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Measuring and Stress-Testing Market-Implied Bank Capital*

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Abstract

We propose a methodology for measuring the market-implied capital of banks by subtracting from the market value of equity (market capitalization) a credit-spread-based correction for the value of shareholders' default option. We show that without such a correction, the estimated impact of a severe market downturn is systematically distorted, underestimating the risk of banks with low market capitalization. We argue that this adjusted measure of capital is the relevant market-implied capital measure for policymakers. We propose an econometric model for the combined simulation of equity prices and CDS spreads, which allows us to introduce this correction in the SRISK framework for measuring systemic risk.

Keywords: Banking, Capital, Stress Test, Systemic Risk, Multifactor Model.

JEL Classification: C32, G01, G21, G28, G32.

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1 Introduction

Since the Global Financial Crisis, bank stress tests have become an important tool for supervisors and regulators ([Sorge, 2004](#); [Drehmann, 2009](#); [Anderson, 2016](#); [Kapinos et al., 2018](#)). Stress tests allow authorities to assess the resilience of the banking sector by estimating the impact of adverse scenarios on the value of banks' assets. However, measuring the loss on assets is complicated because doing so requires a consistent translation of the macroeconomic stress scenario into specific shocks for all asset classes. Furthermore, historical data on stress events similar to those assumed in the stress scenario are not always available. Thus, stress test results are subject to substantial model uncertainty.

Market-based assessments of banks' asset values under stress are considered to be useful complements to model-based stress-tests (e.g., [Acharya et al., 2014](#); [Sarin and Summers, 2016](#); [Pierret and Steffen, 2018](#); [Vickers, 2019](#)). One such approach is based on the framework proposed by [Acharya et al. \(2017\)](#) and [Brownlees and Engle \(2017\)](#) for measuring systemic risk (SRISK).¹ In this framework, the difficulty of measuring asset values under stress is circumvented by proxying the loss on assets by the projected loss on equity under a negative stock market shock, assuming that debt is unaffected by the shock. As banks' equity is the first affected source of funding, this assumption is reasonable for well-capitalized banks and mild downturns. However, in a severe crisis, debt holders can also suffer losses, as shareholders have limited liability. If one wants to assess the total risk or loss potential of banks' assets in a market-based stress test, focusing only on equity is insufficient—instead, one has to consider banks' total liabilities. As banks fund their assets predominantly with debt, a small percentage loss on debt may correspond to a large dollar loss.

In this paper, we address this issue and estimate market-implied losses in a crisis not only for equity but also for debt instruments. We use credit spreads as market-based loss indicators for debt instruments. Using the terminology of [Merton \(1974\)](#), we interpret the spread-implied expected loss on total debt as the value of shareholders' default option. We subtract from the banks' market capitalization (MC) this spread-implied value of sharehold-

¹SRISK is commonly reported in financial stability reports of central banks and related institutions. See, for instance, [Banco de España](#), [Danmarks Nationalbank](#), [European Central Bank](#), [Financial Stability Board](#), or [Office of Financial Research](#).

ers' default option and obtain a market-based measure of capital that reflects the full risk and loss potential of banks' assets. We call this measure *intrinsic capital* (IC), as it measures the intrinsic value of equity without the time value of the default option.

In our empirical implementation of IC, we focus on long-term unsecured debt and estimate, based on notional amounts and maturities, the total sensitivity of this debt category to the banks' credit default swap (CDS) spreads. We use CDS spreads instead of the individual bond issuer spreads because of high standardization, liquidity, and availability of the former.

As a first illustration of the effects of our adjustment, we consider the MC and IC of 18 global systemically important banks (G-SIBs) before and after the Covid-19-induced market downturn in March 2020. Before the downturn, the differences between IC and MC were relatively small, except for a few European banks with relatively low MC. After the market downturn, however, our adjustment becomes much more important and, again, has the largest effect on banks with low MC. Given the limited liability of shareholders, this observation is quite intuitive. The asset losses that shareholders must absorb reduce to zero as MC approaches its zero lower bound. Therefore, the asset losses that debt holders must absorb increase correspondingly. These findings illustrate our main point: if one only considers MC without the adjustments we propose for IC, the loss estimates in market-based stress tests can be significantly distorted, as they systematically underestimate the risks of banks with low MC.

Next, we perform a more systematic analysis of IC and the simulated effect of severe market stress over a longer time period, 2009–2020. For this purpose, we develop an econometric model that allows us to describe the joint dynamics of a bank's equity and CDS returns together with the aggregate CDS and stock market returns. Using this model, based on the dynamic conditional beta approach (Engle, 2012), we simulate severe stock market downturns and infer the stressed MC and IC levels. To compare these capital levels between banks and over time, we divide them by the Basel III leverage ratio denominator (LRD) and introduce the *market leverage ratio* (MLR) and the *intrinsic leverage ratio* (ILR).²

We observe relatively large contributions from debt losses to the simulated stress impact on ILR. Averaged over the sample, the unstressed ILR is at 3.9% and declines to an average

²Thus, these are defined as $MLR = MC/LRD$ and $ILR = IC/LRD$.

of 1.1% under the simulated market stress scenario. Of this simulated 2.8 percentage points (pp) stress impact, 1.1 pp are due to losses on debt instruments. This result shows that our spread-based capital adjustment is quite material in market-based stress tests.

Our analysis of results by jurisdiction reveals large differences between U.S. and euro area banks, with U.K. and Swiss banks being in between. As euro area banks have relatively low unstressed MLR in comparison with U.S. banks, their MLR is also much less affected by the stress simulation. The simulated impacts on the ILR, however, are similar for banks in both jurisdictions, as this metric also takes the losses to debt holders into account. The stressed ILR of euro area G-SIBs is on average negative over the sample period (-0.6%), with particularly low values during the European debt crisis.

We also integrate our IC concept into the market-based capital shortfall measure SRISK, based on MC ([Brownlees and Engle, 2017](#)). Furthermore, we propose aligning the required capital in this shortfall measure with the Basel III leverage ratio requirement. Our resulting aggregate capital shortfalls are, on average, of a magnitude similar to that of results under the standard SRISK. However, our shortfall measure exhibits more variation over time. Because of the zero lower bound of MC, SRISK understates projected asset losses during stress periods, such as the European debt crisis in 2012. In contrast, in a normal market environment, SRISK produces larger capital shortfalls than does our measure due to the higher minimum requirement.

Finally, we compare the simulated impacts for our two market-based capital measures (MC and IC) to two accounting-based regulatory exposure measures (LRD and risk-weighted assets (RWA)). We show that in the cross-section, the estimated IC impacts are better aligned with these regulatory exposure measures than the estimated MC impacts. This comparison again illustrates that the MC impacts are systematically too small for European banks in comparison with U.S. banks. We observe the closest alignment when comparing the IC impacts with RWA.

In summary, our analysis suggests that policymakers should pay attention to spreads on bank debt not only as an indicator of market stress but also because such spreads contain information about the market-implied asset values of banks. Ignoring this information leads to distorted quantitative assessments of bank health both in the cross-section and over time.

Literature Review. Our paper is related to research that empirically evaluates the capital shortfall of financial institutions based on publicly available data (see [Bisias et al., 2012](#), [Giglio et al., 2016](#), and [Benoit et al., 2017](#) for surveys). [Acharya et al. \(2017\)](#) quantify systemic risk as the systemic expected shortfall (SES) of a financial institution, i.e., its propensity to be undercapitalized when the system as a whole is undercapitalized. The SES of a bank is defined as the sum of its expected default losses and the expected contribution to a systemic crisis. As mentioned above, the SRISK measure of [Brownlees and Engle \(2017\)](#) provides an empirical evaluation of this notion using the projected loss on equity to proxy the impact of the crisis on the market value of assets. [Acharya et al. \(2012\)](#), [Acharya et al. \(2014\)](#), and [Engle et al. \(2015\)](#) further explore SRISK measures. [Jondeau and Khalilzadeh \(2017\)](#) also aim at measuring capital shortfall in a severe downturn, but they directly measure the impact of market stress on the market value of assets. As such, their measure of capital shortfall can exceed the current value of equity if asset losses are sufficiently large. [Jondeau and Khalilzadeh \(2021\)](#) provide an empirical application to large U.S. banks.

A few papers use a mark-to-market evaluation of the balance sheet of financial institutions in a market downturn based on the information available in CDS spreads. [Huang et al. \(2012\)](#) define systemic risk as the price of insurance against financial distress. Their “distress insurance premium” is the theoretical premium for a risk-based deposit insurance scheme that guarantees against severe losses incurred by the banking system. They use CDS spreads to estimate individual banks’ probability of default and equity returns to proxy the correlation between banks’ asset returns. [Oh and Patton \(2018\)](#) propose a copula model to estimate a variety of systemic risk measures, such as the joint probability of distress, based on CDS market data. [Jobst and Gray \(2013\)](#) rely on a strategy based on contingent claims analysis. They construct a risk-adjusted balance sheet using option pricing theory and estimate the joint default risk of multiple institutions to measure systemic risk. The resulting measure of systemic risk also uses equity, equity option, and capital structure information. [Giglio \(2016\)](#) exploits information in CDS spreads to measure the joint default risk of financial institutions.

Our research is also related to the literature on the distance-to-default measures for financial and nonfinancial firms (see, e.g., [Duan and Wang, 2012](#) for a review). Analyses in

this literature sometimes approximate the market value of assets, which is not directly observable, by adding the market value of equity to the book value of debt. This approximation systematically overestimates the market value of assets and underestimates asset risk in the same way as we discuss in our paper.

2 Defining Market-implied Intrinsic Capital Ratios

2.1 Market-implied Intrinsic Capital

We consider the measurement of a bank’s *intrinsic capital* (IC) using market prices. By IC, we mean the market value of a bank’s equity if shareholders had full liability for the bank’s outstanding debt. This measure can be thought of as the market assessment of banks’ regulatory common equity tier 1 (CET1) capital, as banks indeed have to correct for the value of the shareholders’ default option in their CET1 calculations. According to the international Basel III standard, banks have to “derecognise in the calculation of CET1, all unrealised gains and losses that have resulted from changes in the fair value of liabilities that are due to changes in the bank’s own credit risk” (Basel Framework, CAP 30.15; see, e.g., Ramirez, 2017). These corrections are particularly important in stress periods, when the credit spread of the bank widens and the value of the bank’s fair-value debt instruments declines.³

We define IC_t as the difference between the market-implied value of assets at a given time t , A_t , and the book value of debt, BD ,⁴

$$IC_t = A_t - BD. \tag{1}$$

³Regulatory CET1 capital is obtained from book equity after a number of regulatory adjustments (cf. Basel Framework CAP 30 at https://www.bis.org/basel_framework/). For instance, certain intangible assets, such as goodwill, are deducted from book equity in the calculation of regulatory capital. The adjustment of own credit risk is, however, particularly important in our context, as it increases during stress periods.

⁴We distinguish between market-based variables (such as the market-implied value of assets, A_t) and accounting variables (such as the book value of debt, BD). The former change daily and carry a time index t . The latter change only infrequently (e.g., quarterly), and we omit the time index.

This value is different from the market value of equity MC_t , which is equal to the difference between A_t and the market value of debt, D_t ,

$$MC_t = A_t - D_t. \quad (2)$$

The challenge in measuring IC_t is that A_t is not directly observable from financial markets. However, rearranging Equations (1) and (2), we can express IC as follows:

$$IC_t = MC_t - (BD - D_t). \quad (3)$$

Thus, the difference between IC and MC is the correction term $BD - D_t$. This term is the value of the shareholders' default option. To recognize this, it is useful to rely on the terminology of the model of Merton (1974): MC_t is the value of a call option to buy the assets of the bank, A_t , by paying the book value of debt, BD . Using put-call parity, we can express the corresponding put option as

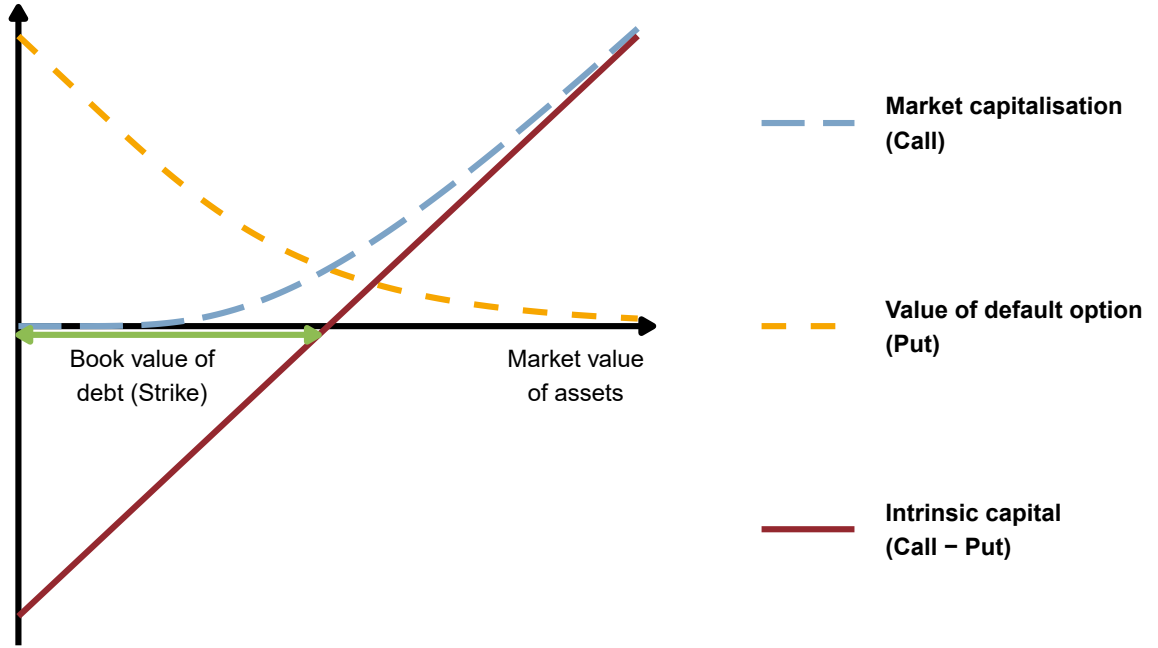
$$P_t = MC_t - A_t + BD = BD - D_t, \quad (4)$$

where we have used Equation (2) in the second step. Figure 1 illustrates this point graphically.

The value of the default option, $BD - D_t$, is still not directly observable in the market because market prices are not available for all categories of debt instruments. Our strategy is to relate the market value of the default option to the bank's credit spread, denoted by S_t . We continue with the terminology of the Merton model and assume that the bank only has a single zero-coupon debt instrument with remaining maturity M and notional amount K outstanding. We further denote by r the risk-free interest rate, which we assume to be constant. The book value of this debt instrument is then given by $BD = Ke^{-rM}$. Based on the definition of the credit spread S_t , we can write the current market value of this debt instrument as $D_t = Ke^{-(r+S_t)M}$. Substituting these definitions in Equation (3), we obtain

$$IC_t = MC_t - BD(1 - e^{-S_t \cdot M}) \approx MC_t - BD \cdot M \cdot S_t, \quad (5)$$

Figure 1: Market-implied Intrinsic Capital



where we have assumed in the second step that $M \cdot S_t$ is small relative to 1.

In reality, banks have not just one single zero-coupon bond but many different types of liabilities with different maturities and contractual terms. To calculate the total value of the shareholders' default option, one has to estimate and sum for all of these instruments the difference between their default-risk-free and actual market valuations. Hence, we can generalize the definition in Equation (5) as follows:

$$IC_t = MC_t - \sum_{k,M} BD_{k,M} \cdot M \cdot S_t^{k,M}, \quad (6)$$

where k indexes various types of liabilities, such as retail deposits, secured debt, liabilities from derivatives as well as short- and long-term unsecured debt, $BD_{k,M}$ denotes the nominal amount of these liabilities with maturity M , and $S_t^{k,M}$ denotes the corresponding credit spread.

2.2 Implementation

We now discuss how we estimate IC_t in practice. Among various types of bank liabilities, long-term unsecured bonds will make a particularly large contribution to the sum in Equation (6). Banks have significant amounts of long-term unsecured debt, generally featuring higher credit spreads than other bank liabilities. The relatively high credit spreads reflect market participants' expectation that long-term unsecured bonds are most likely to absorb losses in a crisis. Retail deposits absorb losses only after senior debt, and also for political reasons are much less likely to be subject to losses. Operational liabilities and liabilities from derivatives are also less likely to be subject to losses in a crisis, due to practical and legal reasons. Secured debt is less sensitive to the market value of a bank's total assets due to its separate collateralization. Finally, short-term debt is better protected against losses and contributes less to the sum in Equation (6) due to its shorter maturity. Therefore, we limit our analysis to long-term unsecured debt instruments, assuming that the contributions from other debt categories can be neglected.

Long-term unsecured debt is, however, still not a homogeneous debt category. There is significant variation in the issuer spread of long-term debt instruments depending on the remaining maturity and the ranking in the creditor hierarchy. Specifically, issuer spreads of an additional tier 1 (AT1) capital instrument are higher than those of a subordinated tier 2 (T2) debt instrument, which in turn are higher than those of senior unsecured debt instruments with the same maturity. For G-SIBs, the Financial Stability Board in 2015 established the total loss-absorbing capacity (TLAC) requirements, and the issuer spreads for instruments eligible for TLAC are generally lower than for subordinated T2 instruments but higher than for long-term senior unsecured debt ineligible for TLAC.⁵

In the following, we assume that the five-year issuer spread of TLAC-eligible debt is representative in terms of not only maturity but also seniority for the entire long-term debt

⁵Under this international standard, G-SIBs are required to establish a loss-absorbing capacity of at least 6.75% of the Basel III LRD by the beginning of 2022. Of this requirement, 3.75% can be met with TLAC-eligible unsecured long-term debt. To be eligible for TLAC, a debt instrument must be contractually or structurally subordinated to operational senior liabilities of a bank. Most jurisdictions in the euro area have adopted the contractual subordination approach by introducing a new debt class of senior non-preferred debt that ranks higher than subordinated debt but lower than senior preferred debt in the creditor hierarchy. G-SIBs in the U.S., the U.K., and Switzerland have adopted the structural subordination approach by issuing senior debt from the G-SIB's holding company to meet the TLAC requirements.

category and can be used as the exposure-weighted average spread for the entire unsecured long-term debt category. Using the issuer credit spread of TLAC-eligible debt, for which a bail-in is more credible than for ineligible senior debt, has the additional advantage that the actual default risk of such debt is less likely to be hidden behind a too-big-to-fail subsidy.

In our analysis, we use the five-year senior CDS spread instead of the five-year issuer spread of TLAC-eligible bonds. The main reason for using CDS spreads is the higher standardization and liquidity of CDS contracts and the longer time series of CDS market data. For a given issuer, we observe in the available market data that the two spreads co-move closely but the CDS spread is significantly lower than the TLAC issuer spread. The empirical analysis in Appendix A.1 shows that the issuer spread for five-year TLAC-eligible bonds is approximately twice as high as the five-year senior CDS spread of the same issuer, i.e., $S_t^{\text{TLAC}, 5y} \approx 2 S_t^{\text{CDS}, 5y}$.

For G-SIBs, the total book value of all long-term unsecured debt instruments amounts to approximately 10% of the total book value of debt, BD_i , and in our implementation we assume this fraction to be constant. In Appendix A.2, we justify, based on banks' regulatory disclosures and financial reports, that this assumption is reasonable for all banks in our sample regardless of their jurisdiction.

With these assumptions about the outstanding amount of unsecured long-term debt, the average maturity of such debt, and the average credit spread of such debt, we can approximate the difference between the default-risk-free and actual debt valuations for a bank i as

$$BD_i - D_{i,t} \approx 10\% \cdot 5 \cdot BD_i \cdot S_{i,t}^{\text{TLAC}, 5y} \approx BD_i \cdot S_{i,t}^{\text{CDS}, 5y}, \quad (7)$$

where we have used in the second step the approximate factor-of-two relationship between the CDS spread and the TLAC issuer spread ($10\% \cdot 5 \cdot 2 = 1$). Based on these considerations, we implement the IC measure as follows:

$$IC_{i,t} = MC_{i,t} - BD_i \cdot S_{i,t}^{\text{CDS}, 5y}, \quad (8)$$

where both time-dependent terms on the right are observable in equity and credit markets.

2.3 Market-based Capital Ratios

We now define and compare different market-based capital ratios. Our main focus is on market-based leverage ratios that relate market-based measures of capital to the Basel III leverage ratio denominator (LRD). Compared to the book value of assets, the LRD has the advantage of being more comparable between U.S. and European banks, as it adjusts for the most important differences in the accounting standards.⁶

We define the intrinsic leverage ratio (ILR) and the market leverage ratio (MLR) of bank i at time t as

$$ILR_{i,t} := \frac{IC_{i,t}}{LRD_i} \quad \text{and} \quad MLR_{i,t} := \frac{MC_{i,t}}{LRD_i}. \quad (9)$$

In Section 3, we will analyze the impact of the Covid-19-induced market downturn on these market-based leverage ratios. In Section 4, we will examine the evolution of these leverage ratios over time. In Section 5, we will assess the relevance of market-based capital ratios that use risk-weighted assets (RWA) instead of LRD in the denominator. Analogously to Equation (9), we define the *intrinsic capital ratio* (ICR) and the *market capital ratio* (MCR) of bank i at time t as

$$ICR_{i,t} := \frac{IC_{i,t}}{RWA_i} \quad \text{and} \quad MCR_{i,t} := \frac{MC_{i,t}}{RWA_i}. \quad (10)$$

2.4 Data

Our empirical analysis focuses on 18 U.S. and European G-SIBs for which CDS data are available over our sample period, 2004–2020. The sample contains 6 U.S. banks, 7 euro area banks, 3 U.K. banks, and 2 Swiss banks. As we require a minimum of five years of data for the estimation of the econometric model (see Section 4), our analysis starts in January 2009.

The main data constraints apply to CDS spreads. For all banks, we use five-year CDS contracts with the market default settings with respect to currency and the restructuring clause. We chose CDS contracts referencing eligible bail-in debt instruments as soon as

⁶For the same reason, we calculate the book value of debt as $BD = LRD - BE$, where BE denotes the book value of equity, so that we have an internationally comparable measure of a bank's total liabilities.

spread data for such CDS contracts were available and of sufficient quality. For G-SIBs that use the structural subordination approach, we use the CDS referring to the holding company, which also issues the TLAC-eligible bonds. For European G-SIBs that issue senior non-preferred debt, we use the corresponding CDS when it becomes available around 2018. We use data from Bloomberg, Eikon, and Markit, depending on the availability and quality of data.

The list of banks and additional accounting and financial information is reported in Table 1.⁷ The average MLR is high in the U.S. and low in the euro area (7.4% versus 2.9%). This reflects the fact that on average, LRD of U.S. banks is 1.4 times higher than LRD in the euro area, while MC is 3.8 times higher. U.K. and Swiss banks have market leverage ratios that are similar and range between those of U.S. and euro area banks. CDS spreads are on average higher in the U.S. and the euro area than in the U.K. and Switzerland.

Table A3 in Appendix A.3 provides summary statistics on stock and CDS returns. Stock returns and volatility are higher in the U.S. and the euro area, whereas CDS returns and volatility are higher in the euro area and the U.K. The cross-correlation between both return series is negative for all banks.

3 Illustration and Implications for Market-based Stress Tests

To illustrate more concretely the effect of the proposed correction, we consider how the different market-based measures of banks' capitalization changed in response to the Covid-19-induced market downturn in March 2020. We then discuss implications for market-based stress testing exercises.

⁷We calculate the LRD by scaling total assets with a bank-specific, constant scaling factor. The factor is chosen so that we can reproduce the disclosed LRD of the banks as of 2020:Q1. From this LRD, we calculate total debt by subtracting book equity. We use LRD instead of total assets to adjust for differences in the accounting standards. Note, however, that G-SIBs started only in recent years to report a consistent LRD according to the Basel III rules. We use the scaling approach to cover the entire sample period.

Table 1: Summary statistics on G-SIBs in our sample

G-SIB		LRD (\$ bln)	Total debt (\$ bln)	Total equity (\$ bln)	Book leverage ratio (%)	MC (\$ bln)	MLR (%)	CDS spread (in bp)	Annual volatility (in %)
Banco Santander	SAN	1304.9	1213.5	91.4	6.97	69.9	5.42	108.9	33.6
Bank of America	BAC	2572.9	2323.7	249.2	9.70	176.9	6.82	92.9	47.5
Barclays	BARC	1270.0	1206.4	63.6	5.13	32.5	2.63	87.7	47.1
BNP Paribas	BNP	1901.2	1805.9	95.3	5.03	59.4	3.15	74.3	37.4
Citigroup	C	2216.5	2020.5	196.0	8.88	133.1	6.02	102.8	50.2
Crédit Agricole	ACA	1467.5	1341.2	126.3	8.66	26.8	1.82	85.1	40.3
Credit Suisse	CS	1048.9	1004.0	44.9	4.33	38.5	3.67	77.8	36.7
Deutsche Bank	DB	1431.7	1372.9	58.8	4.23	28.0	1.96	98.2	39.3
Goldman Sachs	GS	1226.9	1145.5	81.4	6.65	78.0	6.39	104.5	34.8
HSBC	HSBC	2457.1	2277.0	180.1	7.32	170.7	6.97	61.4	25.3
ING	ING	1364.2	1314.0	50.2	3.78	36.7	2.87	72.5	44.6
JP Morgan Chase	JPM	2763.1	2541.3	221.8	7.99	237.1	8.42	65.6	36.8
Morgan Stanley	MS	1032.8	960.5	72.3	6.99	57.9	5.54	123.0	48.8
Société Générale	SOGN	1067.9	1010.1	57.8	5.39	27.7	2.62	90.7	42.3
Standard Chartered	STAN	792.3	740.6	51.6	6.53	41.3	5.23	80.2	35.8
UBS	UBS	984.9	932.3	52.6	5.55	57.7	6.15	71.5	36.3
UniCredit	UCG	1036.5	977.2	59.3	5.72	28.3	2.75	138.0	44.5
Wells Fargo	WFC	1843.4	1672.2	171.2	9.29	209.8	11.29	62.5	39.8
United States		1942.6	1777.3	165.3	8.25	148.8	7.41	91.9	43.0
Euro area		1367.7	1290.7	77.0	5.69	39.5	2.94	95.4	40.3
United Kingdom		1506.5	1408.0	98.4	6.33	81.5	4.94	76.4	36.1
Switzerland		1016.9	968.2	48.7	4.94	48.1	4.91	74.6	36.5

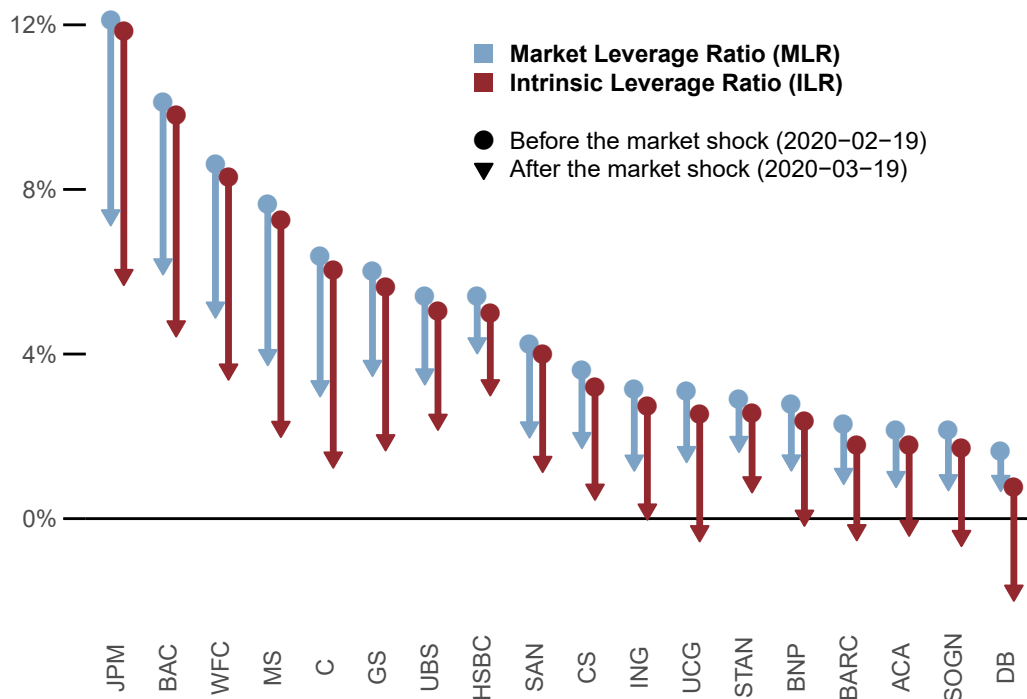
Note: This table describes our list of G-SIBs. It reports the leverage ratio denominator (LRD), total debt, total equity, and the market capitalization (MC) in USD billions; the book leverage ratio and the market leverage ratio (MLR) are presented as percentages, and the CDS spread is in basis points. All numbers are averages over the 2009–2020 sample.

3.1 Covid-19-induced Market Downturn

The global outbreak of Covid-19 in the first quarter of 2020 led to a severe and abrupt market downturn. The MSCI World index dropped by 30% between February 19 and March 19. Over the same period, the average CDS spread of the banks in our sample jumped from 44 basis points (bp) to 150 bp, increasing by 246%.

Figure 2 displays the MLR and the ILR for U.S. and European G-SIBs before the market shock (February 19) and after the market shock (March 19). The figure shows that changes in MLR and ILR were similar for banks with high MLR before the shock. For banks with low MLR, however, the difference between MLR and ILR changes was large. For some of

Figure 2: Effect of the Covid-19-induced Market Downturn on MLR and ILR



Note: This figure displays the effect of the Covid-19-induced market downturn (February 19 to March 19, 2020) on the MLR and the ILR of U.S. and European G-SIBs. The banks are ordered according to their MLRs before the market shock.

these banks, ILR was in fact negative at the trough of the market crisis, while MLR stayed positive throughout by construction (since MC cannot be negative).

Thus, if one focuses on changes in MLR, the market assessment of a bank’s asset value losses in a crisis is systematically underestimated for banks with low MLR pre-crisis. For instance, as the figure reveals, the Covid-19-induced market shock affected the MLR of JP Morgan almost seven times more than it affected that of Deutsche Bank (observe the leftmost vs. rightmost light-blue lines). The onset of the Covid-19 pandemic, however, was a global crisis, and market reactions in Europe and in the U.S. were similarly strong. Furthermore, Deutsche Bank and JP Morgan are both globally active banks and, at least with regard to investment banking, are participating in the same global markets. Against this background, the large difference in the impact is not very plausible.

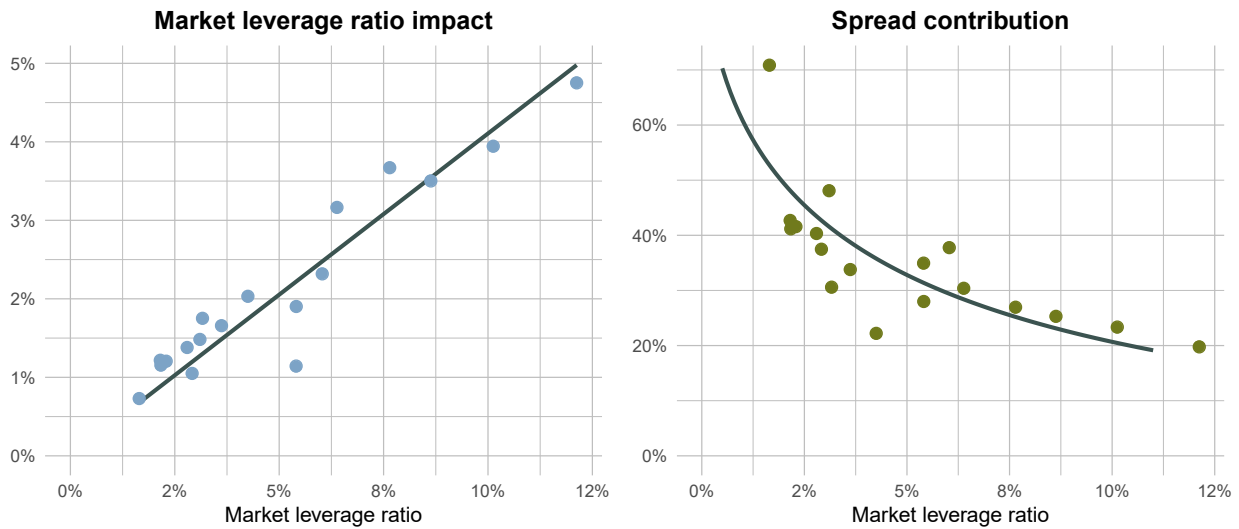
The difference between the two banks actually reflects that the MLR of Deutsche Bank was already very low before the market shock, and that MLR could not fall below zero. As a result, the maximum loss potential of Deutsche Bank inferred from changes in MLR is very limited. In fact, a large impact such as that experienced by JP Morgan in March 2020 would have been impossible for Deutsche Bank under any market shock. It would be incorrect, however, to conclude from this fact that the actual loss potential of Deutsche Bank under severely adverse scenarios is similarly limited. The ILR measure does not have this restriction to positive values, as it also takes the market-assessed impact on debt holders into account. With the ILR measure, the Covid-19-induced impact is only approximately twice as high for JP Morgan as for Deutsche Bank, which is more consistent with regulatory measures.⁸

The left panel of Figure 3 illustrates that the effect of the Covid-19-induced market downturn on MLR is directly proportional to MLR before the shock. If the MLR of a bank approaches zero, the change in MLR for this bank has to vanish, by construction and independently of the actual risks on the balance sheet of this bank. If MLRs are comparable for all banks and clearly above zero, this property is not a major limitation. If some banks have high MLRs and other banks have very low MLRs, however, as was the case in February 2020, the inference one would draw about changes in asset values based on changes in MLRs would be clearly distorted.

In such a situation, the correction to market-based capital that we propose with the IC measure becomes particularly relevant. The right panel of Figure 3 shows the spread contribution to the IC impact, i.e., the ratio of the losses absorbed by the debt holders to the total losses absorbed by debt and equity holders, versus the MLR before the shock. We observe that for banks with high MLRs (typically, U.S. banks), only a small fraction of losses is absorbed by debt holders, whereas for banks with low MLRs (typically, European banks), a substantial part of losses and in some cases even more than 50% is absorbed by debt holders. Our analysis indicates that for U.S. banks most of the loss is absorbed by shareholders themselves, and therefore their default option in the terminology of [Merton](#)

⁸As of 2020:Q1, the RWA density (RWA divided by LRD) was 45% for JP Morgan and 28% for Deutsche Bank. Therefore, a two times higher leverage ratio impact is approximately consistent with this regulatory risk density measure.

Figure 3: Dependence of the Covid-19-induced MLR impact, and spread contribution to IC impact, on MLR



Note: The left panel displays the impact of the Covid-19-induced market shock (from February 19 to March 19, 2020) on the MLR versus the MLR prior to the market shock. The sample of banks is the same as in Figure 2. The right panel shows the ratio of the spread impact to the total IC impact versus the MLR prior to the market shock. Note that this ratio can be interpreted as the moneyness of the shareholders' default option. The lines are drawn to indicate that the MLR impact is approximately proportional to MLR, and the spread contribution to the IC impact is nonlinear in MLR.

(1974) is out of the money. Conversely, for European banks, most of the loss is absorbed by debt holders, and the shareholders' default option is in the money.

Another way to look at the moneyness of the default option is through the sign of ILR in Figure 2. If market-implied IC is positive, the default option has no intrinsic value but the MC has intrinsic value, and vice versa (cf. Figure 1). At the bottom of the market downturn in March 2020, the market-implied IC was negative for several European banks according to our measure.

Negative market-implied capital is clearly a very harsh assessment of banks' resilience, and some caveats are warranted, especially when comparing these ratios with regulatory ratios. Market-based measures contain risk premia, which may account for a substantial fraction of the variation over time. Furthermore, they often react very strongly to new information and may over- or underestimate the resilience of banks, especially at times of

very high uncertainty (as was the case in March 2020). The main reason it is important to consider IC instead of just MC is not that the market-based leverage ratios of European banks would be too high without this correction. Rather, our point is that if we want to estimate the impact of a shock on the banks' assets from a regulatory perspective, using MLR would systematically distort the results by underestimating the risks for banks with a low MC.

3.2 Implications for Market-Based Stress Tests

One can view the Covid-19 shock studied above as a realized stress event. When conducting a market-based stress test, we instead assume a negative market shock—e.g., a stock market downturn of at least a certain size—and calculate predicted market-based leverage ratios after the shock. We will present an implementation of such a market-based stress test in the next section.

For such exercises, the illustration above holds two main lessons. First, from the perspective of *levels* of the leverage ratio either before or after stress, MLR may overstate the capitalization of banks, especially for banks with low MC (such as Deutsche Bank in the example above). This issue is important for measures such as SRISK that are directly based on MC, as we will discuss below.

Second, from the perspective of *changes* between an unstressed environment and a stressed one, the difference in MLR is likely to understate the market assessment of the impact of stress on asset values, again particularly so for banks with low MLR pre-stress. This insight is especially important if one wants to use changes in market-based leverage ratios as a benchmark for model-implied stress tests. Conceptually, ILR is more appropriate for this task, and as observed above, using ILR rather than MLR also can make a sizeable difference in practice.

4 Stressed Intrinsic Leverage Ratios

4.1 Definitions

In this section, we describe in detail how the concept of market-based intrinsic leverage can be integrated into the SRISK framework, which is a well-established market-based stress testing and systemic risk measurement methodology. As we discussed in the previous section, the systematic distortion in measuring market-implied IC using the MC is particularly large in a severe market downturn and for the least-capitalized banks. The purpose of SRISK is to estimate the expected capital impact, or capital shortfall, in a severe market downturn. Hence, distinguishing between MC and IC is particularly important for SRISK.

An important element in the SRISK framework is to calculate at time t for a bank i the expected MC at time $t + T$ conditional on a market decline occurring between t and $t + T$

$$MC_{i,t:t+T}^S := E_t [MC_{i,t+T} | \text{Stress}_{t:t+T}]. \quad (11)$$

We adopt the same approach for IC. To this end, we estimate the impact of the downturn not only on the MC but also on the CDS spread. We define the *stressed* IC as

$$\begin{aligned} IC_{i,t:t+T}^S &:= E_t [IC_{i,t+T} | \text{Stress}_{t:t+T}] \\ &= E_t [MC_{i,t+T} | \text{Stress}_{t:t+T}] - BD_i \cdot E_t [S_{i,t+T}^{\text{CDS}} | \text{Stress}_{t:t+T}]. \end{aligned} \quad (12)$$

If we define the long-run marginal expected shortfall of bank i as

$$LRMES_{i,t:t+T} = -E_t [MC_{i,t+T}/MC_{i,t} - 1 | \text{Stress}_{t:t+T}] = -E_t [R_{i,t:t+T} | \text{Stress}_{t:t+T}], \quad (13)$$

where $R_{i,t:t+T}$ denotes the cumulative stock return between t and $t + T$, we obtain $MC_{i,t:t+T}^S = (1 - LRMES_{i,t:t+T}) \cdot MC_{i,t}$. Similarly, we define the marginal expected increase of the firm's CDS as

$$CDSMEI_{i,t:t+T} = E_t [S_{i,t+T}^{\text{CDS}}/S_{i,t}^{\text{CDS}} - 1 | \text{Stress}_{t:t+T}] = E_t [Y_{i,t:t+T} | \text{Stress}_{t:t+T}], \quad (14)$$

where $Y_{i,t:t+T}$ denotes the cumulative CDS return between t and $t+T$. Then, we can rewrite Equation (12) as

$$IC_{i,t:t+T}^S = (1 - LRMES_{i,t:t+T}) \cdot MC_{i,t} - BD_i \cdot (1 + CDSMEI_{i,t:t+T}) \cdot S_{i,t}^{CDS}. \quad (15)$$

Analogously to Equation (9), we define the *stressed* ILR and the *stressed* MLR as

$$ILR_{i,t:t+T}^S = \frac{IC_{i,t:t+T}^S}{LRD_i} \quad \text{and} \quad MLR_{i,t:t+T}^S = \frac{MC_{i,t:t+T}^S}{LRD_i}. \quad (16)$$

We will also analyze the estimated impact of our stress simulation on these market-based leverage ratios. For a given bank i at time t , the estimated stress impacts on ILR and MLR are defined as

$$\Delta_{i,t:t+T}^{ILR} := ILR_{i,t} - ILR_{i,t:t+T}^S \quad \text{and} \quad \Delta_{i,t:t+T}^{MLR} := MLR_{i,t} - MLR_{i,t:t+T}^S. \quad (17)$$

In Section 5, we will examine the impacts on the market-based capital ratios, ICR and MCR defined in Equation (10). Therefore, we also introduce the definitions

$$\Delta_{i,t:t+T}^{ICR} := ICR_{i,t} - ICR_{i,t:t+T}^S \quad \text{and} \quad \Delta_{i,t:t+T}^{MCR} := MCR_{i,t} - MCR_{i,t:t+T}^S, \quad (18)$$

where $ICR_{i,t:t+T}^S$ and $MCR_{i,t:t+T}^S$ are defined as in Equation (16) with RWA_i instead of LRD_i in the denominator.

4.2 Measuring Stressed ILR

In this section, we describe the estimation of the long-run marginal expected shortfall of the firm's return ($LRMES_{i,t:t+T}$) and the marginal expected increase of the firm's CDS spread ($CDSMEI_{i,t:t+T}$) in a severe market downturn ("Stress" in the equations above).

As we are interested in the joint dynamics of the equity and CDS markets, we model the behavior of the four series $r_{t+1} = \{r_{M,t+1}, y_{B,t+1}, r_{i,t+1}, y_{i,t+1}\}$, where $r_{i,t+1}$ and $y_{i,t+1}$ denote the daily stock log-return and the CDS log-return of bank i in the period from t to $t+1$, and $r_{M,t+1}$ and $y_{B,t+1}$ denote the daily stock market (MSCI World index) log-return and

the CDS log-return of the bank panel on the same day.⁹ Our objective is to model the dependence of the return of a bank's stock and CDS spread on their drivers. To this end, we design a factor model with time-varying parameters, time-varying volatility, and a general, non-normal dependence structure for the innovations. We assume the following recursive multifactor model with time-varying parameters, after having demeaned all return series:

$$r_{M,t+1} = \varepsilon_{M,t+1}, \quad (19)$$

$$y_{B,t+1} = \beta_{B,t+1}^M r_{M,t+1} + \varepsilon_{B,t+1}, \quad (20)$$

$$r_{i,t+1} = \beta_{ir,t+1}^M r_{M,t+1} + \beta_{ir,t+1}^B y_{B,t+1} + \varepsilon_{ir,t+1}, \quad (21)$$

$$y_{i,t+1} = \beta_{iy,t+1}^M r_{M,t+1} + \beta_{iy,t+1}^B y_{B,t+1} + \beta_{iy,t+1}^r r_{i,t+1} + \varepsilon_{iy,t+1}. \quad (22)$$

In this recursive model, the world stock market return can affect the aggregate bank CDS return. Both of these aggregate returns can affect the individual bank's stock and CDS returns. We implicitly assume an instantaneous relation between stock returns and CDS returns, which is allowed to strengthen at times of financial distress, as suggested in [Merton \(1974\)](#). This model can be interpreted as a generalized market model under market efficiency, based on the Dynamic Conditional Beta approach of [Engle \(2012\)](#) and [Bali et al. \(2017\)](#). As the error term $\varepsilon_{t+1} = \{\varepsilon_{M,t+1}, \varepsilon_{B,t+1}, \varepsilon_{ir,t+1}, \varepsilon_{iy,t+1}\}$ may exhibit nonlinear dependence both in the time series (heteroskedasticity) and in the cross section (tail dependence), we allow ε_{t+1} to have univariate GARCH dynamics with skewed t innovations. Tail dependence is captured through a t copula. Details of the econometric methodology are provided in [Appendix A.4](#).

Armed with this model, we predict the long-run marginal expected shortfall ($LRMES_{i,t:t+T}$) and the CDS marginal expected increase ($CDSMEI_{i,t:t+T}$) using Monte-Carlo simulations.

⁹Systemic risk measures are defined using simple returns, but our econometric model is written in log-returns. The main reason for this is that working with log-returns avoids unlimited losses. Indeed, with an unbounded distribution (such as normal or t distributions), simple returns may fall below -100% , and thus the loss may exceed the wealth. With log-returns, this will not happen. Once cumulative log-returns have been computed, we convert them back into simple returns to compute capital shortfall measures.

First, we define the cumulative returns on stocks and CDS as

$$\begin{aligned} R_{i,t:t+T} &= \exp\left(\sum_{k=1}^T r_{i,t+k}\right) - 1 & \text{and} & & R_{M,t:t+T} &= \exp\left(\sum_{k=1}^T r_{M,t+k}\right) - 1, \\ Y_{i,t:t+T} &= \exp\left(\sum_{k=1}^T y_{i,t+k}\right) - 1 & \text{and} & & Y_{B,t:t+T} &= \exp\left(\sum_{k=1}^T y_{B,t+k}\right) - 1. \end{aligned}$$

Second, we define the duration and magnitude of a crisis event. We consider a world stock market decline of at least 30% in the next six months. Recently, stock markets experienced such major drawdowns in October 2008 during the subprime crisis and in March 2020 during the Covid-19 pandemic. This threshold for a systemic event is less severe than the conventional 40% market decline considered by [Brownlees and Engle \(2012\)](#) and [Engle et al. \(2015\)](#). The reason is twofold: first, in our model, the aggregate stock market and CDS returns both affect and usually reinforce the impact on the bank's individual stock return in Equation (21). Second, as tail dependence is allowed between innovation processes, joint crashes in stock and CDS markets are more likely than with Gaussian innovations. Therefore, the overall impact on banks' individual stock prices ($LRMES_{i,t:t+T}$) is usually larger than in a model with only the stock market. Our model also determines the effect of a stock market decline on the CDS market and, ultimately, on the bank's CDS spread, which gives us predictions of $CDSMEI_{i,t:t+T}$.

To ensure consistency of aggregate predictions and reduce the computational burden, we simulate the model in two blocks. First, we run $J_1 = 100,000$ draws of the aggregate model, which includes the aggregate stock and CDS returns, and identify a stress event in a given simulated trajectory j_1 when $R_{M,t:t+T}^{(j_1)} \leq -30\%$. We denote by $N_{S,t} = \sum_{j_1=1}^{J_1} \mathcal{I}(R_{M,t:t+T}^{(j_1)} \leq -30\%)$ the number of stress events in the simulations on date t . Then for each draw corresponding to a stress event, we simulate $J_2 = 1,000$ draws of the bank model, which corresponds to the stock and CDS returns of bank i , and compute LRMES and CDSMEI conditional on the stock market shock, with

$$LRMES_{i,t:t+T} = -\frac{1}{N_{S,t}J_2} \sum_{j_1=1}^{J_1} \sum_{j_2=1}^{J_2} R_{i,t:t+T}^{(j_1,j_2)} \times \mathcal{I}(R_{M,t:t+T}^{(j_1)} \leq -30\%), \quad (23)$$

where the indicator function $\mathcal{I}(x)$ equals 1 if x is true and 0 otherwise. Similarly, CDSMEI is obtained by

$$CDSMEI_{i,t:t+T} = \frac{1}{N_{S,t}J_2} \sum_{j_1=1}^{J_1} \sum_{j_2=1}^{J_2} Y_{i,t:t+T}^{(j_1,j_2)} \times \mathcal{I}(R_{M,t:t+T}^{(j_1)} \leq -30\%). \quad (24)$$

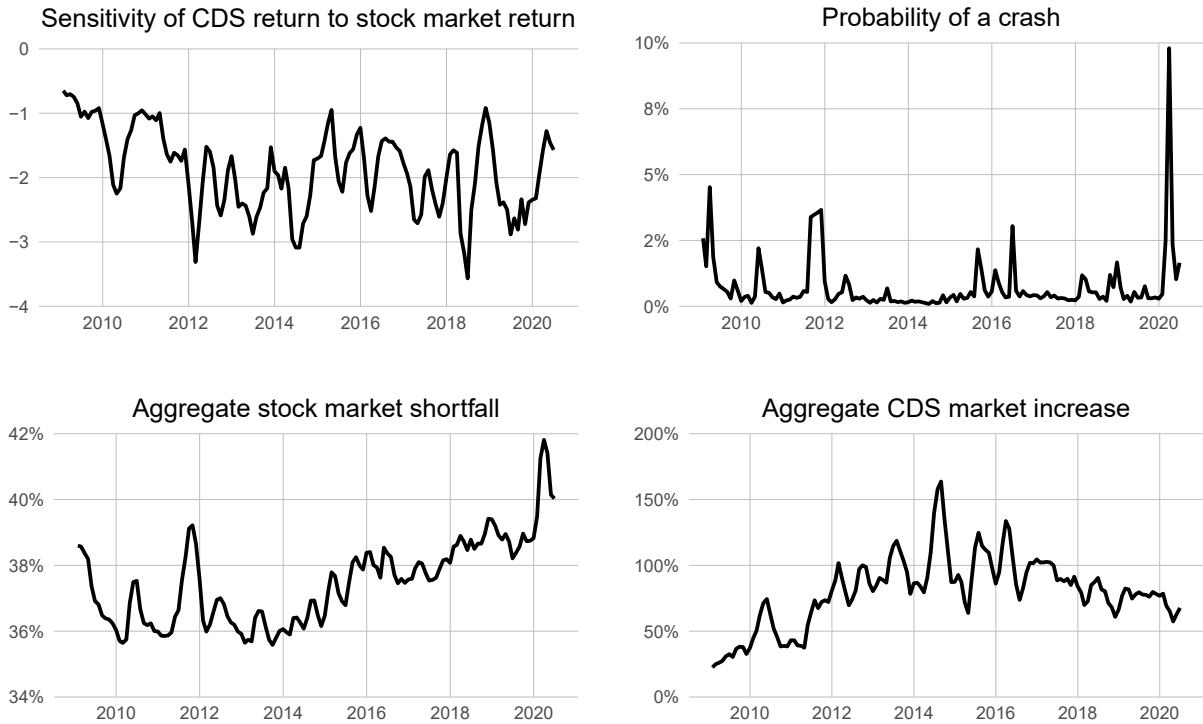
This approach provides accurate estimates of the true expectation, as the number of simulated trajectories is large. A description of the simulation process is provided in Appendix A.4. To deal with the possible time variability of (some of) the model parameters, we estimate the model over a rolling window, moving forward as soon as a new observation is made available. Specifically, we start in January 2009, using five years of data (from January 2004 to December 2008). Then, we use one more month for the next month, using an expanding window until December 2013. From January 2014 onward, we use ten years of data for the rolling-window estimation.

4.3 Temporal Evolution of Aggregate Measures

Figure 4 presents the temporal evolution of estimated model parameters and statistical measures in our aggregate market model. Panel A reports the temporal evolution of the sensitivity of the market CDS return to the market stock return ($\beta_{B,t+1}^M$). This parameter plays an important role because it measures how the CDS market is affected by a stock market decline. The contagion of the CDS market also impacts individual CDS spreads and therefore the potential loss of banks' debt holders. As the model is re-estimated monthly using new data, this parameter is updated monthly. It is close to -1 at the start of the sample and then ranges between -3 and -1 until the end of the sample. In the beginning of 2020, the sensitivity is equal to -1.4 ; thus, a -40% stock market decline is expected to increase the aggregate CDS spread by approximately 60% .

Panel B reports the probability of a world stock market crash obtained using our simulations. It is computed as the number of draws identified as crashes (with cumulative stock market returns below -30% over the next six-month period). High crash probabilities correspond to major drawdowns during the period: the probability was still high (above 2%) in 2009 after the subprime crisis; it reached 3.5% in the middle of 2011 at the start of the

Figure 4: Temporal evolution of aggregate measures



Note: This figure displays the sensitivity of the aggregate CDS spread return to the stock market return ($\beta_{B,t+1}^M$), the probability of a crash ($N_{S,t}/J_1$), the aggregate stock market shortfall ($E_t[R_{M,t:t+T} | \text{Stress}_{t:t+T}]$), and the aggregate CDS market increase ($E_t[Y_{B,t:t+T} | \text{Stress}_{t:t+T}]$), in case of a stock market crash. The sample covers the period from January 2009 to June 2020 at a monthly frequency.

European sovereign debt crisis; it increased again at the end of 2015 at the start of the normalization of the Federal Reserve policy; finally, it jumped up to 10% in March 2020, with the market decline driven by the Covid-19 crisis.

Panel C presents the evolution of the aggregate stock market shortfall, computed as the expected stock market decline when the fall is at least -30% . The simulated average market crash magnitude ranged between 36% and 42%. It was usually low until 2014, with the exception of the episode of the sovereign debt crisis, and then it steadily increased, with a maximum in March 2020. This evidence suggests that a crisis was likely to be more severe in 2020 than in 2012–2015. On average over the sample, the simulated expected stock market crash magnitude is equal to 38%.

Panel D reports the evolution of the average CDS market increase when a world stock market crash occurs. The CDS market became more reactive to stock market crashes over time until 2014, following the downward trend in the $\beta_{B,t+1}^M$ parameter. The highest CDS return was equal to 183% in July 2014. It should be noted that high CDS returns are usually associated with low levels of the CDS spread.

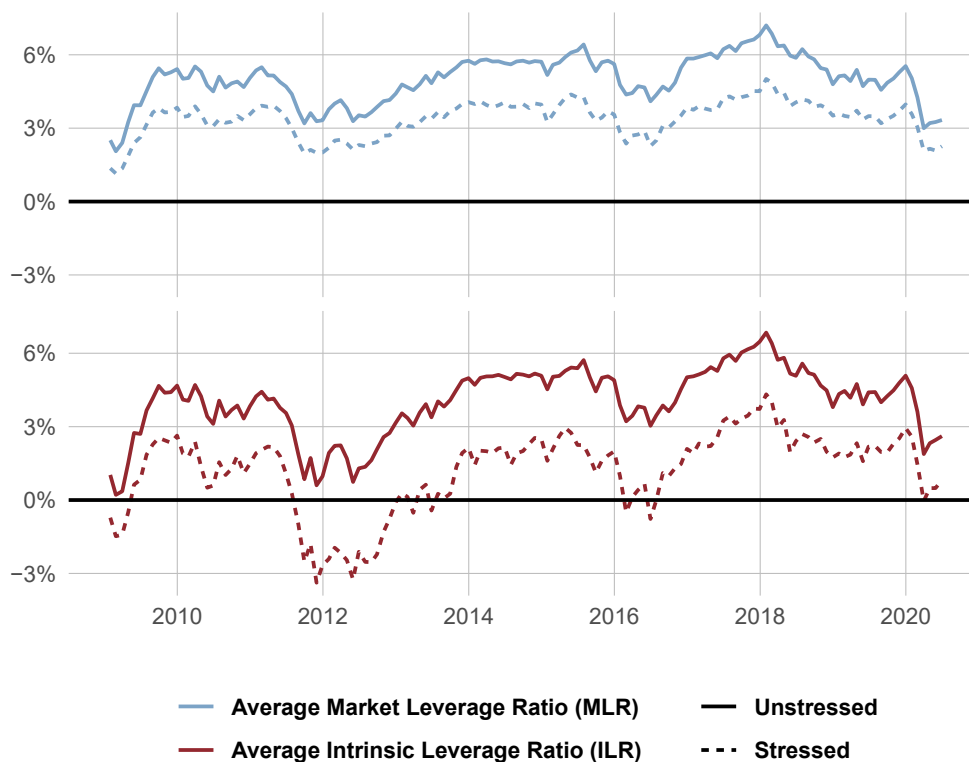
4.4 Temporal Evolution of Stressed Leverage Ratios

Sample Average. The top panel of Figure 5 displays the temporal evolution of MLR, averaged across all banks in our sample. The solid line shows the unstressed (actual) MLR defined in Equation (9), and the dashed line shows the stressed MLR defined in Equation (16). The unstressed MLR is close to 5% on average over the sample period, with particularly low values in the beginning of the sample (the aftermath of the subprime crisis) and at the end of the sample (the Covid-19 market crash). The sample average of the stressed MLR is equal to 3.3%, 1.7 pp below the actual level. Note that the gap between the dashed and solid lines—the implied stress impact—narrows when the solid line is at a lower level to begin with. This is consistent with our earlier discussion and reflects the zero lower bound of MLR, given the shareholders’ default option.

The bottom panel similarly presents the temporal evolution of the average unstressed and stressed ILR. In contrast to MLR, movements in ILR take the fair-value changes of the banks’ debt instruments into account. Averaged over the sample period, the unstressed ILR (the solid red line) is at 3.9% and the stressed ILR (the dashed red line) is at 1.1%, 2.8 pp below the unstressed level. This implies that in addition to the 1.7 pp loss by shareholders, which we mentioned above, an additional loss of 1.1 pp is incurred by debt holders under our simulated market stress. Note that the gap between the solid and dashed lines varies over time but does not appear systematically related to the level of the solid line, unlike in the top panel.

In our sample, there were a few episodes where the average stressed ILR measure turned negative: in 2009 (the aftermath of the subprime crisis), in 2011–2012 (the sovereign debt crisis), and in 2016. Note that for these periods we simulate severe market stress after the

Figure 5: Average Market Leverage Ratio and Intrinsic Leverage Ratio



Note: This figure displays the (unweighted) average of MLR and ILR across banks in our sample. The sample covers the period from January 2009 to June 2020 at a monthly frequency.

market has already suffered losses. The actual ILR never turned negative over this period, though it came close in 2009 when stock prices were low and CDS spreads were high.

Differences Across Jurisdictions. Figures 6 and 7 display the time series of average leverage ratios across banks in the U.S., the euro area, the U.K., and Switzerland. Figure 6 reveals a stark contrast between the U.S. and the euro area. The average MLR in the U.S. is relatively high (7.4% on average) and falls by several pp in our simulated stress scenario. The average MLR in the euro area is relatively low (2.9% on average) but declines only by approximately 1 pp under stress.

The average stressed ILR of U.S. banks remains positive most of the time, with an average equal to 2.5%. The average stressed ILR for euro area banks reaches much lower levels (-0.6% on average, with particularly low values in 2011–2014), for two reasons. First,

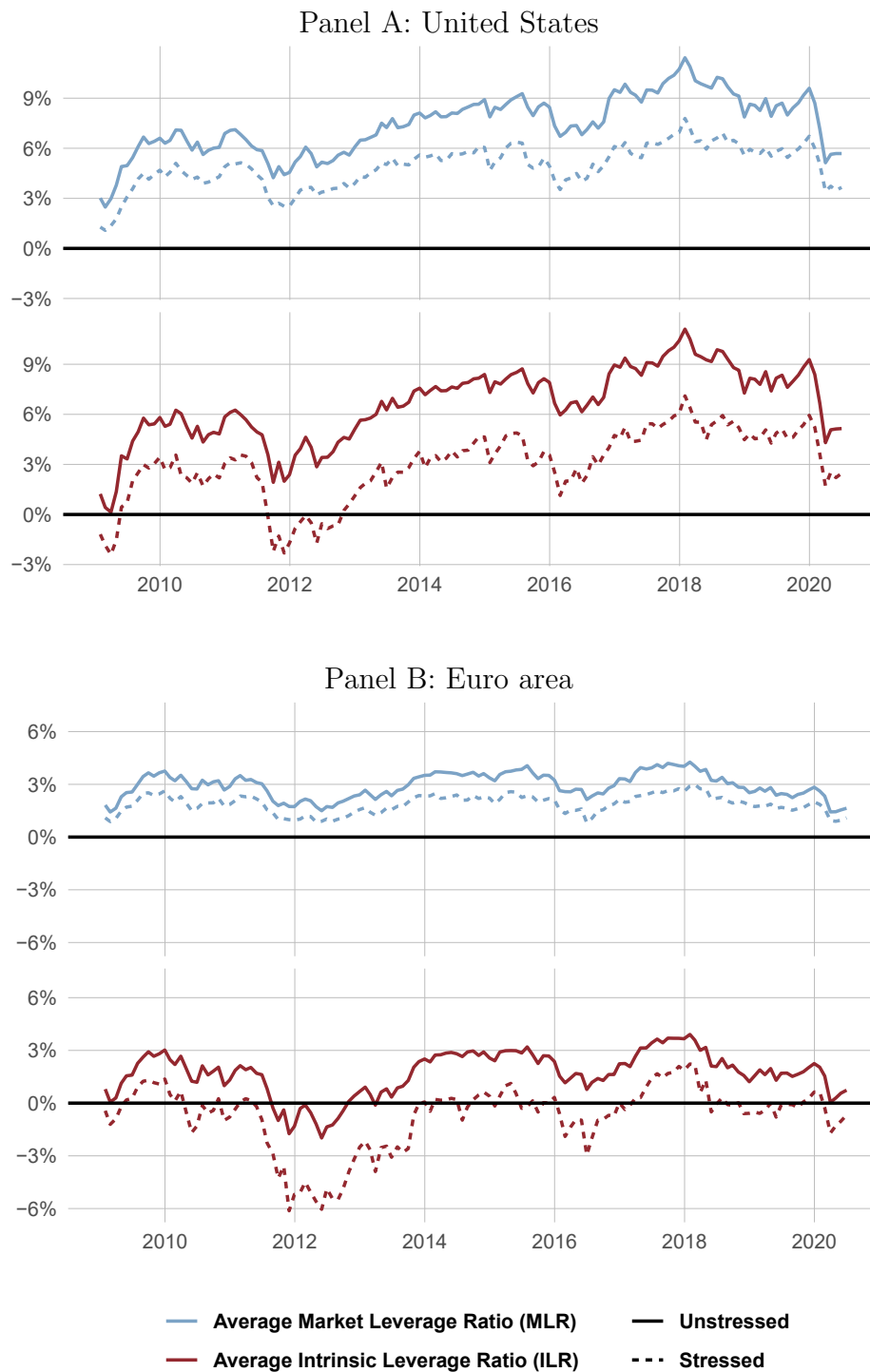
the unstressed ILR level is already quite low for these banks. Second, the impact from the stress scenario is also quite significant, as the loss contribution from debt instruments is important for these banks.

As Figure 7 reveals, the market-implied leverage ratios of U.K. and Swiss banks evolved quite similarly to each other, at levels between those of U.S. and euro area banks. The average MLR is equal to 4.9% in both countries. The average stressed ILR turned negative during the European crisis for Swiss banks and during the Brexit campaign for U.K. banks, but remained in the positive territory the rest of the time, including the spring of 2020.

Figure 8 shows the evolution of the average MLR impact (i.e., taking into account only the equity price shock) and the total ILR impact, with the difference between the two series showing the contribution of the loss on debt. The figure shows that the equity contribution is high in the U.S. and clearly dominates the debt contribution, except around 2012 when the two were approximately equal. The opposite holds in the euro area, and the figure clearly illustrates that one could substantially misestimate the relative possible impact of a market shock on the leverage ratio of U.S. versus European banks if only the MLR impact is considered. In the U.K. and Switzerland, the equity impact only marginally dominates the debt impact, and the impacts for banks in these countries again are between those for U.S. and euro area banks. Overall, the ILR impact ranges between 1% and 5% and therefore often exceeds regulatory capital buffers, which range between 0.5% and 2% in most jurisdictions.

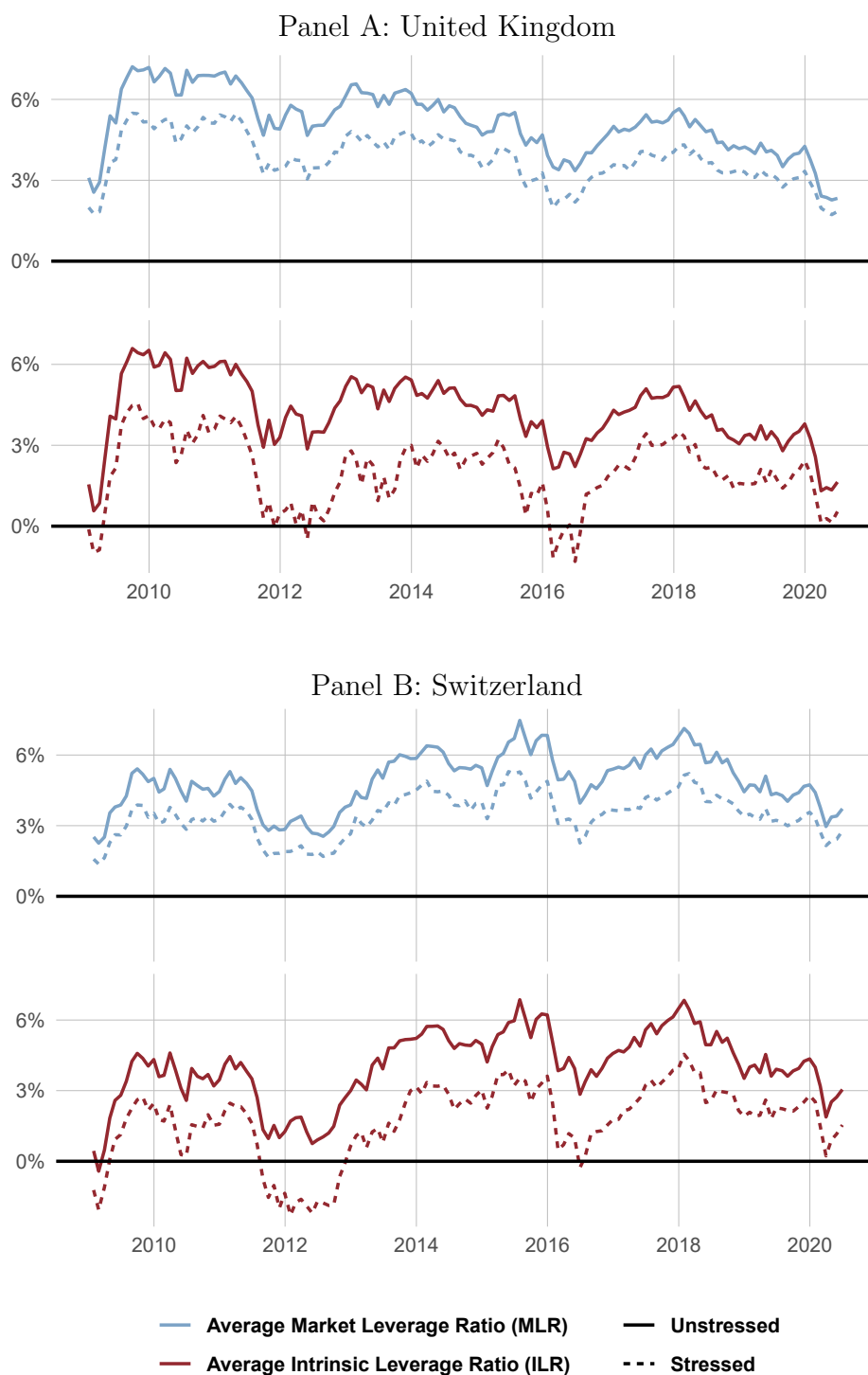
Table A6 in Appendix A.5 confirms the summary results by jurisdiction above, and further reports averages by bank over the sample period. At the bank level, there is even more heterogeneity in terms of the average relative importance of the equity and spread impacts. For instance, for Cr dit Agricole the equity impact on average only accounts for 30% of the total ILR stress impact, while for Wells Fargo the corresponding share is 83%.

Figure 6: Average Market Leverage Ratio and Intrinsic Leverage Ratio



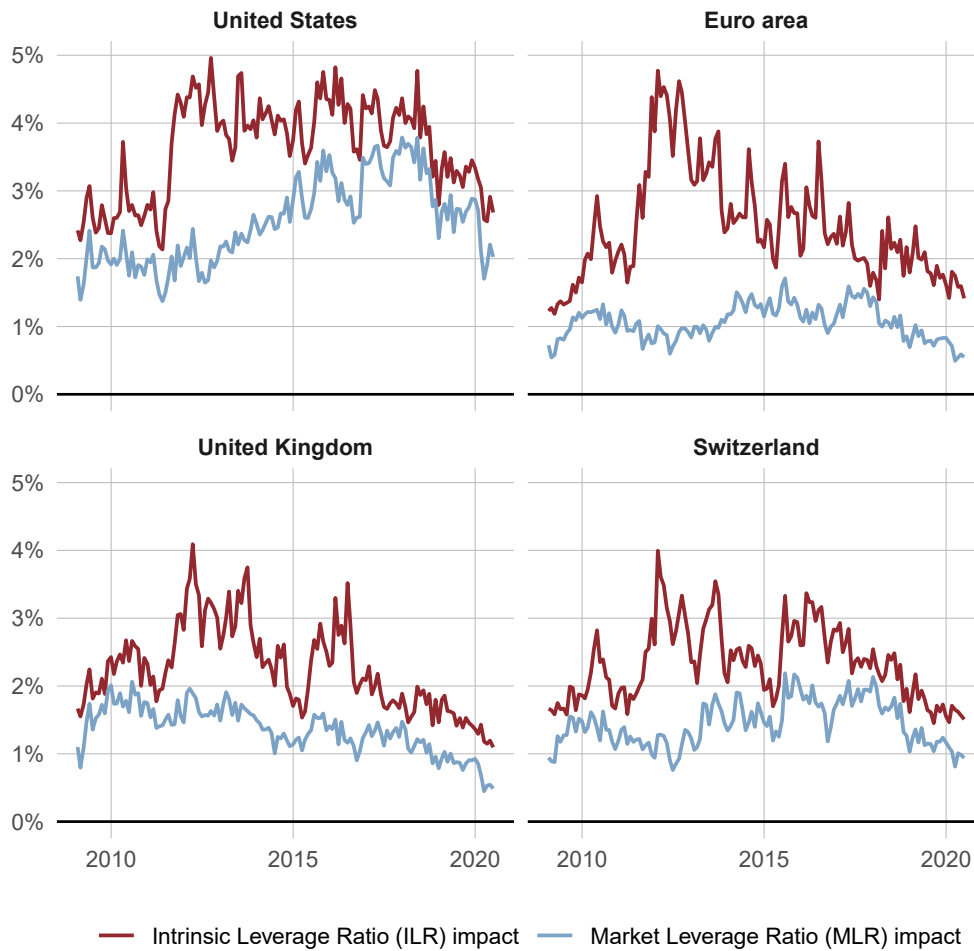
Note: This figure displays the (unweighted) average of MLR and ILR for all banks in a given region in our sample. The sample covers the period from January 2009 to June 2020 at a monthly frequency.

Figure 7: Average Market Leverage Ratio and Intrinsic Leverage Ratio



Note: This figure displays the (unweighted) average of MLR and ILR for all banks in a given region in our sample. The sample covers the period from January 2009 to June 2020 at a monthly frequency.

Figure 8: Time series of the intrinsic and market leverage ratio impacts, aggregated by jurisdiction.



Note: This figure displays the (unweighted) average of the simulated stress impact on the MLR and the ILR for all banks in a given region in our sample. The stress impact on MLR is defined as the difference between the actual (unstressed) MLR and the simulated stressed MLR. The stress impact on ILR is defined analogously. The sample covers the period from January 2009 to June 2020 at a monthly frequency.

4.5 Defining a Capital Shortfall Measure

In this section, we define a capital shortfall measure based on IC and compare the definition of this new measure to the original SRISK measure introduced by [Brownlees and Engle \(2017\)](#), which is based on market capitalization.

We define our IC-based shortfall measure for a bank i at time t as

$$SRISK_{i,t:t+T}^{IC} = (E_t[\theta LRD_i - IC_{i,t+T} \mid \text{Stress}_{t:t+T}])^+, \quad (25)$$

where the expression $(x)^+$ equals x if $x > 0$ and 0 otherwise. A shortfall arises in this measure if IC in a stress scenario, as estimated with our econometric model (the second term), declines below the minimum capital requirement (the first term). The minimum capital requirement is based on the Basel III LRD with $\theta = 3\%$ for all banks, which corresponds to the minimum leverage ratio requirement in the Basel III capital framework.

Our IC-based definition of SRISK is conceptually similar to the original SRISK. The definition differs, however, not only with respect to the estimated capital in a stress scenario, which is MC-based in the original SRISK, but also with respect to the required minimum capital in a stress scenario. The original SRISK for a bank i at time t is defined as

$$SRISK_{i,t:t+T}^{\text{Original}} = (E_t[\theta_i \hat{A}_{i,t+T} - MC_{i,t+T} \mid \text{Stress}_{t:t+T}])^+, \quad (26)$$

where $\hat{A}_{i,t} = BD_i + MC_{i,t}$ denotes the so-called quasi-market value of assets. Because of differences in accounting standards, the threshold in the original SRISK measure depends on the bank: θ_i is 8% for U.S. banks and 5.5% for European banks. This correction is very simple compared to the detailed, exposure-specific accounting corrections in the Basel III leverage ratio framework.¹⁰ Furthermore, LRD takes into account off-balance-sheet exposures, which is not the case in the original SRISK measure. [Acharya et al. \(2021\)](#) have also pointed out that the risks of off-balance-sheet exposures, particularly undrawn credit lines, are not captured in the original SRISK measure and proposed another method to incorporate them.

In the original SRISK measure, the estimated available capital in a stress situation is higher, which reduces the capital shortfall, but the capital requirements are also higher, which increases the shortfall. To disentangle these two effects, we introduce a shortfall measure that is MC-based, similar to the original SRISK, but uses the same Basel III leverage ratio

¹⁰Using this simplified correction can lead to distorted results for some firms. For example, Credit Suisse is a European G-SIB but applies the U.S. accounting standards.

minimum, as in our definition

$$SRISK_{i,t:t+T}^{MC} = (E_t[\theta LRD_i - MC_{i,t+T} \mid \text{Stress}_{t:t+T}])^+. \quad (27)$$

Figure 9 shows the evolution of these three different shortfall measures, aggregated by jurisdiction. The shortfall obtained with the original definition of SRISK (the dashed yellow line) declines substantially if we change the required capital from the original definition to the Basel III leverage ratio requirement, as done in $SRISK^{MC}$ (the blue line). The reduction is particularly high for U.S. banks, for which the aggregate shortfall drops to zero during quiet market periods.

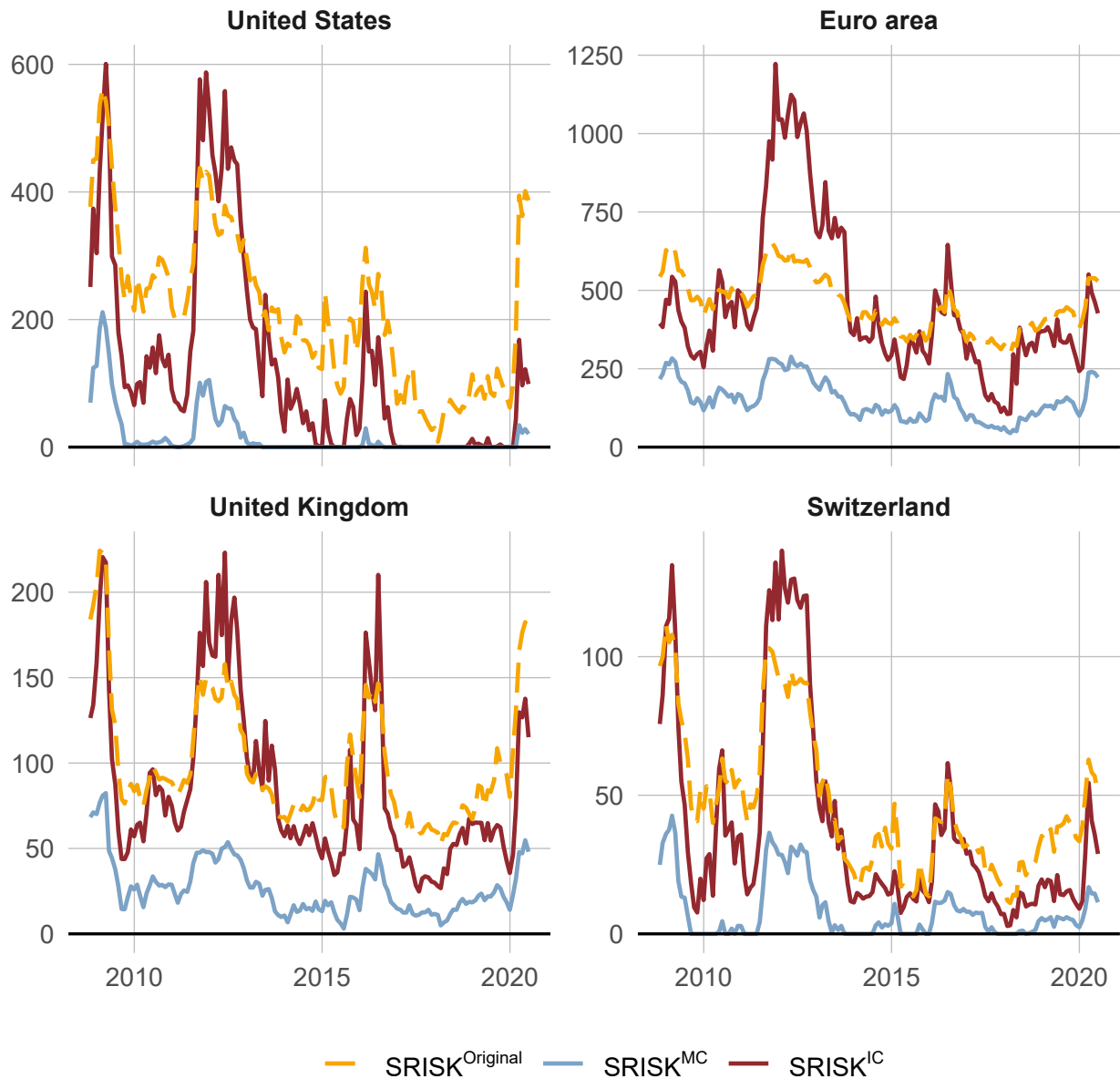
If we also change the definition of capital as done in $SRISK^{IC}$ (the red line), the shortfall increases again and overall reaches a level similar to that of the original SRISK. The capital shortfall in our new measure is, however, more volatile, implying a higher shortfall during periods of stress and a lower shortfall during calm periods. The reason is that our measure reflects the full risk of the banks' assets, whereas the original SRISK only reflects the equity risk. Differences between the two shortfall measures were particularly large for the euro area in 2012–2013 during the sovereign debt crisis, when $SRISK^{IC}$ was much higher than $SRISK^{\text{Original}}$.

To evaluate the impact of the change in definition on the relationship between the various SRISK measures, we compute Kendall's tau and Spearman's rho correlations for banks between the $SRISK^{IC}$ and $SRISK^{\text{Original}}$ measures for a given month. Figure A3 in Appendix A.6 displays the temporal evolution of these rank correlations. The declines in the correlations during the market turbulence in 2016 and during the Covid-19 market stress in 2020 suggests that crisis episodes have a significant impact on the relationship between the SRISK measures.¹¹ During such periods, European banks such as Deutsche Bank, UniCredit, and Credit Suisse had higher rankings according to the $SRISK^{IC}$ measure than according to the $SRISK^{\text{Original}}$ measure (cf. Figure A4 in Appendix A.6).

Our measure has a further advantage of being less sensitive to the assumed minimum required capital. We have also calculated the results with a risk-weighted minimum require-

¹¹The sample average of Kendall's tau equals 69% and that of Spearman's rho equals 83% for correlations between $SRISK^{IC}$ and $SRISK^{\text{Original}}$.

Figure 9: Time series of the three different capital shortfall measures



Note: This figure displays the time series of the three different capital shortfall measures defined in Equations (25), (26) and (27) in \$ billions, aggregated by jurisdiction.

ment (8% of RWA) and obtained quite similar results. We could, in principle, also use a threshold of 0%, which would make our measure completely independent of the definition of minimum capital requirements. In this case, however, we would have to compensate this

lower capital requirement with a more severe stress scenario. Otherwise, the capital shortfalls would be based on a lower resilience target for the banking sector.

5 Benchmarking to Regulatory Exposure Measures

In this section, we compare the estimated impacts on the two market-based capital measures (MC and IC) to two accounting-based regulatory exposure measures (LRD, used throughout the above analysis, and RWA). By design, IC should capture the full risk of banks' assets, whereas MC captures only part of this risk. Depending on the moneyness of the shareholders' default option, debt holders are also exposed to asset risk and will absorb part of the losses.

The regulatory exposure measures, LRD and RWA, are also designed to capture the full risk of banks' assets and, similarly to IC, do not depend on the shareholders' default option. Therefore, we expect the estimated impacts on the IC measure to be roughly proportional to LRD or, even more so, to RWA, assuming that regulatory risk weights are consistent with the markets' assessment of banks' risks. For MC, however, such proportionality could be distorted, as the impacts depend on the moneyness of the shareholders' default option.

We now turn to our cross-section of banks and study how the four different capital ratio impacts defined in Equations (17) and (18) are distributed across banks. To disentangle the overall magnitude of losses, which depends on the prevailing stress and volatility in financial markets, from the distribution of losses across banks, we decompose the capital ratio impacts as

$$\Delta_{i,t:t+T}^{\mu} = \lambda_{t:t+T}^{\mu} \cdot (1 + x_{i,t:t+T}^{\mu}), \quad (28)$$

where μ stands for any of the leverage and capital ratios (ILR, MLR, ICR, or MCR), $\lambda_{t:t+T}^{\mu}$ is the average capital ratio impact over all banks in our sample at time t , and $x_{i,t:t+T}^{\mu}$ is the deviation from this average impact for bank i . If losses estimated under the market-based measure in the numerator are exactly proportional to the regulatory exposure measure in the denominator, $x_{i,t:t+T}^{\mu}$ would be zero for all banks.

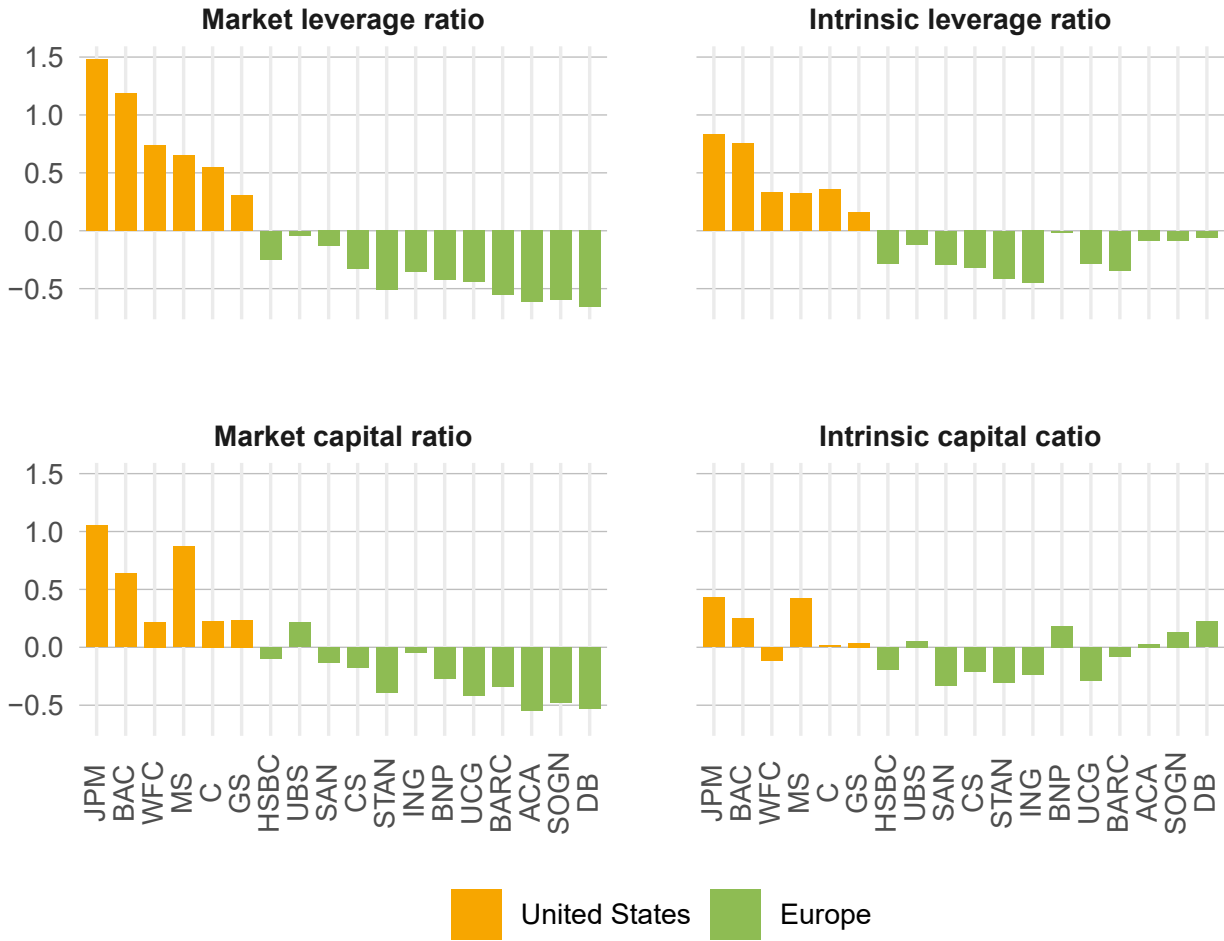
Figure 10 displays the average $x_{i,t:t+T}$ by bank over the recent period from 2019:Q1 to 2020:Q2, which captures significant market volatility.¹² The top left panel shows that for MLR, the distribution of the impact is inhomogeneous across banks. As the banks are shown in the order of decreasing MLR, the figure reveals that banks with high MLR also experience a high impact and banks with low MLR also experience a low impact (consistently with our earlier discussion). This result suggests that loss estimates based on MC, as used in the SRISK measure, are very different from what we would expect based on the regulatory leverage ratio exposure measure.

The bottom left panel shows that the impact distribution of MCR is more homogeneous. However, even if we correct for risk in this way, the impact is still above average for all U.S. banks and below average for almost all European banks. This regional difference in the capital ratio impacts is substantially reduced if we consider ILR (the top right panel) and especially ICR (the bottom right panel). The standard deviations of time-averaged $x_{i,t:t+T}$, corresponding to the four panels in the figure, equal 64% (MLR), 46% (MCR), 37% (ILR) and 23% (ICR). The figure thus shows that using IC instead of MC, i.e., taking into account the contribution from debt instruments, results in capital impacts becoming more uniformly distributed. Therefore, loss estimates using the IC measure are more aligned with the regulatory exposure measures. As regulatory stress tests are based on regulatory exposure measures, i.e., stress loss estimates are typically based on the same risk parameters that determine RWA, the IC impacts would plausibly be better aligned with regulatory stress tests.

We can also use the $x_{i,t:t+T}^\mu$ metric from above to evaluate alternative calibrations for the sensitivity of market-implied capital to CDS changes. As explained in Section 2.1, we have so far calibrated the CDS sensitivity of IC based on the average amount and maturity of bail-in debt. We now analyze how the standard deviations of the distributions in Figure 10 depend on the choice of this sensitivity. To this end, we generalize our definition of IC from Equation (8) and allow the importance of the spread adjustment to depend on a parameter

¹²We restrict this analysis to the recent period because in the years following the financial crisis, there was substantial variability in the way RWA were measured across banks. In December 2017, the Basel Committee finalized the Basel III post-crisis reforms with the objective of reducing such RWA variability. The full implementation of the reform is still pending, but certain mitigating measures have already been implemented.

Figure 10: Deviation from a uniform distribution for different types of market-based capital ratio impacts.



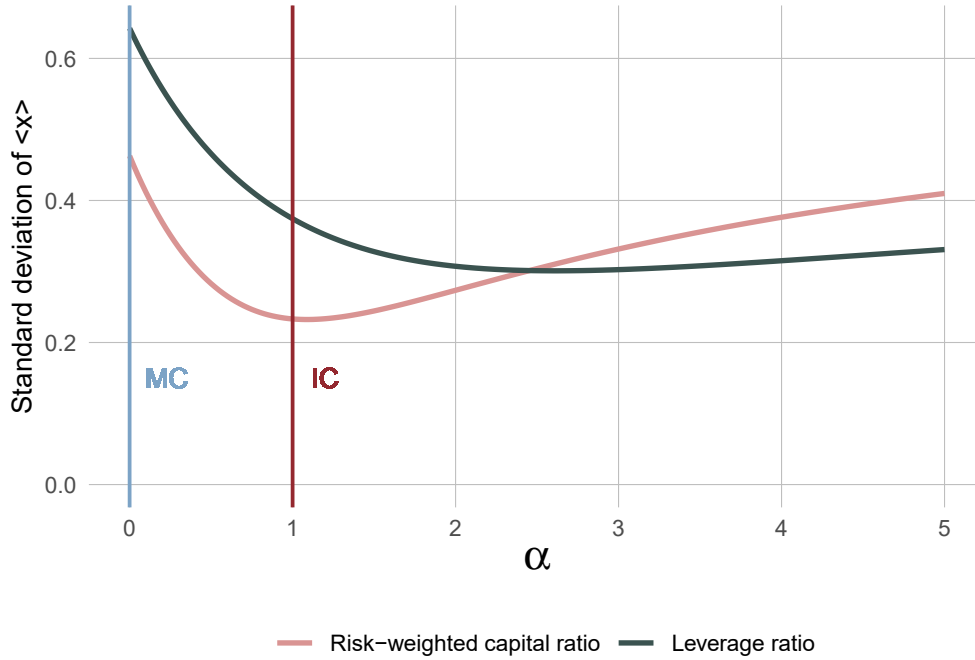
Note: This figure shows $x_{i,t:t+T}^\mu$, as defined in Equation (28), for different types of market-based capital ratio impacts, averaged over the period from 2019:Q1 to 2020:Q2. The top left (bottom right) panel shows that if capital is measured as MC (respectively, IC), the leverage ratio (the risk-weighted capital ratio) impact for JP Morgan, for example, is 150% (40%) above the average impact. The banks are shown in the order of decreasing MLR, averaged over the same period.

α :

$$IC_{i,t}(\alpha) = MC_{i,t} - \alpha \cdot BD_i \cdot S_{i,t}^{\text{CDS}, 5y}. \quad (29)$$

Note that for $\alpha = 0$ this measure equals MC, and for $\alpha = 1$ it equals our definition of IC in Equation (8).

Figure 11: α -dependence of the standard deviation



Note: This figure shows how the standard deviation of time-averaged $x_{i,t:t+T}^{\text{ILR},\alpha}$ and $x_{i,t:t+T}^{\text{ICR},\alpha}$ depends on parameter α , defined in Equation (29). The time period considered is 2019:Q1 to 2020:Q2. The standard deviation for ICR is minimized at $\alpha \approx 1$, which is consistent with our definition of IC. The value $\alpha = 0$ corresponds to MC.

In Figure 11, we illustrate how the standard deviation of time-averaged $x_{i,t:t+T}^{\text{ILR},\alpha}$ and $x_{i,t:t+T}^{\text{ICR},\alpha}$ depends on this parameter α .¹³ For the risk-weighted capital ratio impacts, the standard deviation is minimized at $\alpha = 1.1$. For the leverage ratio impacts, the standard deviation is minimized at approximately 2.6. The minimum for risk-weighted capital ratios is lower, and the region close to the minimum is much narrower than for the leverage ratios. We consider the observation that the minimum standard deviation for the risk-weighted capital ratio is close to 1 as an independent confirmation of our previous calibration based on balance sheet data. The fact that both curves have a minimum at or above 1 also indicates that, according to this benchmark, we did not overestimate the sensitivity of IC to the CDS spread, i.e., we do not overstate the correction of MC due to the expected losses from debt instruments.

¹³Variables $x_{i,t:t+T}^{\text{ILR},\alpha}$ and $x_{i,t:t+T}^{\text{ICR},\alpha}$ are defined as in Equation (28) but with the α -dependent IC measure of Equation (29). The standard deviation is calculated after time-averaging $x_{i,t:t+T}^{\mu,\alpha}$ over the period from 2019:Q1 to 2020:Q2.

6 Conclusions

In this paper, we argue that analyzing market-based measures of bank capital may lead to erroneous conclusions if the limited liability of equity holders and the resulting impact of losses on debt holders are ignored. The bias is particularly important for banks with low market capitalization (relative to their total exposures) and when conducting market-based stress tests, similar to what is done in the SRISK framework.

We introduce the concept of intrinsic capital as market capitalization corrected for the expected loss of debtholders implied by the credit spread. This correction allows the market-implied bank capital to be negative in severe market conditions. Stressed measures provide estimates of the intrinsic leverage ratio and capital ratio in a severe stock market downturn. Our estimates reveal substantial heterogeneity across banks and jurisdictions.

Our intrinsic leverage ratio measure can be calculated in real time as long as bank stock price and CDS spread series are available. We hope that this approach will prove useful to bank regulators looking for market-based complements to their standard stress tests.

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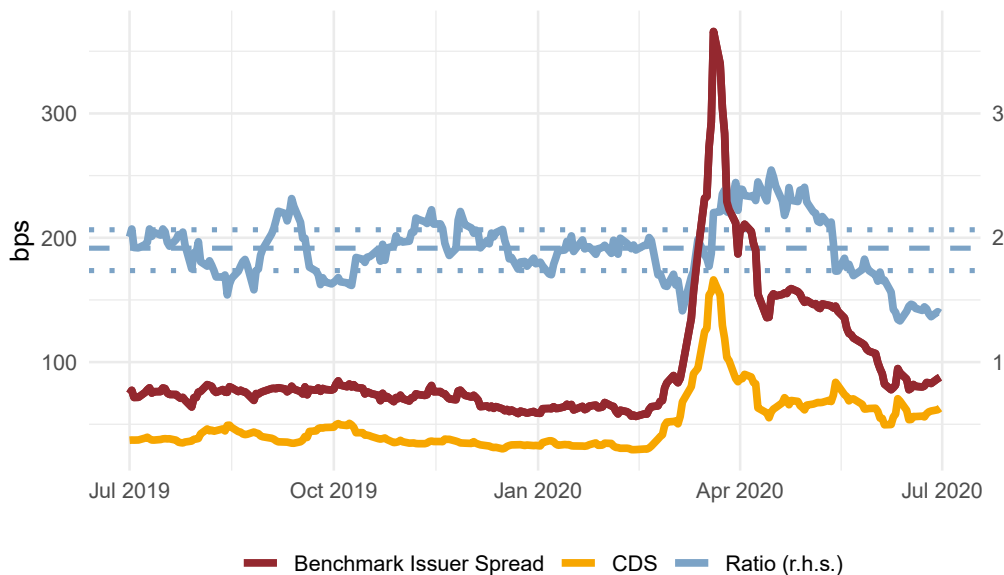
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A Appendix

A.1 Comparing Benchmark Issuer Spreads and CDS Spreads

In our econometric model, we use CDS spreads instead of issuer benchmark spreads. For a given issuer, these two market variables co-move closely. However, there is a significant level difference (or basis) between the two spreads. Figure A1 shows the benchmark issuer spread and CDS spread for JP Morgan over a time horizon of one year. We observe from this chart that the basis between the two spreads increases in a stress period (in this case, the onset of the Covid pandemic). However, the ratio stays roughly constant at approximately two; i.e., the benchmark issuer spread is always approximately twice as high as the CDS spread.

Figure A1: Comparison of benchmark issuer spread and CDS spread for JP Morgan



Note: This figure shows the benchmark issuer spread of senior holding company debt of JP Morgan with a five-year tenor and the corresponding CDS spread over the period 2019:H2-2020:H1. The benchmark issuer spread is obtained from Eikon. The figure also displays the ratio of these two spreads, the median value of this ratio (the dashed line), and the interquartile range (dotted lines).

The summary statistics for this ratio for other U.S. and European G-SIBs are shown in Table A1. For most banks, the median value is also close to two, and the interquartile range (IQR) is relatively narrow. We obtain the benchmark issuer spread data from Eikon, which calculates issuer curves for most G-SIBs. In this analysis, we consider the five-year tenor for the issuer curve of bail-in-eligible debt. However, we did not find suitable issuer curves for all banks in our sample. For UBS and Cr dit Agricole, we found a relatively liquid bail-in debt instrument with the remaining maturity of approximately five years, instead.

Figure A2 displays the ratio of the benchmark issuer spread to the CDS spread for banks in Table A1, averaged for European and U.S. banks. Note that for U.S. G-SIBs, the ratio was somewhat below two in normal times and approximately two during the Covid-19 market shock in March 2020. For European banks, the averaged ratio was approximately two during normal times but was as high as three at the peak of the stress period.

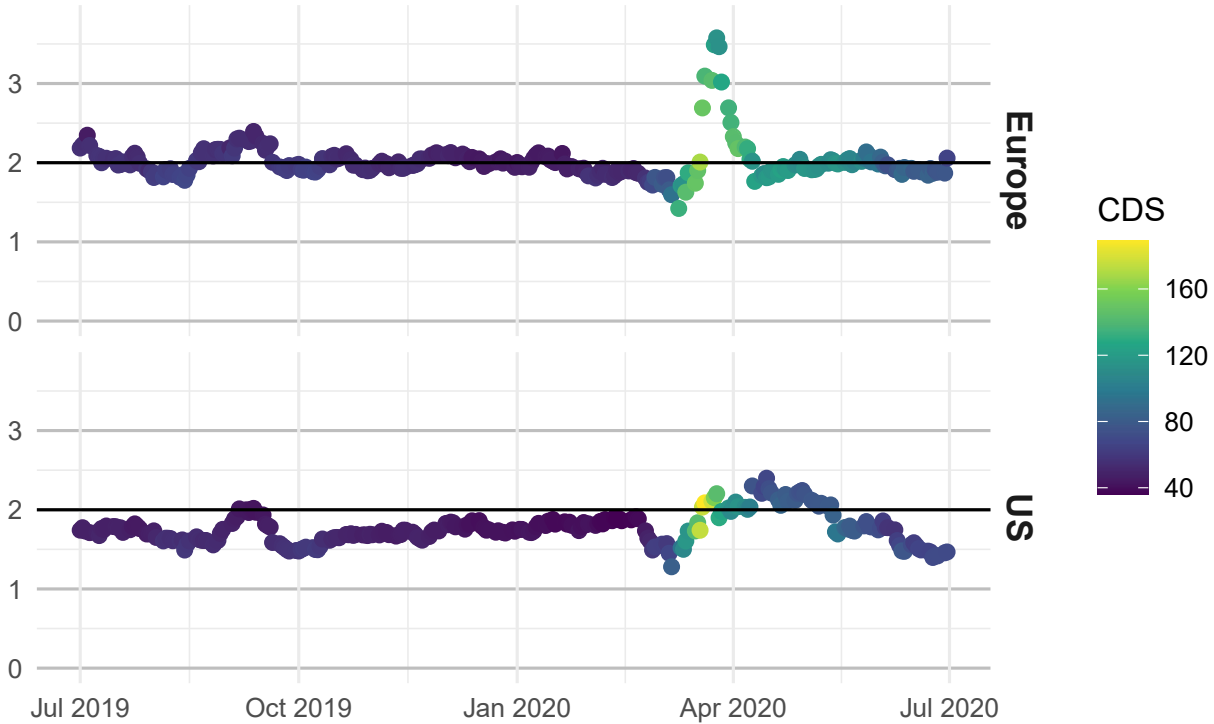
Overall, the benchmark issuer spread can be reasonably well approximated by multiplying the CDS spread by a factor of two for most banks during normal periods. For U.S. G-SIBs, the factor of two seems also to be a good approximation during stress periods. For European G-SIBs, the benchmark issuer spread can be even more than two times higher during stress periods. Because it would be difficult to collect consistent data on issuer spreads for a longer historical period, in this paper we approximate such spreads for all banks by multiplying the CDS spread by a constant factor of two.

Table A1: Ratio of benchmark issuer spread to CDS spread – Summary statistics

G-SIB	Observations	Median	IQR
Bank of America	251	2.00	0.28
Barclays	250	1.84	0.24
BNP	251	1.83	0.24
Citigroup	251	1.96	0.31
Crédit Agricole	258	2.08	0.27
Credit Suisse	252	2.08	0.24
Deutsche Bank	104	1.51	0.19
Goldman Sachs	251	1.29	0.55
HSBC	250	2.02	0.33
JP Morgan Chase	251	1.92	0.33
Morgan Stanley	251	1.55	0.19
Société Générale	251	1.91	0.23
UBS	249	2.24	0.31
Wells Fargo	252	1.91	0.22

Note: This table shows summary statistics for the ratio of the benchmark issuer spread to the corresponding CDS spread over the period 2019:H2-2020:H1. The benchmark issuer spread is obtained from Eikon for an issuer curve that corresponds to bail-in-eligible debt. The tenor for both spreads is five years. The table shows the number of observations, the median value, and the interquartile range (IQR).

Figure A2: Ratio of benchmark issuer spread to CDS spread - averaged per region



Note: This figure shows the ratio of benchmark issuer spread to CDS spread for banks in Table A1. The color scale indicates the level of the averaged CDS spread.

A.2 How Much Bail-in Debt do G-SIBs Have?

In our implementation of IC, we assume that 10% of a G-SIB's total debt is long-term unsecured debt. In this appendix, we provide some further background on this assumption and on our measurement of the book value of total debt. We base the discussion on data as of end-2020, as we found a complete disclosure of bail-in-eligible debt for all banks in our sample only for this date.¹⁴

Table A2 shows the median values of long-term unsecured debt for G-SIBs in our sample, aggregated by jurisdiction. The values are expressed as percentages of the adjusted book value of debt, defined as the LRD less the book value of equity. We use this adjusted value instead of the actual book value of debt to correct for differences in accounting standards.

We calculate long-term unsecured debt as the sum of Additional Tier 1 (AT1), Tier 2 (T2), bail-in debt (TLAC-eligible debt), and other long-term unsecured debt. We obtain the first three elements from banks' regulatory disclosures and the last element from the

¹⁴Not all jurisdictions have implemented standard disclosure requirements for TLAC yet. However, for the year 2020, we were able to find the available amount of TLAC for all banks in their reports or fixed income presentations.

Moody’s balance sheet database. While there are some regional differences, the table shows that the amount of long-term unsecured debt is at least 10% in all regions.

In our implementation of IC, we will treat long-term unsecured debt as a uniform debt category with issuer spread equal to the issuer spread of bail-in debt. In reality, AT1 and T2 capital instruments have higher issuer spreads, whereas other long-term unsecured debt has a lower issuer spread than bail-in debt. The last column shows that if we assign higher weights to capital instruments and lower weights to ineligible long-term unsecured debt, we observe that the typical weighted amount of long-term unsecured debt is approximately 10%. As we do not know the exact maturity distribution of these debt categories, there is significant uncertainty as to the appropriate weights. This is especially true for the other long-term debt (“O.LTD”) category, which could have an average maturity significantly shorter than five years. Due to this uncertainty, we do not take bank-specific or regional differences into account and use the uniform assumption of 10% long-term debt for all banks.

Table A2: Typically amounts of long-term unsecured debt

Jurisdiction	AT1	T2	Bail-in	O.LTD	Total	W.Total
United States	0.9	1.3	6.3	3.3	11.2	11.2
Euro area	0.6	0.9	2.2	9.0	12.2	8.3
United Kingdom	1.0	1.1	3.3	5.0	10.5	9.0
Switzerland	2.0	0.7	4.7	11.7	19.0	14.3
All	0.9	1.0	4.0	5.7	12.0	10.4

Note: This table shows the median values of banks’ liabilities expressed as percentages of the total book value of debt per jurisdiction as of the end of 2020. The last column (“W.Total”) shows the weighted total, where AT1, T2, bail-in debt, and other long-term debt (“O.LTD”) have the following weights: 2, 1.5, 1 and 0.4.

A.3 Stock and CDS Returns

Table A3: Summary statistics on stock and CDS returns

GSIB	Stock return			CDS return			Cross-correl. (%)
	Annual. return (%)	Annual. volatility (%)	AR(1) param. (%)	Annual. return (%)	Annual. volatility (%)	AR(1) param. (%)	
Banco Santander	-3.0	35.5	3.2	17.0	68.2	13.4	-15.6
Bank of America	15.9	48.3	-5.4	11.3	58.6	21.7	-22.9
Barclays	9.8	49.5	4.3	15.3	64.8	13.8	-14.1
BNP Paribas	9.0	39.3	2.5	27.1	77.8	6.9	-11.1
Citigroup	9.6	48.6	2.9	7.4	56.4	19.0	-21.0
Crédit Agricole	8.4	41.0	4.3	24.4	78.1	8.4	-10.8
Credit Suisse	-1.9	35.4	7.4	7.5	54.0	15.5	-12.7
Deutsche Bank	0.1	40.7	2.5	19.8	59.8	14.0	-16.5
Goldman Sachs	12.2	31.8	-8.5	4.1	54.4	18.6	-20.5
HSBC	-0.1	26.1	-3.7	16.3	64.9	8.6	-10.1
ING	10.7	44.7	4.3	12.8	63.9	5.3	-16.6
JP Morgan Chase	15.2	35.0	-13.0	9.4	55.1	18.3	-18.6
Morgan Stanley	17.2	40.3	-7.3	-2.1	51.7	14.2	-19.2
Société Générale	2.7	44.5	3.7	22.3	73.4	9.2	-10.6
Standard Chartered	0.4	33.4	0.7	22.4	79.6	-14.3	-9.7
UBS	3.2	33.8	5.1	7.1	59.0	11.1	-12.9
UniCredit	-2.9	48.2	4.3	24.6	70.7	15.7	-22.4
Wells Fargo	6.9	40.6	-12.2	9.6	52.4	24.1	-19.1
United States	12.8	40.8	-7.2	6.6	54.7	19.3	-20.2
Euro area	3.6	42.0	3.5	21.1	70.3	10.4	-14.8
United Kingdom	3.4	36.3	0.4	18.0	69.8	2.7	-11.3
Switzerland	0.6	34.6	6.2	7.3	56.5	13.3	-12.8

Note: This table reports summary statistics on daily stock and CDS returns: the annualized return, the annualized volatility, the first-order autoregressive (AR(1)) parameter, and the contemporaneous cross-correlation between stock and CDS returns. All numbers are averages over the 2009–2020 sample.

A.4 Econometric Methodology

Econometric model. Our model can be interpreted as a generalized market model under market efficiency. On the one hand, in our specification the return on the CDS of the bank panel ($y_{B,t+1}$) is allowed to depend on the stock market return ($r_{M,t+1}$), and the stock return of firm i ($r_{i,t+1}$) is allowed to depend on the stock market return and the return on the CDS of the bank panel. Finally, the return on the CDS of firm i ($y_{i,t+1}$) is allowed to depend on the stock return of firm i , the stock market return, and the return on the CDS of the bank panel. On the other hand, under market efficiency, returns do not depend on past information. Therefore, our system includes four series, $r_{t+1} = \{r_{M,t+1}, y_{B,t+1}, r_{i,t+1}, y_{i,t+1}\}$.

The objective of the model is to capture the dependence of the return of firm i with respect to the drivers. Our econometric approach aims at capturing this dependence by designing a factor model with time-varying parameters, time-varying volatility, and a general, non-normal dependence structure for the innovations. We begin with a recursive multifactor model with time-varying parameters, after having preliminarily demeaned all return series described in Equations (20)–(21) in the main text.

The model parameters are estimated using the Dynamic Conditional Beta approach proposed by Engle (2012). The estimation is performed as follows. We assume that, conditional on the information set on date t , the return process at $t + 1$ has mean $E_t[r_{t+1}] = 0$ and covariance matrix $V_t[r_{t+1}] = H_{t+1}$. The conditional covariance matrix H_{t+1} is estimated by a DCC model (Engle and Sheppard, 2001; Engle, 2012) as

$$H_{t+1} = D_{t+1}^{1/2} \Gamma_{t+1} D_{t+1}^{1/2}, \quad (\text{A.1})$$

$$\Gamma_{t+1} = (\text{diag}(Q_{t+1}))^{-1/2} Q_{t+1} (\text{diag}(Q_{t+1}))^{-1/2}, \quad (\text{A.2})$$

$$Q_{t+1} = (1 - \delta_1 - \delta_2) \bar{Q} + \delta_1 Q_t + \delta_2 D_t^{-1/2} r_t r_t' D_t^{-1/2}, \quad (\text{A.3})$$

where $\text{diag}(Q_{t+1})$ denotes a matrix with zeros except for the diagonal that contains the diagonal of Q_{t+1} , and D_{t+1} is a diagonal matrix with the variances of r_{t+1} (conditional on t) on its diagonal and zeros elsewhere. Matrix \bar{Q} is the unconditional covariance matrix of the standardized residuals. Parameters δ_1 and δ_2 are restricted to ensure that the conditional correlation matrix Γ_{t+1} is positive definite. Armed with this model, we estimate the parameters associated with the CDS log-return of firm i as

$$\beta_{iy,t+1} = \begin{pmatrix} \beta_{iy,t+1}^{ir} \\ \beta_{iy,t+1}^B \\ \beta_{iy,t+1}^M \end{pmatrix} = \begin{pmatrix} H_{irir,t+1} & H_{irB,t+1} & H_{irM,t+1} \\ H_{irB,t+1} & H_{BB,t+1} & H_{BM,t+1} \\ H_{irM,t+1} & H_{BM,t+1} & H_{MM,t+1} \end{pmatrix}^{-1} \begin{pmatrix} H_{iyir,t+1} \\ H_{iyB,t+1} \\ H_{iyM,t+1} \end{pmatrix},$$

the parameters associated with the stock log-return of firm i as

$$\beta_{ir,t+1} = \begin{pmatrix} \beta_{ir,t+1}^B \\ \beta_{ir,t+1}^M \end{pmatrix} = \begin{pmatrix} H_{BB,t+1} & H_{BM,t+1} \\ H_{BM,t+1} & H_{MM,t+1} \end{pmatrix}^{-1} \begin{pmatrix} H_{irB,t+1} \\ H_{irM,t+1} \end{pmatrix},$$

and the parameter associated with the aggregate CDS log-return as

$$\beta_{B,t+1}^M = (H_{MM,t+1})^{-1} H_{BM,t+1}.$$

The error term $\varepsilon_{t+1} = \{\varepsilon_{iy,t+1}, \varepsilon_{ir,t+1}, \varepsilon_{B,t+1}, \varepsilon_{M,t+1}\}$ may be non-linearly dependent both in the time series (due to heteroskedasticity) and in the cross-section (due to tail dependence). To deal with heteroskedasticity, we assume a univariate GARCH model (Engle, 1982), where, as before, volatility is conditional on the information set on date t :

$$\varepsilon_{k,t+1} = \sigma_{k,t+1} z_{k,t+1}, \tag{A.4}$$

$$\sigma_{k,t+1}^2 = \omega_k + \alpha_k \varepsilon_{k,t}^2 + \beta_k \sigma_{k,t}^2, \tag{A.5}$$

for $k \in \{M, B, ir, iy\}$. The innovation process $z_{t+1} = \{z_{M,t+1}, z_{B,t+1}, z_{ir,t+1}, z_{iy,t+1}\}$ is such that $E[z_{k,t+1}] = 0$, $V[z_{k,t+1}] = 1$ and $Cov[z_{k,t+1}, z_{l,t+1}] = 0$ for $k \neq l$. As innovations z_{t+1} have been preliminarily orthogonalized, they are not correlated across series. However, they cannot a priori be assumed to be independent from each other.¹⁵ As systemic risk measures are based on the marginal expected shortfall (Equations (13 and (14)), they rely on the dependence structure of the innovations. Therefore, we use a joint distribution for z_{t+1} that can capture possible nonlinear dependencies across innovation processes. A convenient approach is to use a copula.¹⁶ First, the marginal distributions are assumed to be univariate skewed t distributions, $z_{k,t+1} \sim f(z_{k,t+1}; \nu_k, \lambda_k)$, where f denotes the pdf of a skewed t distribution with ν_k degrees of freedom and the asymmetry parameter λ_k .¹⁷ We define $u_{t+1} = \{u_{M,t+1}, u_{B,t+1}, u_{ir,t+1}, u_{iy,t+1}\}$ as the value of the marginal distribution evaluated at the observed z_{t+1} . Thus, $u_{k,t+1} = F(z_{k,t+1}; \nu_k, \lambda_k)$, where F is the cumulative distribution function (cdf) of the skewed t distribution $f(z_{k,t+1}; \nu_k, \lambda_k)$. Then, the copula defines the dependence structure of u_{t+1} , denoted by $C(u_{t+1})$. After investigating several alternative copulas, we eventually selected the t copula, which has been found to capture the dependence structure of the data very well. It accommodates tail dependence, and its elliptical structure provides a convenient way to deal with high-dimensional systems. The cdf of the t copula is defined as

$$C_{\Omega, \bar{\nu}}(u_{M,t+1}, \dots, u_{iy,t+1}) = t_{\Omega, \bar{\nu}}(t_{\bar{\nu}}^{-1}(u_{M,t+1}), \dots, t_{\bar{\nu}}^{-1}(u_{iy,t+1})), \tag{A.6}$$

where $t_{\bar{\nu}}$ is the cdf of a univariate t distribution with $\bar{\nu}$ degrees of freedom, and $t_{\Omega, \bar{\nu}}$ is the cdf of the multivariate t distribution with Ω being the correlation matrix of the transformed series and $\bar{\nu}$ being the degrees of freedom.

In summary, our model combines a DCC model for the dynamic of the beta parameters, univariate GARCH models for the dynamic of the volatility of the error terms, and a t

¹⁵The Dynamic Conditional Beta model is likely to capture more than the mere linear dependence between the variables. It is not clear, however, how much of the nonlinear dependence is left in the innovation process. This is why we do not assume a priori that the innovations are independent from each other.

¹⁶Alternatively, the expected shortfall could be estimated using a nonparametric tail expectation estimator, as in Scaillet (2003) or Brownlees and Engle (2017).

¹⁷Innovations in the skewed t distribution are rescaled to ensure that $E[z_{k,t+1}] = 0$ and $V[z_{k,t+1}] = 1$.

copula for the dependence structure between the innovations. To deal with the possible time variability of (some of) the model parameters, we estimate the model over a rolling window of ten years of data, moving forward as soon as a new observation is made available.

Estimation strategy. The estimation strategy is worth describing. Although we have a large number of models to estimate (one for each bank), the component that corresponds to the interaction between the aggregate stock and CDS markets is common to all banks. Therefore, we perform the estimation recursively as follows. We begin with the estimation of the dynamic of CDS and stock market indexes, i.e., the model for $(y_{M,t+1}, r_{B,t+1})$. We estimate the DCC model for these series and the corresponding time-varying beta parameters. We also estimate the univariate GARCH processes for their error terms $(\varepsilon_{M,t+1}, \varepsilon_{B,t+1})$ and the parameters of the t copula. We call this model the *aggregate model*. Next, we introduce the stock and CDS returns, $y_{i,t+1}$ and $r_{i,t+1}$, of firm i and estimate the parameters corresponding to these series, taking as given the parameters of the stock and CDS market returns (the *bank model*).

This approach has three advantages. First, it is coherent with the recursive structure of the model, assuming that the recursive model captures all interconnections between the firms in a given country. Second, it ensures that the dynamics of the stock and CDS market returns are the same for all submodels. Third, it allows for a relatively fast estimation of the complete model and LRMES.

Measuring the Sensitivities to a Stock Market Crash. We now turn to the estimation of the long-run marginal expected shortfall ($LRMES_{i,t:t+T}$) and the CDS marginal expected increase ($CDSMEI_{i,t:t+T}$). Following [Brownlees and Engle \(2012\)](#), we estimate LRMES directly as the expected return of the firm in case of a large stock market decline in the next six months.¹⁸

Directly estimating LRMES relies on a simulation of the model over T periods using all information available on date t . As to the estimation strategy, our simulation strategy takes advantage of the recursive structure of the model. We start by simulating the market model over T periods (125 daily observations corresponding to a six-month period). To this end, we draw a sample s of $(u_{M,\tau}^{(s)}, u_{B,\tau}^{(s)})_{\tau=t+1, \dots, t+T}$ from the t copula. Specifically, we draw a bivariate Gaussian innovation $n_{t+1}^{(s)}$ from $N(0, \Omega_{MB})$ and a chi-squared innovation $c_{t+1}^{(s)}$ from χ_{ν}^2 , where Ω_{MB} is the correlation matrix of the transformed series $(u_{M,t+1}, u_{B,t+1})$. Then, the t innovation is obtained by $n_{t+1}^{(s)} / \sqrt{c_{t+1}^{(s)}}$. We deduce the innovation terms $(z_{M,\tau}^{(s)}, z_{B,\tau}^{(s)})$ from the skewed t distribution. Using the GARCH estimates of volatility, we compute the error terms $(\varepsilon_{M,\tau}^{(s)}, \varepsilon_{B,\tau}^{(s)})$. We then estimate the dynamic betas that depend on the correlation matrix and therefore on $\varepsilon_{\tau}^{(s)}$. Eventually, we recover a six-month time series of CDS and

¹⁸A second approach consists of measuring LRMES based on the expected return of the firm in case of a (relatively modest) 2% decline in the daily market return, which is then extrapolated to match a “once-per-decade” crisis. For this study, we implemented both approaches and observed that they provided similar systemic risk measures. To save space, we describe the methodology and report the results of the first approach only.

tell us whether a crash occurred in CDS and stock markets over this simulated sample s (if cumulative returns satisfy the condition for a crash event). If we do not observe a crash, we simulate a new series. If we indeed observe a crash, we move to the bank model.

In the bank model, we simulate $u_{ir,\tau}^{(s)}$ and $u_{iy,\tau}^{(s)}$ from the t copula.¹⁹ Then, as before, we recover the innovation terms from the skewed t distribution, the error terms from the GARCH models, and eventually, the bank's CDS and stock returns from the DCC model.

It is worth emphasizing that the recursive structure is critical in the simulation step for obtaining systemic risk measures in an acceptable amount of time. To obtain an accurate estimate of the marginal expected shortfall of the firm return conditionally on a stress event, many draws of the aggregate model are required to simulate a sufficient number of crashes.²⁰

This approach provides very accurate estimates of the true expectation if the number of simulated data points is sufficiently large. We simulate $J_1 = 100,000$ draws of the aggregate model (including only the worldwide stock market return and the aggregate bank CDS spread). We define a stress event as a simulation with $R_{M,t:t+T}^{(j_1)} \leq -30\%$. We denote by $N_{S,t}$ the number of stress events in the simulations on date t . For each draw identified as a market crash, we simulate $J_2 = 1,000$ draws of the bank model. The LRMES of firm i conditional on a world shock is estimated by

$$LRMES_{i,t:t+T} = -\frac{1}{N_{S,t}J_2} \sum_{j_1=1}^{J_1} \sum_{j_2=1}^{J_2} R_{i,t:t+T}^{(j_1,j_2)} \times \mathcal{I}(R_{M,t:t+T}^{(j_1)} \leq -30\%), \quad (\text{A.7})$$

where $\mathcal{I}(x) = 1$ if x is true and 0 otherwise. Similarly, the CDS MEI is obtained by

$$CDSMEI_{i,t:t+T} = \frac{1}{N_{S,t}J_2} \sum_{j_1=1}^{J_1} \sum_{j_2=1}^{J_2} Y_{i,t:t+T}^{(j_1,j_2)} \times \mathcal{I}(R_{M,t:t+T}^{(j_1)} \leq -30\%). \quad (\text{A.8})$$

¹⁹We use the same chi-squared $c_\tau^{(s)}$ in the simulation of the t random variables to preserve the same dependence structure between the four shocks $u_{M,\tau}^{(s)}$, $u_{B,\tau}^{(s)}$, $u_{ir,\tau}^{(s)}$ and $u_{iy,\tau}^{(s)}$. The correlation matrix of the Gaussian draw Ω is extended to the four random variables.

²⁰If we had to simulate the complete model for all firms simultaneously, the computational burden of estimating systemic risk measures would be too heavy. To give an order of magnitude of the computational burden, estimating the systemic risk for all firms for one date takes approximately one hour for the model estimation and the simulation steps, whereas it would take several days if we had to estimate and simulate the complete model for all firms simultaneously.

Table A4: Parameter estimates – The aggregate model

	CDS	Equity
Univariate parameters		
ω	0.1396 (0.049)	0.0096 (0.002)
α	0.1441 (0.030)	0.1120 (0.013)
β	0.8483 (0.031)	0.8827 (0.012)
Skewed t distribution		
ν	4.3386 (0.317)	6.2724 (0.597)
λ	0.0700 (0.018)	-0.1387 (0.018)
Multivariate parameters		
δ_1		0.0277 (0.013)
δ_2		0.9588 (0.020)
Copula parameters		
Degree of freedom $\bar{\nu}$		7.7810 (1.131)
Correlation Ω_{MB}		0.0238 (0.001)

Note: This table presents parameter estimates of the DCB model with t copula innovations. Estimates are based on daily data from January 2005 to June 2020 (4,043 observations). Volatility dynamics are for the return series. Estimated parameters of the skewed t distribution are for the individual innovations. The degree of freedom $\bar{\nu}$ and the correlation Ω_{MB} correspond to the t copula of the innovation margins. Numbers in parentheses are the standard errors. Estimates of ω are multiplied by 10^6 .

Table A5: Parameter estimates – The bank model

	ω	α	β	ν	λ
CDS return					
Banco Santander	0.4939	0.2242	0.7746	3.1279	-0.0246
Bank of America	0.1579	0.1441	0.8549	3.7523	0.0238
Barclays	0.8631	0.2759	0.7148	2.8320	-0.0091
BNP Paribas	0.2340	0.1290	0.8700	3.0234	-0.0209
Citigroup	0.3653	0.2447	0.7460	3.6336	0.0055
Crédit Agricole	0.2145	0.1532	0.8458	3.1059	-0.0101
Credit Suisse	0.2181	0.1721	0.8269	2.9100	-0.0277
Deutsche Bank	0.4734	0.2491	0.7499	3.0121	-0.0175
Goldman Sachs	0.2577	0.1666	0.8207	3.3381	0.0170
HSBC	0.5063	0.1156	0.8361	3.4564	0.0103
ING	0.7072	0.1465	0.8525	2.5443	-0.0295
JP Morgan Chase	0.1447	0.1405	0.8584	3.8217	0.0064
Morgan Stanley	0.3473	0.2066	0.7924	3.0351	-0.0054
Société Générale	0.2412	0.1468	0.8522	3.0370	-0.0378
Standard Chartered	2.1249	0.4399	0.5591	2.7806	0.0040
UBS	0.3998	0.2051	0.7939	3.0129	0.0072
UniCredit	0.4529	0.1688	0.8302	2.8864	-0.0299
Wells Fargo	0.2145	0.1660	0.8330	3.6191	0.0254
Stock return					
Banco Santander	0.0374	0.0834	0.9038	5.4737	0.0177
Bank of America	0.0178	0.0749	0.9241	4.3299	0.0452
Barclays	0.0676	0.0865	0.9005	4.1568	0.0486
BNP Paribas	0.0260	0.0550	0.9360	5.6056	0.0540
Citigroup	0.0204	0.0788	0.9198	4.1923	0.0656
Crédit Agricole	0.0216	0.0469	0.9489	4.7220	0.0703
Credit Suisse	0.0256	0.0433	0.9480	4.2585	0.0031
Deutsche Bank	0.0151	0.0456	0.9511	5.0624	0.0115
Goldman Sachs	0.0236	0.0593	0.9311	5.1799	0.0313
HSBC	0.0207	0.0693	0.9185	5.0294	0.0088
ING	0.0267	0.0787	0.9168	4.8209	0.0322
JP Morgan Chase	0.0161	0.0674	0.9275	4.6269	0.0519
Morgan Stanley	0.0257	0.0585	0.9341	4.8788	0.0392
Société Générale	0.0304	0.0803	0.9178	4.6250	0.0547
Standard Chartered	0.1598	0.1341	0.8199	4.2499	0.0449
UBS	0.0200	0.0464	0.9478	3.8728	0.0376
UniCredit	0.0316	0.0843	0.9147	5.5832	0.0295
Wells Fargo	0.0136	0.0821	0.9169	4.6308	0.0460

Note: This table presents parameter estimates of the DCB model with t copula innovations. Estimates are based on daily data from January 2005 to June 2020 (4,043 observations). Volatility dynamics are for the return series. Estimated parameters of the skewed t distribution are for the individual innovations. The degree of freedom ν and the asymmetry parameter λ correspond to the skewed t distribution of the innovation terms. Estimates of ω are multiplied by 10^6 .

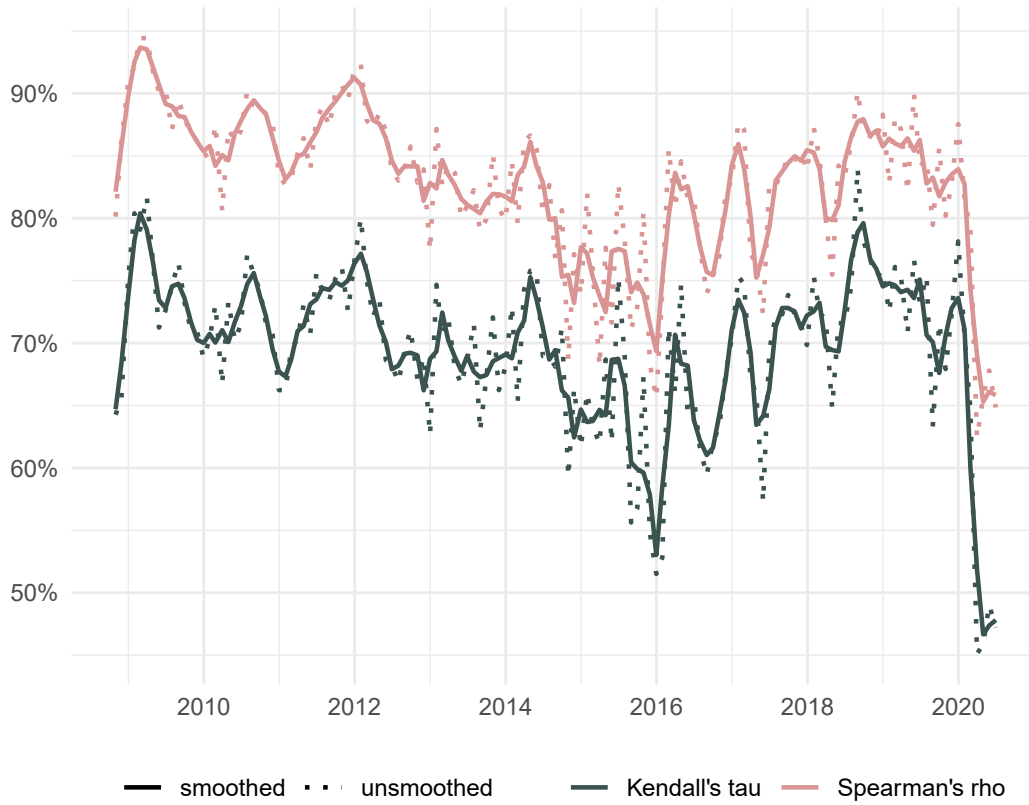
Table A6: Summary statistics for model estimates, by bank

G-SIB	(1)	(2)	(3)		(4)		(5)	(6)	(7)	(8)	(9)
	LRMES	CDSMEI	Unstressed		Stressed		MLR	ILR	Total	Equity	Spread
Banco Santander	36.2	107.6	5.41	4.07	3.46	0.66	3.41	1.95	1.46		
Bank of America	35.9	165.9	6.80	5.75	4.43	1.83	3.92	2.37	1.55		
Barclays	32.7	103.9	2.62	1.57	1.79	-0.33	1.89	0.84	1.06		
BNP Paribas	37.3	131.8	3.15	2.22	2.00	-0.14	2.36	1.15	1.21		
Citigroup	37.4	167.4	6.01	4.85	3.84	1.13	3.73	2.18	1.55		
Crédit Agricole	35.0	151.3	1.81	0.81	1.20	-1.25	2.06	0.61	1.45		
Credit Suisse	29.8	115.1	3.66	2.74	2.58	0.62	2.13	1.07	1.05		
Deutsche Bank	37.9	107.5	1.96	0.74	1.23	-1.27	2.01	0.73	1.28		
Goldman Sachs	34.6	171.8	6.37	5.23	4.19	1.21	4.02	2.18	1.84		
HSBC	22.4	104.1	6.95	6.23	5.41	3.96	2.27	1.54	0.73		
ING	37.7	86.2	2.86	1.98	1.82	0.21	1.77	1.04	0.73		
JP Morgan Chase	34.3	145.8	8.43	7.73	5.58	3.89	3.84	2.85	0.99		
Morgan Stanley	38.8	130.0	5.54	4.24	3.42	0.69	3.55	2.12	1.43		
Société Générale	38.5	124.1	2.62	1.50	1.64	-0.82	2.32	0.98	1.34		
Standard Chartered	28.3	95.6	5.22	4.27	3.74	1.94	2.33	1.48	0.85		
UBS	30.1	101.0	6.15	5.33	4.34	2.76	2.57	1.81	0.76		
UniCredit	36.1	102.4	2.73	0.98	1.76	-1.76	2.74	0.96	1.78		
Wells Fargo	31.1	120.7	11.30	10.62	7.83	6.42	4.20	3.47	0.73		
United States	35.4	150.3	7.41	6.40	4.88	2.53	3.88	2.53	1.35		
Euro area	37.0	115.8	2.93	1.76	1.87	-0.62	2.38	1.06	1.32		
United Kingdom	27.8	101.2	4.93	4.02	3.64	1.85	2.17	1.29	0.88		
Switzerland	30.0	108.0	4.91	4.04	3.46	1.69	2.35	1.44	0.91		

Notes: All amounts are reported as percentages. Column (7) is the difference between columns (4) and (6). Column (8) is the difference between columns (3) and (5).

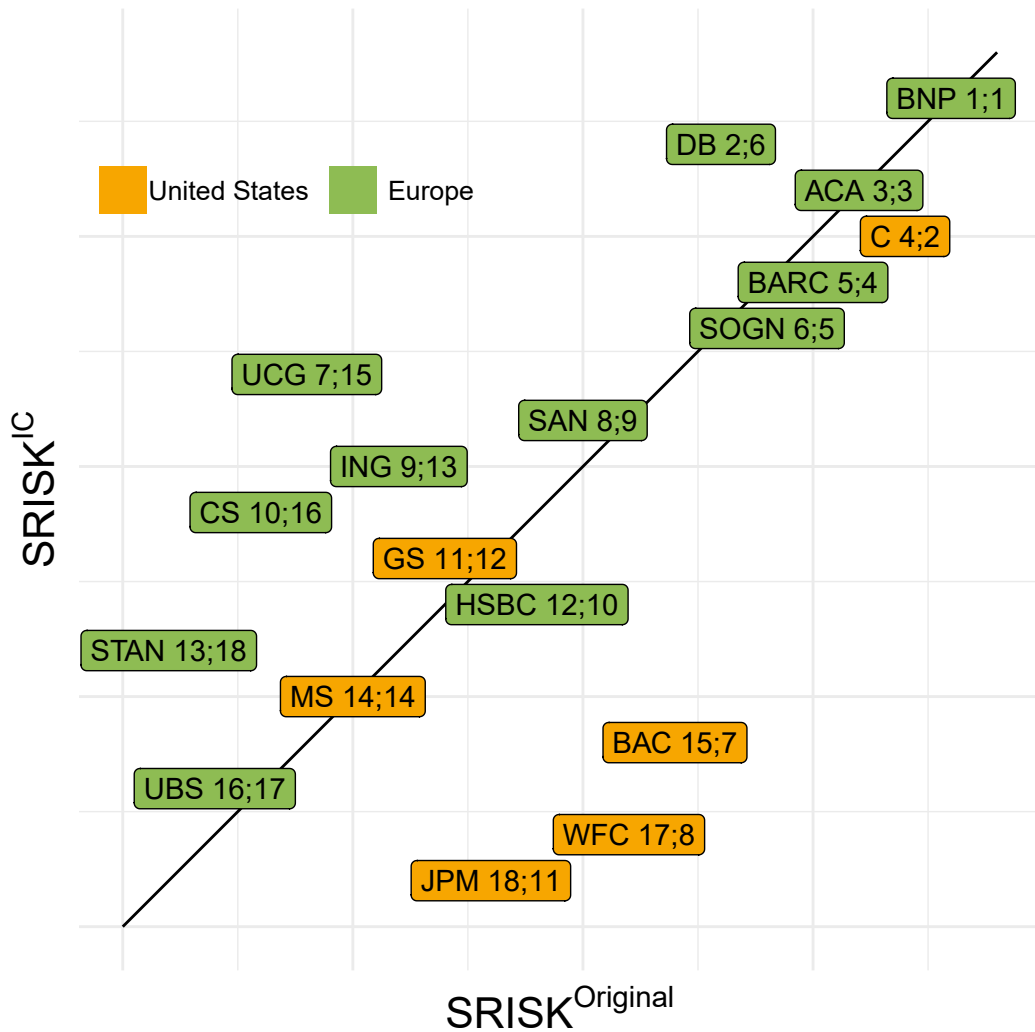
A.6 Rank correlations between SRISK measures

Figure A3: Rank Correlations between SRISK Measures



Note: This figure displays Kendall's tau and Spearman's rho correlations between $SRISK_{i,t:t+T}^{IC}$ and $SRISK_{i,t:t+T}^{Original}$ measures, defined in Section 4.5. Each month, the correlation is computed for the cross-section of banks' SRISK measures. The figure shows the data smoothed over three months (solid lines) and the unsmoothed monthly data (dotted lines).

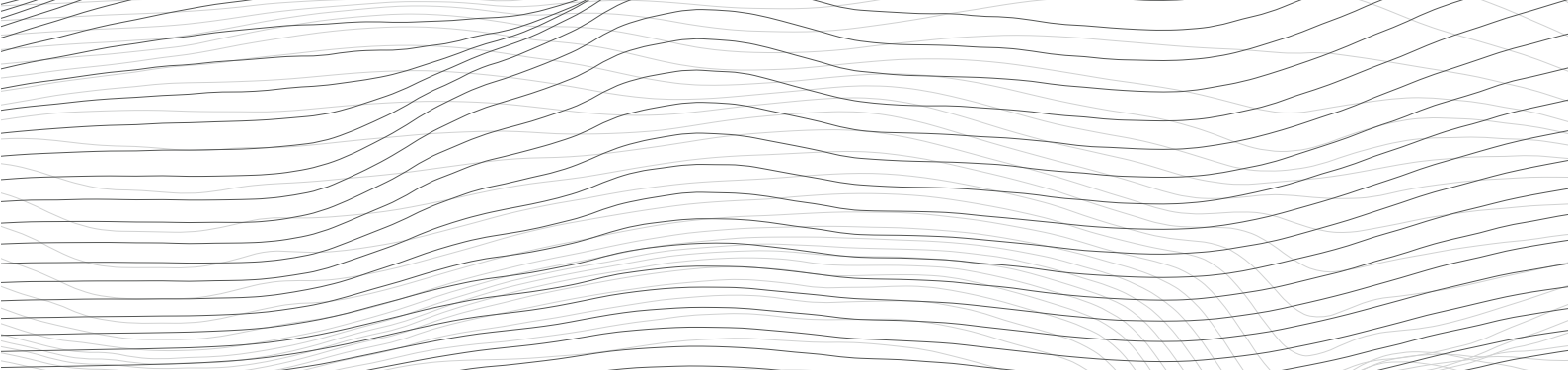
Figure A4: Illustration of banks' ranking by different SRISK Measures



Note: This figure illustrates the banks' ranking by $SRISK_{i,t:t+T}^{IC}$ (the first number in the labels) and $SRISK_{i,t:t+T}^{Original}$ (the second number in the labels) measures, defined in Section 4.5. The banks are ranked in the order of decreasing contribution to systemic risk. The rankings are shown for March 2020, during the Covid-19-induced market stress, when rank correlations were particularly low (cf. Figure A3).

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