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# Credit Rating Downgrades and Systemic Risk

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# Credit rating downgrades and systemic risk

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**Abstract**

Credit ratings aim to reduce information asymmetries and to increase transparency and competition in the financial markets. However, during the 2007-2009 Global Financial Crisis, credit ratings contributed significantly to risk mispricing that led to the build-up of systemic risk, up until the collapse of "*too big to fail*" institutions. In this paper, we examine if changes in issuer credit ratings by the three main providers are associated with changes in systemic risk. Our empirical findings suggest that rating downgrades result in an increase in bank systemic risk, whereas upgrades do not proportionally reduce systemic risk. We also document that the positive relationship between rating downgrades and systemic risk can be mitigated by accounting-based stability factors such as profitability and capital. Finally, we find that the beginning of the COVID-19 crisis that included unprecedented government support towards the banking system globally also mitigated the contribution of rating downgrades to systemic risk. We argue that credit rating agencies have a pivotal role in financial stability and policymakers should adopt a formal assessment to deal with the inherent systemic importance of these agencies that regulate the market.

**Keywords:** *Credit rating agencies; Rating downgrades; Systemic risk; Banks*

**JEL codes:** G21; G24

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## 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. 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). 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.

So far, the literature 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) finds that rating downgrades affect not only the domestic stock market, but also had spillovers effects on the other Euro Area members (Arezki et al., 2011). 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

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

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).

Rating downgrades can increase pressure and directly influence firms' corporate strategies (Kigsen, 2019) and risk-taking behaviour. Surprisingly, there is only scant evidence on the impact of rating downgrades on bank stability. In this paper, we fill this gap by documenting the effect of credit rating changes on bank-level systemic risk. Our main findings indicate that credit rating changes have a significant effect on measures of systemic risk. The effect is primarily driven by downgrades that are associated with increased bank systemic risk, whereas upgrades have a less consistent effect. This asymmetric effect is line with the literature that suggests that downwards changes 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 (Kigsen, 2009; Alsakka and Ap Gilym, 2010; Huang and Shen, 2015). 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. Finally, we also document that the positive relationship between rating downgrades and systemic risk for small and medium banks was mitigated by the beginning of the

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

COVID-19 crisis where a quick and unprecedented government support took place across the world.

Evidently, credit rating changes are associated with systemic events. Sy (2009) argues that systemic risk is inherit 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 onward 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 (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, 2013). 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 the issuers' demands and unduly inflate ratings, slowly contributing to the build-up of systemic risk in the market. Eventually, inflated ratings contribute to the build-up of systemic risk and are likely to be corrected through downgrades that are occasionally sudden and large which can lead to a systemic event (Dilly and Mählmann, 2016).

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

A rating downgrade also has 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 market investors. Sy (2009) supports that CRAs increase procyclicality, while rating crises result in significant market losses and fire sales. Similarly, Perignon et al. (2018) argue that credit ratings drop considerably one month before liquidity dry-ups occur. Importantly, the effect of credit rating changes is coming not only from the new information they provide, but also from the pre-rating warnings that form the market's future expectations (Hill and Faff, 2010; Afonso et al., 2011).[7] Finally, 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). Low credit ratings worsen bank's funding opportunities and limit its access to the capital markets because it is a sign of a higher probability of default (Kisgen and Strahan, 2010; Gu et al., 2018).

[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] 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.

Consequently, the lack of stable funding sources can result in higher systemic risk (Lopez-Espinosa et al., 2013).[8] 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). On the other hand, credit ratings can also be beneficial for financial institutions since they reduce information asymmetries and the cost of equity financing (Frank and Goyal, 2009).

Banks may have different incentives for purchasing credit ratings such as reducing information asymmetries and uncertainty, improving their existing rating and complying with regulatory policies (e.g., Bongaerts et al., 2012). 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; Wojewodski et al., 2018) rating changes. At the same time, under the need to maintain regulatory requirements (based on credit ratings), banks may hold 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.

[8] Adelino and Ferreira (2016) conduct an empirical study and they find that sovereign downgrades directly impact domestic institutions access to funding.

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 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 by the Big 3 CRAs, namely S&P, Moody's and Fitch from S&P Capital IQ Pro. 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 World Bank Open Data website. Table 1 and Table 2 present the definitions and descriptive statistics of all variables used in our analysis, respectively.

[Insert Tables 1 and 2 here]

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 Figure 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), 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 the vary between 12-17%. 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.

Figure 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).

[Insert Figure 1 here]

## 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*". 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, Delta CoVaR 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 Delta CoVaR*

Adrian & 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 (Wosser, 2017).

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

$$P\ (R_t^i < VaR^i) = q \quad (1)$$

where $R_t$ is the average daily returns per quarter and $q$ 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:

$$P\ (R_t^s < CoVaR^{s|i} | R_t^i = VaR^i) = q \quad (2)$$

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

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, 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.[9] All the data is provided by Thomson Reuters Datastream and the choice of these state variables is consistent across all the firms and countries in our sample.

### *3.2 Dynamic Estimation of Delta CoVaR*

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 firm's dynamic VaR, we replace back the estimates of the quantile regression.

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

$$VaR_{q,t}^i = \widehat{a_q} + \widehat{\beta_q} \ M_{t-1} \quad (5)$$

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

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

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 firm's VaR instead of its returns.

$$CoVaR_{q,t}^{system|i} = \hat{a}_q^{system|i} + \ \hat{\beta}_q^{system|i} M_{t-1} + \hat{\gamma}_q^{system|i} \ VaR_t^i \quad (7)$$

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

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

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

[Insert Figure 2 here]

### *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 equity returns of the firm *i*, the days that the market as measured by the Datastream Financials Index, has experienced a tail event. The tail event is as defined by the 5$^{th}$ 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:

$$MES = \frac{\Sigma(R^{i})}{No\ of\ days\ in\ the\ 5th\ percentile} \quad (9)$$

MES captures the marginal contribution of an institution to the expected shortfall of the financial system. In the Appendix, we present the annual global MES and ΔCoVaR based on the median of the examined firms in the sample. The two metrics exhibit a 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 Figure 1, the highest values 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%.

[Insert Table 3 here]

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 delta CoVaR) 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 National Bank's (Greece) systemic risk 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%.

# 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:

$$\Delta CoVaR_{i,t} = \alpha_i + \beta_1 DOWNGRADE_{i,t} + \beta_2 UPGRADE_{i,t} + + \sum_{j=1}^{5} \beta_j \, Bank\ Control_{i,t} + \beta_3 Macro\ Control_{c,t} + T_t + \varepsilon_{i,t} \quad (10)$$

where *i*, *c* and *t* index the bank, country and year of the observation respectively, $\alpha_i$ 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 $\sigma^2$. Using bank fixed-effects allows us to control for unobservable differences among banks and to alleviate correlations across error terms. 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. Finally, to control for heteroskedasticity, we use robust standard errors clustered at the bank level.

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, bank age with the number of years since establishment, profitability with the return on assets, capitalization with the equity ratio and asset quality with the share of loan loss reserves to total loans and leases. We also control for the macroeconomic environment of the bank with the GDP growth of the bank's host country.

### *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[10] and has the expected negative sign, suggesting that rating upgrades by S&P can mitigate a bank's contribution to systemic risk.

[Insert Table 4 here]

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

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

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 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.

[Insert Table 5 here]

The findings are in line with our expectations formed by previous 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).

[Insert Table 6 here]

### *4.2.3 The role of the COVID-19 crisis*

We also examine the role of the COVID-19 pandemic in the relationship between rating downgrades and systemic risk. Fuelled by significant governmental liquidity support, banks were able to act as lenders of first resort and support the real economy during this crisis (Li et al., 2020). However, the limited extant literature debates whether the policies introduced to absorb the systemic risk caused by the COVID-19 crisis were effective. Sedunov (2021) finds that although the liquidity provision during the GFC in the US (and other nations) was effective in reducing systemic risk,[11] no such evidence is found for the first part of the COVID-19 crisis. On the other hand, Duan et al. (2021) document that bank regulation and other policies moderated the increased systemic risk caused by the crisis.

We attempt to provide some further evidence on the role of the COVID-19 crisis by introducing an interaction term between the 2020 dummy variable and our downgrade variables. To account for differential effects across bank size classes we split the sample between small and medium, and large banks.[12] These results are presented in Table 7 and are largely consistent with our expectations. First, the coefficients of most of our downgrade variables are positive and significant. Second, the coefficient of the interaction term is negative and significant in most regressions including small and medium banks, but not in the regressions including large banks. We argue that this result indicates that the policies undertaken during the first year of the pandemic have been beneficial in absorbing a part of the adverse effect of rating downgrades on systemic risk. The COVID-19 crisis started early in 2020 (late February) and in most countries a large part of policy

[11] We do not find any evidence of a moderating effect during the GFC and considering the limited number of observations in our sample in this period we avoid presenting these results.

[12] We define large banks as the ones with average total assets above the 75$^{th}$ percentile in our sample.

responses were implemented by March. For instance, the 2020 economic outcomes in the US were a favourable "surprise" that can be attributed to the significant stimulus programs that the government quickly implemented (Berger and Demirguc-Kunt, 2021). At the same time, this crisis did not originate from financial problems in the banking industry such as excessive leverage or risky financial innovations and therefore there was space for policies to be more effective compared to the past. As a result, we argue that the 2020 policies were able to contain some part of the systemic risk that is inherit to rating downgrades.

[Insert Table 7 here]

## 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 financial sector index when the examined (banking) institution 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 assumes that risk time volatility can be captured by a set of state variables. Our final alternative variable is the ZSCORE, a traditional accounting-based measure of bank stability. ZSCORE is defined as the sum of the equity ratio and the return on assets divided by the standard deviation of the return on assets. It is a widely used measure of bank stability and has been used in comparison to systemic risk measures (e.g., Papanikolaou and Wolff, 2014). We transform the variable by calculating its natural logarithm to mitigate skewness concerns (Laeven and Levine, 2009). The results of these tests are presented in Table 8 and largely confirm our findings as most coefficients maintain their signs and significance.[13]

[Insert Table 8 here]

Second, we attempt to address possible endogeneity concerns. 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).[14] 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; Paganov 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.[15] Moreover, SGMM controls for the persistence of our dependent variable by using

[13] In the regressions where the ZSCORE is the dependent variable, the opposite coefficient signs are expected since higher values indicate greater stability in contrast to the systemic risk variables that their higher values indicate higher instability.

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

[15] We treat $\Delta$CoVaR and the rating changes variables as endogenous and all control variables and year dummies as exogenous.

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.

[Insert Table 9 here]

## 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, VaR and MES as well as overall bank risk measured by the Z-score are positively associated with rating 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, 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 show that this relationship was also moderated by the COVID-

19 crisis. We argue that this finding can be attributed to the support from official authorities that banks received shortly after the pandemic started causing financial issues.

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, the quick response by governments during the first year of the COVID-19 crisis also appears to have absorbed the negative impact of rating downgrades.

## References


Acharya, V.V., Pedersen, L.H., Philippon, T., Richardson, M., 2017. Measuring systemic risk. The Review of Financial Studies 30, 2-47. https://doi.org/10.1093/rfs/hhw088

Adelino, M., Ferreira, M.A., 2016. Bank ratings and lending supply: Evidence from sovereign downgrades. The Review of Financial Studies 29, 1709-1746. https://doi.org/10.1093/rfs/hhw004

Adrian, T., Shin, H.S., 2010. Liquidity and leverage. Journal of Financial Intermediation 19, 418-437. https://doi.org/10.1016/j.jfi.2008.12.002

Adrian, T., Brunnermeier, M.K., 2016. CoVaR. The American Economic Review 106, 1705-1741. https://doi.org/10.1257/aer.20120555

Afonso, A., Furceri, D., Gomes, P., 2011. Credit ratings and the Euro Area sovereign debt crisis. European Central Bank Working Paper Series 1347, 4-18. http://dx.doi.org/10.2139/ssrn.1991159

Agha, M., Faff, R., 2014. An investigation of the asymmetric link between credit re-ratings and corporate financial decisions: "Flicking the switch" with financial flexibility. Journal of Corporate Finance 29, 37-57. https://doi.org/10.1016/j.jcorpfin.2014.08.003

Alsakka, R., Ap Gwilym, O., 2010. Leads and lags in sovereign credit ratings. Journal of Banking and Finance 34, 2614-2626. https://doi.org/10.1016/j.jbankfin.2010.05.001

Alsakka, R., Ap Gwilym, O., 2013. Rating agencies' signals during the European sovereign debt crisis: Market impact and spillovers. Journal of Economic Behavior and Organization 85, 144-162. https://doi.org/10.1016/j.jebo.2011.12.007

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. Journal of Econometrics 68, 29-51. https://doi.org/10.1016/0304-4076(94)01642-D

Arezki, M.R., Candelon, B., Sy, M.A.N., 2011. Sovereign rating news and financial markets spillovers: Evidence from the European debt crisis. IMF Working Papers, 2011/068. https://doi.org/10.5089/9781455227112.001

Badoer, D.C., Demiroglu, C., 2019. The relevance of credit ratings in transparent bond markets. The Review of Financial Studies 32, 42-74. https://doi.org/10.1093/rfs/hhy031

Bar-Isaac, H., Shapiro, J., 2013. Ratings quality over the business cycle. Journal of Financial Economics 108, 62-78. https://doi.org/10.1016/j.jfineco.2012.11.004

Bedendo, M., Cathcart, L., El-Jahel, L., 2018. Reputational shocks and the information content of credit ratings. Journal of Financial Stability 34, 44-60. https://doi.org/10.1016/j.jfs.2017.12.003

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics 87, 115-143. https://doi.org/10.1016/S0304-4076(98)00009-8

Bolton, P., Freixas, X., Shapiro, J., 2012. The credit ratings game. The Journal of Finance 67, 85-111. https://doi.org/10.1111/j.1540-6261.2011.01708.x

Bongaerts, D., Cremers, K.M., Goetzmann, W.N., 2012. Tiebreaker: Certification and multiple credit ratings. The Journal of Finance 67, 113-152. https://doi.org/10.1111/j.1540-6261.2011.01709.x

Crabbe, L., Post, M.A., 1994. The effect of a rating downgrade on outstanding commercial paper. The Journal of Finance 49, 39-56. https://doi.org/10.2307/2329134

Deb, P., Manning, M.J., Murphy, G., Penalver, A., Toth, A., 2011. Whither the credit ratings industry? Bank of England Financial Stability Paper No. 9. https://ssrn.com/abstract=1814999

Dilly, M., Mählmann, T., 2016. Is there a "boom bias" in agency ratings? Review of Finance 20, 979-1011. https://doi.org/10.1093/rof/rfv023

Duan, Y., Ghoul, S., El, Guedhami, O., Li, H., Li, X., 2021. Bank systemic risk around COVID-19: a cross-country analysis. Journal of Banking and Finance 133, 106299. https://doi.org/10.1016/j.jbankfin.2021.106299

Duarte, F., Eisenbach, T.M., 2021. Fire-sale spillovers and systemic risk. The Journal of Finance 76, 1251-1294. https://doi.org/10.1111/jofi.13010

Ferri, G., Liu, L. G., Stiglitz, J.E., 1999. The procyclical role of rating agencies: Evidence from the East Asian crisis. Economic Notes 28, 335-355. https://doi.org/10.1111/1468-0300.00016

Financial Stability Board (FSB), International Monetary Fund (IMF), Bank for International Settlements (BIS), 2009. Report to G20 finance ministers and governors: Guidance to assess the systemic importance of financial institutions, markets and instruments: Initial considerations.

Frank, M.Z., Goyal, V.K., 2009. Capital structure decisions: which factors are reliably important? Financial Management, 38, 1-37. https://doi.org/10.1111/j.1755-053X.2009.01026.x

Griffin, J.M., Nickerson, J., Tang, D.Y., 2013. Rating shopping or catering? An examination of the response to competitive pressure for CDO credit ratings. The Review of Financial Studies 26, 2270-2310. https://doi.org/10.1093/rfs/hht036

Gu, X., Kadiyala, P., Mahaney-Walter, X.W., 2018. How creditor rights affect the issuance of public debt: The role of credit ratings. Journal of Financial Stability 39, 133-143. https://doi.org/10.1016/j.jfs.2018.11.001

He, J., Qian, J., Strahan, P.E., 2012. Are all ratings created equal? The impact of issuer size on the pricing of mortgage-backed securities. The Journal of Finance 67, 2097-2137. https://doi.org/10.1111/j.1540-6261.2012.01782.x

He, J., Qian, J., Strahan, P.E., 2016. Does the market understand rating shopping? Predicting MBS losses with initial yields. The Review of Financial Studies 29, 457-485. https://doi.org/10.1093/rfs/hhv067

Henry, T.R., Kisgen, D.J., Wu, J.J., 2015. Equity short selling and bond rating downgrades. Journal of Financial Intermediation 24, 89-111. https://doi.org/10.1016/j.jfi.2014.02.005

Hill, P., Faff, R., 2010. The market impact of relative agency activity in the sovereign ratings market. Journal of Business Finance and Accounting 37, 1309-1347. https://doi.org/10.1111/j.1468-5957.2010.02220.x

Huang, Y.L., Shen, C.H., 2015. The sovereign effect on bank credit ratings. Journal of Financial Services Research 47, 341-379. https://doi.org/10.1007/s10693-014-0193-7

IMF, 2010. Global Financial Stability Report, October 2010: Sovereigns, funding and systemic liquidity, "Chapter 3: The uses and abuses of sovereign credit ratings", 85-122. https://doi.org/10.5089/9781589069480.082

Jones, L., Alsakka, R., Ap Gwilym, O., Mantovan, N., 2022. Regulating rating agencies: A conservative behavioural change. Journal of Financial Stability 60, 100999. https://doi.org/10.1016/j.jfs.2022.100999

Jorge, J., 2019. Feedback effects between credit ratings and financial markets. Economic Modelling 80, 328-338. https://doi.org/10.1016/j.econmod.2018.11.019

Kemper, K.J., Rao, R.P., 2013. Do credit ratings really affect capital structure? Financial Review 48, 573-595. https://doi.org/10.1111/fire.12016

Kisgen, D.J., 2006. Credit ratings and capital structure. The Journal of Finance 61, 1035-1072. https://doi.org/10.1111/j.1540-6261.2006.00866.x

Kisgen, D.J., 2009. Do firms target credit ratings or leverage levels? Journal of Financial and Quantitative Analysis 44, 1323-1344. https://doi.org/10.1017/S002210900999041X

Kisgen, D.J., 2019. The impact of credit ratings on corporate behavior: Evidence from Moody's adjustments. Journal of Corporate Finance 58, 567-582. https://doi.org/10.1016/j.jcorpfin.2019.07.002

Kisgen, D.J., Strahan, P.E., 2010. Do regulations based on credit ratings affect a firm's cost of capital? The Review of Financial Studies 23, 4324-4347.

Laeven, L., Levine, R., 2009. Bank governance, regulation and risk taking. Journal of Financial Economics 93, 259-275. https://doi.org/10.1093/rfs/hhq077

López-Espinosa, G., Rubia, A., Valderrama, L., Antón, M., 2013. Good for one, bad for all: Determinants of individual versus systemic risk. Journal of Financial Stability 9, 287-299. https://doi.org/10.1016/j.jfs.2013.05.002

Li, L., Strahan, P.E., Zhang, S., 2020. Banks as lenders of first resort: evidence from the COVID-19 crisis. The Review of Corporate Finance Studies 9, 472–500. https://doi.org/10.1093/rcfs/cfaa009

Manso, G. (2013). Feedback effects of credit ratings. Journal of Financial Economics, 109(2), 535-548. https://doi.org/10.1016/j.jfineco.2013.03.007

Mason, J.R., Rosner, J., 2007. How resilient are mortgage backed securities to collateralized debt obligation market disruptions? Hudson Institute presentation, February 15, 2007. https://doi.org/10.2139/ssrn.1027472

Mathis, J., McAndrews, J., Rochet, J.C., 2009. Rating the raters: Are reputation concerns powerful enough to discipline rating agencies? Journal of Monetary Economics 56, 657-674. https://doi.org/10.1016/j.jmoneco.2009.04.004

Memmel, C., Raupach, P., 2010. How do banks adjust their capital ratios? Journal of Financial Intermediation 19, 509-528. https://doi.org/10.1016/j.jfi.2009.10.002

Pagano, M.S., Sedunov, J., 2016. A comprehensive approach to measuring the relation between systemic risk exposure and sovereign debt. Journal of Financial Stability 23, 62-78. https://doi.org/10.1016/j.jfs.2016.02.001

Papanikolaou, N.I., Wolff, C.C., 2014. The role of on-and off-balance-sheet leverage of banks in the late 2000s crisis. Journal of Financial Stability 14, 3-22. https://doi.org/10.1016/j.jfs.2013.12.003

Pérignon, C., Thesmar, D., Vuillemey, G., 2018. Wholesale funding dry-ups. The Journal of Finance 73, 575-617. https://doi.org/10.1111/jofi.12592

Richards, A., Deddouche, D., 2003. Bank rating changes and bank stock returns: puzzling evidence from the emerging markets. Journal of Emerging Market Finance 2, 337-363. https://doi.org/10.1177%2F097265270300200304

Sangiorgi, F., Spatt, C., 2017. Opacity, credit rating shopping, and bias. Management Science 63, 4016-4036. https://doi.org/10.1287/mnsc.2016.2558

Sedunov, J., 2021. Federal Reserve intervention and systemic risk during financial crises. Journal of Banking and Finance 133, 106210. https://doi.org/10.1016/j.jbankfin.2021.106210

Sy, A.N.R., 2009. The systemic regulation of credit rating agencies and rated markets. IMF Working Paper Series, 2009/129 https://doi.org/10.5089/9781451872767.001

Tang, T.T., 2009. Information asymmetry and firms' credit market access: Evidence from Moody's credit rating format refinement. Journal of Financial Economics 93, 325-351. https://doi.org/10.1016/j.jfineco.2008.07.007

Vieira, F.A., Holland, M., Resende, M.F., 2012. Financial dollarization and systemic risks: New empirical evidence. Journal of International Money and Finance 31, 1695-1714. https://doi.org/10.1016/j.jimonfin.2012.03.007

Wojewodzki, M., Boateng, A., Brahma, S., 2020. Credit rating, banks' capital structure and speed of adjustment: a cross-country analysis. Journal of International Financial Markets, Institutions and Money 69, 101260. https://doi.org/10.1016/j.intfin.2020.101260

Wojewodzki, M., Poon, W.P., Shen, J., 2018. The role of credit ratings on capital structure and its speed of adjustment: An international study. The European Journal of Finance, 24(9), 735-760. https://doi.org/10.1080/1351847X.2017.1354900

## Tables and figures

**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 financial system index, when the examined firm is equal or below its VaR, as defined by its historical distribution. | |
| ZSCORE | The natural logarithm of the Z-score defined as the sum of the equity ratio and the return on assets divided by the standard deviation of the return on assets. | S&P Capital IQ Pro (Authors' calculation) |
| **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. | |

**Table 1.** Variable definitions. *(Continued from previous page)*

| | | |
|---|---|---|
| **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 |

**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 |
| ZSCORE | 3691 | 1.072 | 1.258 | 0.972 | -0.777 | 2.366 |
| **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 |
| **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 |

**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).

**Table 4.** Baseline regressions.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | 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). 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 5.** Downgrade and upgrade size.

| | (1) ΔCoVaR | (2) ΔCoVaR | (3) ΔCoVaR | (4) ΔCoVaR | (5) ΔCoVaR | (6) ΔCoVaR | (7) ΔCoVaR | (8) 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). 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 6.** The moderating role of profitability and capital.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | 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). 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.** The moderating role of the COVID-19 crisis.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Small and Medium Banks | Large Banks | Small and Medium Banks | Large Banks | Small and Medium Banks | Small and Medium Banks | Small and Medium Banks | Small and Medium Banks |
| | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR |
| DOWNGRADE | 0.025*** | 0.018** | 0.017*** | 0.008 | | | | |
| | (0.007) | (0.008) | (0.005) | (0.008) | | | | |
| S&P DOWNGRADE | | | | | 0.009 | | | |
| | | | | | (0.007) | | | |
| MOODY'S DOWNGRADE | | | | | | 0.002 | | |
| | | | | | | (0.010) | | |
| FITCH DOWNGRADE | | | | | | | 0.023*** | |
| | | | | | | | (0.008) | |
| SG | | | | | | | | 0.032*** |
| | | | | | | | | (0.009) |
| DOWNGRADE VARIABLE * 2020 | -0.048*** | 0.039 | -0.048*** | 0.036 | -0.062*** | -0.021 | -0.059*** | -0.061** |
| | (0.015) | (0.039) | (0.015) | (0.041) | (0.019) | (0.025) | (0.023) | (0.025) |
| 2020 | 0.116*** | 0.167*** | 0.048*** | 0.094*** | 0.056*** | 0.041* | 0.038** | 0.041*** |
| | (0.016) | (0.028) | (0.014) | (0.020) | (0.019) | (0.021) | (0.018) | (0.014) |
| CONTROL VARIABLES | NO | NO | 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. | 2,913 | 979 | 2,913 | 979 | 1,736 | 1,889 | 1,671 | 2,913 |
| N. OF BANKS | 262 | 75 | 262 | 75 | 174 | 189 | 184 | 262 |
| R2 WITHIN | 0.193 | 0.340 | 0.208 | 0.392 | 0.246 | 0.207 | 0.282 | 0.207 |

The table reports fixed-effects regressions. The dependent variable is Delta CoVaR (ΔCoVaR). Large banks are defined as those with average total assets above the $75^{th}$ percentile in the sample, while the remaining banks are defined as small and medium. 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 8.** Alternative measures of systemic risk and bank stability. *(Continued in next page)*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | MES | MES | MES | MES | MES | VaR | VaR | VaR | VaR | VaR |
| DOWNGRADE | 0.320*** | | 0.472*** | 0.512*** | 0.241*** | 0.029*** | | 0.066*** | 0.113** | 0.037*** |
| | (0.077) | | (0.122) | (0.184) | (0.093) | (0.009) | | (0.015) | (0.047) | (0.013) |
| UPGRADE | -0.103* | | -0.106* | -0.100 | -0.097 | -0.009 | | -0.009 | -0.007 | -0.004 |
| | (0.061) | | (0.062) | (0.062) | (0.073) | (0.009) | | (0.009) | (0.009) | (0.011) |
| SG | | 0.130 | | | | | 0.055*** | | | |
| | | (0.185) | | | | | (0.020) | | | |
| IG | | -0.117 | | | | | -0.009 | | | |
| | | (0.134) | | | | | (0.019) | | | |
| DOWNGRADE * ROA | | | -20.399** | | | | | -4.992*** | | |
| | | | (9.896) | | | | | (1.276) | | |
| DOWNGRADE * EQUITY | | | | -2.132 | | | | | -0.939* | |
| | | | | (2.052) | | | | | (0.495) | |
| DOWNGRADE * 2020 | | | | | -0.502* | | | | | -0.094*** |
| | | | | | (0.296) | | | | | (0.030) |
| MAIN & INTERACTION TERMS | NO | NO | YES | YES | YES | NO | NO | YES | YES | YES |
| 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. | 3,792 | 3,792 | 3,792 | 3,792 | 2,826 | 3,878 | 3,878 | 3,878 | 3,878 | 2,899 |
| N. OF BANKS | 337 | 337 | 337 | 337 | 262 | 336 | 336 | 336 | 336 | 261 |
| R2 WITHIN | 0.538 | 0.534 | 0.540 | 0.538 | 0.4987 | 0.278 | 0.277 | 0.288 | 0.282 | 0.2557 |

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

| | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|
| | ZSCORE | ZSCORE | ZSCORE | ZSCORE | ZSCORE |
| DOWNGRADE | -0.068*** | | -0.262*** | -0.180*** | -0.069*** |
| | (0.020) | | (0.056) | (0.057) | (0.024) |
| UPGRADE | 0.029* | | 0.030* | 0.027 | 0.009 |
| | (0.017) | | (0.016) | (0.017) | (0.016) |
| SG | | -0.187*** | | | |
| | | (0.068) | | | |
| IG | | 0.017 | | | |
| | | (0.028) | | | |
| DOWNGRADE * ROA | | | 20.383*** | | |
| | | | (4.634) | | |
| DOWNGRADE * EQUITY | | | | 1.229** | |
| | | | | (0.552) | |
| DOWNGRADE * 2020 | | | | | 0.083* |
| | | | | | (0.044) |
| MAIN & INTERACTION TERMS | NO | NO | YES | YES | YES |
| CONTROL VARIABLES | YES | YES | YES | YES | YES |
| BANK FE | YES | YES | YES | YES | YES |
| YEAR FE | YES | YES | YES | YES | YES |
| OBS. | 3,691 | 3,691 | 3,691 | 3,691 | 2,757 |
| N. OF BANKS | 334 | 334 | 334 | 334 | 259 |
| R2 WITHIN | 0.620 | 0.620 | 0.630 | 0.621 | 0.621 |

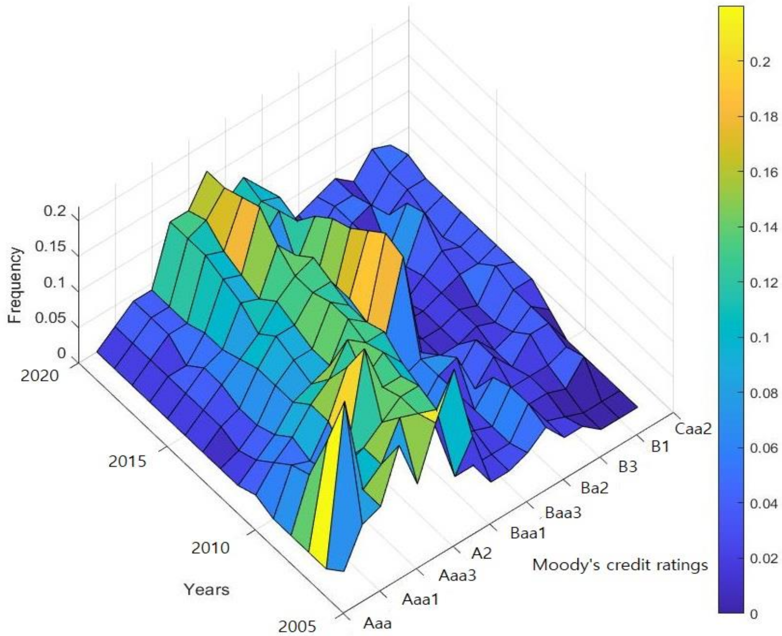
The table reports fixed-effects regressions. The dependent variables Marginal Expected Shortfall (MES), Value at Risk (VaR) and the Z-score (ZSCORE). Robust standard errors clustered at the bank level are reported in parentheses. ***, **, and *denote statistical significance at the 1%, 5%, and 10% level, respectively.

**Table 9.** Controlling for endogeneity.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR | ΔCoVaR |
| L. ΔCoVaR | | | | | 0.694*** | 0.728*** | 0.767*** | 0.738*** | 0.457*** |
| | | | | | (0.035) | (0.033) | (0.026) | (0.031) | (0.096) |
| DOWNGRADE | 0.009** | | 0.034*** | 0.046** | 0.044** | | 0.032** | 0.138** | 0.093** |
| | (0.004) | | (0.011) | (0.020) | (0.022) | | (0.015) | (0.077) | (0.044) |
| UPGRADE | -0.001 | | -0.001 | 0.0002 | 0.018 | | 0.006 | 0.096 | 0.034 |
| | (0.005) | | (0.005) | (0.005) | (0.021) | | (0.019) | (0.483) | (0.035) |
| 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) | |
| DOWNGRADE * 2020 | | | | | | | | | -0.260** |
| | | | | | | | | | (0.116) |
| MAIN & INTERACTION TERMS | NO | NO | YES | YES | NO | NO | YES | YES | YES |
| CONTROL VARIABLES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| BANK FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| YEAR FE | YES | 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 | 2641 |
| N. OF BANKS | 334 | 334 | 334 | 334 | 334 | 334 | 334 | 334 | 259 |
| R2 WITHIN | 0.248 | 0.253 | 0.265 | 0.251 | | | | | |
| AR(2) | | | | | 0.092 | 0.057 | 0.155 | 0.065 | 0.387 |
| HANSEN J | | | | | 0.384 | 0.785 | 0.380 | 0.282 | 0.243 |
| N. OF INSTRUMENTS | | | | | 326 | 326 | 326 | 326 | 234 |
| METHOD | FE(LAGS) | FE(LAGS) | FE(LAGS) | FE(LAGS) | SGMM | 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). Robust standard errors clustered at the bank level are reported in parentheses. ***, **, and *denote statistical significance at the 1%, 5%, and 10% level, respectively.

A. Moody's credit ratings distribution




B. Downgrades & Upgrades

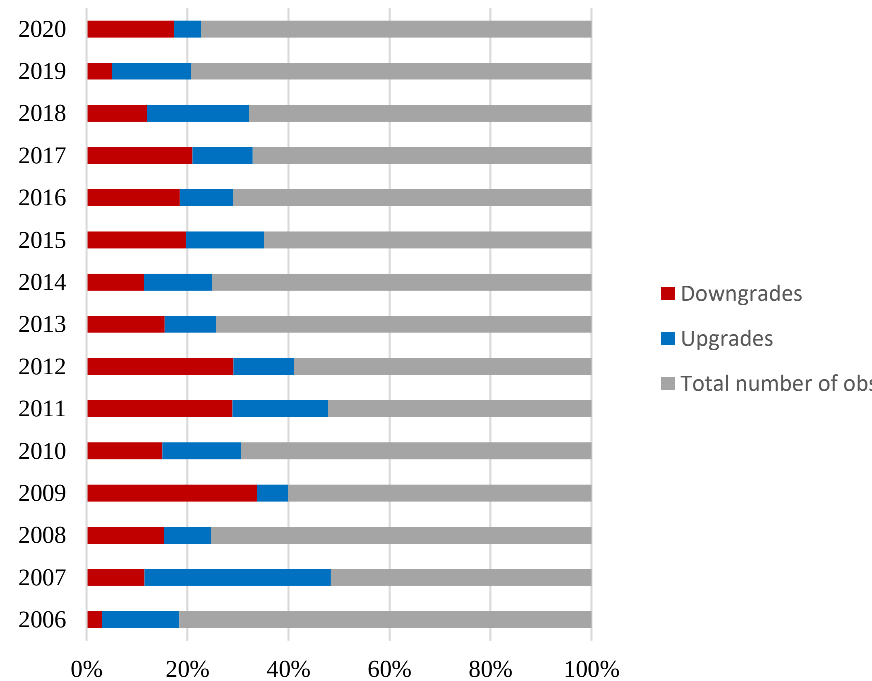



**Figure 1: Credit rating statistics**

Figure 1A displays the distribution of Moody's credit ratings for the examined institutions in our sample and for the entire sample period.

Figure 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.

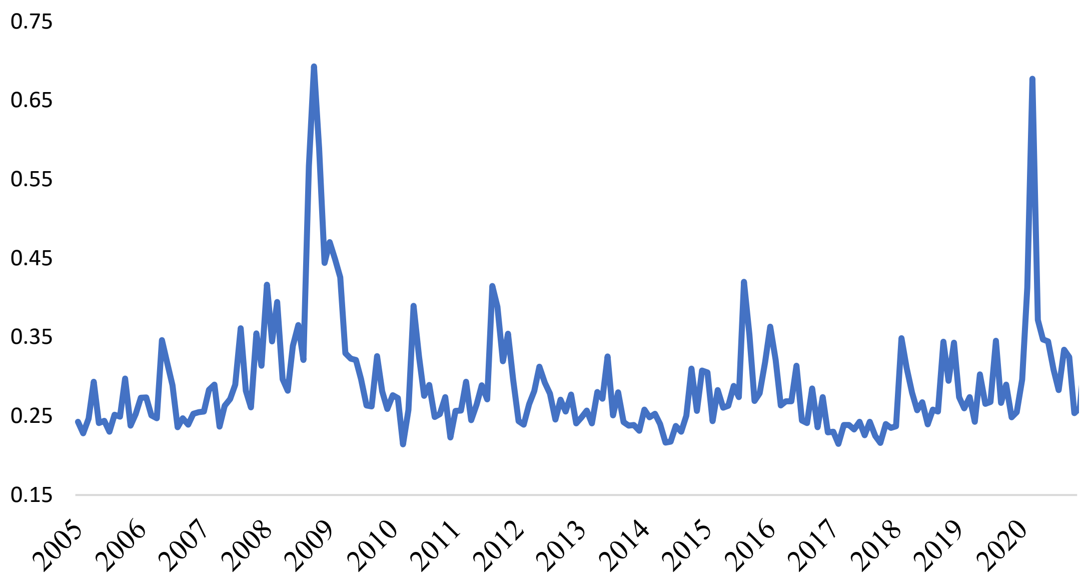



**Figure 2: Global systemic risk**

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.