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Daniel Dimitrov and Sweder van Wijnbergen

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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

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Quantifying Systemic Risk in the Presence of Unlisted Banks: Application to the European Banking Sector*

Daniel Dimitrov† Sweder van Wijnbergen‡

D.K.dimitrov@uva.nl S.J.G.vanwijnbergen@uva.nl

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Abstract

We propose a credit portfolio approach for the market-based attribution of systemic risk across institutions. Using CDS prices, we extend the canonical public equity-based methods to incorporate privately held and coöperative banks for which equity data do not exist. Applying the model to a sample of key European institutions reveals that capital buffers for large banks are relatively low compared to their contributions to systemic risk on a European scale. Our findings underscore the benefits of a unified systemic risk management process across Europe. The results are robust to alternative specifications of the asset dependencies incorporating non-normality of market returns.

JEL codes: G01, G20, G18, G38

Keywords: systemic risk, marginal expected shortfall, CDS rates, implied market measures, financial institutions, fat tails, O-SII buffers

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†De Nederlandsche Bank, University of Amsterdam

‡De Nederlandsche Bank, University of Amsterdam, CEPR and Tinbergen Institute.

1 Introduction

It is widely accepted in the literature that large interconnected banks imply an implicit cost to the financial system (See Gropp et al. (2014); Duffie (2019); Behn et al. (2022) for recent contributions), which in effect constitutes an unpriced negative externality. Their failure can trigger and propagate shocks through the financial system and beyond, justifying differentiated regulatory treatment. Post-2008 reforms aimed to reduce the moral hazard associated with "too big to fail" institutions by strengthening micro-prudential capital requirements, resolution regimes, and bail-in frameworks (Behn and Schramm, 2021; Berndt et al., 2025). However, systemic risk remains a broader and persistent concern, reflecting the vulnerability of the financial system as a whole (Acharya, 2009; Adrian and Brunnermeier, 2016; Acharya et al., 2017). Macroprudential regulation seeks to mitigate these risks through capital buffers calibrated not only to a bank's standalone risk but also to its systemic footprint.

At the same time, the mechanisms used to map systemic risk scores into capital buffer add-on requirements, such as those underlying the global G-SII and European O-SII frameworks, are far from perfect (ESRB, 2017; Passmore and von Hafften, 2019). In particular, in Europe national authorities retain substantial discretion in translating systemic regulatory scores of domestically significant banks (D-SIBs) into capital surcharges. This leads to fragmentation and undermines the objective of achieving a level playing field in the European Banking Union. In addressing this problem regulators face a problem specific to Europe: a substantial number of systemically important banks are not publicly listed, because they are coöperative or state owned banks. This precludes the equity-based approaches recently developed in the academic literature (cf (Zhou, 2010; Adrian and Brunnermeier, 2016; Acharya et al., 2017; Brownlees and Engle, 2017).

To resolve this issue, we propose a consistent and fully market-based measure of systemic risk and systemic risk attribution based on CDS-prices that allows a like-for-like comparison of banks across countries. Our approach blends in a consistent manner the key aspects of systemic importantance: size, probability of a failure, dependency in potential failure with the rest of the sector. This serves two purposes: first, it helps assess whether capital buffers are appropriately aligned with systemic risk contributions; second, it offers a more timely signal of systemic vulnerability than supervisory judgments or score or accounting-based systems, since these unavoidably lag behind. We apply our methodology to a sample of European banks, but our conceptual and methodological contributions are applicable to any jurisdiction grappling with the calibration and consistency of macroprudential capital requirements for systemically important institutions for which no equity data exist.

The canonical market-based approaches rely on equity return co-movements (Zhou, 2010; Adrian and Brunnermeier, 2016; Acharya et al., 2017; Brownlees and Engle, 2017) and therefore cannot be used on a comprehensive basis in the European context due to the presence of state-owned and cooperative banks that are not publicly traded. To address this limitation, we utilize Credit Default Swaps (CDS) rather than equity prices to extract the required information on bank distress dependencies since for those banks equity data do not exist. Through the observed co-movements in CDS prices we evaluate the exposures of individual banks to a set of common latent factors, thus uncovering clusters of bank interconnectivity. We next derive the implicit probabilities of joint distress across banks and from there the size of total losses to which the central bank (or the supervisor) is exposed in case of a systemic crisis, Finally, we attribute this total risk to individual entities by measuring a credit-based Marginal Expected Shortfall (MES) measure, following the set-up of Acharya et al. (2017) but without using equity prices since they are not available for unlisted banks.

We should mention here already that in Section 4.4 we address a commonly voiced concern on the reliability of CDS-implied correlations, that CDS contracts are not as liquid as equity and are subject to intermediation shocks (Siriwardane, 2019), potentially making the corresponding contract prices uninformative about the credit risks of the protection buyer. To assess this criticism, we first estimate our model also on equity correlations for the subsample for which both CDS prices and equity data are available for a comparison of the equity based approach with our CDS prices based approach. Second, we compare our approach to the canonical equity market-based SRISK approach proposed by Acharya et al. (2012); Brownlees and Engle (2017). In both cases we find that the CDS-based approach produces risk-attribution figures that are comparable to the more commonly used equity-derived systemic risk numbers but, contrary to those equity based approaches, allows us to include nonlisted but systemically important banks. Third, we compare our CDS-based estimates to a recent method proposed by Engle et al. (2024), which infers systemic risk contributions for nonlisted banks from their balance sheet data by extrapolating in a linear regression from the contributions of listed banks, in what we label as a *synthetic approach*. We demonstrate that our CDS method more effectively captures the turning points in systemic risk. Moreover, our approach enables the use of higher-frequency data, which the synthetic approach is less equipped to handle.

We contribute to the literature in several ways. First, we point out a modeling choice that overcomes an obvious hurdle in evaluating systemic risk for European banks. While credit-based approaches similar to ours have been used in the past as well (Huang et al., 2012; Puzanova and Düllmann, 2013; Kaserer and Klein, 2019), the focus has typically been on US and global banks, with CDS data being explored as an additional source of information with the advantage of directly reflecting default risk. Studies evaluating systemic risk in Europe mostly use equity-based measures, leaving key players in the industry out of the analysis because they are not listed (see for instance Engle et al. (2015); Buch et al. (2019); Borri and Di Giorgio (2022)). More recent work has attempted to bridge this gap by combining accounting data with equity market information (Engle et al., 2024). In contrast, we demonstrate that the prices of CDS contracts on 5-year subordinated bank debt, despite being less liquid than exchange-traded equity, and despite concerns of potential market segmentation, can be used to construct a robust indicator of systemic risk, performing at least as well as the widely used equity-based measures. To further assess the limitations of the Engle et al. (2024) approach, we conduct a diagnostic exercise in which listed banks are treated as if they were unlisted. The synthetic approach does capture average levels of systemic risk, but contrary to our CDS based approach it systematically lags during episodes of financial stress—highlighting the advantage of market-based indicators like CDS prices in providing timely signals of systemic vulnerability. This finding is in line with the position articulated by Engle et al. (2024), who emphasize that their method enables quarterly stress-testing but is not designed for high-frequency monitoring.

Second, by quantifying banks' systemic importance, we reveal discrepancies in capital buffer requirements across countries at the European level.[1]. But on a European scale discrepancies and inconsistencies arise. Our findings echo Sigmund (2022), who documents heterogeneity in systemic impact scores and buffer assignments across EU states. We

[1]See Section 4.3 for a discussion of the EU's O-SII framework for assigning systemic buffers. We find that on a national scale the buffer structure generally aligns with our risk measures but does not do so when evaluated on the entire European sample. National regulators do impose higher capital requirements on banks with higher systemic risk contributions than on banks with lower systemic contribution

find similar discrepancies using market-based measures instead of regulatory scores. One explanation could be that local regulators do not fully factor in cross-border spillovers in deciding on capital buffer add-ons. Alternatively, different regulators have different tolerances to systemic risk. These findings support the current policy efforts to harmonize buffer methodologies across countries and to introduce a common floor (European Central Bank, 2024).

Third, by aggregating the individual banks' contributions, we construct a European index of financial fragility (Expected Systemic Shortfall, ESS). Given that the only data inputs in our model are CDS prices and the relative liability size of individual banks, our index performs remarkably close to the ECB's CISS index constructed by aggregating inputs from a variety of markets (Hollo et al., 2012; Chavleishvili and Kremer, 2025). Our ESS also correlates with the VSTOXX index, a measure of market sentiment and investor anxiety derived from the implied volatility of the Eurostoxx 50 index. However, unlike the VSTOXX, our index remains tightly focused on the banking sector. And a key advantage of our approach is that it can be broken down into components that are attributable to individual countries or individual banks, assisting policymakers with the identification of silos of systemic risk.

Our ESS index quantifies the systemic impact of more recent events in the banking sector. We observe a sharp rise in aggregate systemic risk during the initial COVID-19 outbreaks and lockdowns in Europe, followed by a gradual decline, presumably after policy interventions (among other measures) aimed at providing liquidity to the financial system. Systemic risk increased also after the onset of the Russian invasion of Ukraine, although the increase was more gradual and presumably driven by inflationary pressures and rapidly rising interest rates.

Finally, this paper also makes a methodological contribution by providing a framework to stress-test some limiting assumptions of the regular credit-based model (Vasicek, 1987; Huang et al., 2012) by incorporating a fat-tailed structure in asset returns and nonlinear dependencies between risk drivers. This allows policymakers to better assess the impact of extreme events and nonlinear factor dependencies that generate greater asset correlations in market downturns than in booms— a pattern consistently observed in financial crises.

The paper continues as follows: Section 2 provides a brief literature review; Section 3 describes the structural credit model; Section 4 reviews the empirical results including the structure of the data and the implications of the model for measuring and attributing systemic risk. In Section 5 we disentangle and discuss the separate features of the model; we test the robustness of our results to various extensions and alternative specifications. In this section, we relax the assumption of asset return normality used earlier, and also provide comparisons between our model and a conventional equity-based estimation for listed institutions, as well as comparisons to the Engle et al. (2024) approach for non-listed institutions. Finally, Section 6 concludes.

2 Review of the Literature

We relate to the broader literature on estimating systemic risk through asset price co-movements (Lehar, 2005; Segoviano and Goodhart, 2009; Zhou, 2010; Huang et al., 2012; Adrian and Brunnermeier, 2016; Brownlees and Engle, 2017; Acharya et al., 2017; Engle, 2018).[2] However, most of that literature builds on the assumption that banks' equity prices can be observed. This is mostly correct in a US context, but in Europe extracting information from equity market data in this way is not comprehensively possible, as many sizable and most smaller banks are not publicly traded. Approaches that rely on equity price co-movements then cannot encompass the full system, cannot be used to track the systemic impact of those institutions, and may in fact not be usable at all, if too few of the quantitatively important institutions have an equity market listing.

We address this challenge estimating a systemic risk model from banks' CDS prices. CDS rates have been used in a systemic risk context previously. For example Rodríguez-Moreno and Peña (2013) find that CDS-based statistical measures generally outperform measures based on interbank rates or stock market prices in predicting bank systemic distress. However, in previous studies, these typically serve as an input to dynamic multivariate econometric models. Examples are Oh and Patton (2018) who estimate a dynamic copula model, and Moratis and Sakellaris (2021) who estimate the transmission of systemic shocks across banks through a panel VAR model. Our approach is different, since we keep the link between statistical factor estimation and asset pricing theory by ensuring that the dependency model is consistent with structural models of credit risk. Furthermore, we take a credit portfolio view, evaluating the regulator's exposure to bank

[2]Benoit et al. (2017) provide an extensive review.

risk as if arising from a portfolio of loans; this allows for a more natural integration of size into the evaluation of systemic risk.[3]

Most of all therefore, we relate to earlier studies that view the regulatory space of banks as a portfolio of risky loans (Huang et al., 2009, 2012; Puzanova and Düllmann, 2013; Kaserer and Klein, 2019) who build on innovations in the securitization literature (Hull and White, 2004; Tarashev and Zhu, 2006). Systemic losses in these studies arise when an institution defaults and cannot cover the value of its liabilities. The tendency of particular institutions to drive the risk of systemic losses will then result in a higher contribution to systemic risk. We add to their approach by using the dependencies not only between distress occurrences, but also their relation to the size of the potential default losses given a distress. Previous studies have not looked at such dependencies, but they are important for a number of reasons. First, there is sound empirical evidence thatlosses realized in default are sensitive to the business cycle and tend to rise in periods when risk probabilities also increase (Altman, 1989; Altman et al., 2004; Galow et al., 2024). Second, in a tail risk scenario, the default of a systemic player can be expected not only to raise the default risk of other participants in the sector but also to simultaneously decrease the value of the assets backing up their liabilities. Since industry-wide distress often triggers fire sales, the value of the assets backing up banks' liabilities will then also be negatively affected and pushed below fair value.

A concurrent study by Engle et al. (2024) takes a different approach to the same problem that we address by estimating the relation between accounting data and equity prices for listed banks and then extrapolating it to unlisted ones. A problem with this approach is that the relation may well change in crisis times; CDS contracts are traded almost continuously so they will pick up changes in market sentiment much earlier than accounting based approaches as accounting data unavoidably lag behind. In Section 4.4 we compare the systemic risk estimates based on our approach to an equity-based alternative, also leveraging accounting data for the nonlisted banks. Within a cross-section our approach yields risk-attribution figures that are very similar to what the SRISK approach comes at. We find further in Section 5.3 that over time our CDS-based measures are more sensitive to market developments affecting the (potential of) tail losses associated with a bank's distress, which is to be expected against the synthetic approach

[3]Refer to Online Annex 1 for a review of how CDS rates are used in the literature and a review of credit risk pricing within the Merton credit risk model.

o fEngle and Jung (2023); Engle et al. (2024) given the higher frequency at which CDS data are available. In practice, the two approaches may complement each other: if there are banks in the sample for which there is not only no publicly traded equity but for whom no traded CDS contracts exist either, the approach becomes the only available alternative.

In our paper we also link the policy debate on measuring systemic risk to the assignment of capital buffer requirements. The use of market data for the identification of systemic banks has been underutilized in the regulatory process, presumably at least partially because of difficulties in doing so for banks that are not publicly traded. Busch et al. (2021) compare the assigned G-SIB scores to the corresponding $\Delta CoVaR$ measure proposed by Adrian and Brunnermeier (2016) to provide a stronger empirical foundation for the construction of the empirical scores. However, this is not possible when banks are not publicly traded because $\Delta CoVaR$ is based on the distribution of equity prices.

3 The Market-based Credit Approach

In this section we provide a modular presentation of our quantitative approach to analyzing systemic risk based on CDS prices. We start by laying down the basic structure of the credit model that serves as a backbone to the systemic risk estimates later on.

3.1 The structural credit model

Modeling Default: Assume that at time t a stochastic latent variable $U_{i,T} \sim N(0,1)$ governs the risks to a bank's creditworthiness in the upcoming period $T > t$. A higher realization of the variable indicates a better state of nature and consequently a lower default probability over the coming period. $U_{i,T}$ is not directly observable by depositors or the regulator, not even when $U_{i,T}$ crosses the critical threshold identified through the default probability ($PD_{i,t}$), more on which follows below. This leads to the following default indicator function:

$$\mathbb{1}_{i,T} \equiv \begin{cases} 1 & \text{if } U_{i,T} \leq \Phi^{-1}(PD_{i,t}) \\ 0 & \text{otherwise} \end{cases} \qquad \text{for } i = 1, ..., n \tag{1}$$

based on available information at t, where $\Phi^{-1}(.)$ is the inverse of the cumulative normal distribution, indicating the quantile threshold below which the bank defaults. $\Phi^{-1}(PD)$ in fact represents the default barrier implicit in the default probability.[4]

Default Dependencies: Furthermore, we assume that part of the bank's asset risk is driven by a set of common factors, and that part of it is entity-specific. The most widely used approach in credit risk analysis is to model default dependency by specifying a Gaussian factor model of the form

$$U_{i,T} = \boldsymbol{\rho}_i M_T + \sqrt{1 - \boldsymbol{\rho}_i \boldsymbol{\rho}_i'} Z_{i,T} \tag{2}$$

where $M_T = [m_{1,T}, \ldots, m_{f,T}]'$ is the vector of stochastic systematic factors, and $Z_{i,T}$ is the firm-specific factor, each of which follows a standard normal distribution. $\boldsymbol{\rho}_i = [\rho_{i,1}, ..., \rho_{i,f}]$ is the vector of factor loadings, such that $\boldsymbol{\rho}_i \boldsymbol{\rho}_i' \leq 1$ All factors are assumed to be mutually independent with zero mean and a standard deviation of one. All factors M and Z_i are characterized by standard normal distributions.[5] In a Gaussian framework, the asset return dependencies are linear, captured by the correlations between the bank latent variables, which in turn are a function of the banks' exposures to the common factors:[6]

$$\mathbb{C}\mathrm{orr}(U_{i,T}, U_{j,T}) = \boldsymbol{\rho}_i \boldsymbol{\rho}_j'$$

Through the factor loadings, we can also evaluate the proportion of total asset return variation for each bank that is attributed to common risk versus idiosyncratic risk. Formally, the inner product of the factor loadings for each bank indicates the proportion of

[4]For more details on the implicit structural model in this relationship in Online Annex 1.2.

[5]We do not provide a concrete interpretation of the factors, even though they can be thought of as economy, industry, or geographically specific risk drivers. See for example Pascual et al. (2006) for a discussion on factor identification in a similar credit risk framework.

[6]Note that if we assume that there is a single risk driver and all banks have the same exposure to that driver we would get as a special case the well-known Vasicek loan pricing model (Vasicek, 1987). In the approach used here, however, we allow for exposure heterogeneity.

factor risk as follows:

$$
\begin{aligned}
\mathbb{Var}(U_{i,T}) &= \boldsymbol{\rho}_i\boldsymbol{\rho}_i'\mathbb{Var}(M_T) + (1-\boldsymbol{\rho}_i\boldsymbol{\rho}_i')\mathbb{Var}(Z_{i,T}) \\
&= \underbrace{\boldsymbol{\rho}_i\boldsymbol{\rho}_i'}_{\text{Factor Risk Share}} + \underbrace{(1-\boldsymbol{\rho}_i\boldsymbol{\rho}_i')}_{\text{Idiosyncratic Risk Share}} = 1
\end{aligned} \tag{3}
$$

This factor-driven risk share provides an initial crude estimate of an institution's systemic sensitivity. The higher the share of factor risk (i.e., the closer it is to one), the more the bank's assets tend to co-move with the broader market. Conversely, the closer this share is to zero, the more the bank's risk is driven by idiosyncratic factors.

Loss Dependencies: The next building block of the model is determining the size of the potential losses given a default. A common simplifying assumption in the systemic risk literature is that the recovery rate RR is either fixed (Puzanova and Düllmann, 2013) or stochastic but independent across firms and independent from the realization of default (Huang et al., 2009, 2012; Kaserer and Klein, 2019). While strong assumptions about default losses are unavoidable—given that bank defaults, particularly those of systemically important financial institutions (SIFIs), are rarely observed—there is substantial empirical evidence indicating that higher default rates in the economy coincide with lower asset recovery values (Altman et al., 2004; Acharya et al., 2007; Chava et al., 2011). More recently, Galow et al. (2024) highlight that this relationship is especially pronounced for loans backed by real estate, underscoring its macroprudential significance. To incorporate this empirical fact, we model the recovery rate, RR as a stochastic process linked to the latent factors driving asset correlations. Structural credit theory, as established by Merton (1974), shows that both a firm's default probability and its recovery rate in the event of default are determined by the value of its assets relative to a default threshold. From this perspective, it is natural to assume that the systemic factors influencing default intensity also drive recovery rates. We define the recovery rate process, as follows:

$$
RR_{i,T} = \Phi\left(\boldsymbol{\rho}_i M_T + \sqrt{1-\boldsymbol{\rho}_i\boldsymbol{\rho}_i'}Z^c_{i,T}\right) \tag{4}
$$

where the same common factor exposures that control the default correlations in (7) now also control the correlation in recovery values between different banks, as well as the correlation between losses and default probabilities. This gives gives the negative link between default probabilities and Loss Given Default (one minus the recovery rate). Z_i^c defines an independent factor capturing possible firm-specific discrepancies between the underlying assets of the firm and the value of recovered collateral. This discrepancy, in theory can be due to a loss in the value of the bank's intangible assets, any other restructuring costs due to liquidation, or legal delays in seizing the collateral. The cumulative standard normal transformation ensures that recovery values and losses in case of default do not exceed 100%, and is inspired by a generalization in Andersen and Sidenius (2005) in a securitization context, where he also explores the mathematical properties of correlated recovery rates. Frye (2000) provides a stylized version of this approach and interprets the RR as the collateral value backing up liabilities.

Factor Estimation: So far, we have defined the multivariate risk model. This type of model is widely used in the securitization literature, where the model parameters are typically estimated from observed loan defaults over time. In the context of systemic risk evaluation, however, we lack this empirical advantage — systemic defaults, by their very nature, are extreme events and rarely observed. To address this challenge, we follow Tarashev and Zhu (2006) who demonstrate that under the assumption of the Merton model the correlation between the (unobserved) market values of bank i and bank j's asset returns is a transformation of the default probabilities (See Annex 1.3 for details). Formally this is defined as

$$a_{i,j} = \mathbb{Corr}\left(\Delta\Phi^{-1}(PD_{i,t}), \Delta\Phi^{-1}(PD_{j,t})\right) \tag{5}$$

where $\Delta\Phi^{-1}(PD_{i,t})$ is the first difference in the transformed PDs over time. We use these correlations as targets toward which to fit the latent factor model established earlier. To do so, note that the factor-implied correlations are $\boldsymbol{\rho}_i\boldsymbol{\rho}_j'$. Then, we can determine these parameters by minimizing the sum of the squared differences between the factor-implied correlations and the correlations implied by the Merton model:

$$\min_{\boldsymbol{\rho}_1,\ldots,\boldsymbol{\rho}_n} \sum_{i=2}^{N}\sum_{j=1}^{N}(a_{ij} - \boldsymbol{\rho}_i\boldsymbol{\rho}_j')^2 \tag{6}$$

Andersen and Basu (2003) develop an algorithm (outlined here in Online Annex 2) which solves this numerical minimization problem in an efficient way through an iteration over the asset correlations' principal components, avoiding a costly direct minimization over all factor model parameters.

The target correlations a_{ij} are key inputs in our credit-based model, as they determine the latent factor exposures driving the model's default correlations. In our baseline approach, we use CDS-inferred PDs (as shown in 5) to establish the target correlations. As a robustness check, in Section 4.3, we also employ the common method of setting a_{ij} directly to equity return correlations. This is feasible only for the sub-sample of listed banks, and we demonstrate that within this sub-sample, the resulting attributions from both approaches are very similar.

Note that the approach outlined here enables us to quantify the correlation structure without requiring a full estimation of the Merton model, as has been done in earlier studies (Lehar, 2005; Duan, 1994). Instead, all that is needed is an estimate of banks' default probabilities over time which come directly from the CDS prices (see Online Annex 3.4). As we do not derive default probabilities directly from the Merton model, our approach is more robust to the potential model misspecifications highlighted by Nagel and Purnanandam (2020).

3.2 Measuring Systemic Risk

We now have the machinery in place to model systemic risk, which we define as the potential for large default losses in the banking system in the aggregate. A single entity's contribution to systemic risk then will be quantified through its propensity to increase this potential, which we capture by modeling the supervised institutions as a structured credit portfolio managed by the central bank or the supervisor. On an intuitive level, thus, several elements can thus drive the systemic risk contributions of an institution: increases in the default probability; decreases in the proportion that can be recovered in case of default; the size of the institution, measured by its outstanding liabilities relative to the size of others; the propensity of the institution to become distressed or to realize large losses whenever other institutions in the portfolio are distressed.

In our setting, an institution becomes distressed if a credit event occurs in its subordinated debt. Thus, formally, we define the default loss on an individual bank as a proportion of the size of its liabilities, as

$$L_{i,T} = \mathbb{1}_{i,T}(1 - RR_{i,T}) \tag{7}$$

where $RR_{i,T}$ is the stochastic recovery rate defined in (8). So, overall, the loss will be zero if bank i does not default and will be equal to the random realization of the recovery rate if the bank does default.

Then, total systemic loss $L_{sys,T}$ is the weighted sum of the individual losses of each bank:

$$L_{sys,T} = \sum_{i=1}^{n} w_i L_{i,T} \tag{8}$$

where $w_i = \frac{B_i}{\sum_{j=1}^{N} B_j}$ is the relative weight of the institution's liabilities (B_i) in the systemic portfolio. Consequently, we capture a bank's systemic risk sensitivity through its Marginal Expected Shortfall (MES, Acharya et al. (2017)), which is the average loss of institution i given that the systemic portfolio is above the worst α-th percentile of its distribution of potential losses:

$$MES_i = \mathbb{E}\left(L_{i,T} | L_{sys,T} \geq VaR_{sys}\right) \tag{9}$$

where VaR_{sys} stands for the Value-at-Risk of the institution at $1 - \alpha$ confidence level: $\mathbb{P}(L_{sys,T} \geq VaR_{sys}) = \alpha$. Typically, α stands for the tail probability. We assume $\alpha = 5\%$ going forward, as a cut-off loss quantile indicative of extreme but plausible tail scenarios.

Finally, we define total systemic risk as the Expected Systemic Shortfall of the Central Bank's regulatory portfolio:

$$ESS = \mathbb{E}(L_{sys,T} | L_{sys,T} \geq VaR_{sys}) \tag{10}$$

One can easily show that the weighted sum of all MESs in the portfolio provides the ESS.[7] This additivity property allows us to break down the total ESS into risk shares

[7] This follows from (15) and (11): $ESS = \mathbb{E}\left(\sum_i w_i L_{i,T} | L_{sys,T} \geq VaR_{sys}\right) = \sum_i w_i \mathbb{E}\left(L_{i,T} | L_{sys,T} \geq VaR_{sys}\right) = \sum_i w_i MES_i$. Note that this implies also that the MES measure can be interpreted as the sensitivity of the system's tail risk to the weight of the institution in the portfolio since $\frac{\partial ES_{sys}}{\partial w_i} = MES_i$.

attributable to each bank. We thus define Percentage Contribution to ESS (PCES) as:

$$PCES_i = \frac{w_i MES_i}{ESS} \tag{11}$$

which will be a useful metric further on in attributing the share of systemic risk across institutions and in ranking them by systemic importance. In Online Annex 1.4 we provide a step-by-step guide to the Monte Carlo simulation underlying our estimates.

4 Empirical Analysis

In this section we show three applications of the model presented so far: first, we use it to evaluate the dependencies between banks and the potential for joint distress; second, we use the model to attribute systemic risk over all banks in the regulatory portfolio in line with Section 3.2; third, we use the model to provide an aggregated indicator which can track the evolution of financial fragility factors over time.

4.1 Data and Parameter Assumptions

We consider a universe of 27 large European institutions. We use weekly mid prices for ISDA2014-compliant CDS contracts on the subordinated debt of the banks. Five-year CDS rates are used for all banks. The data is collected from Bloomberg. The sample universe is based on the list of European G-SIIs for 2022 compiled by the EBA.[8] The list consists of 30 banks, and we drop four for which insufficient CDS data is available: BPCE (France) accounting for 6.8% of the systemic exposure calculated by EBA; Banque Postale (France); DNB ASA (Denmark); Nykredit (Norway), each accounting for less than 1.5% of the systemic exposure calculated by EBA. We add the Netherlands' Volksbank at the request of the Dutch Central Bank.[9] About a third of the banks included are not publicly traded, including the coöperative banks such as France's *CRMU*, Germany's *DZ,*

[8]Table (1) in the Online Annex provides a list of the banks included in the analysis, also available at https://www.eba.europa.eu/risk-and-data-analysis/risk-analysis/risk-monitoring/global-systemically-important-institutions-g-siis. O-SII buffers for 2022 are available in EBA's interactive dashboard: https://www.eba.europa.eu/risk-and-data-analysis/risk-analysis/risk-monitoring/other-systemically-important-institutions-o-siis

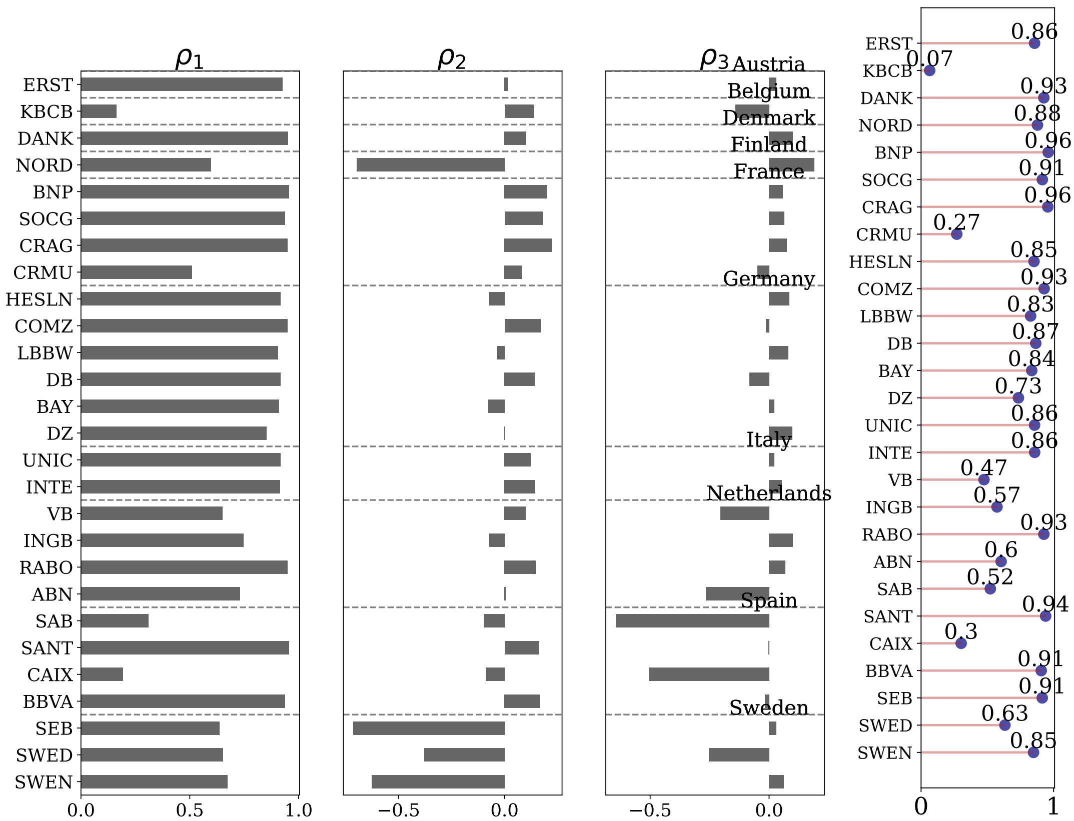
[9]As indicated in Table (1) in the Annex Volksbank accounts for about 0.5% of the sample size measured in terms of aggregate liabilities, so it does not affect the aggregate evaluation of the systemic risk or its attribution across banks. Adding it to the sample, however, allows us to evaluate its MES scores as well.

BAY, LBBW, HESL; Netherland's state-owned *VB*; and private banks such as *RABO* and *INGB*. *ABN*'s equity has been re-listed in 2015 after earlier government intervention, and only just for a minority share. Using CDS rates allows us to include them in the analysis, and as a result, to get a more complete picture of the financial system. Note that we use the CDS rate for ING Bank (*INGB*), a subsidiary of ING Group (which is publicly traded), as it is of relevance for European regulators. As ING Group has no formal obligation on the liabilities of ING Bank, the availability of this CDS contract allows us to focus more accurately on the risks embedded in the European operations of the bank. All of the non-listed banks included in our analysis are large national institutions that play a critical role in domestic financial intermediation. These banks are designated as domestically systemically important banks (D-SIBs), reflecting their potential to disrupt national financial stability in the event of distress. National authorities are responsible for assessing their systemic importance and assigning corresponding capital buffer requirements. Within our sample, eight banks are also designated as globally systemically important banks (G-SIBs) as of 2022, and are therefore subject to the more stringent capital and disclosure requirements under the G-SII framework.

For five banks, domiciled in Germany and Austria, only CDS rates on their senior debt are available. Senior debt is lower-risk than subordinated debt and is sensitive only to very large shocks. As a result, these CDS rates are lower and less responsive to news compared to the subordinated CDS rates of the same issuer. To ensure that these five banks are on the same footing as the rest, we add to them on a period-by-period level the median cross-sectional spread between the subordinate and senior CDS prices.

Annual balance sheet data is collected from FactSet, Bureau van Dijk's BankFOcus and from publicly available financial statements of the firms whenever the data providers have a gap. Annual balance sheet numbers are interpolated to weekly values using a cubic spline to avoid jumps at fiscal year-end due to accounting conventions. The analysis of Sections 4.2 and 4.3 are as of August 29th, 2022 and CDS spreads as of that date are used to evaluate the PDs in Equation (1). To estimate the latent exposures in the factor model (7), we use a time window from August 31st, 2019 to August 29th, 2022.

Figure 1: Factor Model



(a) Factor Loadings (b) Factor Share

Note. This set of figure shows (a) the estimated factor loading for the universe of banks, ranked by domicile country; (b) the share of overall risk attributable to the common factors.

4.2 Systemic Dependencies

The first building block for evaluating the potential systemic losses relies on the estimation of the latent factor model. This is also the first application of the model that we will look into. We use a three-factor specification of Equation (7).[10] Figure 1 displays the estimated factor loadings for each bank. The exposure patterns across factors provide insights into the economic interpretation of the latent factors. The first factor (ρ_1 in Chart 1) captures the dominant co-variation in all banks' asset values and can be interpreted as a broad market factor. All factor loadings are positive, and with few exceptions, close to the upper bound of one, meaning that the overall market already explains most of the covariation in

[10]To determine the appropriate number of factors, we seek the smallest number that can explain the majority of the co-variation in the data. We conduct a Principal Component Analysis (PCA) on the universe of CDS rates and find that the first three principal components (PCs) collectively explain approximately 80% of the variance in weekly CDS price changes. Beyond the third factor, the incremental explanatory power of each additional factor becomes marginal, contributing less than 1% to the total variance (as shown by the dotted blue curve on Figure (2) in Online Annex 3.2.

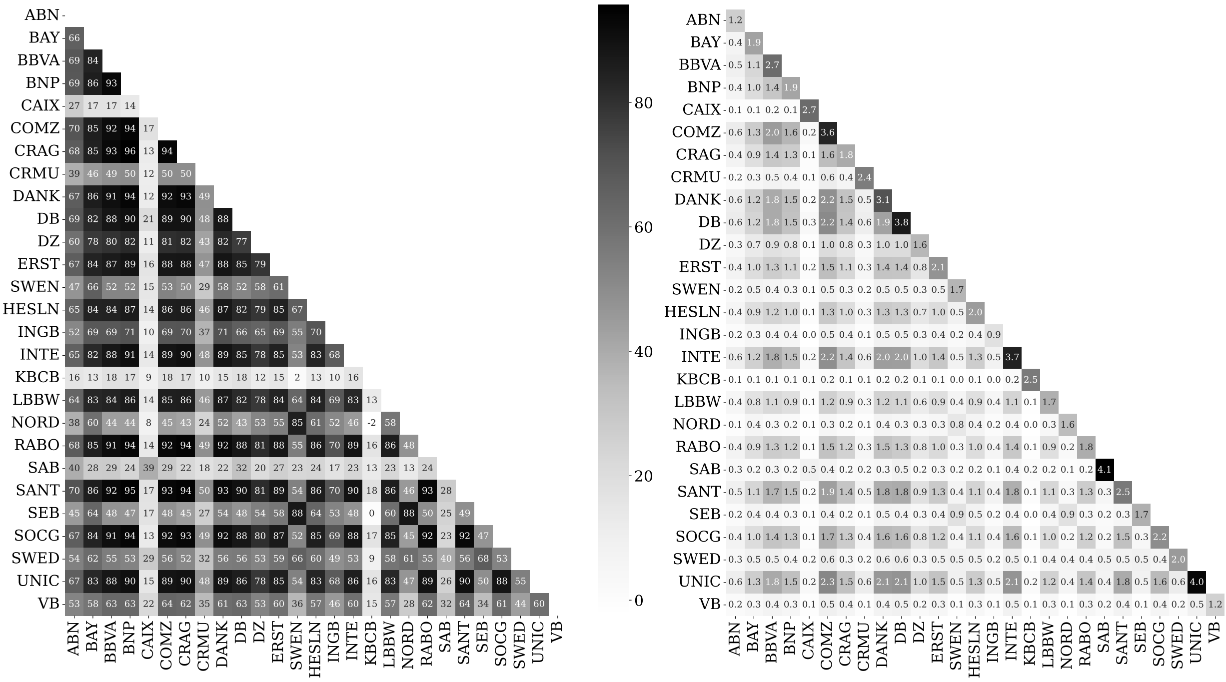
these banks. The second factor accounts for co-variation among banks that deviates from the overall market trend, revealing a distinct clustering of exposures among banks from Sweden and Finland. The third factor captures any remaining co-variation not explained by the first two, notably highlighting a group of Spanish banks with common exposure. Figure 1 also shows the estimated share of factor-driven risk (as opposed to idiosyncratic risk) for each bank. This can be seen as an initial raw unweighted estimate of which banks will be sensitive to shocks. Among the most sensitive institutions, largely driven by their high market factor exposure (ρ_1) are *BNP, CRAG, SANT, COMZ* and *RABO*.

Next, we take a closer look at the dependencies that the model implies. Figure 2 shows the implied correlations between banks' assets, based on the transformation implied by the multivariate Merton model in Equation (5). First of all, banks that have high market exposures (i.e. exposure to ρ_1 closer to one in Figure 1) also have high implied correlations. Most notably, this includes the cluster of German, French, Italian, and Dutch banks (*BAY, BBVA, BNP, DANK, DB, DZ, EST, RABO, SANT, UNIC*).

In addition, the multifactor model allows for certain network effects to crystallize. This can be seen again in Figure 2 where clusters of correlations due to exposures to lower order factors show up. For example, *SEB, SWEN, SWED* and *NORD* appear to be highly correlated among each other, while they otherwise have low correlation to all other banks in the universe. This is due to their relatively low correlation to the market factor (ρ_1) and the high exposure to the second factor (ρ_2). Similarly, *CAIX* and *SAB*, the two banks with the highest exposure to factor ρ_3, appear to have a relatively high correlation to each other, even though other correlations are close to zero. One limitation of interpreting the factor exposures is that they are undirected. This is also a common criticism of MES measures – we cannot distinguish if a shock travels from a bank to the system or from the system to the bank. What we can say from this analysis, however, is that a shock will travel less easily for example between the German banks (with high ρ_1) and *SAB* and *CAIX* which have a high exposure to ρ_3 and very low to ρ_1.

Next, we examine the probabilities of joint default (JPD) between banks. In comparison to the asset correlations, we now also factor in the probability that banks may become distressed at the same time. The underlying intuition is that high asset correlation by itself is not necessarily an indication of systemic distress, as long as the probability of any of the bank pairs to be distressed is low. In that sense, some clusters of high correlations

Figure 2: Implied Dependencies(%)



(a) Asset Correlations

(b) Joint Probability of Default (%)

observed earlier do not lead to significant joint default probability. Figure 2b shows the estimated JPDs as the off-diagonal terms of the plotted matrix. We can see, for example, the relatively high joint distress rate between *COMZB, SANT, UNIC, INTE, DB* and *DANK*. On the other side are *CRAG* and *INGB* which have relatively high correlations to the rest. Yet having relatively low own default rates they do not show up on top of the ranking in terms of joint default potential.

When considering these results, it should be kept in mind that the default probabilities extracted from the CDS rates are based on the risk-neutral distribution and should not be interpreted as physical probabilities of default. Since asset risk premia are typically positive, the risk-neutral estimates can be expected to be more conservative than real-world default probabilities.[11]

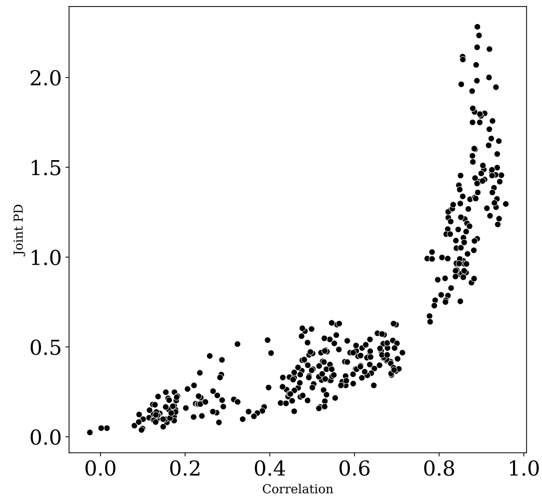
Finally, we highlight a specific aspect of systemic risk: even though the asset correlations and joint default measures largely agree in rankings (cf. Table 3a), higher asset

[11]The discrepancy between risk-neutral and physical default probabilities has been noted among others in Altman (1989); Hull et al. (2005). Translating from one to the other requires an estimation of the respective risk premia. This is not a trivial task, especially considering the time-varying nature of risk premia. There is ongoing research in this area. See Ross (2015); Bekaert et al. (2022) for some suggested approaches, and Figlewski (2018); Cuesdeanu and Jackwerth (2018) for an overview of the challenges. Heynderickx et al. (2016) compare risk-neutral densities estimated from European CDS contracts to physical densities derived from rating agencies.

Figure 3: Dependency Pairs

	AC	JPD	$CPD_{i\|j}$	$CPD_{j\|i}$
AC				
JPD	0.91			
$CPD_{i\|j}$	0.93	0.88		
$CPD_{j\|i}$	0.92	0.88	0.74	

(a) Rank Correlations



(b) Corr. vs. JPD

Note. The table shows a matrix of the rank correlations between dependency pairs, where dependency is measured by the implied asset correlations, joint default probability, and conditional default probabilities. The figure presents a scatterplot of each pair of banks in terms of the estimated asset correlation and probability of joint default.

correlations tend to be associated with exponentially higher probability of joint distress, as shown in Figure 3b. By considering the JPD rather than pure asset correlations, we can capture this nonlinearity.[12]

4.3 Systemic Risk Attribution and Capital Requirements

There exists an apparent disconnect between the academic and regulatory approaches used to measure systemic risk. The academic approaches, as we saw, favor the use of market data and asset pricing methods. Regulators, on the other hand, rely on balance sheet and regulatory data. In particular, for European regulators, the general guidance by the EBA is to focus on several criteria of systemic relevance such as size, importance, complexity, and interconnectedness (EBA, 2020). At a national level, a score is provided in each systemic category, and the four categories are weighted up to a single O-SII score number.[13] The market-based methodology presented in this paper provides an alternative approach, independent of regulatory assumptions, as we attribute the overall

[12]Figure (3) in Annex 3.4 further provides the conditional default probabilities.

[13]O-SII stands for "Other systemically important institutions".

systemic risk to individual banks through the percentage contribution figures (PCES) defined in (10). We first compare (for each country in the sample with at least two banks) our credit-based PCES measure to the systemic importance implied by national O-SII capital buffers, designed to offset each bank's systemic impact.

Within the European Union, banks deemed systemically significant to national economies are subject to the O-SII regulatory framework. Under the guidance of the European Banking Authority (EBA), national authorities assess the systemic risk contributions of banks and determine the size of macroprudential surcharges imposed on these institutions. Banks classified as globally systemic (G-SII) also receive macroprudential add-on buffers, but only the larger of the two buffer rates, O-SII or G-SII, is actually applied as a capital requirement.[14] In our sample, all G-SII buffers are equal to or below the corresponding bank's O-SII buffer; therefore, our analysis focuses exclusively on O-SII rates.

Notably, as shown on Figure 4, while the scoring methodology used by national authorities does not incorporate market data, our credit-based methodology closely aligns with the O-SII buffer rankings. Despite not covering the entire universe of O-SII banks in each country, when applied on a national scale our approach effectively captures systemic risk rankings in France, Germany, Spain, and the Netherlands. The credit-based methodology allows us to attribute risk to the privately held banks as well (the light blue circles in the figure), which would not be possible within the standard equity-based market approaches.

When systemic risk is attributed across all banks simultaneously on a European scale, however, the rankings diverge significantly. We find that the five largest banks in the sample, *BNP, CRAG, SANT, SOCG* and *DB* account for 55% of the total systemic risk, measured by ESS.[15] From a policy point of view, we would like to compare their capitalization to that of banks ranked as less systemic according to their $PCES$. In Figure 4a we plot the regulatory O-SII buffer rates against the corresponding $PCES$ numbers. The size of each bubble in the chart is proportional to the liability size of the bank. The results are striking: although there seems to be a strong positive relationship between systemic contributions and O-SII buffers for most banks, there is a cluster of

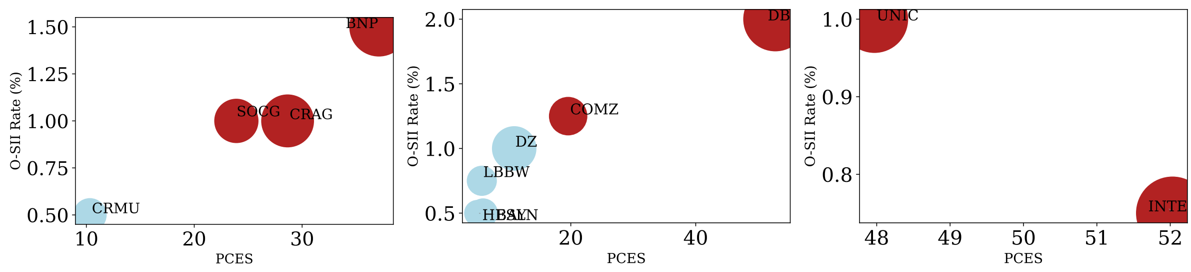
[14]For details, see BCBS (2010); FSB (2020); EBA (2020). In addition, the discretion of national regulators in translating systemic scores into capital buffer add-ons introduces additional heterogeneity across countries (ESRB, 2017) as the average buffer add-ons are also different between countries.

[15]Cf. Table (2) in Online Annex 3.3 for details on our estimates.

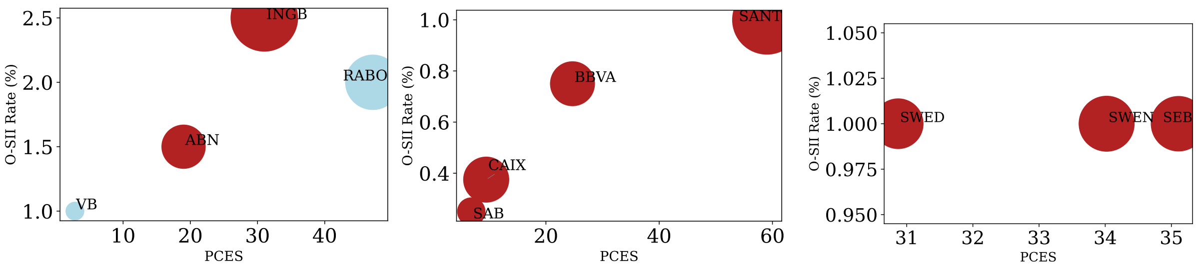
large banks that do not fit the pattern in that their buffers seem low by comparison to the rest of the sample. The cluster is located on the right side of the chart and consists of the four largest banks in our universe, three of them domiciled in France: *SOCG, CRAG, BNP*, and one domiciled in Spain: *SANT*. Location on the right side of the plot implies that their required O-SII buffers are low compared to their contribution to systemic risk: they are required to hold between 1% and 1.5% buffers, even though their respective contributions to systemic risk are several times higher than those of smaller banks with a comparable buffer requirement. In order to verify if other types of capital buffers compensate for their relatively low O-SII rates, Figure 4b sets off their total CET1 capital ratio against their contribution to systemic risk. The same story is revealed: the largest contributors to systemic risk are undercapitalized relative to their share in total systemic risk when compared to the smaller banks.[16]

[16]The higher of the required G-SII and O-SII buffers applies if a bank is subject to the two. In our sample however, the O-SII requirement was at leas as high as the G-SII one for all banks.

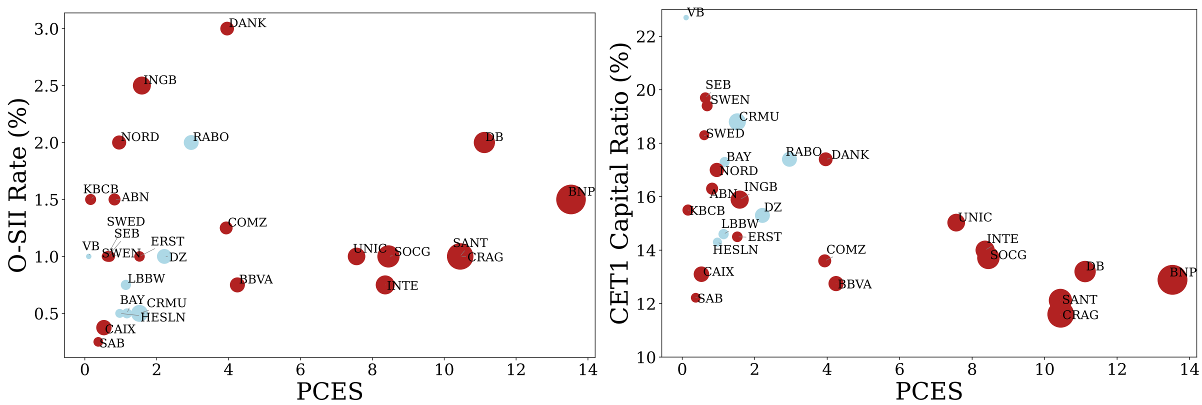
Figure 4: PCES vs. Capitalization



(a) France (b) Germany (c) Italy



(d) Netherlands (e) Spain (f) Sweden



(g) Euro Scale, O-SII Buffers (h) Euro Scale, Current Capitalization

Note. This figure shows our model estimates for systemic risk contribution measured by PCES at 95% confidence level versus (a) the size of the required O-SII buffer rate for 2022, and (b) banks' total CET1 capitalization ratio for 2022. The size of each dot corresponds to the relative liability weight of the bank in the regulatory portfolio. The light blue color indicates the systemic banks which are not exchange listed.

4.4 Comparison of the CDS approach vs. Equity Approaches

A natural question is if these results hold when systemic risk is evaluated using the more common approach based on equity data. Tarashev and Zhu (2006), among others, have voiced the concern that equity and CDS markets may be in disagreement over asset dependencies in periods of extreme distress. To examine if segmentation and intermediation in the CDS market may be polluting our results, first, we carve out the subset of banks for which both CDS and equity market data is available and reevaluate the systemic risk attribution. Using our credit-based approach of Section 3, we replace the bank target correlations (see equations (5) and (6)) derived from CDS co-movements with correlations derived from the equity markets.

In a second approach which does not use CDS prices at all, we construct the percentage contribution to SRISK, ($\%SRISK$) defined in Acharya et al. (2012) as

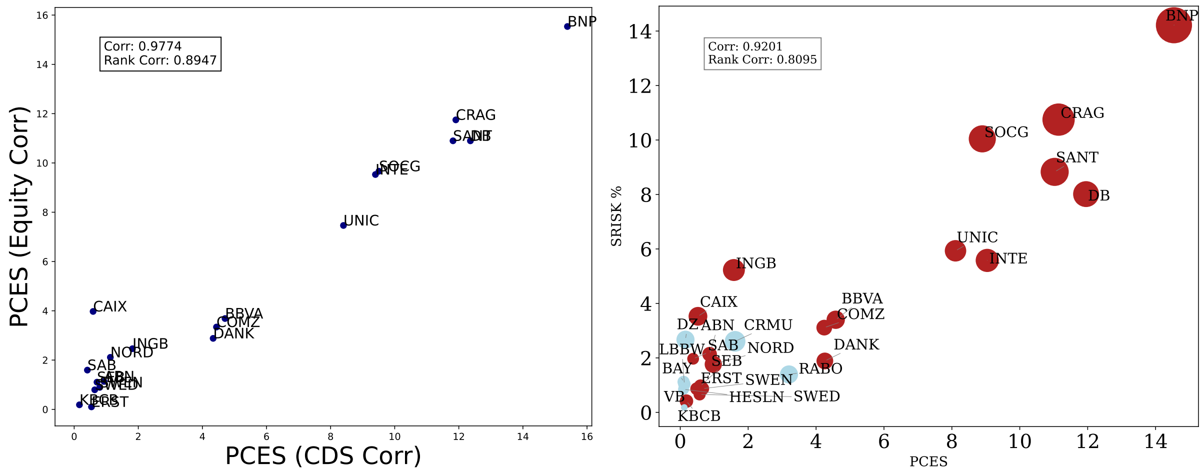
$$SRISK\%_i = \frac{SRISK_i}{\sum_j SRISK_j} \tag{12}$$

SRISK is designed to capture the downside dependency between a bank's market price of equity and the market (see Online Annex 3.6 for details on SRISK and how it compares to our estimation). To get estimates for the non-listed banks, we then leverage the idea outlined in Engle et al. (2024) by bridging between accounting data and equity prices through the listed sub-sample of banks (more on this in Section 5).

Figure 5 compares the results to our credit-based CDS approach. The risk attribution estimates in both cases have a correlation above 90% relative to our approach. The added benefit of using CDS rates, however, as we show in Section 5 and Figure 4a, is that they are more sensitive to risk developments over time and are more closely aligned to the market view, as no extrapolation between market data and accounting data is needed. In Section 5 we also show that our CDS-based results are robust to varying the tail index coefficient of the MES estimate (99% vs. 95% confidence level), and to the assumption of dependent LGDs.

So, finally, we can conclude that for an important subgroup of large European banks, the size of the buffers they are required to hold does not seem to be in proportion to their contribution to systemic risk: the buffers are lower than for other banks with comparable or lower contributions to systemic risk. This leads to two questions. First of all, how appropriate are the current buffer rates when risk spillovers outside of the national economy and within the Eurozone are taken into account? And second: how consistent are the approaches of translating systemic importance into buffer requirements between European countries? In Dimitrov and van Wijnbergen (2023) we explore the calibration of macroprudential capital buffers based on systemic risk, building on the methodology developed in this paper and addressing the capitalization discrepancies observed here.

Figure 5: Equity-based vs CDS-Based Risk Attribution



(a) CDS-based vs EQ-based correlations

(b) SRISK% vs PCES

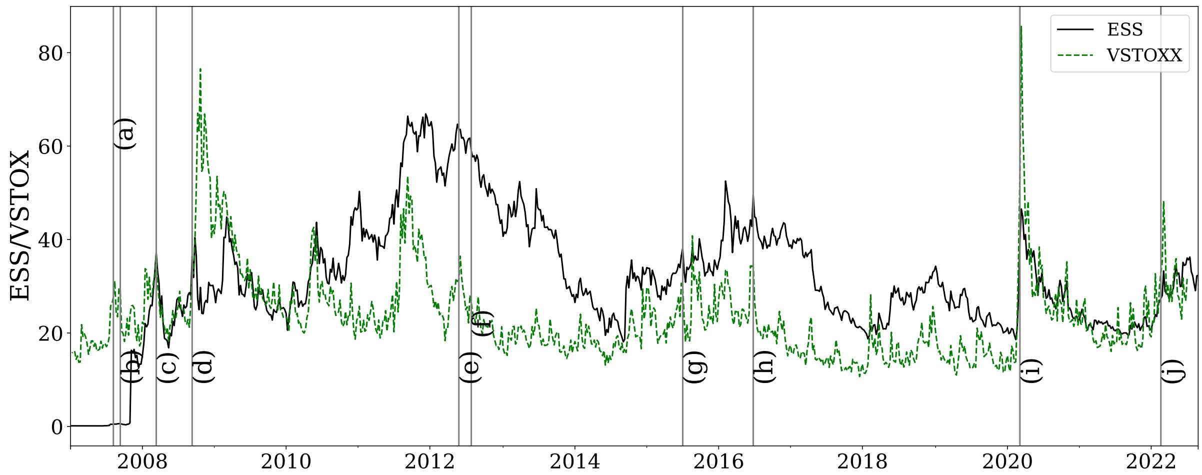
Note. This set of figures shows comparisons in risk attribution between (a) the credit-based approach estimated with CDS-based correlations, and with equity-based correlations (for the listed banks only); and (b) between equity-based SRISK implied measure and credit-based PCES measure.

4.5 Measuring Aggregate Systemic Risk

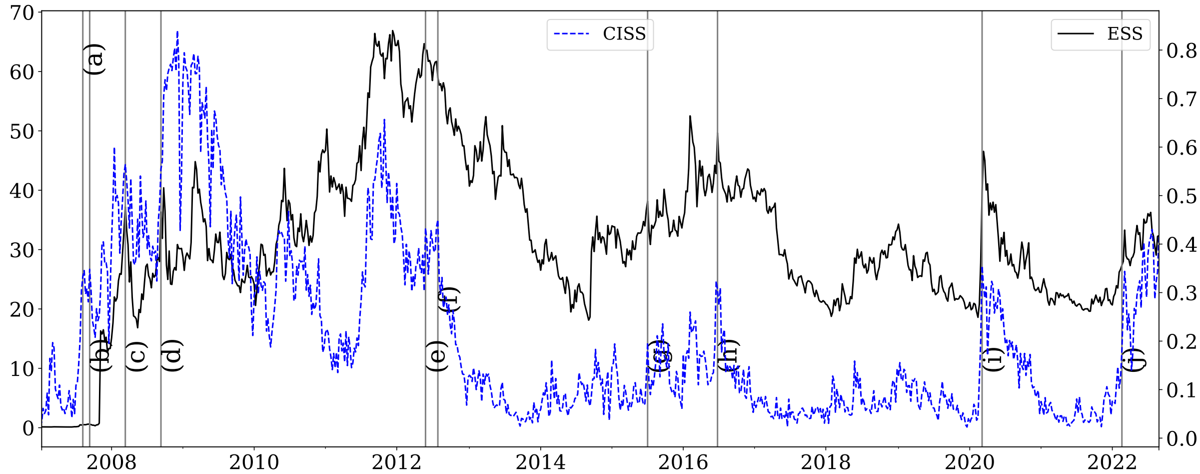
So far, we have discussed the use of the shortfall measures as a way to attribute total systemic risk across banks and to rank institutions by their contribution to systemic risk. Next, we show how systemic risk itself can be quantified by calculating the Expected Systemic Shortfall (cf. Equation (11)), and evaluate the potential of the ESS measure as an early indicator of financial distress. We backtest the ESS measure out-of-sample in the period from January 2007 to August 2022. In that case we evaluate the model using a rolling-window approach as described by Lehar (2005). Specifically, each time a two-year window of weekly observations is used to estimate the model parameters and to evaluate the ESS for the period, the window is then rolled forward by adding one week of new data and dropping the oldest data point, the model is re-estimated and the ESS for the next period is evaluated. This produces a series of ESS numbers, where each dated estimate utilizes only historical information available up to the respective date, thus allowing comparison to alternative measures of systemic risk. For the initial estimations in 2007, a shorter (one-year) and expanding window is used, as data for most series starts in 2006.

We compare our measure to two alternative indicators of aggregate systemic risk. First, Figure 6a compares the *ESS* with the value of the VSTOXX index, which is

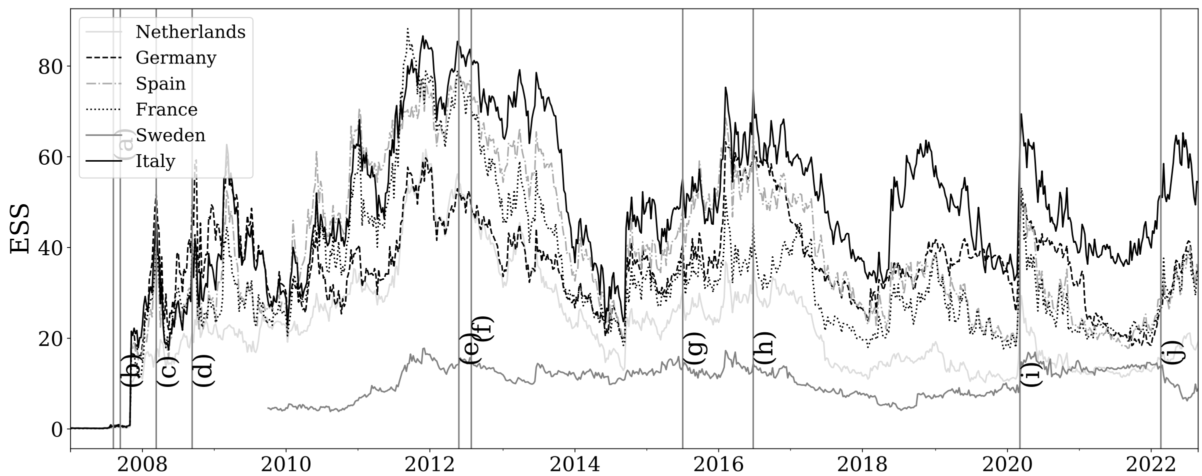
Figure 6: Expected Systemic Shortfall



(a) ESS vs. VSTOXX Index



(b) ESS vs. CISS Index



(c) ESS by Country

Note. This plot shows the tail risk of the systemic portfolio quantified by the *ESS* at a confidence level of 95%. The dotted line in (a) represents the VSTOXX index; the dashed line in (b) represents the ECB's CISS index. The vertical lines indicate the dates for (a) BNP announces CDO-related losses; (b) Northern Rock seeks liquidity support from the BoE; (c) Bear Stearns downgraded; (d) Lehman files for bankruptcy; (e) Mario Draghi's "courageous leap" speech to save the Euro; (f) Draghi's “whatever it takes” speech; (g) Greece misses an IMF payment; (h) Brexit referendum; (i) the first Covid lockdowns in Europe (in Italy); (j) the Russian invasion of Ukraine.

often used to track risk appetite and market panic. VSTOXX, like its US counterpart VIX, measures the implied volatility derived from near-term exchange-traded options on the Euro Stoxx 50 equity index.[17] The options are widely used by investors for hedging purposes, and thus indicates the current price investors are willing to pay in order to hedge extreme risks. Similarly, Figure 6b compares the ESS to ECB's Composite Indicator of Systemic Stress (CISS) within the Euro area.[18] In its overall trend since 2016 our constructed ESS measure matches very closely the VSTOXX and the CISS indices. The match becomes particularly notable from 2018 onward.

To put the systemic risk developments in context, we also place on the charts several key events which are relevant for the development of systemic risks. First, we can see in retrospect that the ESS jumps sharply after the initial signs of the looming Financial Crisis (vertical lines (a) and (b) on the chart) and before the downgrade of Bear Sterns in the US (line (c)). Next, the ESS declines gradually after Draghi's "courageous leap" (e), and "whatever it takes" speeches (f) in 2012, indicating that the measure was able to capture the subsequent decline in systemic risk from the Euro debt crisis.

The ESS peaks in 2012, in contrast to the VSTOXX and the CISS which peak in GFC in 2008/09. It needs to be noted that the CDS market (similarly to other OTC derivatives markets) has changed significantly in the period after the GFC with regulation enforcing stronger transparency and stricter rules on central clearing. As a result, the benefit of the CDS-based measure can be seen more closely in recent periods. First, it directly reacts to distress in the financial sector. We can see the sudden spike in ESS with the first Covid lockdowns in Europe in January 2020 and the subsequent decline after the ECB's involvement to secure liquidity in the market. The Russian invasion of Ukraine in 2022 had a much smaller impact on the ESS than on VXTOXX, possibly because the ESS is strictly focused on the banking sector, while VSTOXX covers the direct effects of the war on all sectors.

Second, the ESS has the advantage that it can be broken down into bank specific or

[17] The composite implied volatility indices are often seen as indicators of the (lack of) risk appetite in the economy. A low appetite for risk (high implied volatility) relates to a greater cost of capital for the economy, thus lower investments and lower asset prices, while a high appetite (lower implied volatility) relates to credit and asset price bubbles, increasing the chance for future recessions and stress in the financial system.

[18] The CISS index aggregates data from the money market, bond, equity and FX markets, and accounts for potential distress in financial intermediation Hollo et al. (2012); Chavleishvili and Kremer (2025).

country specific components, as can be seen in Figure 6c.[19] This allows us to see several trends: Sweden is clearly a outlier in having the lowest ESS. Italy on the other hand tends to be the riskiest. Note however, that this does not necessarily mean that Italy is a high contributor to systemic risk in Europe. As we saw in Figure 4, the two Italian banks are only sixth and seventh in terms of percentage contribution, PCES. The reason lies in the fact that they are smaller in size than for example their French or German counterpart.

5 Model Discussion and Robustness

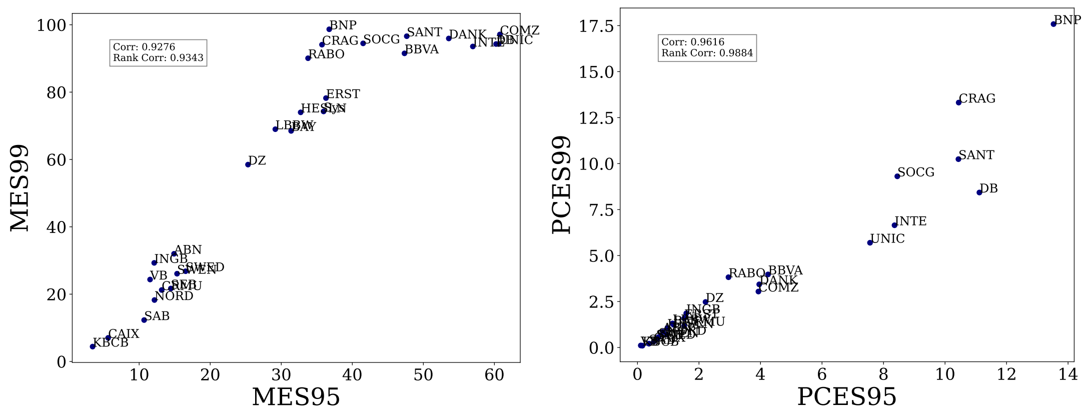
In this section we report on several of robustness checks. First, we examine the robustness of our results to the choice of Confidence Level. Second, we modify the assumption of dependent LGDs, compared to the standard practice of assuming independent LGDs. Third, for the sub-sample of non-listed banks, we compare our CDS-based approach over time to a similar attempt to get around the lack of equity prices but using accounting data rather than market data (cf Engle and Jung (2023); Engle et al. (2024)). Finally, we relax the Gaussian assumption of asset returns.

5.1 The confidence Level $1 - \alpha$:

To assess the robustness of these results, we first examine the sensitivity of the findings from Section 4.3 to the choice of a confidence level parameter. Figures 7a and 7b compare results for MES and PCES respectively at the 99% and 95% confidence levels, i.e., defining the tail of the regulatory portfolio as the worst 1% versus the worst 5% scenarios of the simulated systemic loss distribution. We observe minimal changes in bank rankings, mostly due to the fact that losses are naturally constrained at 100%, so that banks perceived as very systemic naturally cluster at the 100% threshold for the 99% MES level. Any remaining differences further diminish when the MESs are weighted into PCES attribution figures. The rank correlation between MES estimates at the two tail levels approaches 99%, confirming the stability of our rankings across different tail risk thresholds.

[19]We show the ESS only for countries where more than one bank CDS exists in our sample.

Figure 7: Robustness of the Systemic Risk Attribution

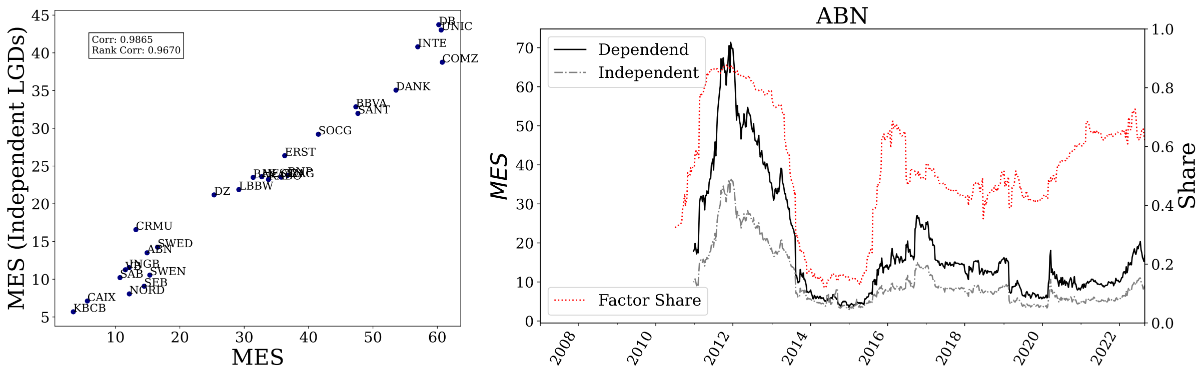


(a) (b)

Note: This set of charts shows the robustness of the risk attribution model against varying the risk confidence level (1-α).

5.2 Dependent losses extension:

Figure 8: Credit-Based Approach: Depdendent vs. Independent Losses



(a) (b)

Note. This figure shows the impact of the correlated LGD assumption on the value of the MES estimates. (a) shows a comparison with the estimates from Section 4.3; (b) shows MES evolution over time (left scale)against factor risk share (right scale) for ABN Amro.

Next, one of the novel assumptions in our model is that LGD rates are correlated, departing from earlier literature that assumes independence for simplicity. Figure 8a demonstrates that incorporating correlated LGDs does not significantly alter the ranking of banks for our analysis in Section 4.3, instead producing a level shift in risk measures. Still, theoretically, our assumption is justified: insights from the Merton model support this assumption, as the underlying factor which determines PDs and LGDs is the unobserved market value of the firm's assets, which, as indicated in our model, will be correlated across banks based on their common factor asset exposures.

To ilustrate when the correlated LGD assumption may make a difference, in Figure 8b we show how shifts in the share of factor exposure can impact the gap over time between the MES estimate with correlated and with uncorrelated losses. As an illustration, we follow ABN Amro's estimates of MES and share of factor risk over time. After the GFC, ABN was nationalized and restructured. It was re-listed on the stock exchange in 2015, and as our model indicates becomes again systemically more important. We can see how the gap between the MES estimated with each assumption on the LGDs widens as the factor share rises again after 2015.

5.3 Engle et al. approach to missing equity market prices:

Engle and coauthors use a different method altogether to uncover the systemic risk contributions of unlisted banks (Engle et al., 2024). Like us, they have a sample consisting of both listed and unlisted banks. In what we label as a *synthetic approach*, they map key balance sheet information into the estimated systemic risk measure for the sub-sample of listed banks. The same mapping is then used to derive estimates of the systemic risk measure for all non-listed banks from their balance sheet data. They compare their results to the banks' projected capital depletion in EU-wide stress tests, and find that in terms of the size of banks' capital shortfall in a systemic crisis this approach offers a realistic alternative to estimation based on equity prices. We compare their approach with our market-based MES method by evaluating its temporal behavior and sensitivity to systemic events. To evaluate the market-based measures, we use a two-year rolling window approach as in Lehar (2005).

Consider first the comparison of our approach with equity based measures estimated directly on banks' stock returns as in Acharya et al. (2017). Formally, the equity based MES can be estimated as $MES^{eq} = -\mathbb{E}(R_i|R_{sys} < VaR_{sys})$ with R_i and R_{sys} the (annualized) percentage returns of bank i's equity price and of the overall systemic portfolio. Figure 9 compares the results. While the CDS-based measure is more reactive, the two clearly follow similar patterns. The CDS-based MES infers probabilities of default directly from end-of-day credit spreads, making it more immediately responsive to market stress. Unlike the equity-based approach, the rolling window in the CDS-based approach is used only to estimate default correlations, not volatility. This structural difference al-

Figure 9: Market-based MES: CDS vs Equity approach

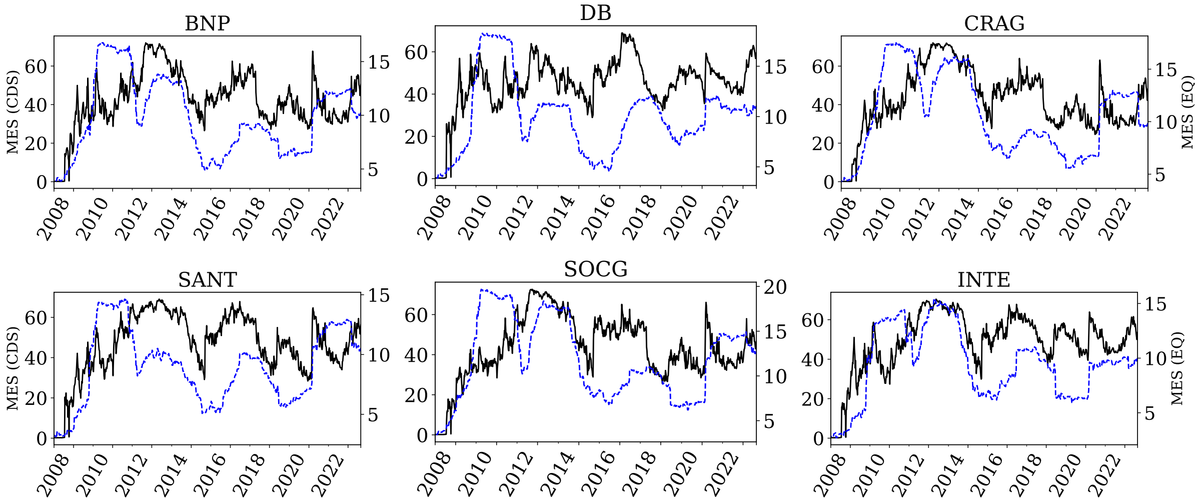
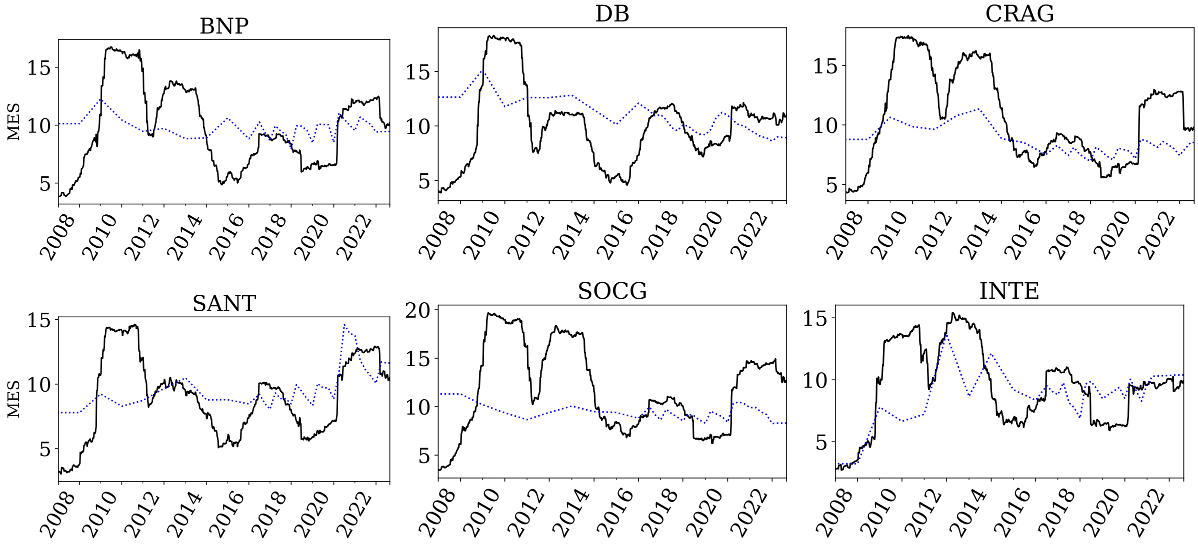


Figure 10: Market-Based vs Engle et al. synthetic approach



Note. This set of figures shows a comparison of the MES for the six largest contributors to systemic risk. The figures in 9 are estimated purely on market market data and show our CDS-based approach (left axis, solid black line) vs. the equity-based approach. The figures in 10 show the equity-based MES (solid black line) against the MES evaluated based on the "synthetic" approach proposed by Engle et al. (2024) which blends accounting and market data (dashed blue line).

lows the CDS-based MES to react slightly more sharply to sudden increases or decreases in risk, without the smoothness introduced by the equity-based method's time-window averaging. Furthermore, note that we plot the two measures in Figure 9 on different scales. In fact, there are reasons why the two measures can be expected to evolve over a different scale. Because of seniority of debt over equity the LGD embedded in equity prices is different from the LGD embedded in CDS prices.[20]

Next comes the comparison with the Engle and Jung (2023) approach. Linking their accounting data to overall systemic risk, we estimate their synthetic MES values via a model trained on the remaining banks, and compare these to actual equity-based MES values. Our in-sample comparison strategy uses the full set of accounting data to fit the underlying regression model, which is then interpolated to weekly frequency for comparison. Figure 10 compares the equity-based approach to the synthetic approach in order to isolate the effect of accounting data instead of market data. The equity-based MES (solid black line) is consistently more responsive to systemic events than the synthetic MES (dashed blue line). While the synthetic MES captures average systemic risk levels reasonably well, it tends to understate both the magnitude and timing of stress peaks. For example, *BNP* and Deutsche Bank (*DB*) show only muted synthetic MES responses during the 2008–09 financial crisis and the Euro Area sovereign debt crisis. During the COVID-19 shock, only *SANT* shows a timely synthetic MES spike; others lag or even decline (e.g., *SOCG*). For *CRAG*, synthetic MES rises slightly during crisis periods but fails to reflect the COVID-19 spike, with fluctuations likely driven by regression noise rather than actual risk changes. on the other hand reflects the Europan debt crisis, but fails to bulge during the Covid stress period.

These results are as one should expect: the market-data-based measures are available at higher frequency than the accounting data used in the Engle et al. (2024) synthetic approach. It is important to also note that while the market-based MESs are estimated out-of-sample in a rolling window fashion, this is an in-sample evaluation for the regression underlying the synthetic approach, thus assuming that the full dataset necessary is known at the start of the period as the regression coefficients are estimated. Thus, additional estimation noise would reduce the performance of the synthetic method further. These findings reinforce our point that the synthetic approach is a valuable fallback in

[20] Carr and Wu (2011) in fact provide a link between the two by comparing the value of CDS contracts to the value of deep out-of-the-money put options traded on the same company.

the absence of any market data, but that it is not a substitute for the richer informational content of market-based measures, whether they are equity or CDS. Also, while the synthetic approach is a useful fallback when both equity and CDS market data are unavailable, it cannot substitute for the timely informational content of market-based measures.

5.4 Non-linear factor specification, the Skewed-t Model:

Finally, we verify how the risk attribution is affected by modifying the Gaussian asset returns assumptions. In order to examine the sensitivity of our baseline model to the realization of extreme risk and dependencies, we modify the factor model in Equation (7) by allowing for fat-tails and for skewness in the distribution of the latent variable U_i and in the dependency between variables. We follow an approach suggested by Chan and Kroese (2010), who modify Equation (16) with a factor $G \sim TN\left(-\sqrt{\frac{2}{\pi}}, 1\right)$ that induces skewness and asymmetric dependencies, where $TN(\mu, \sigma)$ is a normal distribution truncated left at $-\sqrt{\frac{2}{\pi}}$; and a factor $F \sim \chi^2(\nu)$ that induces extreme dependence and fat-tails. They suggest then the following structure of latent variables:

$$U_i = \sqrt{\frac{\nu}{F}}\left(\delta G + \boldsymbol{\rho}_i M + \sqrt{1 - \boldsymbol{\rho}_i \boldsymbol{\rho}_i'} Z_i\right) \tag{13}$$

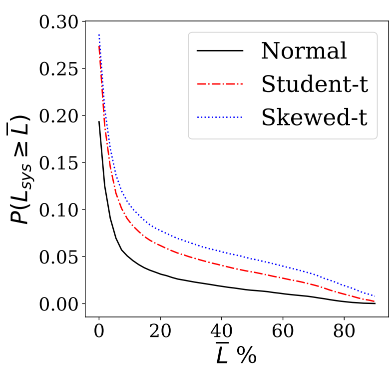
As long as the $\delta = 0$ we are in the multivariate student-t case.[21]

Figures 11b and 11c then show the estimated systemic risk by varying the skewness parameter δ and the tail-fatness parameter ν. It is interesting that the systemic ES appears to be much more sensitive to negative skewness than to symmetric fatter tails, as can be seen in Figure 11c. For ν around 30 and δ of zero, the model becomes normal. The risk estimate then increases sharply with more negative δ, even with otherwise thinner tails (degrees of freedom close to 30). The highest level of risk appears with high skewness and high tail-fatness parameters. Figure 11d compares the risk attribution numbers across the banks in the universe. Overall, we find that while adding a nonlinear or negatively skewed factor to the model has strong implications on the level of aggregate risk, it does little to change the risk attribution, and the risk rankings within the cross-section. The only exception is that banks with high idiosyncratic risk are now pushed up in the

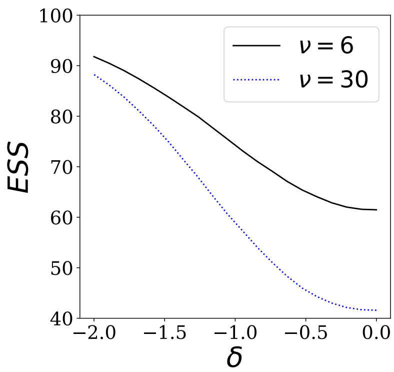
[21] See Online Annex 3.8 for a simulated illustration of how the parameter choice affects the multivariate distribution.

ranking. The implications of these results are twofold. First, given that the estimation of the tail parameters is difficult and subject to misspecification (joint systemic defaults are rarely observed, especially within a reasonable time window of data), working with the Gaussian model of Equation (7) still offers a reliable view into the cross-sectional distribution of risks. At the same time, however, allowing for tail dependence via one of the two extended models could offer a way of performing stress testing. In such a stress test environment, one could evaluate the sensitivity of the projected losses to an increased potential for the materialization of an extreme joint events, while still having the correlations of the model empirically based.

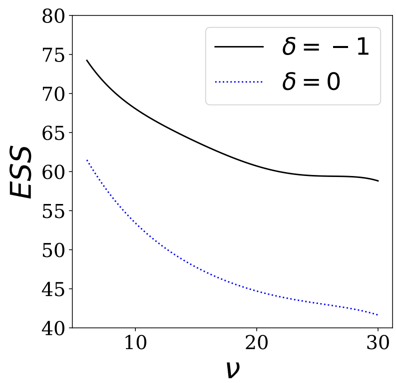
Figure 11: Aggregate Tail Risk, Model Comparison



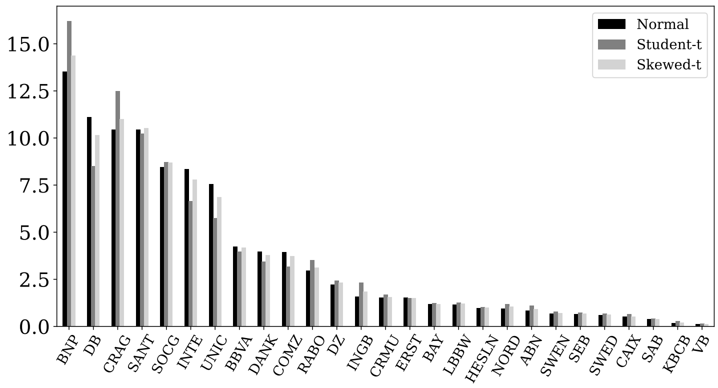
(a) Tail Comparison



(b) Skewed-t



(c) Skewed-t



(d) PCES

Note. This plot shows the overall risk in the system, measured by the systemic portfolio's ES. Figure (a) compares the probability of realizing a loss larger than a given threshold $\overline{L}$ for the Normal, the Student-t with $\nu = 6$, and the Skewed-t model (with $\nu = 6$ and $\delta = -1$). Figures (b) and (c) show the portfolio's ES as a function of the skewness parameter δ and the tail-fatness parameter ν. Figure (d) shows the share of systemic risk for the three asset returns distributional models. The Student-t model uses degrees of freedom ν of 6 and the Skewed-t uses, in addition, a δ parameter of -1.

6 Conclusion

In this paper, we address a common challenge in estimating and monitoring the build-up of systemic risks in many countries and/or regions: a regulator cannot observe the market price of equity for institutions that are privately or state-held. We show that high-frequency data from the CDS market can be used to imply views on co-dependencies and joint losses when equity data are not available. We apply the model to the European banking sector, where key domestically important banks are not publicly traded. The model allows us to rank banks in the Eurozone by their contribution to overall systemic risk in the Euro Area. We find that on a European scale, there is a discrepancy in the capitalization between the largest contributors to systemic risk relative to smaller, less systemically important banks. Our findings are robust even when correlations are evaluated from equity prices, rather than CDS prices. Our findings suggest that large banks in Europe account for a disproportionate share of systemic risk relative to their regulated capital buffers. Of course, policymakers may also impose additional constraints on such institutions, other than capital requirements. Large banks may be subject to more intense supervision, stress testing, and capital planning requirements. However, the degree to which these mechanisms fully internalize systemic risk in practice remains an open question. Behn et al. (2022) for example show counter-evidence that large banks are more likely to benefit from the internal risk models that allow them favorable capital-requirement treatment. In that sense, our CDS-based indicator serves as a complementary market-based signal that can help supervisors assess whether systemic risk is being effectively internalized in practice.

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Online Annex

1 Implying Default Probabilities from CDS prices

1.1 What is a CDS contract and why we use them

A CDS is an insurance contract, which is traded over-the-counter (OTC), and in which the protection buyer agrees to make regular payments, the CDS spread rate over a notional amount, to the protection seller. In return, the protection seller commits to compensate the buyer in case of default of the contractually referenced institution. There are multiple features of the CDS market that make it an attractive source of information on the risks which are evolving in the financial sector.[22]

First, it is more liquid and has fewer trading frictions compared to credit traded directly through the corporate bonds market. In terms of information transmission, CDS spreads have been shown to lead bond markets, especially in distress periods, and have an edge over credit rating agencies (see Bai and Collin-Dufresne (2019); Avino et al. (2019); Culp et al. (2018); Annaert et al. (2013)). This relates to the fact that in contrast to conventional asset markets, the CDS market almost by definition is composed of insiders (Acharya and Johnson (2005)). Furthermore, liquidity and transparency in the market have increased substantially in recent years. After the Financial Crisis of 2008/09, OTC derivatives, and as such also CDS contracts, became subject to increased regulatory scrutiny through the EMIR framework in Europe and the Dodd-Frank Act in the US. To improve financial stability, central clearing was introduced with increased contract standard-

[22] Replication code for the current model can be found at https://github.com/danielkdimitrov/systemicRisk

ization, and transparency was improved by introducing reporting mandates for counterparties.[23]

Second, CDS prices trade on standardized terms and conditions and do not have be pre-processed through bootstrapping or interpolation as do bond yields. Also, comparison between the underlying institutions is easier, because, unlike corporate fixed-income securities, single-name CDS contracts do not contain additional noise from issue-specific covenants, such as seniority, callability, or coupon structure (see Zhang et al. (2009); Culp et al. (2018)).

Several general concerns regarding CDS prices need to be mentioned as well, however. First, CDS rates also price in the risk of default of the protection seller and not only the reference entity. The size of this extra premium, however, has been shown empirically to be economically negligible (Arora et al. (2012)), and with the recent rise of Central Clearing for OTC derivatives it is likely to have decreased further (Loon and Zhong (2014, 2016)). Second, single-name CDS contracts are not as liquid as public equity and this raises concerns that the spreads could be overstating default risk by confounding it with an illiquidity premium. Even though the argument is valid, it misses two important points. Illiquidity risk tends to be correlated with default risk, as protection dries up at times when it is most needed (Kamga and Wilde (2013); Augustin and Schnitzler (2021)). Also, strong illiquidity in the CDS contract even in normal times may be indicative of the market's unwillingness to fund a particular financial institution due to fears that a possible future fire sale could push it into insolvency.[24]

[23]For an overview of the market structure, and recent regulatory reforms of the CDS market see Aldasoro and Ehlers (2018) and Paddrik and Tompaidis (2019).

[24]Cf. Diamond and Rajan (2011) and Shleifer and Vishny (1992) for a theoretical underpinning of firesales and bank assets.

Overall, we take the view expressed in Segoviano and Goodhart (2009), which they back up with empirical evidence, that even though in magnitude CDS spreads may be overreacting to bad news in certain situations, the direction is usually justified by information on the reference institution's creditworthiness. Thus, we use the CDS mid quotes without correcting them further for non-credit related premia.

1.2 Extracting default probabilities from CDS prices

We start with a short discussion on how the observed CDS prices can be used to extract the underlying banks' risk-neutral probabilities of default (PD).

Following Duffie:1999 we assume at this stage that the expected Recovery Rates (RR) are constant and known over the horizon of the contract. The goal at this point is to extract the PDs through a basic and reliable model. For this reason, we do not try to capture the evolution of the RR as a separate process and, accordingly, we do not try to identify it separately from the observed CDS data. There are alternative and more sophisticated approaches in the literature that try to identify separately the RRs and the PDs. Yet, the simplifying assumption we employ in estimation is widely used in the literature and is hard to improve on given the identification problem that exists. At the simulation stage of the model, we will relax the assumption of fixed RRs.[25][26]

[25]For example, Pan and Singleton (2008) identify separately the RR and the default intensity of the credit process exploiting the term structure of the CDS curve constructed from contracts with different maturities. Christensen (2006) models jointly the dynamics of the RR, the default intensity, and interest rate by breaking away from the standard Recovery of Market Value (RMV) approach of Duffie and Singleton (1999) according to which at default the bondholder receives a fixed fraction of the prevailing market value of the firm. Under the RMV approach, the default intensity only shows up within a product with the recovery rate, so the two cannot be identified separately. Having one collateral model when assessing LGD correlations and another one when extracting default probabilities from observed CDS spreads comes down to an inconsistency that is well known in the literature (see Tarashev and Zhu (2006)'s discussion of precisely this issue).

[26]Furthermore, we should point out that we are ignoring correlation risk premia. We rely on evidence

We denote $CDS_{i,t}$ as the price at initiation date t of the CDS contract written on the debt of bank i. By market convention, the spread is set to ensure that the value of the protection leg and the premium leg of the contract are equal, such that the contract has a zero value at time date t:

$$\underbrace{CDS_{i,t} \int_t^{t+T_{CDS}} e^{-r_\tau \tau} \Gamma_{i,\tau} d\tau}_{\text{PV of CDS premia}} = \underbrace{(1 - RR_{i,t}) \int_t^{t+T_{CDS}} e^{-r_\tau \tau} q_{i,\tau} d\tau}_{\text{PV of protection payment}} \tag{1}$$

where T_{CDS} is the term of the contract in years, r_τ is the risk-free rate, $CDS_{i,t}$ is the observed CDS spread for a contract traded on day t with an underlying bank i, $q_{i,\tau}$ is the implied annualized instantaneous risk-neutral default probability for the bank, $\Gamma_{i,\tau} = 1 - \int_t^\tau q_{i,s} ds$ is the risk-neutral survival probability until time τ, and $RR_{i,t}$ is the expected recovery rate in case of default, assumed to be constant over time.

For simplicity, we assume that the risk-free rate r_τ and the annualized default rate $q_{i,\tau}$ are fixed and known at the initiation of the contract. Then the default probability at time t follows from equation (1):

$$q_{i,t} = \frac{aCDS_{i,t}}{a(1 - RR_{i,t}) + bCDS_{i,t}} \tag{2}$$

with $a = \int_t^{t+T_{CDS}} e^{-r\tau} d\tau$ and $b = \int_t^{t+T_{CDS}} \tau e^{-r\tau} d\tau$. Setting $T_{CDS} = 5$ to capture 5-year CDS contracts, we can imply the annualized default probabilities.[27] The choice of expected RR is largely arbitrary in the literature. Kaserer and Klein (2019); Huang et al. (2012); Black et al. (2016) calibrate it to survey data from Markit and find that expectations do not vary signif-

provided by Tarashev and Zhu (2006) that such premia, if they exist at all, are quantitatively very small in CDS prices.

[27]In credit risk (and more generally in survival analysis), the variable q relates to the *hazard rate*, the constant arrival rate (in a Poisson sense) of a credit event. At any instant, given that default has not yet occurred, the time until it does is exponentially distributed with parameter q. For a small Δt and small q, the probability of default is then $\Delta t \cdot q$. See Duffie (1999) for details.

icantly over time and stay between 30% and 40%.. Puzanova and Düllmann (2013) use a conservative 0% recovery.

In line with MarkIt convention[28] we use an expected RR assumption (RR) of 20% for subodinated debt CDS and 80% for un-subordinated debt. In any case, the LGD assumption made here affects the *levels* of the estimated PD and the MES numbers. We are interested, however, in *changes over time* of the risk trends, and in the relative risk attribution across banks. Since we are interested in relative systemic risk attribution, and in trends over time, the levels are irrelevant.

1.3 The Structural Model Underpinning Default Correlations

We define the structural credit risk model behind the occurrence of systemic losses. Key here will be the assumption driving asset value correlations, as it will effectively determine the correlations in the default probabilities of banks, and in their default losses. First, assume that the aggregate value of assets for bank i follows the process:

$$d \ln V_{i,t} = r dt + \sigma_i dW_{i,t} \tag{3}$$

under the risk-neutral measure, where r is the risk-free rate, σ_i is the variance of asset returns, and W_t is a Brownian Motion.

In Merton's setting, default occurs at maturity $(t+T)$ when the market value of a firm's assets V_t fall below the face value of its debt D. Defining the unobserved stochastic variable $U_i \equiv W_{i,t+T}/\sqrt{T}$ and defining

$$X_{i,t} = -\frac{\ln \frac{V_{i,t}}{D_i} + \left(r - \frac{\sigma_i^2}{2}\right) T}{\sigma_i \sqrt{T}} \tag{4}$$

[28] See the Markit CDS primer for details.

we can write the one-year ahead probability of default given information available at time t as $PD_{i,t} = \mathbb{P}(U_i \leq X_{i,t})$. By inverting this, we can relate the default probability inferred from the observed CDS spread in (2) to the default barrier $X_{i,t}$ implicit in Merton's model, such that:

$$X_{i,t} \equiv \Phi^{-1}(PD_{i,t}) \tag{5}$$

where $\Phi(.)$ is the cumulative standard normal distribution. Any realization of the standard normal variable U_i below the threshold $X_{i,t}$ would indicate a default of bank i.

The next step is to determine how the asset value changes between different institutions correlate. For this purpose, note first that based on (4) we can link changes in a bank's DD between two periods to the log changes in the unobserved bank's market asset values. The discrete first difference of the $X_{i,t}$ becomes:

$$\Delta X_{i,t} = \frac{\Delta \ln V_{i,t}}{\sigma_i}$$

The correlation between asset returns can be written as:

$$\begin{aligned} a_{i,j} &\equiv \mathbb{Corr}(\Delta \ln V_{i,t}, \Delta \ln V_{j,t}) = \mathbb{Corr}(\sigma_i \Delta X_{i,t}, \sigma_j \Delta X_{j,t}) \\ &= \mathbb{Corr}\left(\Delta\Phi^{-1}(PD_{i,t}), \Delta\Phi^{-1}(PD_{j,t})\right) \end{aligned} \tag{6}$$

This equation is of crucial importance as it relates the co-dependencies in changes in the (transformed) probabilities of default (PDs) to the unobserved asset return correlations of the underlying banks.

This allows us to use PDs that can be derived from observed single-name CDS prices to pinpoint values for the correlations between institutions. In the following section, we discuss in detail how these asset correlations can be used as targets against which to estimate the parameters of a factor model.

Our reliance on the Merton (1974) framework implies that we assume default to occur when a fixed default barrier is crossed at debt maturity.[29] Even though the Merton framework may be conceptually restrictive, it is widely used as a raw approximation of default. Note that the latent threshold variable $X_{i,t}$ that we defined in (5) corresponds simply to the negative of Merton's Distance-to-Default (DD) measure often used as an indicator of banks' fragility. It has a wide application to risk management as a predictable indicator of bank fragility (Gropp et al. (2006),Chan-Lau and Sy (2007)), and actual defaults (Bharath and Shumway (2008)). One prominent critique of the use the Merton model for banks belongs to Nagel and Purnanandam (2020) who show that the model's log-normality assumption of asset values misses a key property of the asset structure of banks: a bank does not share in the upside of the assets of the borrower. Banks' assets typically represent revolving collateralized loans whose payoff strongly deviates from the log-normality assumption embedded in the Merton model. As a result, estimating the Merton model in good times from observed equity value and variance may underestimate the true default probability of a bank. However, as we have shown so far, our approach implies default probabilities from observed CDS rates rather than estimating them from the Merton model. The model serves only to inform bank asset correlations. In addition, the fact that we focus explicitly on downside tail risk scenarios, where the Merton model is relatively robust, mitigates concerns that systemic risk estimates may be underestimated due to the model's normality

[29]Further refinements have been developed to relax this assumption, of which we mention in particular Leland (1994) who endogenizes the default barrier and defines it as the boundary beyond which equity holders refuse to supply new equity to avoid default.

assumptions. Furthermore, Jessen and Lando (2015) also shows that it has certain robustness against model misspecification. As a result, for the sake of model tractability we do not pursue any of the structural extensions in this study.

1.4 Algorithm for the Model Simulation

We have the following model (see the full paper for details):

$$U_{i,T} = \boldsymbol{\rho}_i M_T + \sqrt{1 - \boldsymbol{\rho}_i \boldsymbol{\rho}_i'} Z_{i,T} \tag{7}$$

$$RR_{i,T} = \Phi \left(\boldsymbol{\rho}_i M_T + \sqrt{1 - \boldsymbol{\rho}_i \boldsymbol{\rho}_i'} Z^c_{i,T} \right) \tag{8}$$

$$MES_i = \mathbb{E} \left(L_{i,T} | L_{sys,T} \geq VaR_{sys} \right) \tag{9}$$

$$PCES_i = \frac{w_i MES_i}{ESS} \tag{10}$$

$$ESS = \mathbb{E}(L_{sys,T} | L_{sys,T} \geq VaR_{sys}) \tag{11}$$

Finally, we assemble all modelling pieces together and perform a Monte Carlo simulation in order to evaluate systemic risk and attribute it across banks. On a step-by-step basis this is done as follows:

- We draw 500K independent simulation scenarios for the idiosyncratic and the common factors of Equation (7). Based on the estimated factor exposures we can translate the factor simulations into scenarios of standardized asset value changes over the coming year for all assets.

- The default boundary per each bank has been derived by inverting the default probability in Equation (5). In the Monte Carlo approach we can then evaluate in each set of simulated scenarios if any (and potentially how many) banks would default. The average number of joint default scenarios then gives us the overall probability that multiple banks jointly fall into default.

- In addition, based on factor scenarios, we can also simulate the potential correlated losses in case of default for each bank as indicated in Equation (8). The steps so far provide a multivariate distribution of the potential losses across all banks.

- By applying liability weights for each bank, we estimate the distribution of potential losses for the regulatory portfolio.

- Based on the distribution of individual bank losses and the portfolio loss, we evaluate MES through Equation 9. Consequently we can evaluate aggregate systemic risk (ESS, cf. Equation (11)) for the portfolio, and attribute it across the institutions in the system via the PCES breakdown (cf. Equation (10)).

2 Factor Model Estimation Algorithm

We apply the following algorithm based on Andersen and Basu (2003) to estimate the latent factor model from time-series data of the institutions' CDS prices.

Assume that Σ is an $n \times n$ matrix containing the target asset correlations between the key institutions. Assume the following factor model

$$\boldsymbol{U} = \boldsymbol{A}\boldsymbol{M} + \boldsymbol{Z}$$

where $\boldsymbol{U}$ is an $n \times 1$ vector of standardized asset returns for the n institutions, $\boldsymbol{A}$ is an $n \times f$ common factor loadings matrix, $\boldsymbol{M}$ is an $f \times 1$ vector of common factors and $\boldsymbol{Z}$ is a $n \times 1$ vector of idiosyncratic factors. All factors are independent of each other with zero expectation and unit variance.

The problem is one of solving for $\boldsymbol{A}$ by minimizing the least squared difference of the model correlation matrix to the target one, such that:

$$\min_{\boldsymbol{A}} \left\{ (\boldsymbol{\Sigma} - \boldsymbol{A}\boldsymbol{A}' - \boldsymbol{F}) (\Sigma - \boldsymbol{A}\boldsymbol{A}' - \boldsymbol{F})' \right\}$$

where $\boldsymbol{F}$ is a diagonal matrix such that $diag(\boldsymbol{F}) = 1 - diag(\boldsymbol{A}\boldsymbol{A}')$.

The numerical solution algorithm then is

1. Guess $\boldsymbol{F}^0$

2. Perform PCA on $\boldsymbol{\Sigma} - \boldsymbol{F}^i$ and compute $\boldsymbol{A}^i = \boldsymbol{E}^i \sqrt{\boldsymbol{\Lambda}}^i$, where i is an iterations counter, $\boldsymbol{E}$ is a matrix of the normalized column eigenvectors of $\boldsymbol{\Sigma} - \boldsymbol{F}$, $\sqrt{\boldsymbol{\Lambda}}$ is Cholesky decomposition of the diagonal matrix containing the f largest eigenvalues of $\boldsymbol{\Sigma} - \boldsymbol{F}$.

3. Calculate $\boldsymbol{F}^{i+1}$

4. Continue with Step 2, until $\boldsymbol{F}^{i+1}$ is sufficiently close to $\boldsymbol{F}^i$.

3 Additional Charts and Statistics

3.1 Data Description

Table 1 provides an overview of the bank CDS rates included in the analysis.

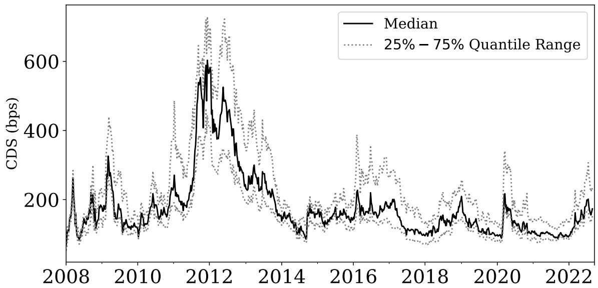
Table 1: Data Sample Descriptive Table

Short Code	Country	Bank Full Name	Public	CDS Type	Start Date	G-SIB	D-SIB
ERST	Austria	Erste Group	Y	SR	1/3/2006	N	Y
KBCB	Belgium	KBC	Y	SUB	1/4/2006	N	Y
DANK	Denmark	Danske Bank	Y	SUB	1/10/2006	N	Y
NORD	Finland	Nordea	Y	SUB	1/3/2006	N	Y
BNP	France	BNP Paribas	Y	SUB	1/3/2006	Y	Y
CRAG	France	Credit Agricole	Y	SUB	1/3/2006	Y	Y
CRMU	France	Credit Mutuel	N	SUB	2/23/2010	N	Y
SOCG	France	Societe Generale	Y	SUB	1/3/2006	Y	Y
COMZ	Germany	Commerzbank	Y	SUB	1/3/2006	N	Y
DB	Germany	Deutsche Bank	Y	SUB	1/3/2006	Y	Y
DZ	Germany	DZ Bank	N	SR	6/30/2008	N	Y
BAY	Germany	Bayern LB	N	SR	5/13/2019	N	Y
LBBW	Germany	LBBW	N	SR	5/13/2019	N	Y
HESLN	Germany	Helaba	N	SR	5/13/2019	N	Y
INTE	Italy	Intesa Sanpaolo	Y	SUB	1/3/2006	N	Y
UNIC	Italy	Unicredit	Y	SUB	1/3/2006	Y	Y
RABO	Netherlands	Rabobank	N	SUB	1/3/2006	N	Y
ABN	Netherlands	ABN Amro	Y	SUB	1/3/2006	N	Y
INGB	Netherlands	ING Bank	N	SUB	1/3/2006	Y	Y
VB	Netherlands	Volksbank	N	SUB	1/3/2006	N	Y
CAIX	Spain	Caixabank	Y	SUB	8/12/2016	N	Y
SAB	Spain	Sabadell	Y	SUB	1/3/2006	N	Y
SANT	Spain	Santander	Y	SUB	1/3/2006	Y	Y
BBVA	Spain	BBVA	Y	SUB	1/3/2006	Y	Y
SWEN	Sweden	Handelsbanken	Y	SUB	5/14/2008	N	Y
SEB	Sweden	Skandinaviska Enskilda Banken	Y	SUB	1/3/2006	N	Y
SWED	Sweden	Swedbank	Y	SUB	1/3/2006	N	Y

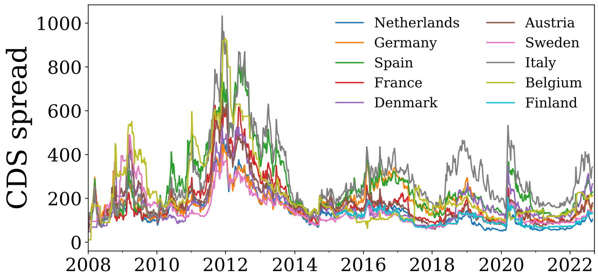
Note. This table shows the basic properties of the dataset: the country to which each bank belongs, the bank short code used throughout this paper, whether the bank's equity is traded on the market ('Y') or it is privately owned ('N'); and the type of CDS spreads used as input for the study (on senior debt (SR) or on subordinate debt (SUB)). Senior Debt CDSs are corrected for the median spread between senior and subordinate debt.

Figure 1 below provides an initial overview of the distribution and evolution of the CDS prices over time. 1b shows the median spreads per country over time, providing a perspective into the possible dependencies across countries, and consequently the potential for (co)occurrence of credit events. At the same time, the level of the CDS spreads indicates which country's banks may be subject to higher credit risk. Figure 1b shows the distribution of cross-bank correlations over time.

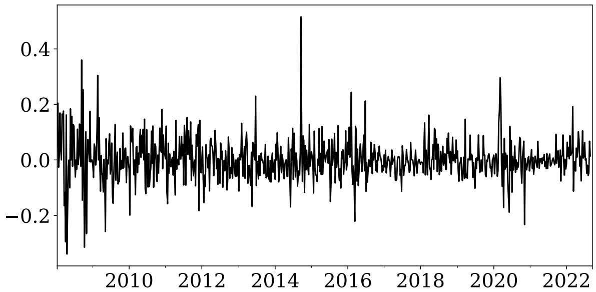
Figure 1: Data Overview: CDS Time Series



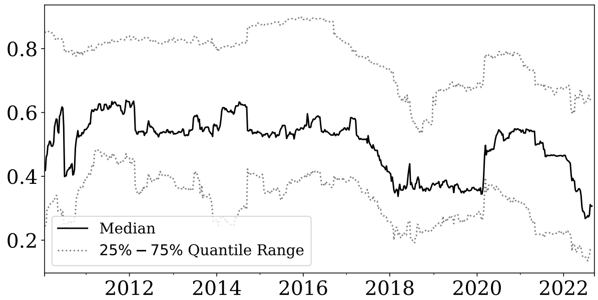
(a) CDS Prices



(b) CDS Prices by Country Median



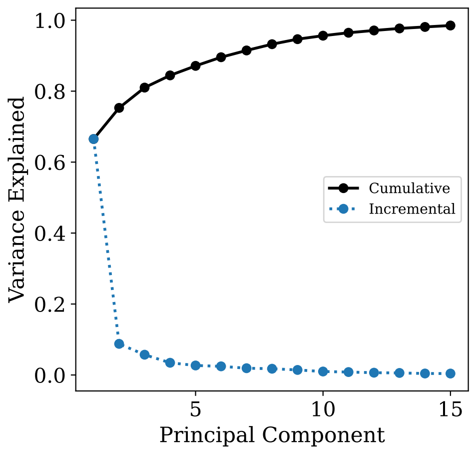
(c) Median Weekly Log-Changes



(d) 2-Year Weekly Rolling Correlation

3.2 PCA-based Factor Selection

Figure 2: Share of Total Explained Variance



Note. This figure shows the cumulative share of explained variance (the solid curve) and the incremental share (dashed curve) over the CDS price log-changes in our sample.

3.3 Systemic Risk Attribution

Table 2 shows the systemic attribution in the sample of banks. First, we show the standalone tail risk for each bank, measured by its ES. Second, we also provide each bank's sensitivity to systemic risk, assessed through its MES, following Acharya:2017:MES.

Table 2: Systemic Risk Attribution Ranking

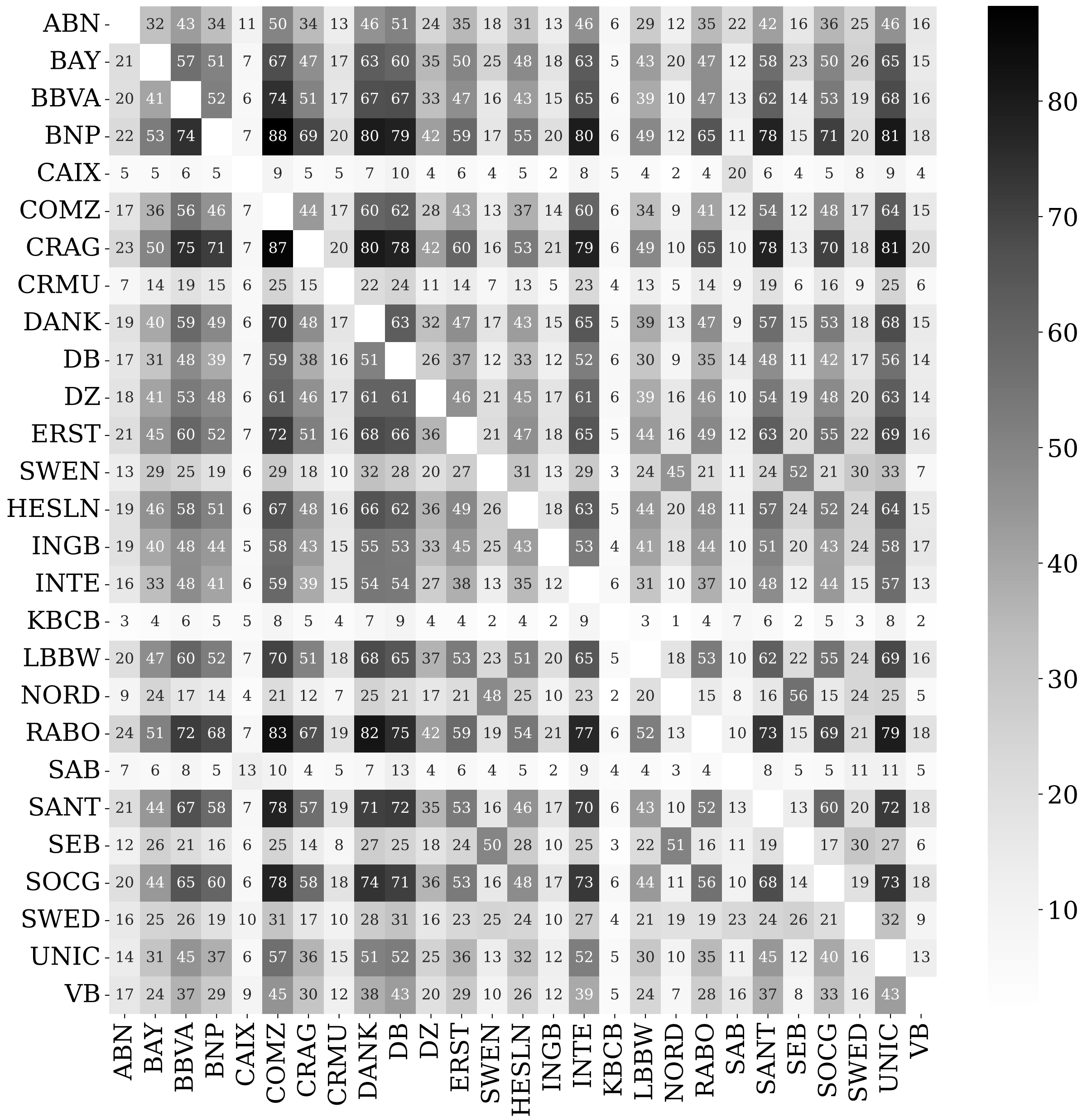
Short Code	w		EL		ES		MES		$PCES$	
BNP	13.24	(1)	0.91	(18)	1.84	(14)	36.75	(9)	13.53	(1)
DB	6.64	(5)	3.17	(1)	3.57	(2)	60.23	(3)	11.12	(2)
CRAG	10.51	(2)	0.82	(23)	1.79	(15)	35.73	(11)	10.44	(3)
SANT	7.87	(3)	1.05	(13)	2.44	(8)	47.66	(6)	10.44	(4)
SOCG	7.32	(4)	1.02	(14)	2.14	(9)	41.52	(8)	8.45	(5)
INTE	5.28	(6)	2.13	(3)	3.46	(4)	56.96	(4)	8.36	(6)
UNIC	4.49	(8)	2.09	(4)	3.80	(1)	60.60	(2)	7.56	(7)
BBVA	3.22	(11)	1.32	(8)	2.60	(7)	47.34	(7)	4.25	(8)
DANK	2.66	(15)	1.37	(7)	2.97	(6)	53.58	(5)	3.96	(9)
COMZ	2.33	(16)	1.44	(6)	3.47	(3)	60.77	(1)	3.93	(10)
RABO	3.15	(12)	0.69	(25)	1.74	(17)	33.77	(12)	2.96	(11)
DZ	3.14	(13)	1.08	(12)	1.52	(22)	25.32	(16)	2.21	(12)
INGB	4.71	(7)	0.50	(27)	0.77	(27)	12.12	(23)	1.59	(13)
CRMU	4.15	(9)	1.15	(9)	1.63	(20)	13.17	(21)	1.52	(14)
ERST	1.51	(21)	0.88	(19)	2.04	(10)	36.29	(10)	1.52	(15)
BAY	1.34	(23)	0.85	(20)	1.85	(13)	31.39	(14)	1.17	(16)
LBBW	1.41	(22)	0.91	(18)	1.68	(19)	29.16	(15)	1.14	(17)
HESLN	1.07	(26)	0.95	(15)	1.93	(11)	32.73	(13)	0.97	(18)
NORD	2.82	(14)	0.85	(22)	1.52	(23)	12.15	(22)	0.95	(19)
ABN	1.99	(17)	0.59	(26)	1.11	(25)	14.91	(19)	0.83	(20)
SWEN	1.61	(19)	0.72	(24)	1.61	(21)	15.33	(18)	0.69	(21)
SEB	1.59	(20)	0.85	(22)	1.69	(18)	14.46	(20)	0.64	(22)
SWED	1.32	(24)	1.14	(10)	1.78	(16)	16.54	(17)	0.61	(23)
CAIX	3.38	(10)	1.51	(5)	1.87	(12)	5.63	(26)	0.53	(24)
SAB	1.25	(25)	2.32	(2)	3.33	(5)	10.70	(25)	0.37	(25)
KBCB	1.67	(18)	1.09	(11)	1.34	(24)	3.45	(27)	0.16	(26)
VB	0.34	(27)	0.94	(16)	0.98	(26)	11.54	(24)	0.11	(27)
System	100.00		1.25		35.96		35.96		100.00	

Note. This table shows the liability weight (w), Expected Loss (EL), Expected Shortfall (ES), Marginal Expected Shortfall (MES), and the Percentage Contribution to Expected Shortfall ($PCES$) evaluated at 95% Confidence Level. The numbers in brackets show the ranking based on the corresponding statistic. The statistics are evaluated for August, 29, 2022 using a two-year weekly time window to estimate the factor model loadings

3.4 Conditional Probabilities of Default

We can translate the joint probabilities into probabilities of one institution's default conditional on the default of another institution using the relationship: $CPD_{i|j} \equiv \mathbb{P}(\mathbb{1}_{d_i} = 1|\mathbb{1}_{d_j} = 1) = \frac{\mathbb{P}(\mathbb{1}_{d_i}=1,\mathbb{1}_{d_j}=1)}{\mathbb{P}(\mathbb{1}_{d_j}=1)}$ Through the definition above we can also see that as long as the probability of bank j to default is low, observing a high probability of joint distress between i and j would indicate high potential for i to go down given that j goes down.

Figure 3: Conditional Probability of Default



Note: This chart shows the risk-neutral probabilities that an institution j may default, conditional on institution i being in default. The estimates are evaluated as of the end of August 2022.

3.5 Engle et al. approach

First, we evaluate the MES^l of each listed bank on a rolling-window basis, based on equity data following the approach by Acharya et al. (2017). Then, we run a regression of MES^l on a set of balance sheet variables $X_{i,t}$ over the full time window of the listed sample:

$$MES^l_{i,t} = X_{i,t}\beta + \epsilon_{i,t} \tag{12}$$

Following, Engle et al. the covariates vector $X_{i,t}$ contains Log-value of total assets, Log-value of total assets-squared, Profits over total assets, Equity over total assets, CET1 Ratio, and a Periphery dummy.

Table 3 below shows the results.[30] The signs of the coefficients are as one would expect: lower CET1 ratio, higher size of assets, lower profitability, and lower equity to total assets increase systemic risk (i.e. the MES estimate) given everything else.

As in engle2023estimatingLA,engle2023estimatingNonList, the next step is to use the estimated regression to forecast in-sample the MES for the unlisted banks, $M\hat{E}S^{nl}_{i,t}$:

$$M\hat{E}S^{nl}_{i,t} = X_{i,t}\hat{\beta} \tag{13}$$

The balance sheet data is available quarterly at best, while we are interested in a comparison that develops at higher frequency; so we interpolate over the balance sheet ratios to allows us to get weekly estimates of $M\hat{E}S^{nl}_{i,t}$.

[30]Note that we exclude an intercept from the model in order to alleviate potential strong forward-looking bias, which would be induced from regime breaks affecting the mean of the relationship. We also exclude a Liquidity ratio variable from the regression specification due to incomplete of data over time. In Engle et al., however, the variable is not significant, so we are still close to their approach.

Table 3: Pooled OLS Regression Results

	coef	**std err**	**t**	**P>$\lvert$t$\rvert$**	**[0.025**	**0.975]**
CET1r	-0.0590	0.038	-1.556	0.120	-0.133	0.015
lnTA	1.1393	0.058	19.665	0.000	1.026	1.253
Prof_TA	-2.9278	0.441	-6.636	0.000	-3.794	-2.061
EQ_TA	-1.1870	0.120	-9.879	0.000	-1.423	-0.951
Periphery	3.7121	0.330	11.249	0.000	3.064	4.360

Omnibus:	57.244	**Durbin-Watson:**	1.274
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	79.575
No. Observations:	573	**Prob(JB):**	5.25e-18
R-squared (uncentered):	0.890		

3.6 SRISK vs. Credit-based MES

The credit-based MES approach that we introduced is conceptually close to SRISK, another widely used measure of systemic risk acharya2012capital,BE:2017, typically estimated on equity prices. SRISK evaluates the potential capital shortfall (CS_i) that a financial institution may experience in a certain scenario, where $CS_{i,T} = kA_{i,T} - E_{i,T}$, with $E_{i,T}$ as the observed stochastic market value of equity at the end of the period under investigation; $A_{i,T}$ is the corresponding end-of-period value of assets, typically proxied by the sum of the market value of equity and the face value of liabilities; and k represents the fixed regulatory capital ratio. A positive CS_i indicates that the institution requires additional capital to remain afloat. In essence, then, SRISK can be seen as a measure of the expected capital needed by the institution to meet regulatory requirements in the event of a financial crisis. So, formally it is expressed as:

$$SRISK_{i,t} = \mathbb{E}(CS_{i,T}|R_{M,T} < C)$$

with $R_{M,T}$ as the return on the equity market, and C as a predefined fixed threshold drop in a broad market index indicating a systemic crisis. As suggested by Brownlees and Engle (2017) SRISK can also be used to attribute total risk on a proportional basis to individual institutions, similarly to our $PCES$ measure as:

$$SRISK\%_i = \frac{SRISK_i}{\sum_j SRISK_j} \tag{14}$$

Using the equity-based MES evaluated above plus the "synthetic" evaluation of the non-listed banks in the style of Engle et al. (2024), we can test the robustness of the systemic rankings presented in Section 4.3. To keep the two approaches on the same footing, we deviate from the standard procedure of parameter estimation for the SRISK model. We use the weekly frequency for equity returns, and do not apply DCC-GARCH filter to the data, as these features were not included in estimating the CDS-based correlation structure. Furthermore, to be in line with the MES approach, we define a systemic even with respect to the systemic portfolio, rather than to a broad market index. Also, instead of defining the domain of systemic events with respect to a broad market index, we define it with respect to the systemic portfolio (see Equation (15)), and we set C as the Value at Risk of the systemic portfolio.

$$L_{sys,T} = \sum_{i=1}^{n} w_i L_{i,T} \tag{15}$$

Then one case show that

$$SRISK = kD_t + (k-1)MES^{eq}$$

where for k we use 8% as in Engle et al. (2024). Note also that we evaluate MES^{eq} already on the annualized distribution of equity return, so it corresponds to the Long-Run MES in Brownlees and Engle (2017) with a 1-year horizon.

While our estimation approach differs significantly in implementation, it remains conceptually similar. There are several nuances, however, primarily driven by the fact that SRISK is tailored to a world in which equity market prices are directly observable:

- There is a distinction in how systemic risk is quantified. SRISK looks for a large drop in an overall equity market index, i.e. the space of systemic events is defined as $R_M < C$ with C typically defined as a 40% drop in a broad market index over asix month period. In contrast, we defined as systemic all events in which the system generates default losses above 5% of the system's credit VaR, i.e. $L_{sys} > VaR_{sys}$.

- There is a nuanced difference in how a bank's exposure to systemic risk is defined. For SRISK, this is the capital shortfall below the regulatory requirement. In our model, somewhat more general this is the LGD loss in case of default. The two approaches can be reconciled by setting $w_i LGD_i = CS_i$, where CS_i is scaled by the overall size of the liabilities in the system. In that case, losses that are part of (9) can be defined as
$$L_i = \begin{cases} CS_i, \text{ if } CS_i > 0 \iff E_i < kA_i \\ 0, \quad \text{otherwise} \end{cases}$$

- Losses in the credit MES approach are weighted by the default probability, and are truncated at the individual level, i.e. they only count if the institution is in default. To see how the two relate, assume that the space of systemic evens is the same and defined as $\mathcal{S}$. Then we write our credt MES as

$$MES_i = \mathbb{E}(L_i|\mathcal{S}) = \mathbb{E}(LGD_i \mathbb{1}_i|\mathcal{S}) = \mathbb{E}(LGD_i|\mathcal{S}\&1_i = 1)PD_i$$

or making the reconciliation from the point above, and assuming a default is equivalent to a bank experiencing capital shortfall, we have

$$MES_i = \mathbb{E}(CS_i|\mathcal{S}\&CS_i > 0)PD_i$$

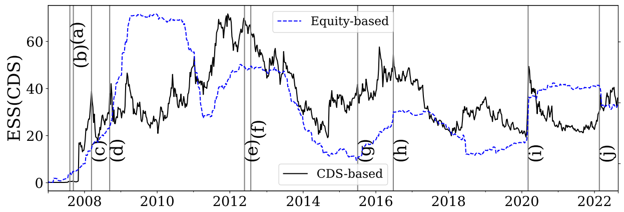
- The final nuance is that given historical equity prices, the estimation of SRISK typically relies on a Dynamic Conditional Correlation (GARCH-DCC) estimation to forecast the distribution of the capital shortfalls in the upcoming period. The credit-based model, in contrast, uses the co-movements of historical CDS spreads to forecast correlations.

3.7 CDS-based Approach vs. Engle et al. approach for non-listed banks

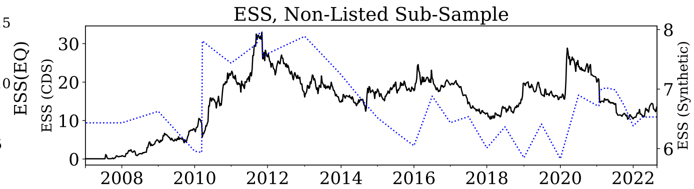
Figures 4 show, at 95% confidence level (i.e. MES at 5% of the worst potential outcomes) the comparison in the estimated numbers with the CDS approach and with the synthetic approach. Clearly, the CDS measure is more sensitive to shorter-run market developments. This is as one should expect, given that our measure is purely based on market data which are available at higher frequency than the accounting data used in Engle:2018.

Overall, we can see that the two approaches may be significantly different in magnitude, but they roughly follow similar patterns over the longer run. This is especially visible in the aggregate ESS estimate in Figure 4. What the CDS approach offers then is the advantage of having estimates that are sensitive to market information that is available on a higher frequency than accounting data.

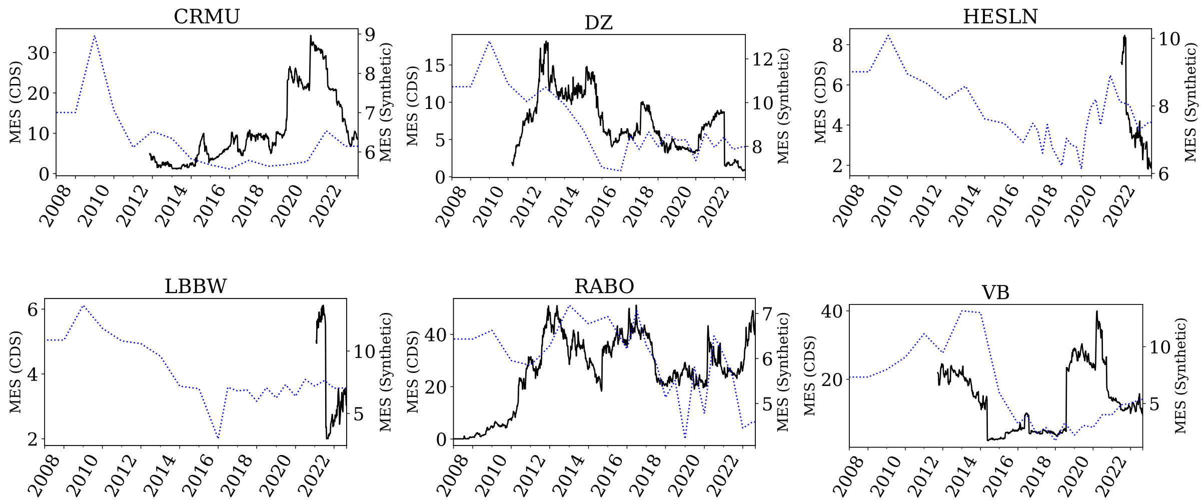
Figure 4: CDS-based vs Equity-based measures



(a) ESS, listed banks



(b) ESS, Nonlisted banks



(c) MES, Nonlisted banks

Note. This set of figures shows (a) a rolling window comparison of the ESS measure estimated on CDS data and on equity data; (b) the aggregated ESS based on the CDS approach (solid line) and the measure based on Engle's "synthetic" approach for nonlisted banks (dotted line); (c) the MES for individual nonlisted banks. The dashed lines in panel (a) define the selection of systemically relevant events.

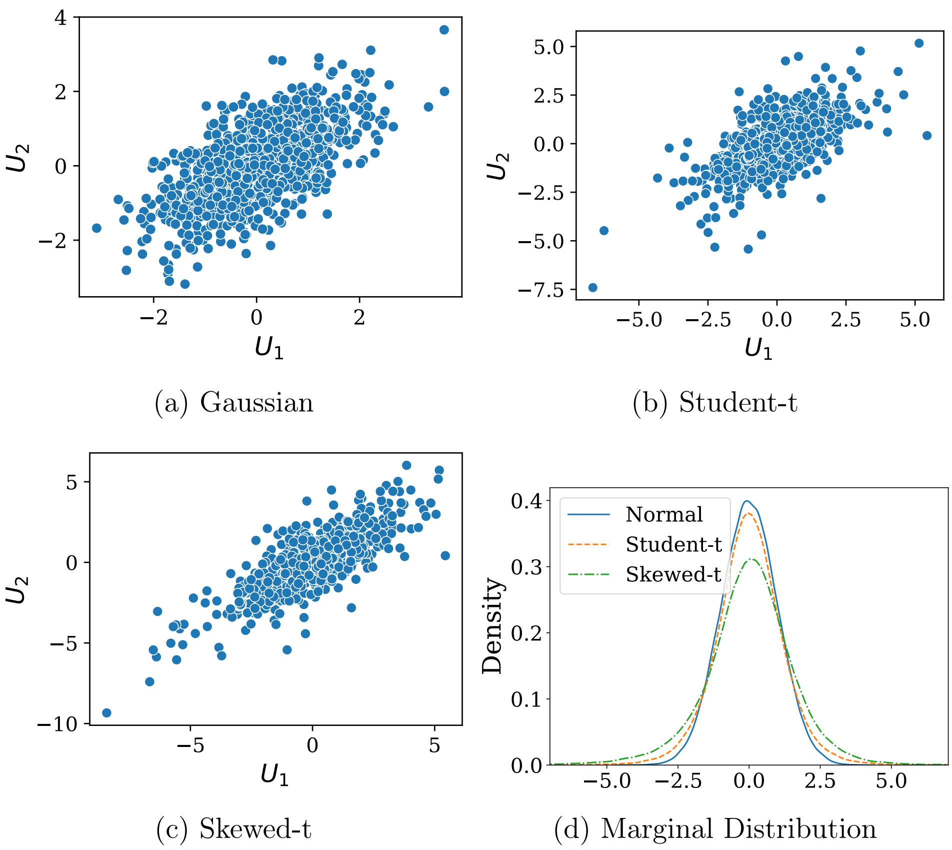
3.8 Non-Gaussian Factor Copula Model: Illustration

As an illustration of how the different models behave, Figure 5 below shows a simulation of two latent variables U_i and U_j with each of the three models define so far.

Chart 5a shows clearly how the standard normal multivariate distribution forms between the two variables. The realization of scenarios further away from zero than three standard deviations is not at all likely. Chart 5b on the other hand, shows how symmetric extreme events start to appear, in line with a multivariate Student-t distribution with six degrees of freedom. Figure 5d finally visualizes the multivariate model implied by the specification of Equation (16) with a skewness parameter $\delta = -2$. We can see that in this chart the occurrence of joint large negative events is much larger than that of joint positive events.

$$U_i = \sqrt{\frac{\nu}{F}} \left(\delta G + \boldsymbol{\rho}_i M + \sqrt{1 - \boldsymbol{\rho}_i \boldsymbol{\rho}_i'} Z_i \right) \tag{16}$$

Figure 5: Simulated Factor Copula



(a) Gaussian

(b) Student-t

(c) Skewed-t

(d) Marginal Distribution

Note. This plot shows 1,000 simulations using the three specifications of the factor model. Common factor loading of .8 is used in each of the cases. For the Student-t and the Skewed-t versions, we use degrees of freedom of $\nu = 6$, and skewness parameter $\delta = -2$.

Annex References

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De Nederlandsche Bank N.V.
Postbus 98, 1000 AB Amsterdam
020 524 91 11
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