we utilize the ratings provided by S&P because they are more active in making rating revisions (Kaminsky and Schmukler, 2002) the ratings issued by other agencies may differ with the S&P ratings on some occasions. For example, Hill, Brooks and Faff (2010) suggest that the credit quality assessment of sovereigns can differ among the major credit rating agencies. At the same time, both sovereign and corporate ratings may be prone to subjective judgements that may vary across different raters (De Moor et al., 2018; Shin and Moore, 2003). Therefore, we repeat our baseline regressions using the long-term foreign currency ratings provided by other major credit rating agencies – Moody's and Fitch.[17]

[15] These results are also similar when we use bank fixed effects in the regressions.
[16] We refer to the list of G-SIBs published in November 2020, and in our sample the G-SIBs are Santander from Spain and UniCredit from Italy.
[17] We convert the ratings into a numerical scale of 1 to 21, where 1 denotes the lowest (default) rating and 21 indicates the highest rating. We collect the ratings from the Refinitiv Eikon database.

First, in Table IA.8 of the Internet Appendix, we show a correlation matrix of the ratings provided S&P, Moody's, and Fitch. While the ratings are positively correlated between all three agencies at both the sovereign and bank levels, as expected there are still some deviations between these ratings issued by the different agencies. Second, we report the regression results in Table 8, where columns (1) and (2) show our findings related to Moody's ratings whereas columns (3) and (4) show results for Fitch ratings. For both raters, our key interaction term, *Bound*Downgrade,* is positive and significant at the 5% level. Collectively, these outcomes indicate that our baseline results remain robust to the ratings provided by all three major credit rating agencies even though they may differ in terms of the credit assessments of the ratee.

< Insert Table 8 >

4.8.4 Systemic risk and bond yields including corporate governance and non-core liabilities

In this section, we expand our baseline analysis by including some corporate governance controls as these can affect bank systemic risk (Andrieş and Nistor, 2016). In particular, following Díez-Esteban et al. (2021) we include the annual percentage of female board members (*Female directors*) and independent board members (*Independent board directors*), and the total number of board members (*Board size*) for each bank. In addition, given that Mallin, Mullineux and Wihlborg (2005) highlight that the strategic entities (i.e., corporations, holding companies and individuals) can play a major role in the corporate governance systems, we also control for an annual % change in the shares of *Strategic investors* of our banks.

Furthermore, to account for the internal risk management of banks, we include indicator variables that take the value of one for the presence of a *Corporate governance committee*, *Audit committee* for financial reporting quality checks, *Compensation committee* for executive remuneration and *Nomination committee* for overall board functions for a given year, and zero otherwise. Finally, we also add *Non-core liabilities*, computed as other liabilities (those excluding core deposits) to total assets, to control for the level of interconnectedness of banks which can affect the systemic risk.[18] In columns (1) and (2) of Table 9, we present our analysis of the baseline specification including the above-mentioned controls, and we find that the results remain qualitatively similar to our initial baseline findings.

Additionally, we also examine the bond yields of banks around the sovereign downgrade event. This is important because in some cases the expectations of a bank's risks can be different to that signaled by the bank's credit rating outlook (Finnerty, Miller and Chen, 2013; Jacobs et al., 2016). Therefore, we first focus on the *Eurobond yields* since we rely on the S&P foreign currency issuer ratings of our banks. In column (3) of Table 9, we see that our key interaction variable, *Bound*Downgrade*, is positive and significant ($p < 0.01$), hinting that the bound banks face about 3 times larger yields than the non-bound banks during the sovereign downgrade years.

Moreover, we also focus on the banks' Credit Default Swap (CDS) – bond basis, which captures the price difference between the underlying bond and the CDS (Oehmke and Zawadowski, 2016). Our findings, presented in column (4) of Table 9, show that the *Bound*Downgrade* interaction term is negative and significant ($p < 0.05$), suggesting that the bound banks face about 1.88 times wider negative basis and their bonds are considered riskier compared to the non-bound banks when a sovereign downgrade occurs.[19] Collectively, these results are in line with Adelino and Ferreira (2016) and indicate that the bound banks face a higher cost of accessing the capital markets in post-sovereign downgrade period.

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[18] We collect our corporate governance and non-core liabilities data from the Refinitiv Eikon database. For the regressions including these variables, we cluster the standard errors by country.

[19] We collect the bond yields and the CDS-bond basis data from the Refinitiv Eikon database. Moreover, for the regressions of *Eurobond yields* and *CDS-bond basis*, we follow Adelino and Ferreira (2016) and use Bank and Year-Country fixed effects. Furthermore, we also cluster our standard errors by the lender country. We also exclude the *Audit committee* indicator in column (4) of Table 9 as all banks used in the sample for the regression had an audit committee comprised of board members.

< Insert Table 9 >

4.8.5 Alternative measure of systemic risk

While we rely on the growth in *MES (transformed)* as our main outcome variable, we also test another prominent measure, Δ *CoVaR* (conditional value at risk), proposed by Adrian and Brunnermeier (2016) as an alternative to capture systemic risk. We are interested in this measure because, in contrast to the growth in *MES (transformed)* which captures the banks' increase in exposure to a systemic crisis, Δ *CoVaR* estimates a financial institution's contribution to the system's level of systemic risk given that the institution experiences financial distress (Duarte and Eisenbach, 2021). To compute the Δ *CoVaR*, we follow the lead of Adrian and Brunnermeier (2016) and provide the details of the methodology in section A of the Internet Appendix.

In our sample, the mean Δ *CoVaR* is 1.94%, implying that a distress condition in the financial institution can raise its systemic risk by 1.94 percentage points, on average, in a year.[20] For our regression analysis, we estimate a panel OLS specification of our baseline model with Δ *CoVaR* as our outcome variable to proxy for the systemic risk. In addition, based on our previous discussion, we also exclude the banks with large government bond holdings and also the too-big-to-fail banks to remove the impact they might have on our analysis.

We report the results of this test in Table 10. Specifically, in panel A we find a positive coefficient on *Bound*Downgrade,* implying that, as opposed to the non-bound banks, the bound banks show a larger Δ *CoVaR* in the post sovereign downgrade period. These results are consistent with our initial baseline findings, therefore further supporting our hypothesis. Moreover, for additional robustness we also conduct a DiD test using matched samples of the bound (treated)

[20] The standard deviation of Δ *CoVaR* is 1.57% which suggests that there is reasonable variation in systemic risk during the sample period. Both the mean and the standard deviation are in line with Laeven, Ratnovski and Tong (2016) who also study systemic risk for an international sample of banks.

and the non-bound (control) banks, where the sovereign downgrade is employed as the treatment effect. As shown in panel B, we find similar results as the OLS estimates, which adds further to the robustness of our main analysis. In sum, we find evidence that the sovereign ceiling rule can raise the bound banks' exposure to systemic risk when using Δ *CoVaR* as an alternative measure.

< Insert Table 10 >

5. Conclusion

We examine the impact of the sovereign ceiling rule on systemic risk in the banking sector. While previous literature, such as Adelino and Ferreira (2016), has reported that due to this rule business activities, including investment and lending, can decline, we shed light on how the rule has a first-order effect on bank systemic risk resulting in substantial negative externalities. Specifically, we provide robust evidence that in a sovereign downgrade event the bound banks, i.e., financial institutions which have the same rating as or higher rating than the sovereign, exhibit around three times larger growth in systemic risk than the lower rated non-bound banks. Consequently, following a sovereign downgrade the decline in the growth of equity of these bound banks is also double that of the non-bound banks, generating more uncertainty about bank solvency positions. Moreover, relative to the non-bound banks, the bound banks also remain more profitable in the post sovereign downgrade episode calling into question the rationality of the sovereign ceiling rule. Therefore, in the same spirit as Manso's (2013) theory of a feedback effect stemming from a rating downgrade, our findings support a stickier rating regime to minimize the worsening of systemic risks around a sovereign downgrade phenomenon.

Our study also bears several policy implications for the financial regulators. First, our findings hint that under Pillars 1 and 2 of the Basel III rules it may be necessary for the bound banks to maintain greater capital buffers as these banks face greater insolvency in a sovereign downgrade period. Moreover, in updating the regulatory framework such that it takes a more macroprudential direction globally, we propose that the Basel Core Principles can consider the sovereign ceiling doctrine as an important factor that induces bank systemic risks. At the same time, our findings can also facilitate evidence-based policy making and help discourage the use of the sovereign ceiling policy en masse.

Furthermore, as the sovereign ceiling rule leads to negative outcomes for the real economy and the banking system, future research could explore how this rule can affect the quality of lending and bank risk-taking. In particular, it may be worthwhile to gauge how the accounting-based risk measures, such as loan loss provisions, are impacted by the rule. Other research avenues can also investigate whether the rule has any labor market consequences, including, reduction in office staff, pay cuts of key personnel, turnover of the Chief Executive Officer (CEO), among others.

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FIGURE 1

Evolution of growth in systemic risk for the bound and non-bound banks, surrounding the sovereign downgrade event

This figure shows the trend of growth in systemic risk (Δ MES) for the bound banks and non-bound banks, around the sovereign downgrade year. In total, 4 years of evolution of Δ MES is depicted within the figure, for both the pre- and post- sovereign downgrade periods.

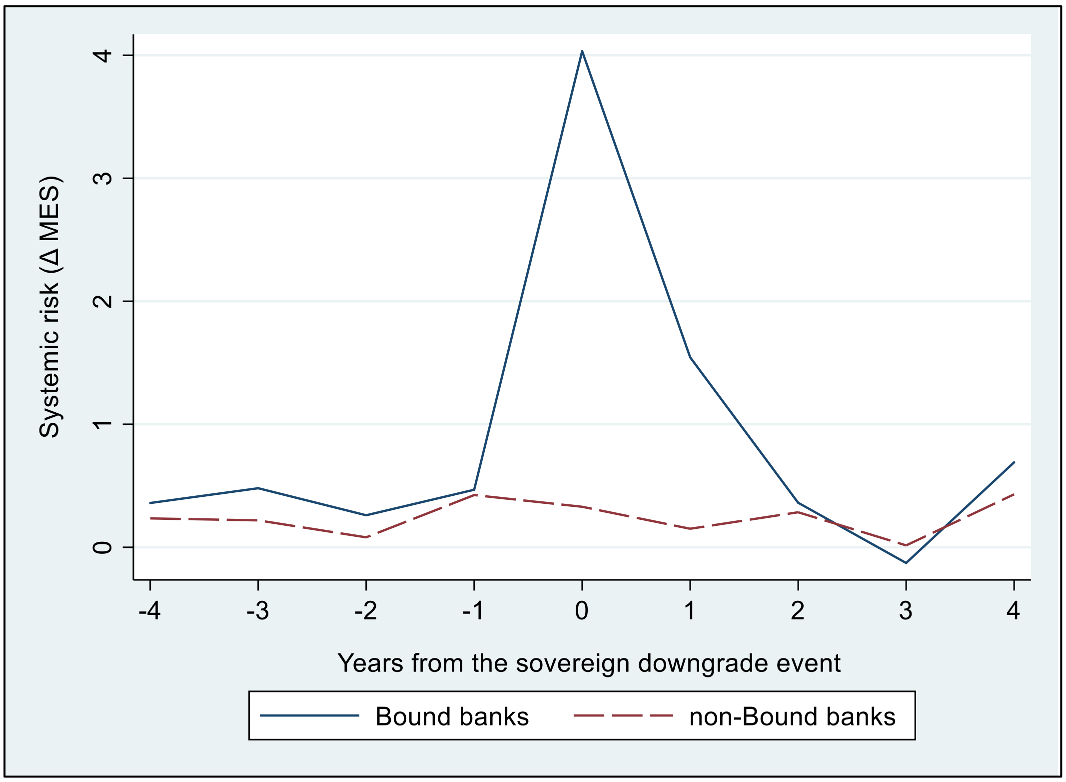

TABLE 1

Descriptive Statistics and Correlation Matrix

Table 1 reports the descriptive statistics and Pearson correlation coefficients of the main dependent and all control variables included in the baseline regressions. N = 715. In addition, MES (systemic risk) has also been reported. All variables are defined in Appendix II. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1	MES (transformed)	0.028	0.029	1												
2	Δ MES	0.559	6.763	-0.006	1											
3	Bank size (natural log)	23.398	2.142	0.457***	0.041	1										
4	Profitability	0.077	0.06	-0.266***	-0.010	-0.398***	1									
5	Capital	0.055	0.073	-0.260***	-0.022	-0.505***	0.374***	1								
6	Liquidity	0.081	0.073	-0.057	-0.016	-0.075**	0.071*	-0.174***	1							
7	Deposits	0.604	0.206	0.125***	-0.051	-0.132***	-0.181***	-0.238***	0.215***	1						
8	Non-interest income	0.464	0.369	-0.061	0.031	-0.035	0.158***	0.082**	-0.045	-0.231***	1					
9	Loan loss provisions	0.022	0.253	-0.013	-0.007	-0.050	-0.037	-0.023	0.017	0.094**	-0.024	1				
10	GDP growth rate	0.586	4.008	-0.177***	0.043	-0.149***	0.175***	0.123***	0.023	-0.078**	0.138***	-0.033	1			
11	Deposit insurance	0.987	0.112	-0.096***	0.014	0.008	0.067*	0.053	-0.126***	-0.093**	0.048	0.008	0.110***	1		
12	Stock market turnover	75.976	60.784	0.081**	0.059	0.320***	-0.424***	-0.234***	-0.107***	-0.138***	-0.006	-0.046	-0.143***	0.075**	1	
13	Monetary policy rate	7.417	7.49	-0.260***	-0.026	-0.351***	0.602***	0.399***	0.010	-0.215***	0.187***	0.022	-0.019	-0.019	-0.453***	1

TABLE 2

Univariate Analysis

Table 2 reports the univariate results for tests of differences in means and medians for the main dependent variable and the bank specific variables with respect to the bound and non-bound banks. We perform *t*-tests to compare the means and Wilcoxon/Mann-Whitney tests to compare the medians. All variables are defined in Appendix II. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Bound banks		Non-bound banks		Difference		*p*-value	
Variables	Mean	Median	Mean	Median	Mean	Median	Mean	Median
MES (transformed)	0.032	0.028	0.025	0.020	0.007***	0.008***	0.003	0.000
Δ MES	1.807	-0.074	0.264	0.000	1.543***	-0.074	0.004	0.553
Bank size (natural log)	24.586	24.660	22.649	22.704	1.937***	1.956***	0.000	0.000
Profitability	0.087	0.078	0.105	0.059	-0.018	0.019***	0.729	0.010
Capital	0.048	0.032	0.305	0.036	-0.257	-0.004	0.340	0.137
Liquidity	0.084	0.076	0.095	0.072	-0.011	0.004	0.159	0.425
Deposits	0.460	0.481	0.650	0.671	-0.190***	-0.190***	0.000	0.000
Non-interest income	0.533	0.489	0.442	0.395	0.091***	0.094***	0.001	0.000
Loan loss provisions	0.008	0.003	0.024	0.002	-0.016	0.001***	0.325	0.004

TABLE 3

Baseline analysis: Systemic risk surrounding a sovereign downgrade

The table below shows the OLS regressions of the growth in systemic risk on bound banks, relative to non-bound banks, around the sovereign downgrade event. The dependent variable is Δ *MES* which captures the annual growth in systemic risk of a bank in year *t*. *Bound* is a dummy variable that takes the value of one if a bank has a rating equal to or above the sovereign rating in year $t – 1$, and zero otherwise. *Downgrade* is a dummy variable that takes a value of one if a bank's country is downgraded in year *t*, and zero otherwise. Column (1) shows the regression results in absence of the controls and in presence of year and country fixed effects. Column (2) shows the regression results with all bank specific and country specific controls alongside year and country fixed effects. Column (3) shows the regression results in absence of the controls and in presence of year and bank fixed effects. Column (4) shows results with all controls as well as bank and year fixed effects. All other variables (controls) are defined in Appendix II. Robust standard errors clustered by bank type are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:	Δ MES	Δ MES	Δ MES	Δ MES
Bound	0.318	0.126	-1.106*	-1.423**
	(0.134)	(0.150)	(0.104)	(0.094)
Downgrade	0.191	0.549	0.183	0.605
	(0.207)	(0.224)	(0.176)	(0.259)
Bound*Downgrade	3.336***	3.684**	3.080**	3.425**
	(0.052)	(0.093)	(0.055)	(0.142)
Bank size		0.055***		-0.281
		(0.000)		(0.081)
Profitability		-1.589		-5.390
		(0.770)		(1.567)
Capital		0.004		-6.080
		(2.270)		(4.374)
Liquidity		-2.378		0.670
		(0.767)		(0.128)
Deposits		0.610**		-1.050
		(0.043)		(0.672)
Non-interest income		0.511***		-0.032
		(0.005)		(0.025)
Loan loss provisions		-2.599		4.206
		(4.208)		(3.949)
GDP growth rate		0.033		0.039
		(0.017)		(0.029)
Deposit insurance		4.994		6.182
		(1.960)		(2.679)
Stock market turnover		0.018*		0.017***
		(0.002)		(0.000)
Monetary policy rate		0.028		0.045
		(0.012)		(0.020)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	No	No
Bank FE	No	No	Yes	Yes
Observations	904	715	904	715
R-squared	0.059	0.072	0.443	0.456

TABLE 4

Difference-in-Differences estimation of systemic risk surrounding a sovereign downgrade

This table presents the difference-in-differences (DiD) estimates of the growth in systemic risk of bound banks, relative to non-bound banks, around sovereign downgrade events based on a matched sample. The dependent variable in this DiD regression is Δ *MES* which captures the annual growth in systemic risk of a bank in year *t*. The treated banks are the bound banks and their matched control banks are the non-bound banks. The matching of the treated and control banks is based on a propensity score matching procedure where the sovereign downgrade is used as the treatment effect. Panel A of the table shows the propensity score matching diagnosis results of the bank-specific covariates of the matched treated (bound) and control (non-bound) bank observations. The covariates used for the matching process include pre-treatment bank specific characteristics such as MES, size, capital, profitability, liquidity, deposits, non-interest income and loan loss provisions. These variables are defined in Appendix II. In addition, the treated and control banks were also subject to exact matching of country and year. The *t*-statistics and the *p*-values of the differences in the mean of the covariates between the treated and control banks are shown in panel A. The sample consists of 95 (56) treated and 320 (101) control bank-year observations before (after) the matching process. Panel B of the table shows the DiD estimates. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Propensity score matching diagnostics

	Mean		t-test	
Variables	Treated	Control	t-statistic	p-value
MES (Systemic Risk)	-0.032	-0.036	1.12	0.263
Size	24.532	24.753	-0.87	0.384
Profitability	0.092	0.08	1.63	0.104
Capital	0.053	0.044	1.17	0.242
Liquidity	0.083	0.072	1.32	0.188
Deposits	0.456	0.448	0.26	0.795
Non-interest income	0.562	0.495	1.49	0.138
Loan loss provisions	0.055	0.044	0.44	0.659

Panel B: DiD estimates of systemic risk

Sample:	Treated Banks	Control Banks	Difference
Dependent variable:	Δ MES	Δ MES	
Year before downgrade	0.352	0.283	0.069
	(0.753)	(0.779)	(1.084)
Year of downgrade	4.206	0.228	3.978**
	(0.982)	(1.310)	(1.637)
Difference in Differences			3.909**
			(1.963)

TABLE 5

Impact on systemic risk due to alternative macroeconomic shocks

The table below shows the OLS regressions of the growth in systemic risk on bound banks, relative to non-bound banks, around macroeconomic crises which are used as a placebo shock. The dependent variable is Δ *MES* which captures the annual growth in systemic risk of a bank in year *t*. *Bound* is a dummy variable that takes the value of one if a bank has a rating equal to or above the sovereign rating in year *t* – 1, and zero otherwise. *Placebo shock* is a dummy variable that takes a value of one if a bank's country undergoes a given macroeconomic crisis in year *t* (excluding the years that also experience a sovereign downgrade), and zero otherwise. Columns (1) and (2) report the outcome from currency crises, columns (3) and (4) report the outcome from banking crises and columns (5) and (6) report the outcome from stock market crises (as defined and recorded by Reinhart and Rogoff (2011)). All control variables are defined in Appendix II. Robust standard errors clustered by bank type are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Placebo shock:	Currency crisis		Banking crisis		Stock market crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Δ MES	Δ MES	Δ MES	Δ MES	Δ MES	Δ MES
Bound	-0.052	0.271	-0.061	0.074	-0.276	0.103
	(0.094)	(0.297)	(0.023)	(0.202)	(0.101)	(0.336)
Placebo shock	-0.398	-0.099	1.108**	1.214**	1.778	1.931
	(0.504)	(0.797)	(0.052)	(0.068)	(0.344)	(0.469)
Bound*Placebo shock	-0.715	-0.886	-0.059	0.609	1.144	1.027
	(0.549)	(0.853)	(0.218)	(0.328)	(0.273)	(0.379)
Bank specific controls	Yes	Yes	Yes	Yes	Yes	Yes
Country specific controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	Yes	No	Yes	No
Bank FE	No	Yes	No	Yes	No	Yes
Observations	385	385	397	397	385	385
R-squared	0.118	0.310	0.121	0.327	0.150	0.343

TABLE 6

Transmission mechanism: Bank equity and profitability around a sovereign downgrade

This table presents the regression estimates of the change in equity and profitability of the bound banks, relative to non-bound banks, around sovereign downgrade events. Particularly, panel A includes the OLS regressions and panel B includes the difference-in-differences (DiD) estimates based on matched samples of banks. The dependent variable, Δ *ln (Equity)* is the natural log of the annual change in equity, whereas, *Profitability* is the *Bank Total Revenue* scaled by *Total Assets*. *Bound* is a dummy variable that takes the value of one if a bank has a rating equal to or above the sovereign rating in year $t-1$, and zero otherwise. *Downgrade* is a dummy variable that takes a value of one if a bank's country is downgraded in year *t*, and zero otherwise. In panel B, the treated banks are the bound banks and their matched control banks are the non-bound banks. The matching of the treated and control banks is based on propensity score matching where the sovereign downgrade is used as the treatment effect. The covariates used for the matching process of the DiD regressions include pre-treatment bank specific characteristics such as size, capital, profitability, liquidity, deposits, non-interest income and loan loss provisions. These variables are defined in Appendix II. Moreover, column (1) of panel B includes additional covariates of bank equity and Δ *MES* lagged by one year. In addition, the treated and control banks were also subject to exact matching by country and year. The matching estimator includes 60 treated bank-year observations in column (1) of panel B and 134 treated bank-year observations in column (2) of panel B. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: OLS estimates of bank equity and profitability channels

	(1)	(2)	(3)	(4)
Dependent variable:	Δ ln (Equity)	Δ ln (Equity)	Profitability	Profitability
Bound	-0.161	-0.367	-0.004	-0.007*
	(0.053)	(0.181)	(0.001)	(0.001)
Downgrade	0.837**	0.581*	0.002*	0.002*
	(0.048)	(0.081)	(0.000)	(0.000)
Bound*Downgrade	-0.700*	-0.239*	0.006***	0.008*
	(0.088)	(0.036)	(0.000)	(0.001)
Bank specific controls	Yes	Yes	Yes	Yes
Country specific controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	No	Yes	No
Bank FE	No	Yes	No	Yes
Observations	336	336	994	994
R-squared	0.301	0.501	0.782	0.869

Panel B: DiD estimates

	(1)	(2)
Dependent variable:	Δ ln (Equity)	Profitability
Year before downgrade		
Treated Banks	-1.738	0.090
	(0.132)	(0.004)
Control Banks	-1.793	0.083
	(0.171)	(0.009)
Difference	0.055	0.007
	(0.216)	(0.010)
Year of downgrade		
Treated Banks	-2.471	0.085
	(0.248)	(0.007)
Control Banks	-1.670	0.052
	(0.259)	(0.006)
Difference	-0.801**	0.033***
	(0.359)	(0.009)
Difference in Differences	-0.856**	0.026**
	(0.419)	(0.013)

TABLE 7

Baseline tests barring banks with high government debt, and which are too-big-to-fail and G-SIBs

The table below shows the OLS regressions of the growth in systemic risk on bound banks, relative to non-bound banks, around sovereign downgrade events, excluding the banks with high government debt and those that are too-big-to-fail and G-SIBs. The dependent variable is Δ *MES* which captures the annual growth in systemic risk of a bank in year t. *Bound* is a dummy variable that takes the value of one if a bank has a rating equal to or above the sovereign rating in year t – 1, and zero otherwise. *Downgrade* is a dummy variable that takes a value of one if a bank's country is downgraded in year t, and zero otherwise. Banks with greater than the median ratio of the distribution of the treasury securities to total assets are considered to have high government debt, whereas banks with greater than the 75th percentile of the distribution of total liabilities to GDP ratio are the too-big-to-fail financial institutions. G-SIBs are as per the list provided by the Financial Stability Board in November 2020. Columns (1) and (2) show the results excluding the banks with high government debt and columns (3) and (4) show the results excluding the banks that are considered too-big-to-fail. Columns (5) and (6) show results excluding the G-SIBs. All other variables (controls) are defined in Appendix II. Robust standard errors clustered by bank type are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Sample:	Excluding banks with high government debt		Excluding the too-big-to-fail banks		Excluding G-SIBs	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Δ MES	Δ MES	Δ MES	Δ MES	Δ MES	Δ MES
Bound	0.644	0.043	0.716*	-0.097	0.329	0.119
	(0.150)	(0.064)	(0.091)	(0.110)	(0.125)	(0.160)
Downgrade	-0.101	0.225	-0.250	0.007	0.223	0.549
	(0.039)	(0.115)	(0.125)	(0.049)	(0.209)	(0.229)
Bound*Downgrade	2.384***	2.631**	1.721**	2.594**	3.686**	3.989**
	(0.026)	(0.130)	(0.032)	(0.051)	(0.060)	(0.088)
Bank size		-0.131		0.035		0.060**
		(0.022)		(0.008)		(0.001)
Profitability		-47.366*		-2.845		-1.348
		(6.642)		(2.101)		(0.618)
Capital		-19.074		-3.471*		-0.250
		(13.531)		(0.411)		(2.290)
Liquidity		-5.116		-1.601*		-2.023
		(1.441)		(0.224)		(0.746)
Deposits		0.263		-1.382		0.607**
		(0.076)		(0.256)		(0.045)
Non-interest income		0.973**		0.368**		0.501***
		(0.072)		(0.023)		(0.004)
Loan loss provisions		-10.108		-0.254		-0.022
		(5.011)		(0.106)		(0.044)
Country specific controls	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	275	249	670	518	876	692
R-squared	0.295	0.370	0.062	0.083	0.061	0.074

TABLE 8

Systemic risk around the sovereign downgrade using Moody's and Fitch ratings

The table below shows the OLS regressions of the growth in systemic risk on bound banks, relative to non-bound banks, around the sovereign downgrade event. The dependent variable is Δ *MES* which captures the annual growth in systemic risk of a bank in year *t*. *Bound* is a dummy variable that takes the value of one if a bank has a rating equal to or above the sovereign rating in year *t* – 1, and zero otherwise. *Downgrade* is a dummy variable that takes a value of one if a bank's country is downgraded in year *t*, and zero otherwise. Column (1) and (2) show the regression results using the credit ratings provided Moody's. Column (3) and (4) show the regression results using the credit ratings provided by Fitch. All other variables (controls) are defined in Appendix II. Robust standard errors clustered by bank type are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Credit rating agency:	Moody's		Fitch	
	(1)	(2)	(3)	(4)
Dependent variable:	Δ MES	Δ MES	Δ MES	Δ MES
Bound	1.090**	1.076**	-0.139	0.047
	(0.023)	(0.025)	(0.293)	(0.063)
Downgrade	3.384**	3.218*	1.076	0.627
	(0.219)	(0.368)	(0.380)	(0.203)
Bound*Downgrade	0.895*	2.514**	3.919*	3.510**
	(0.128)	(0.166)	(0.402)	(0.150)
Bank specific controls	Yes	Yes	Yes	Yes
Country specific controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes
Bank FE	Yes	No	Yes	No
Observations	306	306	303	303
R-squared	0.500	0.116	0.499	0.093

TABLE 9

Systemic risk and yields analysis including corporate governance and non-core liabilities

The table below shows the OLS regressions of the growth in systemic risk and bond yields of bound banks, relative to non-bound banks, around the sovereign downgrade event. The dependent variable, Δ *MES*, captures the annual growth in systemic risk of a bank in year *t*. Another dependent variable, *Eurobond yield*, is the yield on the Eurobond issued by the bank and expressed as unit rate. The other dependent variable, *CDS-bond basis*, is the price difference between the underlying bond and the CDS (Credit Default Swap) and expressed as unit rate. *Bound* is a dummy variable that takes the value of one if a bank has a rating equal to or above the sovereign rating in year *t* – 1, and zero otherwise. *Downgrade* is a dummy variable that takes a value of one if a bank's country is downgraded in year *t*, and zero otherwise. Other controls include *GDP per capita (natural log)*, *GDP growth squared*, *Inflation* and *Current account balance.* All variables (controls) are also defined in Appendix II. Robust standard errors clustered by country are reported in columns (1) and (2), and those clustered by lender-country are reported in columns (3) and (4), and shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Variables:	Δ MES	Δ MES	Eurobond yield	CDS-bond basis
Bound	-2.893	-3.553	-3.080***	-0.953
	(1.578)	(2.802)	(0.399)	(0.793)
Downgrade	2.212	0.741		
	(2.680)	(1.973)		
Bound*Downgrade	3.542***	3.607*	3.710***	-1.885**
	(0.974)	(1.627)	(0.446)	(0.753)
Female directors	-0.030	0.218	0.070***	0.002
	(0.223)	(0.233)	(0.009)	(0.027)
Board size	0.000	-0.092	-0.060***	-0.271***
	(0.166)	(0.095)	(0.007)	(0.099)
Independent directors	-0.014	-0.013	-0.009***	-0.029***
	(0.017)	(0.012)	(0.001)	(0.011)
Strategic investors	-0.001	-0.001	-0.039***	0.002**
	(0.001)	(0.001)	(0.006)	(0.001)
Corporate governance committee	-1.944	0.200	1.823***	-1.376**
	(2.661)	(0.490)	(0.232)	(0.531)
Audit committee	-0.619	-2.026	-5.087***	
	(1.185)	(3.132)	(0.797)	
Compensation committee	-3.272	2.057	3.668***	44.223**
	(4.634)	(2.377)	(0.523)	(17.885)
Nomination committee	5.045	0.540	-0.844***	4.393***
	(5.432)	(0.767)	(0.083)	(1.637)
Non-core liabilities	12.646	-7.206	3.058***	-9.113*
	(18.075)	(9.049)	(0.531)	(5.278)
Bank specific controls	Yes	Yes	Yes	Yes
Country specific controls	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
Country FE	No	Yes	No	No
Bank FE	Yes	No	Yes	Yes
Year*Country FE	No	No	Yes	Yes
Observations	165	165	239	598
R-squared	0.615	0.238	0.393	0.407

TABLE 10

Alternative measure of systemic risk

This table presents the regression estimates of an alternative measure of systemic risk, the conditional value at risk (Δ *CoVaR*) of the bound banks, relative to non-bound banks, around the sovereign downgrade event. Panel A includes the OLS regressions and panel B includes the difference-in-differences (DiD) estimates based on matched samples of banks. In panel A, the regression estimates exclude the banks with high government debt and those that are too-big-to-fail banks. The dependent variable is Δ *CoVaR* which captures the systemic risk of a bank in year *t*. *Bound* is a dummy variable that takes the value of one if a bank has a rating equal to or above the sovereign rating in year *t* – 1, and zero otherwise. *Downgrade* is a dummy variable that takes a value of one if a bank's country is downgraded in year *t*, and zero otherwise. Column (1) shows the results with the controls and in the absence of fixed effects. Column (2) shows the results in the presence of controls as well as year and bank fixed effects. Column (3) and (4) show results that include an additional control of a banking crisis indicator based on Reinhart and Rogoff (2011) database, and include year and country fixed effects as well as year and bank fixed effects, respectively. In panel B, the treated banks are the bound banks and their closely matched control banks are the non-bound banks. The matching of the treated and control banks is based on propensity score matching where the sovereign downgrade is used as the treatment effect. The covariates used for the matching process of the DiD regressions include pre-treatment bank specific characteristics of size, capital, profitability, liquidity, deposits, non-interest income and loan loss provisions. These variables are defined in Appendix II. In addition, Δ *CoVaR* lagged by one year was also included as a covariate and the treated and control banks were also subject to exact matching by country and year. The sample consists of 102 treated bank-year observations. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: OLS estimates of Δ CoVaR

	(1)	(2)	(3)	(4)
Dependent variable:	Δ CoVaR	Δ CoVaR	Δ CoVaR	Δ CoVaR
Bound	-1.479*	-0.489**	-1.914**	-2.330*
	(0.168)	(0.01)	(0.086)	(0.268)
Downgrade	0.035	-0.04	0.124	0.105
	(0.024)	(0.032)	(0.172)	(0.145)
Bound*Downgrade	1.722**	0.478**	2.503*	3.140*
	(0.114)	(0.015)	(0.379)	(0.433)
Bank specific controls	Yes	Yes	Yes	Yes
Country specific controls	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Country FE	No	No	Yes	No
Bank FE	No	Yes	No	Yes
Observations	177	177	137	137
R-squared	0.311	0.919	0.753	0.91

Panel B: DiD estimates of Δ CoVaR

Sample:	Treated Banks	Control Banks	Difference
Dependent variable:	Δ CoVaR	Δ CoVaR	
Year before downgrade	2.481	2.061	0.420***
	(0.098)	(0.114)	(0.151)
Year of downgrade	2.577	1.676	0.900***
	(0.142)	(0.130)	(0.192)
Difference in Differences			0.480**
			(0.244)

APPENDIX I

List of bound bank observations in the year of a sovereign downgrade

Country	Year of downgrade	Number of bound bank observations
Argentina	2001	4
	2008	3
	2012	3
	2013	3
	2014	3
Brazil	2002	4
	2014	5
	2015	6
Spain	2011	3
	2012	2
Greece	2004	1
	2009	2
	2010	1
	2011	1
India	1998	1
Italy	2011	2
	2012	2
	2013	2
	2014	2
Mexico	2009	1
Malaysia	1998	1
Portugal	2011	2
Russia	2014	2
	2015	2
Thailand	1998	1
Turkey	2016	4
Total number of bound banks		63

APPENDIX II

Definitions and sources of the main systemic risk measure and controls

Variables	Definition	Source
Main systemic risk measure		
MES (Marginal Expected Shortfall)	Average return of a bank conditional on the market experiencing 5% lowest returns in a year	Own calculation
MES (transformed)	MES multiplied by negative 1	Own calculation
Δ MES	Annual growth in MES (transformed)	Own calculation
Bank specific controls		
Bank size	Natural logarithm of total assets	Refinitiv Eikon
Profitability	Bank total revenue divided by total asset	Refinitiv Eikon
Capital	Common equity divided by total asset	Refinitiv Eikon
Liquidity	Cash due from banks divided by total assets	Refinitiv Eikon
Deposits	Total deposits divided by total assets	Refinitiv Eikon
Non-interest income	Non-interest income divided by total revenue	Refinitiv Eikon
Loan loss provisions	Loan loss provisions divided by total assets (in %)	Refinitiv Eikon
Country specific controls		
GDP growth rate	Annual real GDP growth rate (in %)	World Bank database
Deposit insurance	Dummy variable equal to one when there is explicit deposit insurance available in the country, and otherwise it is equal to zero	Demirgüç-Kunt et al. (2008)
Stock market turnover	Ratio of value of domestic shares divided by market capitalization. Monthly average ratio was annualized by multiplying with 12	World Bank database
Monetary policy rate	Central bank policy rate to signal monetary policy stance. Annual rate was computed from the 12-month average	Bank for International Settlements (BIS) database
Corporate governance and internal risk management practices controls		
Female directors	% of the female board members	Refinitiv Eikon
Independent directors	% of the independent board members	Refinitiv Eikon
Board size	Number of board members	Refinitiv Eikon
Strategic investors	Annual % change in the shares of strategic entities	Refinitiv Eikon
Corporate governance committee	Dummy variable equal to one when the bank has a committee for the corporate governance, and zero otherwise	Refinitiv Eikon
Audit committee	Dummy variable equal to one when the bank has a committee for the auditing the financial reporting quality, and zero otherwise	Refinitiv Eikon
Compensation committee	Dummy variable equal to one when the bank has a committee for the executive compensation, and zero otherwise	Refinitiv Eikon
Nomination committee	Dummy variable equal to one when the bank has a committee for nominating board members and their functions, and zero otherwise	Refinitiv Eikon
Other controls		
Non-core liabilities	Other liabilities, excluding the core deposits, divided by total assets	Refinitiv Eikon
Bank size (squared)	Natural logarithm of total assets, squared	Refinitiv Eikon
GDP per capita (natural log)	Natural log of GDP per capita	World Bank database
GDP growth squared	Annual real GDP growth rate (in %), squared	World Bank database
Inflation	Inflation, consumer prices (in %) per annum	World Bank database
Current account balance	Current account (% of GDP) per annum	World Bank database