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Credit rating downgrades and systemic risk

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ABSTRACT

We examine whether changes in issuer credit ratings by the three main providers are associated with changes in systemic risk. First, we find that rating downgrades result in an increase in bank systemic risk, whereas upgrades do not proportionally reduce systemic risk. Second, we document that the positive relationship between rating downgrades and systemic risk can be mitigated by accounting-based stability factors, such as profitability and capital, but also enhanced by sovereign rating downgrades. Finally, we show that sovereign rating downgrades have a greater effect on bound banks' systemic risk compared to non-bound banks.

1. Introduction

Credit Rating Agencies (CRAs) act as information intermediaries aiming to increase transparency by providing credit risk assessment of issues and issuers to investors. However, they are hardwired into financial contracts and their role has broadened to a degree where their decisions have important systemic consequences (Deb et al., 2011). The 2007–09 Global Financial Crisis (GFC) revealed the weaknesses in the CRA market and resulted in massive criticism towards the agencies on which the market and regulators were over-relying. Powered by asset complexity and the freedom of issuers to shop for ratings, the CRA market produced systematically upward ratings.[1] Before the crisis, multiple CRAs used to unanimously give AAA ratings to collateralized debt obligations (CDOs) worth trillions of dollars that eventually lost most of their value in a short period of time. The misrating of such products is widely cited as an important contributor to the GFC. However, whether these shortcomings in the CRA market can contribute to the build-up of systemic risk is largely unknown and we aim to fill this apparent gap in the literature.

Systemic risk is broadly defined as a distressed financial institution's contribution to the financial system's probability of collapse.[2] Importantly, the level of contribution to systemic risk is not determined or controlled by the institution's strategic decisions, but it is mostly driven by the market's response to the firm's performance. Consistent with that, we employ two widely used systemic risk measures, namely, ΔCoVaR by Adrian and Brunnermeier (2016) and MES by Acharya et al. (2017).

Our main findings indicate that credit rating changes alter the market's perspectives on the examined institution and have a significant effect on its contribution to systemic risk. The effect is primarily driven by downgrades that are associated with increased

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[1] In the US, CRAs under-evaluated important factors, such as the joint probability of default of large obligors, mainly in the assessment of creditworthiness of structured securities (see Mason and Rosner, 2007; Mathis et al., 2009, He et al., 2016).

[2] It is important to distinguish between systematic risk and systemic risk for proper measurement and interpretation. Systematic risk is the inherent market risk that cannot be eliminated through diversification. Our focus is on systemic risk, which relates to the impact that the collapse of one or more institutions could have on the financial market.

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bank systemic risk, whereas upgrades have a less consistent effect. We also find that this effect strengthens with downgrade size and is maximized in downgrades where the rating classification changes from investment to speculative grade. Additionally, we find that the positive relationship between rating downgrades and systemic risk can be mitigated by accounting-based stability factors such as profitability and capital. We then expand our baseline analysis using three separate difference-in-differences settings that also mitigate endogeneity concerns. First, we document the presence of a sovereign effect as during sovereign rating downgrades of the bank's home country (treated), bank-level downgrades have a significantly stronger effect. Second, we find that Global Systemically Important Banks' (G-SIBs) (treated) idiosyncratic risk is higher than other banks' due to rating downgrades. The results on systemic risk are mixed as we find a significant effect on MES, but not on ΔCoVaR. Finally, we use the setting by Almeida et al. (2017) to test whether sovereign rating downgrades have a greater effect on systemic risk for bound banks (i.e., banks that have a credit rating equal to or above their country's rating in the previous year) relative to non-bound banks. The results are in line with our expectations since bound banks' systemic risk is significantly more affected by sovereign rating downgrades.

Our findings make a significant contribution to the literature that, so far, only focuses on the impact of sovereign credit ratings on financial stability. Alsakka and ap Gwilym (2013) argue that persistent downgrades on sovereign ratings resulted in great pressure in many Euro Area economies, such as Greece, Ireland and Portugal. IMF (2010) and Arezki et al. (2011) find that rating downgrades affected not only the domestic stock market, but also had spillover effects on the other Euro Area members. However, changes in sovereign credit ratings also directly affect individual firms' stock market returns and creditworthiness (Williams et al., 2013; Huang and Shen, 2015) through the "*sovereign effect*".[3] When a country is under distress with high probability of default, the currency will devalue and domestic financial institutions might not be able to repay foreign debt which may result in immediate bank credit rating downgrades by CRAs.[4] The impact is significant in the case of Euro Area where banks possessed a significant fraction of domestic national debt that increased their probability of default during the GFC (Brunnermeier et al., 2012). In this paper, we revisit the sovereign effect and extend our knowledge on the direct relationship between rating downgrades and banks' contribution to systemic risk.

Despite the limited evidence on this relationship, past events strongly indicate that credit rating changes are associated with systemic events. Sy (2009) argues that systemic risk is inherent to credit ratings because of their pro-cyclical characteristics; during "*good times*" they fuel economic activity (through investments) but can also trigger crises in periods of distress when they deliver bad news. During the upward phase of the business cycle, CRAs focus on increasing their profitability by issuing as many ratings as possible. The competition from other agencies and the low default probability at this phase of the business cycle can lead to a negative relationship between rating quality and economic activity (Becker and Milbourn, 2011; Bar-Isaac and Shapiro, 2013). Dilly and Mählmann (2016) find evidence of a "*boom bias*" in CRAs, whose incentives conflict is stronger during boom periods.[5] Concerns about their reputation are expected to incentivise CRAs to report truthfully (Mathis et al., 2009), however this incentive may not be sufficient compared to the incentive to attract more business by inflating ratings (Bolton et al., 2012; Sangiorgi and Spatt, 2017). Griffin et al. (2013) show that CRAs engage in rating catering where the more stringent agency reduces its standards to match the ones of its most lenient competing agency. In this fight for market share, CRAs cater to issuers' demands and unduly inflate ratings, slowly contributing to the build-up of systemic exposures in the market. Eventually, the inflated ratings are likely to be corrected through downgrades that are occasionally sudden and large, leading to a systemic event (Dilly and Mählmann, 2016).

A rating downgrade may also have a direct market effect since stock prices reflect the valuable information that CRAs convey to market participants (Badoer and Demiroglu, 2019). Investors treat credit ratings as a proxy for the probability of default and a downgrade worsens the marketability of an asset (Ferri et al., 1999).[6] In the aftermath of the GFC, both regulatory authorities and researchers have emphasized the detrimental effects that regulation-driven overreliance on credit ratings can have on financial stability. Overreliance on inflated ratings can lead to increased risk-taking by systemically important institutions and significant underestimation of risk by investors.[7] Importantly, the effect of credit rating changes is driven not only by the new information they provide, but also by the pre-rating warnings that form the market's future expectations (Hill and Faff, 2010; Afonso et al., 2011).[8] Consequently, rating downgrades tend to create pressure to the issuer and to be followed by further downgrades, which enhances the initial effect and creates negative market expectations (Manso, 2013).

In addition to direct market losses, rating downgrades are generally unfavourable by banks since a downgrade leads to an increase in the cost of borrowing (Kisgen, 2006, 2009). Although credit ratings are used to reduce information asymmetries and the cost of equity financing (Frank and Goyal, 2009), lower credit ratings worsen banks' funding opportunities and limit their access to the capital

[3] Williams et al. (2013) find that the impact size depends on several factors such as financial freedom and the macroeconomic environment.

[4] Arezki et al. (2011) find that news about sovereign ratings have a considerable effect on European banking sector' stock prices.

[5] CRAs remain "systematically more optimistic" during boom periods which cannot be explained by changes in issuers' creditworthiness.

[6] Investors perceive ratings as inflated following downgrades, especially after reputational shocks and in the absence of improvement in rating quality (Bedendo et al., 2018). Sy (2009) argues that credit ratings change when CRAs believe that there is a significant change in issuer's creditworthiness or there is new information available, thus are quite informative and the market reacts to that.

[7] Sy (2009) supports that CRAs increase procyclicality, while rating crises result in significant market losses and fire sales. Similarly, Pérignon et al. (2018) argue that credit ratings drop considerably one month before liquidity dry-ups occur.

[8] Jorge (2019) argues that the relationship between CRAs and financial markets is bidirectional. Agencies react to new publicly available information in the market, but also create expectations about future market developments.

Table 1
Variable definitions. *(Continued in next page)*.

	Definition	Source
Systemic risk and stability variables		
VaR	Value-at-Risk (VaR) is defined as the left tail tail (5th percentile) of the historical daily returns.	Thomson Reuters EIKON Datastream (Authors' calculation)
ΔCoVaR	The difference between the Conditional VaR of the financial system when a firm is under distress (5th percentile) and during normal times (50th percentile).	
MES	The mean of the daily returns of the examined banking institution, when the financial sector index is equal or below its VaR, as defined by its historical distribution.	
Downgrade and upgrade variables		
DOWNGRADE	Equals 1 if at least one of S&P, Moody's and Fitch has downgraded the bank, 0 otherwise.	S&P Capital IQ Pro (Authors' calculation)
UPGRADE	Equals 1 if at least one of S&P, Moody's and Fitch has upgraded the bank, 0 otherwise.	
S&P DOWNGRADE	Equals 1 if S&P has downgraded the bank, 0 otherwise.	
S&P UPGRADE	Equals 1 if S&P has upgraded the bank, 0 otherwise.	
MOODY'S DOWNGRADE	Equals 1 if Moody's has downgraded the bank, 0 otherwise.	
MOODY'S UPGRADE	Equals 1 if Moody's has upgraded the bank, 0 otherwise.	
FITCH DOWNGRADE	Equals 1 if Fitch has downgraded the bank, 0 otherwise.	
FITCH UPGRADE	Equals 1 if Fitch has upgraded the bank, 0 otherwise.	
S&P DOWNGRADE SIZE	The absolute difference between the transformed in numerical values ratings by in time t-1 and t if S&P has downgraded the bank, 0 otherwise.	
S&P UPGRADE SIZE	The absolute difference between the transformed in numerical values ratings by in time t-1 and t if S&P has upgraded the bank, 0 otherwise.	
MOODY'S DOWNGRADE SIZE	The absolute difference between the transformed in numerical values ratings by in time t-1 and t if Moody's has downgraded the bank, 0 otherwise.	
MOODY'S UPGRADE SIZE	The absolute difference between the transformed in numerical values ratings by in time t-1 and t if Moody's has upgraded the bank, 0 otherwise.	
FITCH DOWNGRADE SIZE	The absolute difference between the transformed in numerical values ratings by in time t-1 and t if Fitch has downgraded the bank, 0 otherwise.	
FITCH UPGRADE SIZE	The absolute difference between the transformed in numerical values ratings by in time t-1 and t if Fitch has upgraded the bank, 0 otherwise.	
SG	Equals 1 if at least one of S&P, Moody's and Fitch has downgraded the bank from investment to speculative grade, 0 otherwise.	
IG	Equals 1 if at least one of S&P, Moody's and Fitch has upgraded the bank from speculative to investment grade, 0 otherwise.	
SOVEREIGN DOWNGRADE	Equals 1 if Moody's has downgraded the bank's country, 0 otherwise.	Moody's
Table 1. Variable definitions. *(Continued from previous page)*		
Other bank variables		
G-SIB	Equals 1 if the bank is one of the Global Systemically Important Banks (G-SIBs) in the 2021 list, 0 otherwise.	FSB and BCBS (Authors' calculation)
BOUND	Equals 1 if the bank's Moody's rating is equal to or above the respective sovereign rating in the prior year, 0 otherwise.	Authors' calculation
Control variables		
LNTA	The natural logarithm of total assets.	S&P Capital IQ Pro (Authors' calculation)
AGE	Bank age since its establishment in years.	
ROA	The return on assets.	
EQUITY	Total equity normalized by total assets.	
LLR	Total loan loss reserves divided by total loans and leases.	
GDP	The real GDP growth of the bank's country.	World Bank Open Data

markets because it is a sign of a higher probability of default (Kisgen and Strahan, 2010; Gu et al., 2018). As a result, the lack of stable funding sources can lead to higher systemic risk (López-Espinosa et al., 2013).[9] A poor credit rating also creates greater funding needs, such as for insurers in the CDS market (Sy, 2009), and reduces profitability (Richards and Deddouche, 2003).

Our findings have important policy implications. Basel II received considerable criticism for relying significantly on credit ratings, leading to largely inflated ratings for issuers and issues. Although Basel III has attempted to reduce the regulatory reliance on credit ratings, the CRA business model still contains important weaknesses and the global banking system remains closely attached to CRAs. The literature documents that capital structure decisions are tied to credit ratings since firms adjust their leverage level in the anticipation of (Servaes and Tufano, 2006; Adrian and Shin, 2010) or reaction to (Faulkender et al., 2012; Wojewodzki et al., 2018) rating changes.[10] At the same time, under the need to maintain regulatory requirements (based on credit ratings), banks may hold

[9] Adelino and Ferreira (2016) conduct an empirical study and they find that sovereign downgrades directly impact domestic institutions access to funding.
[10] Kisgen (2019) finds that even changes in the CRA methodology can affect corporate leverage decisions.

Table 2
Descriptive statistics.

	OBS.	MEAN	MEDIAN	ST. DEV.	5^{TH} PERC.	95^{TH} PERC.
Systemic risk and stability variables						
ΔCoVaR	3892	0.320	0.293	0.193	0.070	0.637
MES	3792	3.039	2.562	2.286	0.375	7.572
VaR	3878	0.620	0.560	0.330	0.255	1.215
Downgrade and upgrade variables						
DOWNGRADE	3892	0.171	0.000	0.377	0.000	1.000
UPGRADE	3892	0.135	0.000	0.341	0.000	1.000
S&P DOWNGRADE	2550	0.107	0.000	0.309	0.000	1.000
S&P UPGRADE	2550	0.069	0.000	0.254	0.000	1.000
MOODY'S DOWNGRADE	2769	0.118	0.000	0.323	0.000	1.000
MOODY'S UPGRADE	2769	0.099	0.000	0.298	0.000	1.000
FITCH DOWNGRADE	2518	0.114	0.000	0.318	0.000	1.000
FITCH UPGRADE	2518	0.073	0.000	0.260	0.000	1.000
S&P DOWNGRADE SIZE	2595	0.138	0.000	0.515	0.000	1.000
S&P UPGRADE SIZE	2595	0.063	0.000	0.270	0.000	1.000
MOODY'S DOWNGRADE SIZE	2815	0.162	0.000	0.583	0.000	1.000
MOODY'S UPGRADE SIZE	2815	0.016	0.000	0.143	0.000	0.000
FITCH DOWNGRADE SIZE	2557	0.148	0.000	0.555	0.000	1.000
FITCH UPGRADE SIZE	2557	0.013	0.000	0.132	0.000	0.000
SG	3892	0.025	0.000	0.157	0.000	0.000
IG	3892	0.020	0.000	0.138	0.000	0.000
SOVEREIGN DOWNGRADE	3892	0.071	0.000	0.257	0.000	1.000
Other bank variables						
G-SIB	3892	0.082	0.000	0.274	0.000	1.000
BOUND	2553	0.212	0.000	0.408	0.000	1.000
Control variables						
LNTA	3892	17.702	17.515	1.660	15.379	20.986
AGE	3892	90.770	74.000	67.370	15.000	196.000
ROA	3892	0.009	0.009	0.009	−0.001	0.022
EQUITY	3892	0.092	0.087	0.035	0.047	0.151
LLR	3892	0.028	0.018	0.030	0.004	0.083
GDP	3892	0.023	0.023	0.034	−0.039	0.077

more capital than intended (Memmel and Raupach, 2010). These transmission channels connect credit rating changes with individual institutions' systemic risk by directly affecting the market's beliefs on their creditworthiness. Therefore, we argue that rating changes can significantly influence the contribution of an institution to systemic risk and that policymakers should address the systemic importance that is inherently associated with CRAs and their existing business model.

Our analysis makes a number of unique contributions to the literature. First, we contribute to the strand that examines the determinants of banks' contribution to systemic risk. Controlling bank systemic risk is at the centre of regulators' attention and our analysis is the first to examine the relationship between issuer credit rating downgrades and bank systemic risk. Second, we add empirical evidence to the important role of more common stability factors for banks such as profitability and capital. Policymakers have been particularly concerned with stabilising bank profits and increasing bank capital buffers after the GFC and our analysis supports this direction. Finally, our results expand the extant literature on the significance of sovereign credit ratings for bank stability and systemic risk. We show that they are a key element in the relationship between downgrades and systemic risk and that the sovereign ceiling rule by CRAs can have adverse consequences for systemic risk.

The rest of the paper is organised as follows. In Sections 2 and 3, we describe our data and the measurement of systemic risk, respectively. In Section 4, we present the empirical model and the findings. In Section 5, we discuss the robustness tests, while in Section 6, we conclude and discuss the main policy implications of our findings.

2. Data and descriptive statistics

Our analysis is based on a panel of 337 publicly listed banks from 50 countries and the sample period spans between 2005 and 2020. 43 % of our bank-year observations are from North America, followed by Asia-Pacific (19 %), and Europe (17 %). We obtain long-term issuer credit ratings[11] by the Big 3 CRAs, namely S&P, Moody's and Fitch from S&P Capital IQ Pro and sovereign credit

[11] The long-term issuer credit ratings used in our analysis are forward-looking opinions by the CRAs about the ability and willingness of banks to meet their financial obligations on time and in full. CRAs use comprehensive methodologies that are often updated in line with developments in the financial sector. The current methodology by each of the three CRAs for rating banks can be found in the following webpages: S&P: https://www.spglobal.com/ratings/_division-assets/pdfs/070813_howweratebanks.pdf; Moody's: https://bankratings.moodys.io/#:~:text=Our%20Baseline%20Credit%20Assessment%20(BCA,financial%20factors%20and%20qualitative%20factors.&text=A%20measure%20of%20default%20probability%20excluding%20external%20support; Fitch: https://www.fitchratings.com/research/banks/bank-rating-criteria-01–09-2023.

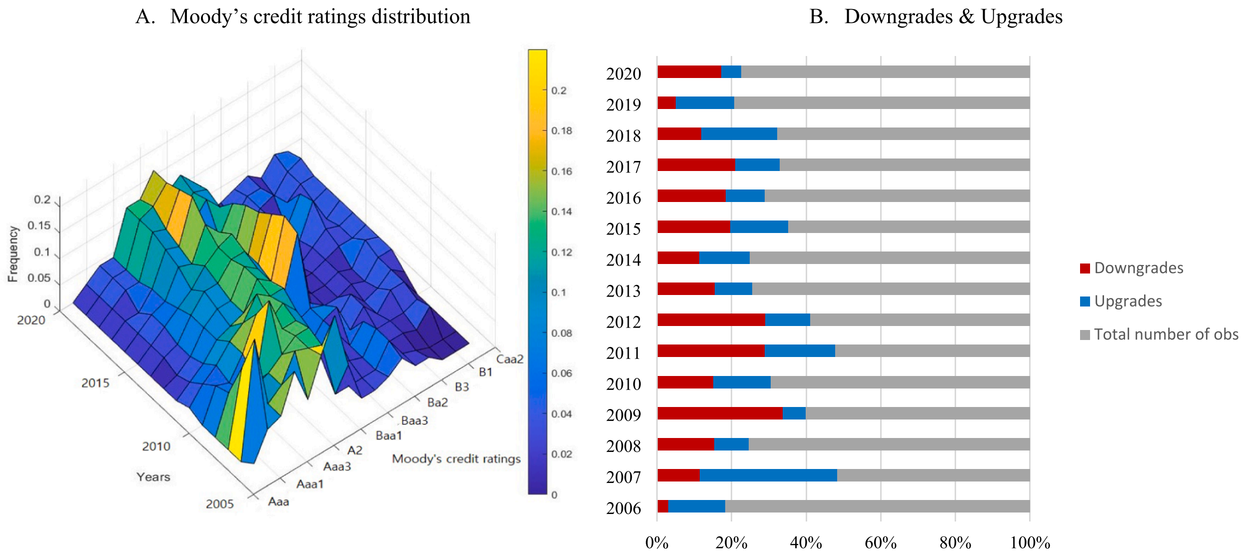

Fig. 1. Credit rating statistics. Fig. 1A displays the distribution of Moody's credit ratings for the examined institutions in our sample and for the entire sample period (2006–2020). Fig. 1B presents the percentage of credit rating downgrades and upgrades per year during our sample period. Rating changes by all three agencies, namely Moody's, Standard & Poor's and Fitch are included.

ratings from Moody's. The market data for the estimation of systemic risk is provided by Thomson Reuters EIKON Datastream. To examine the relationship between credit ratings changes and systemic risk, we need to account for various bank-specific factors that are also obtained from S&P Capital IQ Pro. Finally, macroeconomic control variables are provided by the World Bank Open Data website. Tables 1 and 2 present the definitions and descriptive statistics of all variables used in our analysis, respectively.

We construct three types of rating changes variables. First, we create eight downgrade and upgrade dummy variables that take the value of 1 based on whether the bank has experienced a downgrade or an upgrade and 0 otherwise. The variables DOWNGRADE and UPGRADE take the value of 1 if any of the three CRAs have downgraded or upgraded the bank respectively. The remaining six variables denote the downgrades and upgrades of each CRA separately. Second, we create six downgrade and upgrade size variables for each CRA separately. Finally, we create SG that takes the value of 1 if the bank has been downgraded from investment to speculative grade and 0 otherwise. On the contrary, IG takes the value of 1 if the bank has been upgraded from speculative to investment grade and 0 otherwise.

In Fig. 1A, we present the three-dimensional distribution of Moody's credit ratings' classification for all banks in our dataset and for the entire sampling period. Our global dataset consists of a diverse set of banks with a wide range of credit ratings from highly speculative (European and Asian banks) to prime (located in Canada and Switzerland). In the Y-axis we present the different investment grades from Moody's that vary from extremely speculative (Caa2) to prime (Aaa). The Figure illustrates how the credit ratings distribution changes over time. In 2007, 40 % of the banks were in the High grade category (Aa3-Aaa). However, after the GFC, the fraction of the banks in our sample belonging in the investment grade range dropped to 33 % in 2008 and to 19 % in 2009. Since 2012, around 10 % of the sample is classified as High grade. On the other hand, since 2008, more banking institutions moved to medium or speculative grade. In 2009/10, 20 % of the examined banks belonged in the Lower Medium Grade category (Baa), which increased by 14 % compared to 2007. The highest value is in the period 2012–2014 with a fraction of the sample just below 40 % to be classified as Baa. In the period after 2016, the percentage dropped to 30 % and more institutions obtained Upper Medium investment grade (A1-A3). Finally, the speculative-rated assets (Ba and B) were just 11 % of the distribution in 2007, increased to 18 % in the period 2008–2010 and since then they vary between 12 and 17 %. For 2020, the last year of our dataset, the majority of banks are in the Medium Grade (Baa3-A1) range (70.2 %), whereas 20.4 % is considered to be speculative (Ba3 or lower), of which 14.2 % is classified as extremely speculative. Only 9.3 % of the sample has a High grade credit rating in 2020.

Fig. 1B shows the percentage of credit rating upgrades and downgrades per year. In the period before 2008, the number of rating changes was limited, but in the period 2008–2009 more than 80 firms (25 % of our sample) were downgraded by at least one of the three agencies. We do not observe any significant differences across regions in our sample. The majority of rating adjustments occur during the sovereign debt crisis period (2011/12), when almost one out of three banking institutions in our sample (67 European and 24 US banks) were downgraded. In the two-year period 2018–2019, upgrades overcame downgrades mostly for banks from Europe and North America. However, due to the pandemic shock in 2020, 58 (17 % of the sample) banking institutions were downgraded. Most of these institutions are based in Asia (25), followed by Europe (14).

3. Measuring systemic risk

According to the joint report of Financial Stability Board (FSB), International Monetary Fund (IMF) and Bank for International

Settlements (BIS) for the G20, systemic risk is defined as "*the risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy*" (Financial Stability Board (FSB), International Monetary Fund (IMF), Bank for International Settlements (BIS), 2009). Although a number of different systemic risk measures have been proposed in the literature, there is not a commonly accepted approach. To measure firm-level systemic risk, we employ two alternative measures namely, ΔCoVaR and Marginal Expected Shortfall (MES). These measures are the most popular approaches in the literature and are commonly used by policymakers and financial institutions.

3.1. *ΔCoVaR*

Adrian and Brunnermeier (2016) introduced Conditional *VaR (CoVaR*), which measures the tail dependency between the financial system and an examined institution. More specifically, CoVaR is defined as the Value-at-Risk (*VaR*) of one institution at a specific probability quantile, conditional on the other institution being under distress (at its *VaR* threshold). The authors suggest measuring the systemic importance of a firm as the increase in the *CoVaR* of the financial system index when an institution shifts from its *VaR* to its median value. This difference between the *CoVaR* at the 5th percentile and the median (50th percentile) is defined as ΔCoVaR and indicates the additional tail risk for the financial system when the examined institution moves from normal to distress times.

The *VaR* of the institution i is defined as:

$$P\left(R_t^i < VaR^i\right) = q \tag{1}$$

where R_t is the average daily returns per quarter and q is the examined quantile. To capture the developments in the financial sector, we use the Datastream Financials index, that consists of large financial institutions including banks, insurers, financial services and real estate companies.

The mathematical representation of *CoVaR* of the system (s) when a firm (i) is under distress is:

$$P\left(R_t^s < CoVaR^{s|i} \middle| R_t^i = VaR^i\right) = q \tag{2}$$

$$\Delta CoVaR^{s|i} = CoVaR_{q=0.05}^{s|i} - CoVaR_{q=0.5}^{s|i} \tag{3}$$

Higher values of Δ*CoVaR* indicate that the examined institution is more systemically important or in other words, if the examined firm experiences a tail event, this would have a significant effect on the *VaR* of the financial system or the other institution. Following Adrian and Brunnermeier (2016), the estimation of the dynamic form of Δ*CoVaR* is based on a set of state variables, which are highly liquid and tractable assets, and capture the time volatility of systemic risk. More specifically, we use the stock market index quarterly average returns and volatility, the 10-year government bond yield and the spread with the 1-year government bond.[12] All data is provided by Thomson Reuters Datastream and the choice of these state variables is consistent across all the banks and countries in our sample.

3.2. *Dynamic estimation of ΔCoVaR*

The estimation of systemic risk is based on the method of quantile regressions. In the first step, we run the quantile regression between the average daily returns of the examined firm (R_t^i) and the state variables (M_{t-1}). To obtain a bank's dynamic VaR, we replace the estimates of the quantile regression.

$$R_t^i = a_q + \beta_q M_{t-1} + \varepsilon_{q,t} \tag{4}$$

$$VaR_{q,t}^i = \widehat{a}_q + \widehat{\beta}_q M_{t-1} \tag{5}$$

In the second step, we run the quantile regression model with financial system index as the dependent variables and the returns of the examined firm (R_t^i) and the state variables (M_{t-1}).

$$R_t^{system} = a_q^{system|i} + \beta_q^{system|i} M_{t-1} + \gamma_q^{system|i} R_t^i + \varepsilon_{q,t} \tag{6}$$

The VaR of the financial system conditional on the examined institution being under distress is obtained by replacing back the coefficient estimates and the previously estimated bank's VaR instead of its returns.

$$CoVaR_{q,t}^{system|i} = \widehat{a}_q^{system|i} + \widehat{\beta}_q^{system|i} M_{t-1} + \widehat{\gamma}_q^{system|i} VaR_t^i \tag{7}$$

$$\Delta CoVaR_{q,t}^{system|i} = \widehat{\gamma}_q^{system|i}\left(VaR_t^i - VaR_{0.5}^i\right) \tag{8}$$

In Fig. 2, we present the development in global systemic risk for the period of 2005 to 2021. The global index is the median value of

[12] For the cases that the 1-year government bond was not available, we use data on the 2-year bond instead.

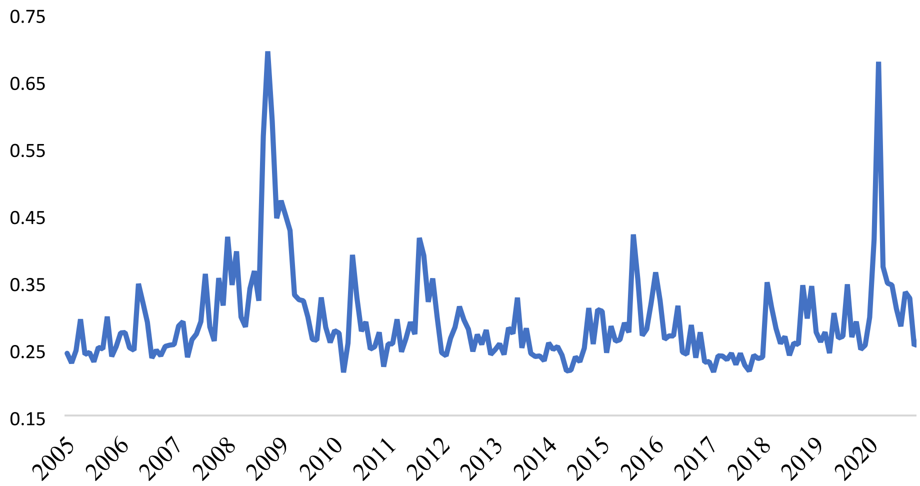

Fig. 2. Global systemic risk. The Figure displays the median systemic risk (ΔCoVaR) of all the examined firms in our sample and the period 2005–2020. The estimation is based on Equity returns and the Datastream Financials Index for each country.

Table 3
Systemic risk statistics.

	ΔCoVaR		MES	
Year	Average (%)	Upper quartile (%)	Average (%)	Upper quartile (%)
2005	0.253	0.295	1.465	2.49
2006	0.275	0.362	1.997	3.44
2007	0.347	0.464	3.088	3.71
2008	0.513	0.630	6.861	7.68
2009	0.401	0.496	5.427	6.12
2010	0.318	0.380	3.039	3.51
2011	0.336	0.406	3.856	4.84
2012	0.306	0.359	2.360	2.82
2013	0.280	0.343	2.221	2.90
2014	0.267	0.339	2.191	2.77
2015	0.320	0.397	2.787	3.29
2016	0.313	0.394	2.973	3.78
2017	0.261	0.324	1.735	2.35
2018	0.302	0.375	2.393	3.14
2019	0.308	0.379	2.031	2.75
2020	0.380	0.479	5.315	7.03
Full sample	0.293	0.401	3.648	3.824

The table presents the average and the right quartile (upper threshold) absolute values of the two measures of systemic risk, Delta CoVaR (ΔCoVaR) and Marginal Expected Shortfall (MES).

systemic risk of all banks in our sample. ΔCoVaR is based on VaR and it is not additive. Therefore, the global index does not have particular information of the level of systemic risk globally, but it is a good measure for examining its time variation. There are two main peaks in the examined period, the Great Recession in 2008/09 and the beginning of the COVID-19 pandemic that affected the financial markets in 2020. During the sovereign debt crisis (2012) and the Brexit referendum (2016) we also observe some smaller peaks, but not as significant at the global level.

3.3. Marginal Expected Shortfall (MES)

In addition to CoVaR, we employ Marginal Expected Shortfall (MES) introduced by Acharya et al. (2017). MES stands for the average daily equity returns of bank *i*, the days that the market as measured by the Datastream Financials Index, is below its 5th percentile as defined by the historical monthly distribution. The tail event is as defined by the 5th percentile of its historical return distribution. The metric is estimated at an annual frequency with average daily returns.

The mathematical representation of MES is the following:

$$MES = \frac{\Sigma(R^i)}{Noofdaysinthe5thpercentile} \tag{9}$$

MES captures the marginal contribution of an institution to the expected shortfall of the financial system. The two metrics exhibit a

Table 4
Baseline regressions.

	(1) ΔCoVaR	(2) ΔCoVaR	(3) ΔCoVaR	(4) ΔCoVaR	(5) ΔCoVaR	(6) ΔCoVaR	(7) ΔCoVaR	(8) ΔCoVaR
DOWNGRADE	0.019***				0.014***			
	(0.005)				(0.004)			
UPGRADE	−0.006				−0.003			
	(0.005)				(0.005)			
S&P DOWNGRADE		0.017***				0.010		
		(0.006)				(0.006)		
S&P UPGRADE		−0.015**				−0.013**		
		(0.007)				(0.007)		
MOODY'S DOWNGRADE			0.007				0.001	
			(0.005)				(0.007)	
MOODY'S UPGRADE			−0.004				−0.001	
			(0.007)				(0.007)	
FITCH DOWNGRADE				0.022***				0.011*
				(0.008)				(0.006)
FITCH UPGRADE				0.000				0.009
				(0.006)				(0.006)
LNTA					−0.008	−0.003	−0.006	−0.018
					(0.014)	(0.020)	(0.016)	(0.016)
AGE					0.009***	0.010***	0.010***	0.012***
					(0.001)	(0.002)	(0.002)	(0.002)
ROA					−1.053*	−2.200**	−0.605	−1.244***
					(0.572)	(0.944)	(0.712)	(0.460)
EQUITY					−0.446	−0.217	−0.943**	−0.945**
					(0.306)	(0.373)	(0.453)	(0.412)
LLR					0.226*	−0.135	0.190	0.415*
					(0.120)	(0.159)	(0.121)	(0.231)
GDP					−0.095	−0.050	−0.105	−0.205
					(0.133)	(0.148)	(0.163)	(0.157)
CONSTANT	0.255***	0.259***	0.269***	0.231***	−0.254	−0.531	−0.393	−0.382
	(0.009)	(0.011)	(0.013)	(0.014)	(0.221)	(0.327)	(0.276)	(0.262)
BANK FE	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
OBS.	3,892	2,550	2,769	2,518	3,892	2,550	2,769	2,518
N. OF BANKS	337	241	262	255	337	241	262	255
R2 WITHIN	0.220	0.253	0.213	0.247	0.236	0.271	0.235	0.290

The table reports fixed-effects regressions. The dependent variable is Delta CoVaR (ΔCoVaR). DOWNGRADE and UPGRADE equal 1 if the bank has been downgraded or upgraded, respectively, by any of the three CRAs, 0 otherwise. The DOWNGRADE and UPGRADE variables referring to S&P, MOODY'S and FITCH equal 1 if the bank has been downgraded or upgraded by the respective CRA only, 0 otherwise. LNTA is the natural logarithm of total assets. AGE is the bank's age since its establishment in years. ROA is the return on assets. EQUITY is the ratio of total equity to total assets. LLR is the ratio of total loan loss reserves to total loans and leases. GDP is the annual GDP growth of the bank's host country. Robust standard errors clustered at the bank level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

very similar pattern with peak values in 2008 and 2020. The findings indicate that the estimation of systemic risk is robust to alternative methodological approaches.

3.4. Systemic risk summary statistics

In Table 3, we present the summary statistics for the two measures of systemic risk. As depicted in Fig. 2, the highest values are observed in 2008/09 and in 2020. Additional to the average values, we present the upper threshold (right quartile) of the distribution of risk across our sample for each year. In 2008, the average ΔCoVaR indicates that the VaR of the financial system will increase, on average, by 0.51 % when the examined institution is at its VaR. With regards to the MES during the GFC, the average daily returns when the system is under distress is −6.3 %.

Our sample covers the period up until the end of 2020, when the COVID-19 pandemic had already impacted the financial markets. During this year, systemic risk (as measured by average ΔCoVaR) increased significantly by 23 %, which was the largest increase since 2007/08. In the last row of the Table is the summary for the entire sampling period. In terms of individual banks' systemic risk, the greatest value is at the sovereign debt crisis (2012) when the systemic risk of the National Bank of Greece (Greece) was 2.47 %, whereas AIB's (Ireland) ΔCoVaR, in 2008, reached 2.28 %. The results are similar for MES. During the GFC, the two largest Irish companies' (AIB and BoI) MES was at 21 %.

Table 5
Downgrade and upgrade size.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
S&P DOWNGRADE SIZE	0.015***				0.007*			
	(0.006)				(0.004)			
S&P UPGRADE SIZE	−0.015***				−0.014***			
	(0.005)				(0.005)			
MOODY'S DOWNGRADE SIZE		0.008**				0.003		
		(0.004)				(0.004)		
MOODY'S UPGRADE SIZE		−0.013				−0.009		
		(0.011)				(0.012)		
FITCH DOWNGRADE SIZE			0.018***				0.007**	
			(0.006)				(0.003)	
FITCH UPGRADE SIZE			−0.017*				−0.014	
			(0.010)				(0.011)	
SG				0.035***				0.022***
				(0.010)				(0.008)
IG				−0.006				0.001
				(0.011)				(0.011)
CONTROL VARIABLES	NO	NO	NO	NO	YES	YES	YES	YES
BANK FE	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
OBS.	2,550	2,769	2,518	3,892	2,550	2,769	2,518	3,892
N. OF BANKS	241	262	255	337	241	262	255	337
R2 WITHIN	0.260	0.219	0.263	0.218	0.276	0.239	0.298	0.234

The table reports fixed-effects regressions. The dependent variable is Delta CoVaR (ΔCoVaR). The DOWNGRADE SIZE and UPGRADE SIZE variables refer to the absolute difference between the transformed in numerical values ratings in time t-1 and t if the respective CRA has downgraded or upgraded the bank, 0 otherwise. SG equals 1 if at least one of the CRAs has downgraded the bank from investment to speculative grade, 0 otherwise. IG equals 1 if at least one of the CRAs has upgraded the bank from speculative to investment grade, 0 otherwise. Robust standard errors clustered at the bank level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

4. Empirical model, results and discussion

4.1. Empirical framework

Our investigation of the relationship between rating changes and systemic risk is based on fixed-effects regressions in the following form:

$$\Delta CoVaR_{i,t} = \alpha_i + \beta_1 DOWNGRADE_{i,t} + \beta_2 UPGRADE_{i,t} + \sum_{j=1}^{5} \beta_j BankControl_{i,t} + \beta_3 MacroControl_{c,t} + T_t + \varepsilon_{i,t} \tag{10}$$

where *i, c* and *t* index the bank, country and year of the observation respectively, α_i is the bank fixed-effect, T_t is the year fixed-effect and $\varepsilon_{i,t}$ is the error term, assumed to be normally distributed with mean 0 and variance σ^2. Using bank fixed-effects allows us to control for unobservable differences among banks and to alleviate correlations across error terms and address the problem of heterogeneity (Arellano, 2003). On the other hand, using year fixed effects we can control for serial correlation and eliminate bias from unobservables that are constant across banks but change over time. To control for heteroskedasticity, we use robust standard errors clustered at the bank level. Moreover, the selection of a fixed-effects model over a random-effects model is supported by the Hausman test. At the same time, seminal research papers that examine the effects of rating downgrades as well as those that study the determinants of systemic risk use similar specifications (e.g., Kisgen, 2009; Badoer and Demiroglu, 2019; Brunnermeier et al., 2020).

ΔCoVaR is our main measure of systemic risk as outlined in Section 3, while DOWNGRADE and UPGRADE represent our rating changes variables as described in Section 2. We control for five commonly used bank characteristics in systemic risk literature, i.e., bank size with the natural logarithm of total assets (Brunnermeier et al., 2020), bank age with the number of years since establishment (Yang et al., 2020), profitability with the return on assets (Anginer et al., 2014; Varotto and Zhao, 2018), capitalization with the equity ratio (Davydov et al., 2021) and asset quality with the share of loan loss reserves to total loans and leases (Davydov et al., 2021). We also control for the macroeconomic environment of the bank with the GDP growth of the bank's home country (Anginer et al., 2014; Brunnermeier et al., 2020).

4.2. Results and discussion

4.2.1. Main results

Table 4 presents the results of our baseline regressions on the relationship between rating changes and systemic risk. More specifically, we regress ΔCoVaR on our downgrade and upgrade variables that represent both the overall and the CRA-specific rating changes. We present the results both with and without our six control variables. Consistent with our expectations, we observe that the variable DOWNGRADE maintains a positive and highly statistically significant coefficient in both sets of regressions. This suggests that regardless of which CRA downgrades the bank, a rating downgrade can significantly increase the bank's contribution to systemic risk. This finding is also economically significant as a rating downgrade in any of the three Big 3 CRAs is associated with a 1.4 percentage point increase in ΔCoVaR. We do not observe the same consistency across the CRA-specific variables. The positive coefficients of S&P DOWNGRADE and FITCH DOWNGRADE lose part or all of their significance after the inclusion of control variables, while the rating changes by Moody's do not appear to contribute to systemic risk. With respect to upgrades, S&P UPGRADE is statistically significant in both regressions[13] and has the expected negative sign, suggesting that rating upgrades by S&P can mitigate a bank's contribution to systemic risk.

We extend our analysis by looking into the size of rating changes as well as changes in the classification of issuer ratings from investment to speculative grade and vice versa. These results are presented in Table 5. The coefficients of the size variables appear to be largely similar to the ones in our baseline regressions, although slightly more statistically significant. More importantly, the coefficient of SG is positive, highly significant and the greatest in size across all other coefficients of the downgrade variables in our regressions. This is in line with our expectations of the turbulence that the loss of the investment grade status of an issuer can cause. At the same time, gaining the investment grade status does not seem to have the equivalent beneficial effect for systemic risk.

The findings are in line with our expectations formed by the extant literature. We focus on two channels that may nurture a positive relationship between rating downgrades and systemic risk. First, powered by poor rating quality in the upward phase of the business cycle, rating inflation can make rating downgrades very informative announcements (Bar-Isaac and Shapiro, 2013). At the same time, the reputational effects for CRAs being tardy in the case of downgrades further worry investors who may respond faster than they would do with rating upgrades, leading to asymmetries in the transmission of upgrades and downgrades (Huang and Shen, 2015). Second, significant underestimation of risk as reflected in inflated credit ratings can lead to increased risk-taking by systemically important institutions. Considering that banks rely the calculation of their credit risk on the assessments provided by CRAs, misrating of creditworthiness can mislead all market participants and result in system-wide vulnerabilities (Sy, 2009). Consistent with this framework, our results demonstrate that systemic risk increases with rating downgrades and their size, while only upgrades by S&P can mitigate systemic risk. Moreover, our results are in line with the "fallen angel" effect, suggesting that the change in classification from investment to speculative grade can lead to significantly reduced capital ratios due to greater borrowing costs (Wojewodzki et al., 2020) and thus to increased risk-taking.

4.2.2. The role of profitability and capital

We further examine the moderating role of accounting-based stability measures such as profitability and capital in the relationship between rating downgrades and systemic risk. More specifically, we introduce an interaction term between each of our downgrade variables and the variables ROA and EQUITY. The results are presented in Table 6 and confirm our expectations. First, the coefficients of our downgrade variables are all positive and highly significant apart from MOODY'S DOWNGRADE that appeared to have the weakest effect in the previous regressions too. Second, the coefficient of the interaction term is negative and significant in most regressions, particularly for the interaction term with ROA. This finding suggests that profitability and capital can act as stabilizing factors and absorb part of the added systemic risk from rating downgrades. A bank that is more profitable or has a higher capital ratio can more easily reassure market investors regarding the consequences of the downgrade. For instance, the better financial condition of the bank at the announcement of the downgrade can protect the bank's cost of funding (Kisgen, 2006, 2009) and provide some reassurance for future profitability (Richards and Deddouche, 2003) that are normally affected by rating downgrades. Therefore, influencing the market's belief in the bank's stability can prevent some of the adverse consequences such as excessive short selling by investors (Henry et al., 2015).

4.2.3. Difference-in-differences estimations

In this section, we conduct three separate difference-in-differences estimations which extend our findings and alleviate endogeneity concerns. We employ two approaches to validate our results. First, we conduct difference in mean differences analyses and denote statistical significance with t-tests. Second, we extend our baseline regression framework with the main and interaction terms included. The results of these estimations are presented in Panels A and B of Table 7.

In the first approach, our treatment group consists of the bank-years when the country of the bank is downgraded and our control group contains the bank-years without a sovereign downgrade. We argue that through the "sovereign effect", bank-level downgrades increase the contribution of banks to systemic risk more during sovereign downgrades. Huang and Shen (2015) attribute the sovereign effect to the inability of a country in default to attract foreign cash flows and repay foreign debt which may affect the creditworthiness of domestic banks considering that their assets are denominated in the local currency. As a result, bank-level downgrades may have a stronger effect on systemic risk during sovereign downgrades and a weaker effect during other periods. The results presented in Table 7 confirm our expectations with respect to the sovereign effect. More specifically, the difference in mean differences in Panel A and the coefficient of the interaction term between DOWNGRADE and SOVEREIGN DOWNGRADE in Panel B are both positive and statistically significant.

In the second approach, our treatment group contains the banks that are classified as Global Systemically Important Banks (G-SIBs), while the control group consists of all other banks. One of the primary goals of policymakers in the post-2009 period has been the

[13] Hill and Faff (2010) finds that the market's response to S&P ratings is stronger compared to the other agencies.

Table 6
The moderating role of profitability and capital.

	(1) ΔCoVaR	(2) ΔCoVaR	(3) ΔCoVaR	(4) ΔCoVaR	(5) ΔCoVaR	(6) ΔCoVaR	(7) ΔCoVaR	(8) ΔCoVaR	(9) ΔCoVaR	(10) ΔCoVaR
DOWNGRADE	0.029***					0.069**				
	(0.009)					(0.027)				
S&P DOWNGRADE		0.020**					0.036**			
		(0.008)					(0.016)			
MOODY'S DOWNGRADE			0.010					0.018		
			(0.008)					(0.019)		
FITCH DOWNGRADE				0.021**					0.092**	
				(0.009)					(0.049)	
SG					0.031***					0.092***
					(0.009)					(0.030)
DOWNGRADE VARIABLE * ROA	−2.093**	−1.495**	−1.508**	−1.516*	−2.192***					
	(0.849)	(0.664)	(0.651)	(0.850)	(0.601)					
DOWNGRADE VARIABLE * EQUITY						−0.612**	−0.286*	−0.195	−0.866*	−0.774**
						(0.287)	(0.149)	(0.177)	(0.499)	(0.301)
ROA	−0.107	−1.559*	−0.050	−0.459	−0.490	−1.040*	−2.193**	−0.589	−1.052**	−0.958*
	(0.522)	(0.914)	(0.679)	(0.525)	(0.501)	(0.546)	(0.920)	(0.705)	(0.444)	(0.532)
EQUITY	−0.441	−0.242	−0.929**	−0.944**	−0.446	−0.304	−0.180	−0.911*	−0.814**	−0.422
	(0.292)	(0.369)	(0.449)	(0.403)	(0.303)	(0.269)	(0.374)	(0.465)	(0.330)	(0.307)
CONTROL VARIABLES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
BANK FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
OBS.	3,892	2,550	2,769	2,518	3,892	3,892	2,550	2,769	2,518	3,892
N. OF BANKS	337	241	262	255	337	337	241	262	255	337
R2 WITHIN	0.243	0.274	0.238	0.294	0.239	0.242	0.273	0.235	0.300	0.236

The table reports fixed-effects regressions. The dependent variable is Delta CoVaR (ΔCoVaR). DOWNGRADE equals 1 if the bank has been downgraded by any of the three CRAs, 0 otherwise. The DOWNGRADE variables referring to S&P, MOODY'S and FITCH equal 1 if the bank has been downgraded by the respective CRA only, 0 otherwise. SG equals 1 if at least one of the CRAs has downgraded the bank from investment to speculative grade, 0 otherwise. ROA is the return on assets. EQUITY is the ratio of total equity to total assets. Robust standard errors clustered at the bank level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 7
Difference-in-differences analysis.

Panel A: Difference in mean differences

	Treatment group	**Control group**
	Sovereign downgrade	No sovereign downgrade
Bank downgrade	0.428	0.354
No bank downgrade	0.293	0.310
Difference	0.135***	0.043***
Diff-in-diff	0.092***	
	G-SIB	Non-G-SIB
Bank downgrade	0.381	0.366
No bank downgrade	0.343	0.307
Difference	0.038**	0.059***
Diff-in-diff	−0.020	
	Bound	Non-bound
Sovereign downgrade	0.612	0.314
No sovereign downgrade	0.404	0.318
Difference	0.208***	−0.005
Diff-in-diff	0.213***	

Panel B: Difference-in-differences regressions

	(1)	(2)	(3)
	ΔCoVaR	ΔCoVaR	ΔCoVaR
DOWNGRADE*SOVEREIGN DOWNGRADE	0.041**		
	(0.017)		
DOWNGRADE*G-SIB		0.017	
		(0.014)	
BOUND*SOVEREIGN DOWNGRADE			0.078*
			(0.043)
DOWNGRADE	0.009**	0.013***	
	(0.005)	(0.004)	
SOVEREIGN DOWNGRADE	−0.020***		−0.009
	(0.007)		(0.008)
G-SIB		−0.054	
		(0.034)	
BOUND			0.028**
			(0.012)
CONTROL VARIABLES	YES	YES	YES
BANK FE	YES	NO	YES
YEAR FE	YES	YES	YES
OBS.	3,892	3,892	2,553
N. OF BANKS	337	337	258
R2 WITHIN	0.238	0.232	0.261

The table reports difference-in-differences estimations. Panel A reports difference in mean differences of ΔCoVaR and significance is denoted with t-tests. Panel B reports fixed-effects regressions. The dependent variable is Delta CoVaR (ΔCoVaR). DOWNGRADE or Bank downgrade equals 1 if the bank has been downgraded by any of the three CRAs, 0 otherwise. SOVEREIGN DOWNGRADE equals 1 if Moody's has downgraded the bank's host country, 0 otherwise. G-SIB qquals 1 if the bank is one of the Global Systemically Important Banks (G-SIBs) in the 2021 list, 0 otherwise. BOUND equals 1 if the bank's Moody's rating is equal to or above the respective sovereign rating in the prior year, 0 otherwise. Robust standard errors clustered at the bank level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

reduction of the systemic risks from G-SIBs. G-SIBs are identified by the BCBS using several indicators including bank size, interconnectedness, substitutability of services, cross-border operations, as well as portfolio complexity. Considering their systemic importance, regulators are trying to eliminate these banks' chances of failure. In our test, we are examining whether rating downgrades increase G-SIBs' contribution to systemic risk more than they do for the rest of the banks. In the results presented in Table 7, we find that rating downgrades increase systemic risk for both groups. However. we fail to find that there is a difference in the effect of downgrades on our main measure of systemic risk ΔCoVaR[14] between the groups as both the difference in mean differences in Panel A and the coefficient of the interaction term between DOWNGRADE and G-SIB in Panel B are statistically insignificant.

In the final approach, our treatment group consists of the bank-years when the bank had a Moody's rating equal to or above the respective sovereign Moody's rating in the previous year (bound banks). By using this setting, we can exploit CRAs' sovereign ceiling rule, which prevents firms from having a credit rating higher than their home country's rating. Due to this rule, bound banks are more likely to experience a downgrade as a response to a sovereign downgrade. However, the sovereign ceiling rule leads to an asymmetric change in credit ratings that can have different consequences for bound firms. Previous studies that use a similar setting find that following a sovereign downgrade, bound banks reduce their lending and have limited access to funding (Adelino and Ferreira, 2016), while other types of firms cut investment (Almeida et al., 2017), suffer negative cumulative annual returns (Massa et al., 2022) or increase voluntary disclosure (Basu et al., 2022; Wang and Xie, 2022) more than non-bound firms. We posit that a sovereign rating downgrade would increase bound banks' contribution to systemic risk more compared to non-bound banks due to the asymmetric downgrade that bound banks are subject to. Our findings are in line with our expectations as the difference in mean differences in Panel A and the coefficient of the interaction term between SOVEREIGN DOWNGRADE and BOUND in Panel B are both positive and statistically significant.

5. Robustness tests

We conduct two sets of empirical tests to ensure that our results are consistent and free from biases. For brevity, we reproduce only a small set of the highlights of our results, but our findings hold for all regressions. First, we use alternative measures of bank systemic risk and stability. Our first alternative measure of systemic risk is MES, which stands for the mean of the daily returns of the examined banking institution when the financial sector index is at its historical distribution left tail. In addition, we examine if changes in credit ratings affect banks' idiosyncratic risk, as measured by VaR. The dynamic VaR is obtained in line with the CoVaR methodology that

[14] However, we do find a difference in the effect of downgrades on MES (systemic risk) and on VaR (idiosyncratic risk) in our robustness tests.

Table 8
Alternative measures of systemic risk and bank stability. *(Continued in next page)*.

	(1) MES	(2) MES	(3) MES	(4) MES	(5) MES	(6) MES	(7) MES
DOWNGRADE	0.320*** (0.077)		0.472*** (0.122)	0.512*** (0.184)	0.287*** (0.083)	0.249*** (0.077)	
UPGRADE	−0.103* (0.061)		−0.106* (0.062)	−0.100 (0.062)	−0.106 (0.061)	−0.087 (0.060)	
SG		0.130 (0.185)					
IG		−0.117 (0.134)					
DOWNGRADE*ROA			−20.399** (9.896)				
DOWNGRADE*EQUITY				−2.132 (2.052)			
DOWNGRADE*SOVEREIGN DOWNGRADE					0.386** (0.195)		
DOWNGRADE*G-SIB						0.904*** (0.273)	
BOUND*SOVEREIGN DOWNGRADE							0.093 (0.306)
MAIN & INTERACTION TERMS	NO	NO	YES	YES	YES	YES	YES
CONTROL VARIABLES	YES	YES	YES	YES	YES	YES	YES
BANK FE	YES	YES	YES	YES	YES	NO	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES
OBS.	3,792	3,792	3,792	3,792	3,792	3,792	3,792
N. OF BANKS	337	337	337	337	337	337	337
R2 WITHIN	0.538	0.534	0.540	0.538	0.540	0.540	0.561

Table 8. Alternative measures of systemic risk and bank stability. *(Continued from previous page)*

	(8) VaR	(9) VaR	(10) VaR	(11) VaR	(12) VaR	(13) VaR	(14) VaR
DOWNGRADE	0.029*** (0.009)		0.066*** (0.015)	0.113** (0.047)	0.021** (0.010)	0.026*** (0.010)	
UPGRADE	−0.009 (0.009)		−0.009 (0.009)	−0.007 (0.009)	−0.009 (0.009)	−0.008 (0.009)	
SG		0.055*** (0.020)					
IG		−0.009 (0.019)					
DOWNGRADE*ROA			−4.992*** (1.276)				
DOWNGRADE*EQUITY				−0.939* (0.495)			
DOWNGRADE*SOVEREIGN DOWNGRADE					0.061* (0.031)		
DOWNGRADE*G-SIB						0.051* (0.029)	
BOUND*SOVEREIGN DOWNGRADE							0.151** (0.074)
MAIN & INTERACTION TERMS	NO	NO	YES	YES	YES	YES	YES
CONTROL VARIABLES	YES	YES	YES	YES	YES	YES	YES
BANK FE	YES	YES	YES	YES	YES	NO	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES
OBS.	3,878	3,878	3,878	3,878	3,878	3,878	3,878
N. OF BANKS	336	336	336	336	336	336	336
R2 WITHIN	0.278	0.277	0.288	0.282	0.280	0.277	0.292

The table reports fixed-effects regressions. The dependent variables are the Marginal Expected Shortfall (MES) and Value at Risk (VaR). DOWNGRADE and UPGRADE equal 1 if the bank has been downgraded or upgraded, respectively, by any of the three CRAs, 0 otherwise. SG equals 1 if at least one of the CRAs has downgraded the bank from investment to speculative grade, 0 otherwise. IG equals 1 if at least one of the CRAs has upgraded the bank from speculative to investment grade, 0 otherwise. SOVEREIGN DOWNGRADE equals 1 if Moody's has downgraded the bank's host country, 0 otherwise. G-SIB qquals 1 if the bank is one of the Global Systemically Important Banks (G-SIBs) in the 2021 list, 0 otherwise. BOUND equals 1 if the bank's Moody's rating is equal to or above the respective sovereign rating in the prior year, 0 otherwise. ROA is the return on assets. EQUITY is the ratio of total equity to total assets. Robust standard errors clustered at the bank level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

assumes that risk time volatility can be captured by a set of state variables. The results of these tests are presented in Table 8 and largely confirm our findings as most coefficients maintain their signs and significance. A noteworthy difference compared to our results presented in Table 7 is that the coefficient of the interaction term between DOWNGRADE and G-SIB is positive and statistically significant in line with our initial expectations that downgrades are more impactful on the systemic risk of G-SIBs.

Table 9
Controlling for endogeneity.

	(1) ΔCoVaR	(2) ΔCoVaR	(3) ΔCoVaR	(4) ΔCoVaR	(5) ΔCoVaR	(6) ΔCoVaR	(7) ΔCoVaR	(8) ΔCoVaR
L. ΔCoVaR					0.694***	0.728***	0.767***	0.738***
					(0.035)	(0.033)	(0.026)	(0.031)
DOWNGRADE	0.009**		0.034***	0.046**	0.044**		0.032**	0.138**
	(0.004)		(0.011)	(0.020)	(0.022)		(0.015)	(0.077)
UPGRADE	−0.001		−0.001	0.0002	0.018		0.006	0.096
	(0.005)		(0.005)	(0.005)	(0.021)		(0.019)	(0.483)
SG		0.052***				0.074**		
		(0.019)				(0.043)		
IG		−0.003				0.045		
		(0.010)				(0.041)		
DOWNGRADE * ROA			−3.152**				−3.842***	
			(1.302)				(1.051)	
DOWNGRADE * EQUITY				−0.413*				−1.293*
				(0.220)				(0.750)
MAIN & INTERACTION TERMS	NO	NO	YES	YES	NO	NO	YES	YES
CONTROL VARIABLES	YES	YES	YES	YES	YES	YES	YES	YES
BANK FE	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
OBS.	3,540	3,540	3,540	3,540	3,540	3,540	3,540	3,540
N. OF BANKS	334	334	334	334	334	334	334	334
R2 WITHIN	0.248	0.253	0.265	0.251				
AR(2)					0.092	0.057	0.155	0.065
HANSEN J					0.384	0.785	0.380	0.282
N. OF INSTRUMENTS					326	326	326	326
METHOD	FE(LAGS)	FE(LAGS)	FE(LAGS)	FE(LAGS)	SGMM	SGMM	SGMM	SGMM

The table reports fixed-effects regressions which use the 1-year lagged values of the independent variables and System GMM regressions. The dependent variable is Delta CoVaR (ΔCoVaR). DOWNGRADE and UPGRADE equal 1 if the bank has been downgraded or upgraded, respectively, by any of the three CRAs, 0 otherwise. SG equals 1 if at least one of the CRAs has downgraded the bank from investment to speculative grade, 0 otherwise. IG equals 1 if at least one of the CRAs has upgraded the bank from speculative to investment grade, 0 otherwise. ROA is the return on assets. EQUITY is the ratio of total equity to total assets. Robust standard errors clustered at the bank level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Second, following our difference-in-differences analysis that provides some support of causal interpretation of our results, we attempt to further address possible endogeneity concerns associated with our baseline findings. While CRAs have private access to banks' true financial condition that can shape their future contribution to systemic risk and in turn be reflected in rating changes, we argue that this private access is unlikely to drive our empirical results. It is widely documented that rating changes precede market reactions (Badoer and Demiroglu, 2019) and corporate behaviour (Kisgen, 2006, 2009). Nevertheless, we mitigate endogeneity concerns using two methods. First, following the literature on the impact of rating downgrades, we include our independent variables in their 1-year lagged form (e.g., Tang, 2009; Agha and Faff, 2014).[15] These results are presented in the first four columns of Table 9 and we observe that the coefficients of interest maintain their sign and significance, while some of them have also increased in size such as the coefficient of SG. Our second approach is to use the two-step System Generalized Method of Moments (SGMM) estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). Previous studies on the determinants of systemic risk also use GMM estimators to address endogeneity concerns (e.g., Vieira et al., 2012; Pagano and Sedunov, 2016; Duarte and Eisenbach, 2021). The estimator uses a system of equations in both first-differences and levels, while it allows the use of lagged values of the endogenous variables as instruments.[16] Moreover, SGMM controls for the persistence of our dependent variable by using its lagged value as an independent variable. We report two goodness-of-fit tests, namely, the Arellano-Bond test for second-order serial correlation of the error term and the Hansen J test for overidentifying restrictions (instrument validity). In all regressions, we cannot reject the null hypothesis of both tests. The results are presented in the last four columns of Table 9 and confirm our findings.

6. Conclusions and policy implications

CRAs play a pivotal role in the market as information intermediaries. However, the GFC exposed several issues associated with the CRA market such as rating inflation, rating shopping and overreliance on CRAs among others. The unprecedented rating downgrades that took place during the GFC raised concerns over the systemic importance of CRAs too. Yet, there is no empirical evidence of the contribution of rating changes on bank systemic risk. In this paper, we attempt to examine this issue and fill the apparent gap in the literature.

Our analysis provides strong evidence that systemic risk, measured by ΔCoVaR and MES, is positively associated with rating

[15] We do not run these regressions for the moderating role of the COVID-19 crisis because our sample ends in 2020.

[16] We treat ΔCoVaR and the rating changes variables as endogenous and all control variables and year dummies as exogenous.

downgrades. Moreover, we show that rating downgrade size matters and in line with the "fallen angel" effect, rating downgrades from investment to speculative grade have the greatest contribution to systemic risk. Consistent with previous studies that argue that rating downgrades are more informative than upgrades,[17] we do not find almost any consistent evidence that upgrades can mitigate systemic risk. Furthermore, our results suggest that the positive relationship between rating downgrades and systemic risk is mitigated by accounting-based stability factors such as profitability and capital. Finally, we conduct three difference-in-differences analyses that highlight the importance of sovereign downgrades. We show that sovereign rating downgrades increase the effect of bank-level ratings on systemic risk, while they also further raise systemic risk for bound banks. At the same time, we find mixed evidence on whether G-SIBs' systemic risk is affected more compared to other banks' systemic risk.

Several policy recommendations arise from our empirical findings. First, regulatory authorities need to consider further reducing reliance on CRAs. While this has been a primary goal for regulators in the aftermath of the GFC, our results suggest that the market is still largely dependent on credit ratings as demonstrated by increased systemic risk following rating downgrades. Second, our findings support the recent call for greater transparency in the CRA market. Since inflated ratings can increase the impact of large and unexpected rating downgrades (Dilly and Mählmann, 2016), greater transparency will limit the adverse systemic consequences of credit ratings. Third, our results are not in line with the recent work by Jones et al. (2022) who find that the new European regulatory framework shifted the CRA market to a more conservative rating evaluation and that rating downgrades have become less informative. Our results suggest that the market reacts strongly to rating downgrades increasing the systemic vulnerabilities of the financial system that policymakers need to continue addressing. Fourth, we show that regulatory policies on enhancing bank capital and stabilizing profitability remain powerful stabilizing tools as they can absorb part of the systemic risk associated with rating downgrades. Finally, in line with the recent literature, our findings highlight the importance of sovereign rating downgrades for systemic risk, especially for bound banks. Our results raise a cautionary flag for the role of the sovereign ceiling rule that leads to increased systemic risk due to the asymmetric changes in credit ratings.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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[17] The literature suggests that downgrades are more informative, since CRAs have no incentive to publish negative news prior to a downgrade but they will include a positive outlook review prior to an upgrade (Alsakka and ap Gwilym, O., 2010, 2013; Huang and Shen, 2015).

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