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# Quantifying Systemic Risk in the Presence of Unlisted Banks: Application to the Dutch Financial Sector

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# Quantifying Systemic Risk in the Presence of Unlisted Banks: Application to the Dutch Financial Sector*

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**Abstract**

We propose a credit portfolio approach for evaluating systemic risk and attributing it across institutions. We construct a model that can be estimated from high-frequency CDS data. This captures risks from privately held institutions and cooperative banks, extending approaches that rely on information from the public equity market. We account for correlated losses between the institutions, overcoming a modeling weakness in earlier studies. A latent risk factor with heterogeneous exposures fitted on the implied default probabilities quantifies the potential for joint distress and losses. We apply the model to a universe of Dutch banks and insurers.

***JEL codes:*** G01, G20, G18, G38
***Keywords:*** systemic risk, CDS rates, implied market measures, financial institutions

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## Executive Summary

We propose a credit portfolio approach for evaluating systemic risk and attributing it across institutions. For this purpose, we construct a model that can be estimated from credit default swap (CDS) data. Our goal is to capture risks from privately held institutions and cooperative banks, extending approaches that rely on information from the public equity market. We apply the model to key private institutions in the Dutch financial sector to measure systemic risk, and to rank the systemic players on this market according to the fraction of systemic risk that can be attributed to them.

The canonical approach to measuring various aspects of systemic risk in banking relies on equity return correlations to assess interdependencies between banks' losses above Value at Risk (Adrian and Brunnermeier, 2016; Acharya et al., 2017). But for many countries this approach is thwarted by the presence of state-owned and/or co-operative banks. To circumvent this problem we extend the Adrian and Brunnermeier (2016)'s CoVaR approach and Acharya et al. (2017)'s Marginal Expected Shortfall approach by relying on CDS contracts rather than equity returns to extract the required information on covariance structure.

First, we show that monitoring the financial risk of an institution in isolation of the risks of its counterparties, and of the system as a whole, may offer a misleading ranking of systemically important financial institutions. We relate our systemic ranking to the O-SII regulatory framework and pointing out similarities and differences argue that a holistic risk approach could improve the regulatory process for setting systemic risk buffer requirements.

Second, we illustrate that high-frequency data from the CDS market can be used to monitor *ex-ante* the build-up of systemic risk and systemic dependencies. This is particularly valuable in the context of the Dutch financial sector, where key institutions are privately held, and market data on their equity value is not available.

Third, we evaluate tail dependencies and link systemic risk to the potential for joint distress between institutions and consequently joint large joint losses. A latent risk factor with heterogeneous exposures fitted on the implied default probabilities quantifies this potential. In this way, we overcome a modeling weakness in earlier studies.

Our framework does not require a particular view on what is causing systemic losses, but rather offers an approach that can identify the potential for high joint distress based on observed dependencies between traded credit protection on the market whatever the underlying channels of interdependencies are. In reality, we know that systemic linkages arise directly from the channels by which banks operate on the interbank market. Banks and insurers also tend to trade directly with each other on the derivative markets. Also, systemic dependencies may arise indirectly, due to common exposure of the key institutions to the same risk sources - either on the liability side, when funding sources are similar, or on the asset side, when the institutions hold similar or correlated asset portfolios.

A natural extension of the current study would be to expand the universe of institutions that are considered and to observe if those rankings systematically differ across European countries. Also, our framework could be extended to provide a quantitative basis for determining the size of the capital buffers that institutions need once they are designated as systemic. A larger sample would also allow exploring non-linear structures of systemic risk dependencies using for example a factor Copula or a deep learning approach. Alternatively, network models could be used to mimic the often observed core-periphery structure of the financial sector.

# 1 Introduction

The canonical approach to measuring various aspects of systemic risk in banking relies on equity return correlations to assess interdependencies between banks' losses above Value at Risk (Adrian and Brunnermeier (2016)). But in many countries this approach is thwarted by the presence of state-owned and/or co-operative banks. To circumvent this problem we extend the Adrian-Brunnermeier approach (and the related Marginal Expected Shortfall (MES) approach introduced by Acharya et al. (2017)) by relying on CDS contracts rather than equity returns to extract the required information on covariance structure. We extend the portfolio-of-loans approach suggested by Huang et al. (2009, 2012) by explicitly focusing on tail risk and by modelling tail dependencies in distress. We look at key private institutions in the Dutch financial sector (insurance and banking) and develop a valuation-of-loans approach to measure systemic risk and identify and rank the systemic players on this market. Our approach is appropriate whenever potentially systemic institutions are not publicly traded on the equity market. Our analysis confirms that financial institutions need to be monitored in the context of other financial institution, as Adrian and Brunnermeier (2016) also argue. In particular, we show that important linkages exist between banking and insurance firms that need to be explored further and taken into account when measuring systemic risk.

Systemic linkages arise naturally through various channels. A direct link stems from the channels by which banks operate on the interbank market. Banks and insurers also tend to trade directly with each other on the derivative markets. Finally systemic dependencies may also arise indirectly, due to common exposure of the key institutions to the same risk sources - either on the liability side, when funding sources are similar, or on the asset side, when the institutions hold similar or correlated asset portfolios (Moore and Zhou, 2012; de Haan et al., 2019). We present a framework that does not require a particular view on what is causing systemic losses, but rather offers an approach that can identify the potential for high joint distress based on observed dependencies between traded credit protection on the market whatever the underlying channels of interdependencies are.

First, we show that monitoring the financial risk of an institution in isolation of the risks of its counterparties, and the system as a whole, may offer a misleading ranking between systemically important financial institutions (SIFIs). Second, we illustrate that high-frequency data from the credit default swap (CDS) market can be used to monitor *ex-ante* the build-up of systemic risk and systemic dependencies. This is particularly valuable in the context of the Dutch financial sector, where key institutions are privately held, and market data on their equity value is not available. Third, we link systemic risk to the potential for joint distress between institutions by evaluating the tail dependencies in their losses if a default of one institution were to occur.

We define systemic risk both through the prospect that several key institutions become distressed at the same time, and through the prospect that the common losses they generate may have a large social impact. To quantify such risk, our model relies on several building blocks. First, we use a contingent balance sheet approach (Merton, 1974) and define distress as the situation in which the market value of a firm's assets falls below a default barrier. The observed CDS spreads allow us to estimate the probability of such distress occurring. Second, a latent factor is assumed to drive common changes in the asset values of firms. Systemic risk will thus have two related components: first, the possibility that several companies realize a credit event at the same time; and second, the magnitude and the dependency in the losses that are generated among the financial institutions once a default occurs. We aggregate the two components using a credit portfolio approach and estimate the MES for the institutions in the portfolio (Acharya et al., 2017). The $MES$ measures the average potential loss of an institution if the system as a whole realizes a tail event, thus quantifying the sensitivity of an institution to other institutional losses in the system. In addition, we relate the liability-weighted $MES$ to the share of systemic risk that can be attributed to a single institution.

To the best of our knowledge, we are the first to model empirically, in a systemic risk context, dependencies between default occurrences and the potential losses given a default. Such dependencies are crucial for a number of reasons. First, there is sound empirical evidence that realized losses tend to rise in periods when risk probabilities also increase (Artzner, 1999). Second, the potential default of a SIFI by definition will have a strong impact on other players in the industry by increasing their default risk and at the same time lowering the value of the assets backing up their liabilities below fair value as industry-wide distress triggers fire sales. From that point of view, we argue that reliable systemic risk estimation should cover the potential for LGD (Loss Given Default) dependencies.

We use a flexible modeling approach which allows for factor exposure heterogeneity fitted on CDS data. This is an improvement over the well-known Vasicek credit model (Vasicek, 1987) which assumes a single correlation parameter driving the dependencies in the whole portfolio.

We look at seven Dutch financial institutions: two insurers (Aegon and NN) and five banks (ING Bank, Rabo, ABN, VB, Rabo, and NIBC). Our model allows us to rank the companies by their contribution to risk, where risk is quantified by the Expected Shortfall of the systemic portfolio.

The current paper continues as follows. In Section (2) we review the relevant literature. Section (3) describes the structural credit model we employ to describe co-dependencies between institutions in the system. Section (4) discusses the credit risk approach used to quantify the sensitivity and the contribution of each institution to systemic risk. Section (5) reviews the dataset and defines the regulatory portfolio. Sections (6) and (7) discuss the results and respectively their policy relevance, while Section (8) concludes.

# 2 Literature Review

Our paper is part of the wider literature using high-frequency asset prices to inform central bank policies. Examples are Hattori et al. (2016); Olijslagers et al. (2019) who use option-implied asset volatilities and risk-neutral distributions to evaluate the effectiveness of central bank stabilization policies. Market-implied views have also been seen as a valuable tool for monitoring financial stability and for advising on macro-prudential policies (Jayaram and Gadanecz, 2016). Acharya et al. (2014) use co-movements in CDS rates of sovereigns and local banks during the Euro sovereign debt crisis to show how a *doom-loop* channel evolves, in which a bail-out of a local bank in trouble, because it is deemed systemically important, leads to a deterioration in the creditworthiness of the government, which then further depresses the credit-worthiness of the bailed-out bank due to its large exposure to local sovereign bonds; after which there are further hits to the solvency of the government and so on.

Also, our paper relates closely to the literature of systemic risk which utilizes equity market information. In many cases, especially in Europe and certainly in the sample of Dutch institutions that we consider, the major challenge in exposing market-implied views is that some of the key players in the financial sector are not publicly traded. Approaches that rely on equity price co-movements (like Adrian and Brunnermeier (2016)) 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. For this reason, we develop a structural approach that utilizes information from the CDS market.

The intuition behind the mechanism that we employ is simple. We know through Merton (1974) that the market value of a company's assets is related both to the market value of its equity and of its liabilities. The level of the firm's CDS spread at any particular instance relates to the chance that the value of its assets may drop and that it may experience distress in the form of a credit event captured by the CDS contract[1]. What is more important for us however, is that co-movements in default probabilities can provide information on the tendency of the institutions to become distressed at the same time. Tarashev and Zhu (2006) also follow this line of reasoning. Rather than estimating the unobservable asset values, as is done for example in Duan (1994, 2000) and in Lehar (2005), we add a model of the losses in case of default that allows us to quantify the distribution of systemic losses and the potential for large losses by several institutions at the same time.

A CDS is in essence 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. The value of a CDS contract thus provides information on the fair value spread that should be used to discount the company's debt.[2].

The CDS market has several features that make it an attractive source of information for the financial sector. 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 (Bai and Collin-Dufresne, 2019; Avino et al., 2019; Culp et al., 2018; Annaert et al., 2013). Some evidence exists that they may even lead equity markets, especially in revealing negative credit news. 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 cope with systemic risk issues, central clearing was introduced with increased contract standardization and transparency was improved by

[1] For a similar line of thinking, cf Carr and Wu (2011) who provide a link between the value of a CDS contract and deep out-of-the-money put options on a company's stock.

[2] Apart from a hedging opportunity, CDSs are used to arbitrage away any relative mispricing between the equity and bond prices of the reference entity (capital structure arbitrage (Kapadia and Pu, 2012)), or to exploit mispricings in the value of traded debt (Augustin and Schnitzler, 2021). There is a large empirical literature dealing with such possibilities and the limits to arbitrage, which we do not consider in the current study.

introducing reporting mandates for counterparties[3].

Furthermore, CDS prices trade on standardized terms and conditions and do not have be bootstrapped or interpolated as do bond yields. Also, comparison between firms 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 (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; Augustin and Schnitzler, 2021). Also, strong illiquidity in the CDS contract 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 (cf Diamond and Rajan (2011)), and may well reflect a private cost of leverage as in Shleifer and Vishny (1992). Overall, we take the view of Segoviano and Goodhart (2009), backed up by 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.

Part of the literature on bank distress relies on reduced-form statistical modelling to link bank CDS movements to periods of financial adversity. Avino et al. (2019), for example, look at the spreads of single-name CDS contracts for European and US banks and evaluate the propensity of spread changes to predict bank distress in the form of recapitalization or nationalization. One standard deviation increase in the CDS spread changes, is estimated to correspond to a 7% to 14% increase in the (physical) probability of financial distress of a bank. Annaert et al. (2013) look at the determinants of CDS spread changes for a universe of European banks and separate them into a firm-specific credit risk component, a trading liquidity component, and a business cycle components capturing common variation linked to the business environment.

On the methodological front, Oh and Patton (2018) link bank distress to large upticks in the CDS prices of the reference banks, and measure the probability of joint distress through a factor copula dependency model. Billio et al. (2012) offer an early econometric model which quantifies interconnectedness through Granger-causality networks. Bräuning and Koopman (2016) extend the idea with time-varying heterogeneity in the link formation between banks using CDS spreads of US and European institutions. The goal is to capture the dynamic formation of potential core-periphery clusters, which are natural for the financial sector. Moratis and Sakellaris (2021) on the other hand use a panel VAR model to decompose the transmission of systemic shocks across a universe of global banks. These studies offer preliminary evidence that CDS fluctuations can serve as an early warning signal of bank risk, supplementing data from the stock market, credit rating agencies, and accounting data. Our contribution to this literature is to embed

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

CDS spreads into a structural model of the firm's capital, which allows for non-linear relationships to form naturally.

An earlier branch of the empirical literature also uses structural firm models to imply bank fragility (Gropp et al., 2006; Chan-Lau and Sy, 2007; Bharath and Shumway, 2008). Most notable is the distance-to-default (DD) measure (Merton, 1974; Crosbie and Bohn, 2002) which compares the current market value of assets to the default barrier of the firm[4]. While the foundation in our study is similar, we aim to evaluating cross-linkages and the impact each bank has on the system as a whole, rather than on modelling the individual default risk of each bank in isolation.

Most of all, we relate to the broader literature on measuring and quantifying 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; Acharya et al., 2017; Engle, 2018). Some of the approaches developed in that area can be seen as largely model-free since they do not rely on particular capital structure assumptions of the individual firms. The CoVaR approach of Adrian and Brunnermeier (2016) for example, along with an earlier study by Baur and Schulze (2009), relies on a quantile regression on equity prices to determine tail co-dependencies and risk contributions. Wang (2021) adapt this approach by embedding a neural network. Most of these studies rely on high-frequency data on equity prices.

Another strand of the systemic literature, most notably Lehar (2005), relies on Merton's theory of contingent claims to imply the market value of firm assets and the correlations between institutions as a measure of systemic risk. In contrast, our approach does not aim to imply the value of assets themselves. Rather, we directly focus on the potential for systemic events to materialize and evaluate the potential losses for the systemic portfolio when defaults occur. Using a structural model in combination with copula default dependencies, Segoviano and Goodhart (2009) comes to the PAO measure, the probability of at least one more bank defaulting given a default in particular bank. We develop the idea further by also calculating the probability of two or more defaults given that at least one has occurred. This allows us to concentrate specifically on periods of financial contagion.

We view the regulatory space as a portfolio of risky loans, similar to Chan-Lau and Gravelle (2005); Huang et al. (2009, 2012); Puzanova and Düllmann (2013); Kaserer and Klein (2019). In that approach, systemic losses arise when an institution defaults and cannot cover the value of its liabilities. The tendency of particular institutions to drive systemic losses will result in a higher contribution to systemic risk.

From this perspective, the modeling tools developed by the securitization literature, typically used to value n-th to default derivatives on loan portfolios, can be applied (Hull and White, 2004; Tarashev and Zhu, 2006). In particular, Tarashev and Zhu (2006) link the correlation structure embedded in CDS prices to the correlation between asset values in the Merton capital structure framework. A latent factor model driving the asset return variations can then be used to connect the default probabilities of the different institutions.[5]

Our innovation is to also embed a model of correlated losses between the institu-

[4] Various extensions of the DD measure exist, capturing for example volatility clustering (Nagel and Purnanandam, 2019), and asymmetric volatility shocks (Kenc et al., 2021).

[5] The approach here can be traced back to an early latent factor credit model developed by Vasicek (1987) to price loan portfolios. In general, using a factor model to drive the correlations structure between portfolio positions is referred to as a factor copula model.

tions, overcoming a modeling deficiency in earlier studies, which typically assume a fixed Loss Given Default (LGD) (Puzanova and Düllmann, 2013) or assume that Recovery Rates (RRs) are random but sampled independently from each other (Huang et al., 2012; Kaserer and Klein, 2019). In a tail scenario, a SIFI's default 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. From that point our approach of endogenizing the LGD relates to the literature on fire sales. See for example Shleifer and Vishny (1992) who argue that in times of industry-wide distress and increased default rates, assets tend to go to industry outsiders who may lack the necessary skills to manage them and will thus be willing to buy them only at a discount to fair value. As a result, LGDs will tend to rise with the drop in liquidation prices. This has been empirically observed among others by Acharya et al. (2007).[6]

We finish by quantifying systemic risk through a Monte Carlo simulation of the possible scenarios over the coming year by evaluating the average loss of an institution if the portfolio as a whole is its tail (Acharya et al., 2017).

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# 3 A Structural Model of Defaults and Losses

We begin by defining the structural credit risk model behind the occurrence of systemic losses. Key here will be the assumptions driving asset value correlations and loss correlations. These asset value processes will be at the core of the data-generating processes that we define in sections (3.1) and (3.2), dealing respectively with default correlations and correlations of Losses Given Default. These data-generating processes will then guide factor model estimation in Section (3.3), and tail-risk estimation later in Section (4).

## 3.1 Default and Asset Correlations

We start from Merton (1974) and describe the evolution of the value of assets of each institution $i = 1, ..., n$ under the risk-neutral measure through the process

$$d \ln V_{i,t} = r dt + \sigma_{v,i} dW_{i,t} \tag{1}$$

Note that we can write (1) as $dW_{i,t} = \frac{d \ln V_{i,t} - r dt}{\sigma_{v,i}}$ which gives the statistical interpretation of $dW_{i,t}$ as the standardized excess asset returns under the risk-neutral measure.

We assume that the risk component of asset value changes is driven by a common factor component $M_t$ and an idiosyncratic component $Z_{i,t}$:

$$dW_{i,t} = A_i M_t + \sqrt{1 - A_i A_i'} Z_{i,t} \tag{2}$$

where $M_t = [m_1, \ldots m_f]'$ is the vector of stochastic latent factors and $Z_{i,t}$ is the firm-specific factor. $A_i = [\alpha_{i,1}, ..., \alpha_{i,f}]$ is the vector of factor loadings, such that $A_i A_i' \leq 1$. All factors are assumed to be mutually independent with zero mean and a standard deviation of one. Note that if one assumes $A_i = A_j$ for all $i, j$, one gets the well known Vasicek loan pricing model which assumes the same averaged-out factor exposure across all loans.

[6]See also IJtsma and Spierdijk (2017) for a discussion of fire sales, endogenous LGDs and the relation to systemic risk.

In the approach used here, we allow for exposure heterogeneity. One could interpret the factors as independent economy-wide and industry-wide shocks affecting the uncertainty in the firm's asset value.

In Merton's setting[7], default occurs at maturity ($T = t + \Delta t$) when assets fall below the face value of debt:

$$\begin{aligned} PD_t &= \mathbb{P}(V_{t+\Delta t} \leq D) \\ &= \mathbb{P}\left(V_t \exp\left((r - \frac{\sigma_v^2}{2})\Delta t + \sigma_v W_{t+\Delta t}\right) \leq D\right) \end{aligned}$$

Consider next the well known concept Distance to Default $DD_t$[8]:

$$DD_t = \frac{\ln \frac{V_t}{D} + \left(r - \frac{\sigma_v^2}{2}\right) \Delta t}{\sigma_v \sqrt{\Delta t}}$$

which allows us to rewrite the expression for the probability of default as:

$$PD_t = \mathbb{P}\left(\frac{W_{t+\Delta t}}{\sqrt{\Delta t}} \leq -DD_t\right)$$

As a result, we get:

$$PD_t = \Phi(-DD_t) \tag{3}$$

where $\Phi(.)$ is the cumulative normal distribution.

We can then write the discrete first difference of $DD_t$ as:

$$\Delta DD_t = \frac{\Delta \ln V_t}{\sigma_v}$$

The correlation between asset returns can be written as:

$$\begin{aligned} \rho_{i,j} &= \mathbb{Corr}(\Delta \ln V_{i,t}, \Delta \ln V_{j,t}) \\ &= \mathbb{Corr}(\sigma_{v,i} \Delta DD_{i,t}, \sigma_{v,j} \Delta DD_{j,t}) \end{aligned}$$

Correlations are invariant to linear transformation, so we can drop the $\sigma_v$ term. Then after substituting in the inverted relationship (3), the asset correlations can be implied from the correlations between the transformed probabilities of the default:

$$\rho_{i,j} = \mathbb{Corr}\left(\Delta\Phi^{-1}(PD_{i,t}), \Delta\Phi^{-1}(PD_{j,t})\right) \tag{4}$$

Equation 4 is of crucial importance because it relates the co-dependencies in the probabilities of default (PDs) to the asset correlations of the underlying institutions. 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 Section (3.3) we discuss in detail how these asset correlations can be used to estimate the parameters of the latent factor model in (2).

[7]See Appendix (A) for presentation of Merton's firm value model and the role spreads play in it.

[8]The DD measure has a wide application to risk management as a predictable indicator of bank fragility (Gropp et al., 2006; Chan-Lau and Sy, 2007).

Our reliance on the Merton (1974) framework implies that we assume default to occur when a fixed default barrier is crossed at debt maturity. 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. Even though the Merton framework maybe conceptually restrictive, it is a widely used as a raw approximation of default. The related Merton-based DD has also been shown to be predictive of actual defaults (Bharath and Shumway, 2008) and has certain robustness against model misspecification (Jessen and Lando, 2015). As a result, we do not pursue any of the structural extensions in this study.[9]

In section (3.3) we discuss in detail how observed CDS rates can be used to imply default probabilities for the period, how the target correlations $\rho_{i,j}$ are set and in turn how the factor model driving asset returns is estimated, but before doing that we have to specify the processes driving losses conditional on default.

## 3.2 A Model of Loss Correlations

The next step is determining the size of the potential losses if a default were to occur. A common deficiency in the systemic risk literature which uses the portfolio-of-loans approach is that the realized recovery rate RR is assumed to be either fixed (Puzanova and Düllmann, 2013) or stochastic but independent across firms and from the realization of default (Huang et al., 2009, 2012; Kaserer and Klein, 2019).[10] Relying on strong assumptions on default losses is inevitable, as defaults, especially of SIFIs, are rarely observed. Yet, we try to addresses the empirical evidence that as default rates in the economy increase, the recovery values on assets decrease (Altman et al., 2004; Acharya et al., 2007). Therefore in an extension of the existing literature we allow default losses to be dependent on the latent factors driving asset correlations. Accounting for this is likely to have significant consequences for the quantification of systemic risk which inevitably depends on the tail risk dependencies between institutions.

To do so we follow Frye (2000) and Andersen and Sidenius (2005) and model the RRs based on the value of a stochastic collateral process $C_{i,t}$ which backs up liabilities. Dependency is achieved by making the value of the collateral dependent on the same set of factors that drive the asset value processes. In particular, we define the value of collateral per euro of liabilities as:

$$d\ lnC_i = \sigma_c dW_i^c \tag{5}$$

where $dW_i^c$ is a term driving the total recovery risk and $\sigma_c$ is a scaling parameter.

We assume that common collateral value variation is driven by the same common factors defining the asset correlations in (2). $Z_i^c$ defines an independent factor capturing possible firm-specific discrepancies between the underlying assets of the firm and the value of recovered collateral, which could be due to a loss on the value of intangible assets, or any other restricting costs due to, liquidation, or delay costs. The same factor loadings determined in (2) are assumed to hold here as well. Formally, we therefore have

$$dW_i^c = A_i M + \sqrt{1 - A_i A_i'} Z_i^c \tag{6}$$

[9]See Sundaresan (2013) for a review of structural credit models and their applications.

[10]This relies on a modelling approach often used in the credit risk literature to sample simulations of the random RRs independently from triangular or beta distributions (Hull, 2018).

Finally, in case of default, the recovery rate ($RR_i$) as a proportion of liabilities is never larger than 100% of the recovered liabilities:

$$\begin{aligned} RR_i &= \mu_{c,i} \min(1, C_i) \\ &= \mu_{c,i} \min\left(1, \exp\{\sigma_c dW_i^c\}\right) \end{aligned} \tag{7}$$

where $\mu_{c,i}$ is calibrated to match the assumption of the expected RR.

We do not have a reliable way to estimate $\sigma_c$ for each institution in the portfolio, so we match it to the VSTOXX index (Figure (14)) as a way of generating time variation which is tied to the willingness of investors to take risks and thus to the overall asset valuation sentiment in the economy. VSTOXX, similarly to its US counterpart VIX, measures the implied volatility derived from near-term exchange-traded options on the Euro Stoxx 50 index. The options are widely used by investors for hedging purposes, so the two composite indices constructed from their prices are indicative of the risk appetite prevalent in the economy. A low appetite for risk relates to a greater cost of capital, lowering investments, and driving down prices, while a high appetite relates to credit and asset price bubbles, increasing the chance for future recessions and stress in the financial system (Illing and Aaron, 2005; Gai and Vause, 2006; Aven, 2013).

## 3.3 Estimation of the Latent Factor Model

We now proceed with the estimation of the factor loadings of equation (2). The first step is to find the institutions' default probabilities over time. Once we have these time series, relation (4) allows us to pin down the asset correlation matrix between the various institutions under consideration. These will serve as target correlations against which the model is fitted when estimating the factor loadings.

So, first, we extract the (risk-neutral) default probabilities needed in Equation (4) from the observed CDS rates. Following Duffie (1999) we assume, in this subsection only, that RRs are constant over the horizon of the contract, setting aside the equation (7) we use in analyzing correlated LGDs. We do not try to identify expected recovery rates separately from the observed CDS data. There are alternative and more sophisticated approaches; 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 (cf Tarashev and Zhu (2006)'s discussion of precisely this issue). Yet, the simplifying assumption we employ in estimation is widely used in the literature and is hard to improve on given the identification problem we just discussed.

With this in mind we can proceed with the pricing equation of the CDS contract. By market convention, at the initiation date $t$ of the contract the spread $CDS_t$ 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:

$$\underbrace{CDS_t \int_t^{t+T} e^{-r_\tau \tau} \Gamma_\tau d\tau}_{\text{PV of CDS premia}} = \underbrace{(1 - ERR_t) \int_t^{t+T} e^{-r_\tau \tau} q_\tau d\tau}_{\text{PV of protection payment}} \tag{8}$$

$r_\tau$ is the risk-free rate, $CDS_t$ is the observed CDS spread for the day, $q_\tau$ is the annualized instantaneous risk-neutral default probability , $\Gamma_\tau = 1 - \int_t^\tau q_s ds$ is the risk-neutral survival probability until time $\tau$, and $ERR_t$ is the expected recovery rate in case of default, assumed to be constant over time.

For simplicity we assume that the risk-free rate $r$ and the annualized default rate $q$ are fixed over the horizon of the contract. Then the default probability $q$ at time $t$ follows from equation (8):

$$q_t = \frac{aCDS_t}{a(1 - ERR_t) + bCDS_t} \tag{9}$$

with $a = \int_t^{t+T} e^{-r\tau} d\tau$ and $b = \int_t^{t+T} \tau e^{-r\tau} d\tau$. Setting $T = 5$ to capture 5 year CDS contracts, we can imply the annualized default probabilities.[11] We can then substitute the implied risk neutral probability $q_t$ for $PD_t$ in Equation (4), which then allows us to fix the asset correlations between all pairs of institutions.

Next we find the loadings of the latent factor model (2) by minimizing the squared error between the target correlations derived from co-movements in the default probabilities and the correlations implied by the factor loadings:

$$\min_{\hat{A}_1,\ldots,\hat{A}_n} \sum_{i=2}^{N} \sum_{j=1}^{N} (\rho_{ij} - \hat{A}_i \hat{A}_j')^2 \tag{10}$$

An efficient algorithm that solves to minimization problem is provided by Andersen and Basu (2003). It operates through an iterative principal component analysis rather than by brute force numerical optimization. Appendix (B) clarifies the algorithm.[12]

Finally we should point out that we are ignoring correlation risk premia. We rely on evidence provided by Tarashev and Zhu (2006) that such premia, if they exi at all, are quantitatively very small in CDS prices.

# 4 Measuring Systemic Risk: A Credit Portfolio Approach

We now have the machinery in place to start modeling systemic risk. We model the space of institutions falling under the regulator's supervision as a structured credit portfolio. An institution becomes distressed if a credit event occurs in its subordinated debt. Each

[11] 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 a default has not yet occurred, the time until it does is exponentially distributed with parameter $q$. For a small $\Delta t$ and small $q$, the probability of default is then $\Delta t.q$. See Duffie (1999) for details.

[12] An alternative is to use Kalman Filtering techniques. As shown by Tarashev and Zhu (2006), the two produce very similar results.

institution's liability can be seen as a loan from the public and amounts to the total Exposure at Distress (EAD). A loss occurs whenever an institution defaults and cannot deliver the full promise of its outstanding liabilities to its counterparties.

Formally, the systemic loss $L_{sys}$ is the sum of the individual losses of each institution in case of distress over the following year; the sum is scaled by the total liabilities in the system:

$$\begin{aligned} L_{sys} &= \sum_{i=1}^{n} w_i L_i \\ L_i &= \mathbb{1}_{d_i}(1 - RR_i) \end{aligned} \tag{11}$$

where each loss $L_i$ stands for the percentage losses in default as a proportion of the own liabilities of institution $i$, and $w_i = \frac{B_i}{\sum_{j=1}^{N} B_j}$ is the relative weight of the institution's liabilities ($B_i$) in the systemic portfolio. $\mathbb{1}_{d_i}$ is a default indicator function, where in line with the structural assumptions made so far default occurs when $dW_i \leq -DD_i$, in line with the expression from equation (3).

We define systemic risk as the potential for large default losses in the financial system. A single entity's contribution to systemic risk then will be measured as its propensity to increase that potential. Several elements can thus drive the systemic risk contributions of an institution. First of all, both increases in the default probability and decreases in the proportion that can be recovered in case of default will lead to a higher contribution. Second, the size of the institution, measured by its outstanding liability relative to the size of others, will determine how important the institution's potential losses are for the system as a whole. Third, the propensity of the institution to become distressed or to realize large losses whenever other institutions in the portfolio are distressed will also affect its systemic risk contribution.

Formally, we quantify downside risk through Expected Shortfall[13] (ES), which measures the average losses of an institution, or, where relevant, the portfolio as a whole, in the worst $q$-th percentile of its potential loss distribution:

$$ES_i = \mathbb{E}(L_i | L_i \geq VaR_i) \tag{12}$$

where $VaR_i$ stands for the Value-at-Risk of the institution at confidence level (CL) $1-q$:[14]

$$\mathbb{P}(L_i \geq VaR_i) = q$$

The $ES$ thus measures the average loss once the $VaR$-threshold of an institution has been exceeded. An appealing feature of this measure is that it is coherent, in the sense of Artzner (1999), and thus allows for capturing diversification in an intuitive way when the losses of a system are aggregated.[15]

The $VaR$ and the $ES$ of a financial institution quantify the potential losses that could occur if an institution is distressed. These measures however do not take into account the

[13]The measure is often referred to as Expected Tail Loss or Conditional Value at Risk (Rachev et al., 2008)

[14]Typically, $q$ stands for the tail probability and takes value of e.g. $5\%, 1\%, .01\%$ depending on how far in the tail we want to measure the potential for extreme losses. Then, given the potential loss distribution, we are $(1-q)\%$ certain that losses will not exceed the corresponding $VaR$ estimate.

fact that banks operate in a network and each institution's failure may trigger failures of other institutions.

As a measure of tail codependency, we follow Acharya et al. (2017) to define Marginal Expected Shortfall ($MES$) as the average loss of institution $i$ given that the system is in the worst $q$-th percentile of its distribution of potential losses:

$$MES_i = \mathbb{E}\left(L_i | L_{sys} \geq VaR_{sys}\right) \tag{13}$$

Note that the weighted sum of all $MES$s in the portfolio provides the $ES$ of the system. This follows from (12) and (11):

$$\begin{aligned} ES_{sys} =& \mathbb{E}\left(\sum_i w_i L_i | L_{sys} \geq VaR_{sys}\right) \\ =& \sum_i w_i \mathbb{E}\left(L_i | L_{sys} \geq VaR_{sys}\right) \\ =& \sum_i w_i MES_i \end{aligned} \tag{14}$$

This additivity property allows us to break down the total $ES$ of the portfolio into percentage contributions due to each institution as

$$PC \text{ to } ES_i = \frac{w_i MES_i}{ES_{sys}} \tag{15}$$

which will be a useful metric further on in attributing risk across institutions and ranking them by systemic importance. Note that (14) 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 as we have $\frac{\partial ES_{sys}}{\partial w_i} = MES_i$

# 5 Data

## 5.1 Note on the Dutch Financial Sector

The Dutch banking sector is comparatively large relative to other EU countries: the total cumulative balance sheet value of all banks accounts to about 400% of GDP in the beginning of 2013, a rise from about 100% in the 1970s. For comparison that figure amounted to about 300% in the EU and in Germany according to figures by DNB (2015). By 2018, The Netherlands is in the top 5 countries ranked by the ratio of value of bank assets to GDP DNB (2019) The sector is highly concentrated, and domestic banks are dominating the market. We look at the five largest Dutch banks:

[15] The set of coherent risk measures are defined axiomatically through a number of intuitive properties: (1) *Monotonicity*: comparing several random payoffs, lower losses in all states of nature imply lower risk; (2) *Positivide homogeneity*: scaling a portfolio random payoff by a positive factor also scales its risk by the same factor; (3) *Sub-additivity*: the risk of the portfolio is not greater than the sum of the risks of the assets which comprise it; (4) *Invariance*: adding cash to a portfolio reduces its risk by the amount added. ES covers all of the properties, while VaR fails at sub-additivity. In fact, functionals which satisfy (2) and (3) are convex, a feature that defines mathematically the concept of diversification in modern portfolio theory (Rachev et al., 2008).

[15] In the risk management jargon (Hull, 2018), the weighted $MES$s are often referred to as *Component* Expected Shortfall.

- **ING Bank**: privately held by ING Group, it is the most internationally oriented Dutch bank with operations also in Mexico, Taiwan, etc.
- **ABN AMRO**: mostly focused domestically with some operations abroad. Equity on the company is publicly traded, providing a little less than half of the capital of the bank. The remainder is Government held, down from 100 % after a nationalization/rescue in 2008. It is the only bank in our sample whose equity is publicly traded.[16]
- **Rabobank**: a cooperative bank, largely focused on the agricultural and consumer sector with certain activities abroad.
- **NIBC Bank N.V.**: a commercial bank, subsidiary of NIBC Holding N.V. which is publicly traded
- **De Volksbank**: a bank holding operating exclusively in the Netherlands owned by the Dutch state since the nationalization of its predecessor SNS in 2012

Out of the 5 institutions, ABN AMRO, ING, and Rabobank are designated as systemically important by the European Banking Authority.

In addition, we look at two insurance companies, which have CDS swaps traded on their name:

- **NN Group**: one of the largest insurance holdings in the Netherlands. It is active in life and non-life insurance, and also has an asset management branch. NN was part of the ING Group and was split off from it between 2013 and 206. Its equity is currently publicly traded.
- **Aegon NV**: a holding company engaging in insurance, pensions, and asset management services. It is globally active in its operations.

The goal is to check if the market perceives dependencies between the insurance sector and the banking sector in the Netherlands and to check if any of the insurance firms will show up as systemically important when looked at in the context of the total financial sector. Also, we want to capture any potential interlinkages between insurers and banks that could drive systemic losses. The equity of both insurers is publicly traded on the equity market.

## 5.2 Dataset and Data Assumptions

We use weekly data for ISDA'14 compliant CDS mid prices on subordinated debt. The data is collected from Bloomberg. Figure (12) in Appendix (C) shows the evolution of CDS rates for each institution and Figure (13) (also in Appendix (C)) shows a scatter matrix and distribution plots for the CDS rate log changes. This gives an initial view of the possible dependencies in the occurrence of credit events between institutions.

We evaluate systemic risk in a cross section and over time. First we use the period September 9th, 2019 to September 13th, 2021 to evaluate and rank the institutions by

[16] ING Group's equity is publicly traded, but it owns a large number of subsidiaries operating worldwide that are operationally and legally disjoint from the Dutch subsidiary. NIBC's equity has been de-listed since February, 2021.

their contribution to systemic risk. Then we use a rolling window backtest in the period January 1st, 2010 up to September 13th, 2021 to evaluate the evolution of the systemic risk measures. In the spirit of Lehar (2005), the time window consists of 2 years of weekly observations to evaluate the model and project the risk metrics, after which the window is shifted forward by a week and the model is re-evaluated. This produces a series of out-of-sample metrics.

Annual balance sheet data is collected from FactSet and from publicly available financial statements of the firms, whenever the data provider has a gap. The annual numbers are interpolated to weekly with a cubic spline to avoid jumps at year-end, driven by accounting standards rather than the arrival of new market information.

The structure of the liabilities of each company is used to induce the expected recovery rate (ERR) in case of default (Figure (15) and Table (1)). Following Kaserer and Klein (2019), an expected recovery rate of 80% is assumed on deposits (in case the institution is a bank) or policy insurance liabilities (in case the institution is an insurer) and 40% on other liabilities. The reasoning is that the collateral on the former type of liabilities is regulated to be more liquid and low-risk and thus higher recovery in case of default can be expected. Kaserer and Klein (2019) provides an overview of the empirical studies which underpin the numbers on the expected recovery rates ERR.

Figure (15) (in Appendix (C)) shows for each institution the value of the deposits and insurance policies, the value of other liabilities, and the resulting ERR assumptions. There is little variation in the ERR over time but diversity across institutions is large. Table (1) below shows the average liability weights (LW), the weight of the institution in the systemic portfolio; the liability ratio (LR), the ratio of deposits and policy liabilities to other types of liabilities, and the ERR and per institution. Ranked by LW, the largest institutions are ING Bank, Rabobank, and Aegon. In terms of ERR, Volksbank has the highest value, while Aegon has the lowest (note that RR is a ratio).

Table 1: Recovery Assumptions

| | LW | LR | ERR |
|---|---|---|---|
| ABN | 0.15 | 0.64 | 0.66 |
| INGB | 0.35 | 0.72 | 0.69 |
| RABO | 0.23 | 0.61 | 0.64 |
| NIBC | 0.01 | 0.57 | 0.63 |
| VB | 0.02 | 0.83 | 0.73 |
| AEGO | 0.16 | 0.31 | 0.52 |
| NN | 0.09 | 0.72 | 0.69 |

*Note.* This table shows the average Liability Weights (LW) over the period 2010-2021 in the regulatory portfolio, the Liability Ratio (LR) as the average ratio of deposits (or respectively policy weights) in the company's balance sheet, and average recovery rate (RR) per company.

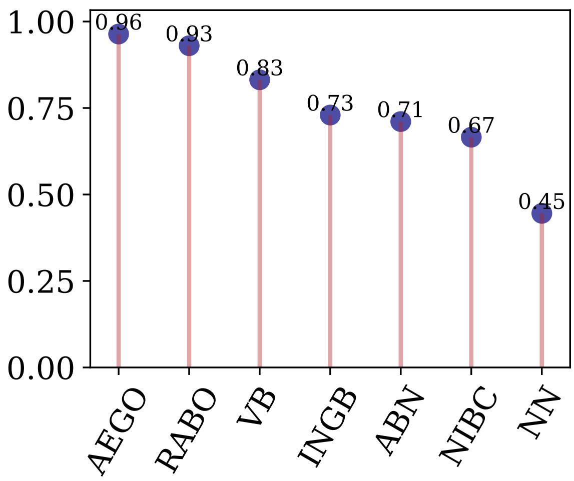
# 6 Results: an Overview

## 6.1 Factor Exposures and Asset Correlations

The first building block for evaluating the potential systemic losses driven by individual institutions consists of the estimation of the latent factor model,cf Section (3.1). The latent factor, synthesized from the common asset return variation in the sample, is often interpreted as a market driver of risk. From that point of view, the factor loadings on their own provide a useful interpretation as market exposures. They measure the sensitivity of an institution to market movements, and indicate the number of standard deviations the asset return of an institution will fall below the mean in response to one standard deviation drop in the return of the market.

Figure (1) shows the exposure values for each institution. The factor loadings are estimated based on the observed CDS prices over the considered time window. We can already see that three groups of institutions start to form - those with high sensitivity to the common factor (Aegon, Rabo, and VB), those with median exposure (ING, ABN, NIBC), and those with low factor sensitivity (NN).

Figure 1: Common Factor Loadings




*Note.* This figure shows the estimated exposure (loading) of each institution to the common latent factor.

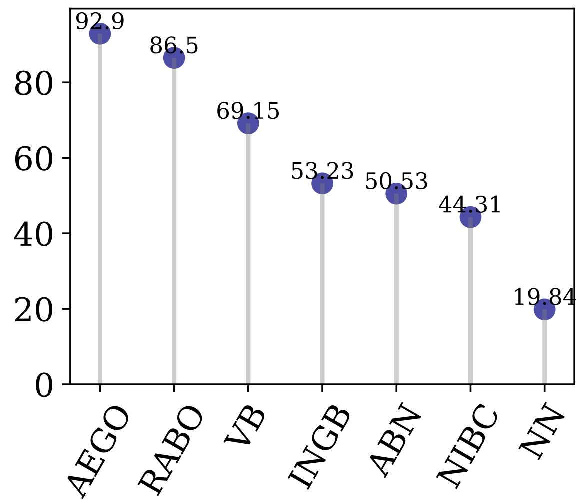
For interpretation purposes, it is also useful to translate the exposure figures into the share of total asset return variation due to market risk vs. the share due to idiosyncratic variation. In fact, squaring the loadings provides the share of market risk:

$$\begin{aligned} \frac{\mathbb{V}\mathrm{ar}(\Delta \ln V_i)}{\sigma_i} &= a_i^2 \mathbb{V}\mathrm{ar}(M_i) + (1-a_i^2)\mathbb{V}\mathrm{ar}(Z_i) \\ &= \underbrace{a_i^2}_{\text{Factor Risk Share}} + \underbrace{(1-a_i^2)}_{\text{Idiosyncratic Risk Share}} \end{aligned} \tag{16}$$

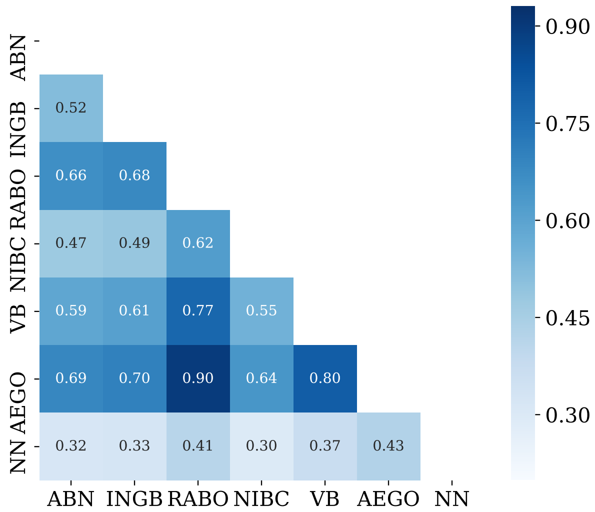
In the same line of thought, cross-multiplying the loadings of two institutions provides the implied correlation between the return of their asset holdings, since we have:

$$\mathbb{C}\mathrm{orr}(\Delta \ln V_i, \Delta \ln V_j) = a_i a_j$$

Figure 2: Common Factor Loadings




(a) Share common factor risk (% of Total)




(b) Implied Asset Correlations

Figures (2) below illustrate the results. Naturally, the smaller the factor loading of an institution is, the more the risk of that institution is purely idiosyncratic, and the less correlated it is with all other institutions in the market.

## 6.2 Probabilities of Joint and Systemic Defaults

The next building block of the model is the default simulation based on a fixed default barrier in line with the Merton firm model. To do this we draw 500K independent Monte Carlo simulations for the idiosyncratic and the common factors. Based on each institution's factor exposures, outlined in the previous section, these can be translated into scenarios of (standardized) asset value changes over the coming year. The default probability implied through the observed CDS rate for the period provides the default boundary for the institution, as indicated in equation (3). Subsequently, in each simulated scenario of asset value drops, we can evaluate whether the barrier would be crossed and whether a default would occur. The common factor provides co-variation in the occurance of defaults, which will guide the probability of multiple defaults occurring at the same time.

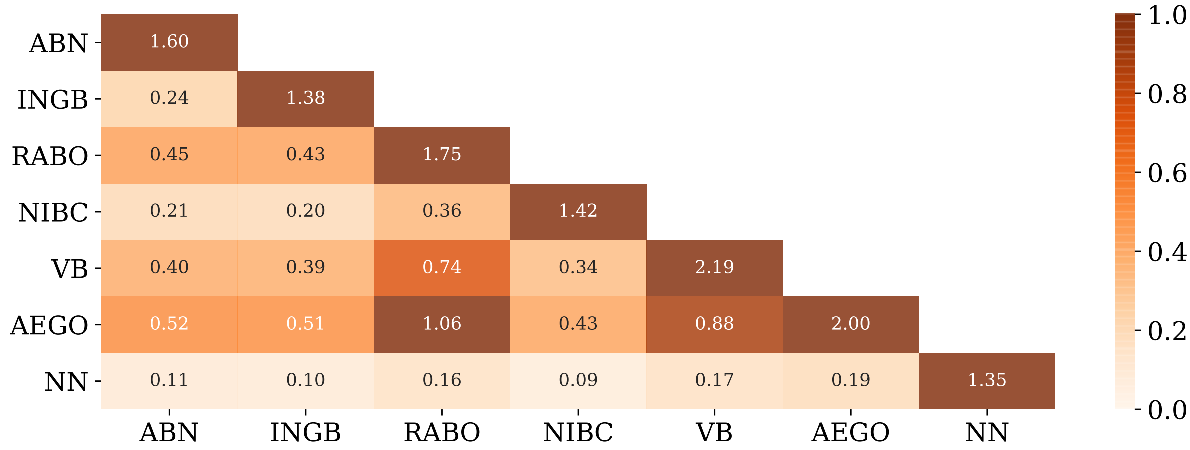
In aggregate, this allows us to estimate the average share of default scenarios per institution, matching the estimated individual default probability from the observed CDS spread. More importantly, we can find the average share of joint defaults, illustrating the tendency of institutions to become distressed at the same time. Figure (3a) shows these numbers. The diagonal corresponds to the standalone default probabilities. VB, Aegon, and Rabo are ranked highest. The off-diagonal terms show the probability of joint defaults. The three highest pairs here are, maybe not surprisingly, again among the group of institutions that have the highest common factor exposure: Aegon with Rabo, Aegon with VB, and VB with Rabo.

Next, we can translate the joint default probabilities into conditional probabilities of one institution's default conditional on a default of another institution using the definitional relationship:

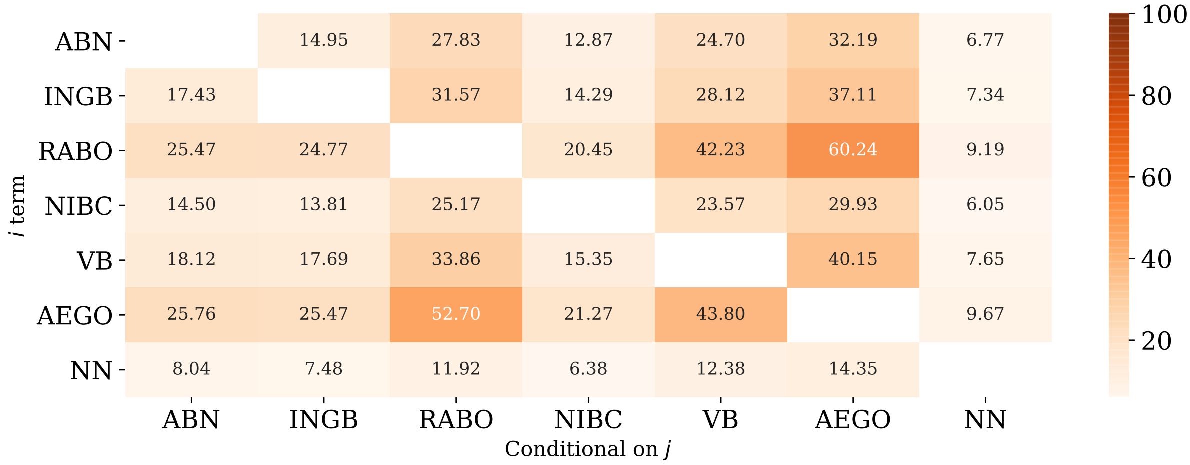
$$\mathbb{P}(\mathbb{1}_{d_i} = 1 | \mathbb{1}_{d_j} = 1) = \frac{\mathbb{P}(\mathbb{1}_{d_i} = 1, \mathbb{1}_{d_j} = 1)}{\mathbb{P}(\mathbb{1}_{d_j} = 1)}$$

where in each case $\mathbb{P}(\cdot)$ indicates the probability of default. Figure (3b) below shows the results. We can see that the high asset correlations also translate into high joint and conditional default probabilities.

Figure 3: Default Probability Matrix




(a) Joint Probability of Default




(b) Conditional Probability of Default

*Note*: This set of charts shows (a) the probability that two institutions may default together over a one year horizon; (b) the probability that institution $i$ may default, conditional on $j$ being in default.

We also want to look at the potential for a systemic event to trigger cascading defaults. For the purpose, we define the random variable $N_d$ which will measure the number of defaults that will materialize over the coming period as:

$$N_d = \sum_{i=1}^{N} \mathbb{1}_{d_i} \tag{17}$$

The factor-based simulation, outlined in Section (3), allows us to evaluate the proportion of cases where more than $k = 1, 2, 3, 4$ defaults happen at the same time. This

Table 2: Probability of Systemic Defaults

| $k$ | $\mathbb{P}(N_d \geq k)$ | $\mathbb{P}(N_d \geq k \mid N_d \geq 1)$ | $\mathbb{P}(N_d \geq k \mid N_d \geq 2)$ |
|---|---|---|---|
| 1 | 7.17 | - | - |
| 2 | 2.50 | 34.88 | - |
| 3 | 1.24 | 17.27 | 49.50 |
| 4 | 0.61 | 8.52 | 24.43 |

*Note.* The first column in the table indicates the threshold number of defaults $k$. The second column shows the unconditional probability that more than $k$ out of 7 firms default at the same time. The third and fourth columns show respectively the conditional probability that more than one or two additional institutions will default given that at least one or respectively two have already defaulted.

produces $\mathbb{P}(N_d \geq k_1)$, as summarized in column two in Table (2). There is about 7% chance that at least one of the considered institutions may default over the next year. The probability is relatively high, but the overall trend, as Figure (4a) indicates, has been decreasing since the 2008/09 financial crisis.

We also compute the probability that there are more defaults, given that one or two have already materialized. Using the law of conditional probabilities, these can be computed as

$$\frac{\mathbb{P}(N_d \geq k)}{\mathbb{P}(N_d \geq \overline{k})}$$

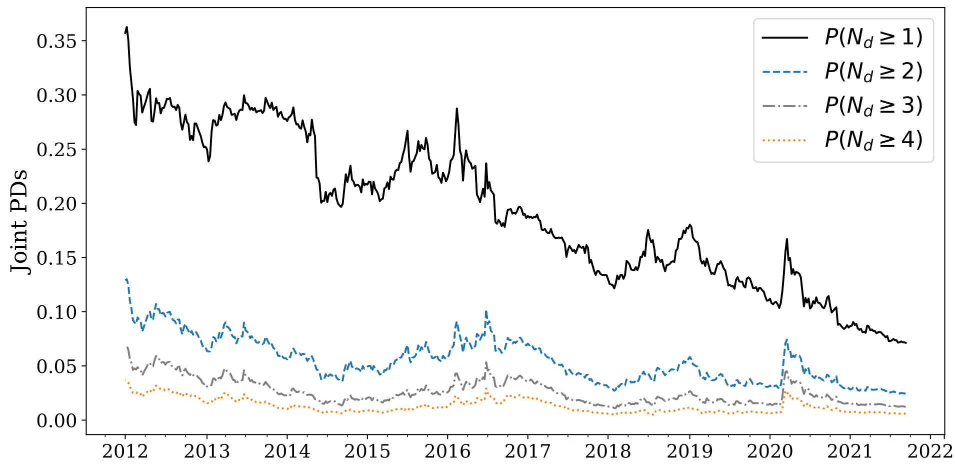
where $k$ is the total number of defaults given that at least $\overline{k}$ have already happened. The results are reported in column three and column four of Table (2) for $\overline{k}$ equal to one or two, respectively. If a default, occurs, there is a substantial chance (about 34%) that other defaults may follow. Examining the trend of conditional defaults over time, Figure (4b) shows that the cyclical pattern here is different - the probability decreases after the Euro government debt crisis in 2010-2011, increases in 2016, possibly due to Brexit concerns, and spikes suddenly in March 2020, which is when the first Covid waves came up in Europe.

It is worth noting that, since our model is not identifying causality in any form, the conditional probability of additional defaults could stand either for potential spillovers from one distressed bank to another, or could represent a common external shock affecting multiple institutions.

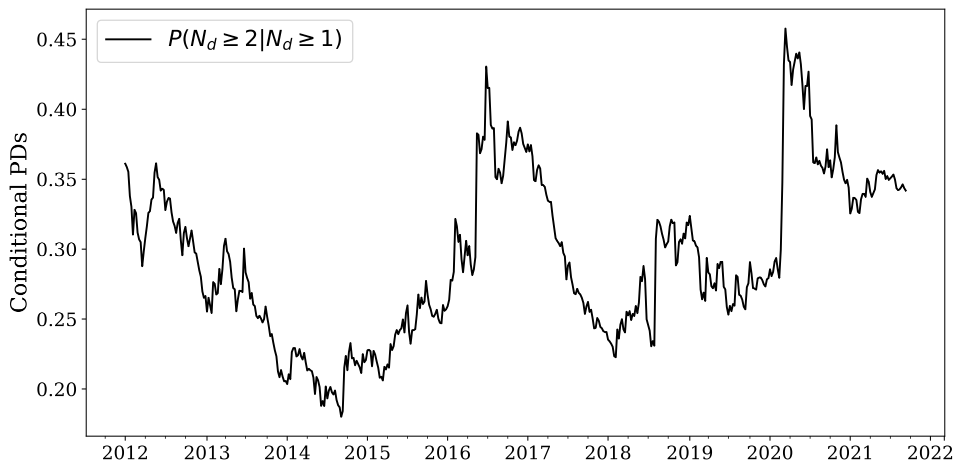
## 6.3 Marginal Expected Shortfall

Evaluating only systemic default probabilities as was done in Section 6.2 does not take into account the fact that the default of some institutions may have a much larger impact than that of others. Everything else fixed, bailing out a larger institution, will be more costly for the regulator, and its default and the possibility that it cannot cover its liabilities will have a wider impact on the economy. A proper systemic risk appraisal should also capture the size of the potential losses given that joint distress occurs. So our next step is to assess the size of the expected losses if tail risk events do in fact happen. Now we need to incorporate the stochastic nature of expected losses and the way they are correlated across institutions and, equally important, the way they depend on default probabilities, following the approach outlined in Section (3.2).

Figure 4: Probability of Systemic Defaults



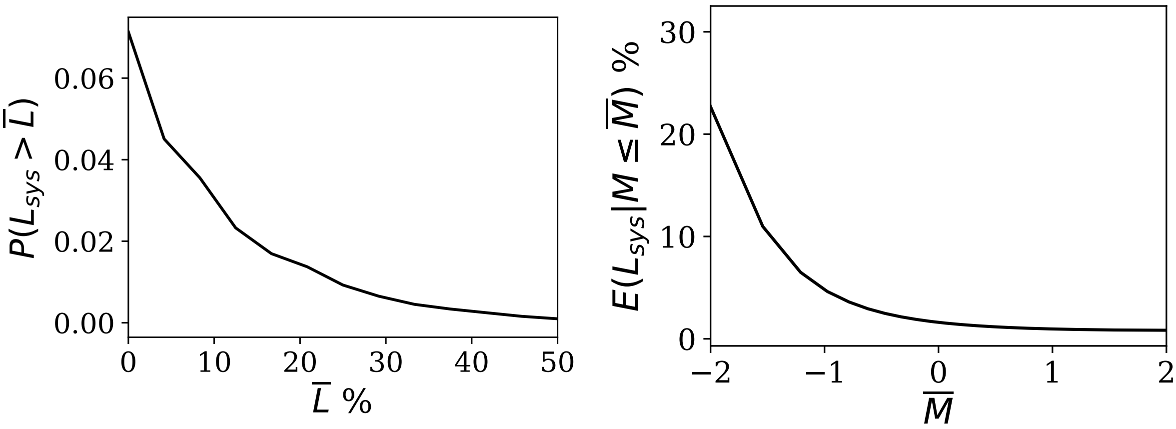

(a) Unconditional




(b) Conditional on One Default

*Note.* This set of charts shows (a) the probability that more than one, two, three or four defaults occur at the same time; (b) the probability that more than two defaults could occur is one has alreadyy happened.

Figure 5: Systemic Default Loss Distribution.




(a) Systemic Losses

(b) Factor-driven Expected Loss

*Note.* The first figure presents the probability that systemic losses (as percent of total liabilities in the system) will be larger than a threshold $\overline{L}$ as a function of that threshold. The second figure shows the expected systemic loss, as percent of total liabilities in the system, conditional on the factor dropping by more than $\overline{M}$ standard deviations away from the mean.

The charts in Figure (5) show an initial view into the potential size of the systemic losses and the probability that such losses could be realized. First, Figure (5a) shows the distribution of the simulated cumulative losses as a percent of the total outstanding liabilities in the system. Consistent with the earlier estimates in Table (2), in about 93% of the cases (corresponding to $1 - \mathbb{P}(L_{sys} > 0)$), the system is resilient and does not encounter any distress which would lead to default losses for any of its composite institutions. In about 3% of the cases, systemic losses could be above 10%.

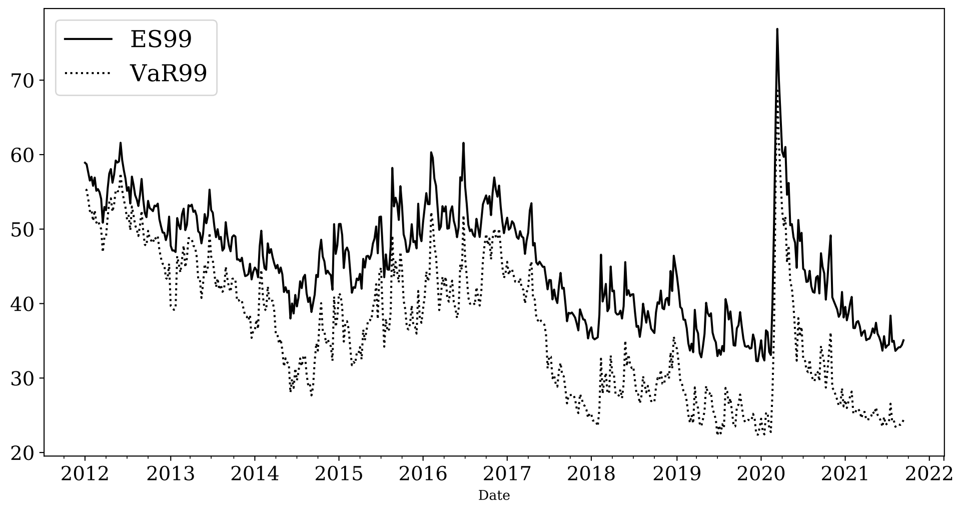
Figure (5b) on the other hand, relates the size of the aggregate losses that can be expected to the size of a potential systemic shock driven by a drop in the common factor $M$. By our estimates, for example, a drop of more than two standard deviations in the latent factor (e.g. a shock of the magnitude of the 2008/09 Financial Crisis) can be expected to bring losses of about 20% of the size of aggregate liabilities. In other words, given the defaults that this large systemic shock would generate, some of the financial institutions will experience asset value drops by such a magnitude that they will not be able to deliver about 20% of their outstanding liability commitments.

A standard approach to quantify the risk of losses within a portfolio in a single number is to employ the downside risk measures defined in section (4). In particular, we use the Expected Shortfall to measure the average of the worst 1% of the possible outcomes for the coming year. Using the simulated systemic losses, we evaluate the systemic risk by the $ES$ of the portfolio of institutions, and arrive at an estiamte of 35.05% (cf Table (3)). Table (3) summarizes the risk for the system and for each individual institution, where the $ES$ will be indicative of standalone risk.

For the system as a whole, Figure (6) puts the risk evaluation in context, plotting over time the $ES$ and the $VaR$ of the systemic portfolio. Note that in contrast to the downward trend of Figure (4a), the tail risk of the systemic portfolio is not on a downward trend over time but seems to be more in line with the cycles in Figure (4b).

Overall, these estimates allow regulators not only to track the resilience in the system and to look for increased probability of large systemic losses, but also to verify whether

Figure 6: Systemic Risk (ES, VaR)




*Note.* This plot shows the tail risk of the systemic portfolio quantified by the $ES$ and $VaR$.

the buffers currently in the system are enough to cover the potential losses once a systemic event materializes. If the buffers are not sufficient, regulators could either require higher buffers to be set aside, or could look for ways to increase the resilience of the system, by closely examining the institutions which are the highest contributors to risk.

In order to attribute the potential systemic losses to the individual institutions comprising the system, we employ the MES measure suggested by Acharya et al. (2017) and defined in (13). In particular, we look at the percentage contributions defined in (15).

Table (3) summarizes the results. First of all, it points to a certain discrepancy between bank vulnerability rankings in relation to banks' own risk, as measured by $ES99$, and in relation to the vulnerability of the system as a whole, as measured by $MES99$. The two riskiest institutions on their own are Aegon and Rabo. They are also the most sensitive to shocks in the system, followed by VB which is number five when ranked by $ES$.

Second, taking institutional size into account, the top three contributors to systemic risk shift. Ranking by *PC to ES*, Rabo becomes first, owning about 32% of the total systemic risk, followed by ING with about 28%, Aegon, an insurer, with 26% and ABN with about 9%.

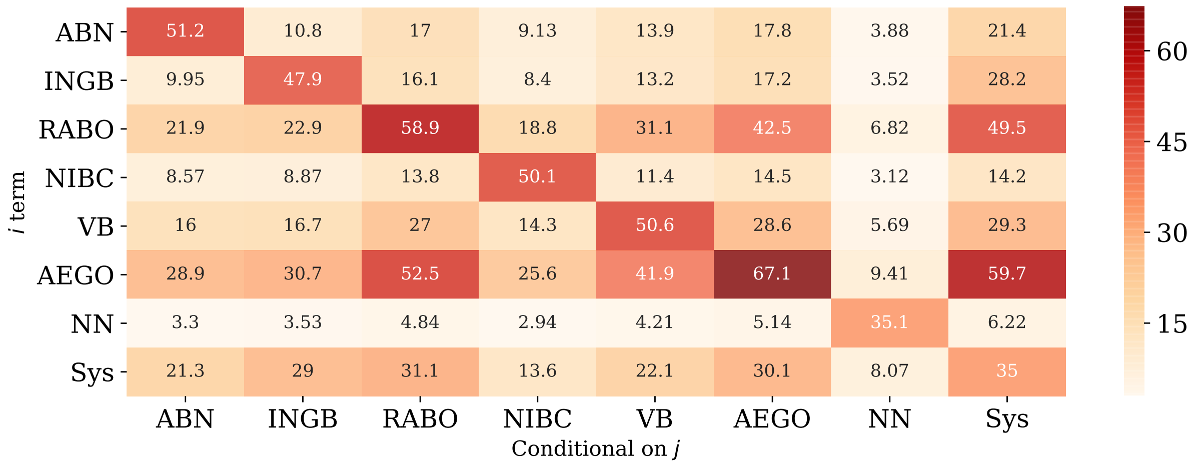
We can also define a so-called network relation based on ES as:

$$NES_{i,j} = \mathbb{E}\left(L_i | L_j \geq VaR_j\right) \tag{18}$$

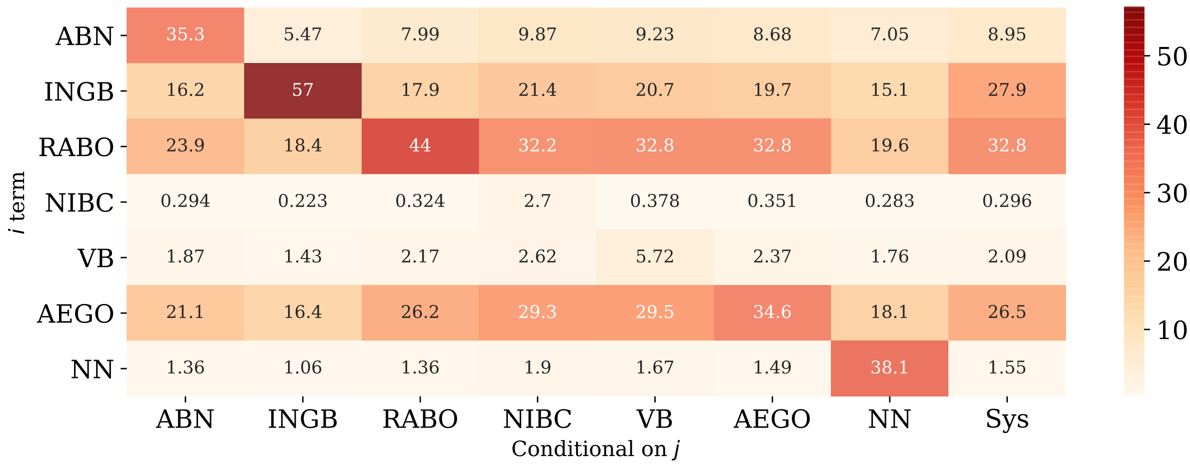
to measure the average losses of institution $i$ when institution $j$ is in distress. In contrast to the asset correlations and the conditional default probabilities, this distress dependency metric also takes into account the size of the losses.

Figure (7a) then shows the expected loss of the row entry given that the column entry is below its 99% $VaR$, where the diagonal of the table corresponds to the $ES$ of each entity, and the last column corresponds to the $MES$ of each institution. More interesting are the off-diagonal entries, which quantify loss co-dependencies between the different institutions, corresponding to the $NES_{i,j}$ measure defined earlier: the average loss of institution $i$ given that $j$ is in distress. In contrast to the asset correlations and the conditional default probabilities, this distress dependency metric takes into account the

Figure 7: Network Expected Losses, $q = .99$




(a) Network ES




(b) Network PC to ES

*Note*: These set of charts illustrate the network effects of tail losses. The first chart shows the expected loss of the $i$ entry, conditional on the $j$ entry. The last column and the last row, labeled Sys, stand for Systemic losses. The diagonal of the table corresponds to the $ES$ of each entity, and the last column corresponds to the $MES$ of each institution, the last row measures the $CoES$ of the column item, and the off-diagonal terms measure $NES_{i,j}$ with $i$ as the row entry and $j$ as the column entry.
The second chart shows the percentage contributions to systemic losses given that the column item is in its tail. Column items sum up to 100% and can be interpreted as percentage contributions to $CoES$.

Table 3: Systemic Risk Statistics

| | EL | | $w$ | | ES99 | | MES99 | | PC to ES99 | |
|---|---|---|---|---|---|---|---|---|---|---|
| ABN | 0.73 | (4) | 14.67 | (4) | 51.21 | (3) | 21.38 | (5) | 8.95 | (4) |
| INGB | 0.60 | (6) | 34.57 | (1) | 47.87 | (6) | 28.24 | (4) | 27.86 | (2) |
| RABO | 0.97 | (2) | 23.24 | (2) | 58.88 | (2) | 49.45 | (2) | 32.80 | (1) |
| NIBC | 0.65 | (5) | 0.73 | (7) | 50.07 | (5) | 14.22 | (6) | 0.30 | (7) |
| VB | 0.94 | (3) | 2.50 | (6) | 50.56 | (4) | 29.33 | (3) | 2.09 | (5) |
| AEGO | 1.29 | (1) | 15.54 | (3) | 67.15 | (1) | 59.65 | (1) | 26.46 | (3) |
| NN | 0.47 | (7) | 8.75 | (5) | 35.09 | (7) | 6.22 | (7) | 1.55 | (6) |
| System | 0.81 | | 100.00 | | 35.05 | | 35.05 | | 100.00 | |

*Note.* This table shows the Expected Loss, Liability Weight, ES, MES, and Percentage Contribution to ES statistics. All statistics are in percentage loss format. The numbers in the brackets provide the ranking relative to the group.

size of the losses. The largest co-dependent loss here occurs between Aegon and Rabo. In particular, if Rabo is in its tail, Aegon would lose 52.5%, which is not far from the loss it would realize in its tail, an $ES$ of 58.9%.

Note that the last row of Figure (7a) shows, the average loss of the system given that the institution is in its tail, a measure which we can call the $CoES$.This is an inverted version of the $MES$ presented in (13). The additivity property of the expectation combined with common conditioning, allows us to break down the $CoES$ of an institution into its weighted network components:

$$\begin{aligned} CoES_j &= \mathbb{E}(L_{sys}|L_j \geq VaR_j) \\ &= \mathbb{E}(\sum_i w_i L_i | L_j \geq VaR_j) = \sum_i w_i NES_{i,j} \end{aligned} \tag{19}$$

One possible interpretation of the $CoES$ is as a stress scenario, measuring the expected systemic loss if one institution becomes distressed. Note that all other institutions in that scenario will not be held fixed but will react following their tail dependencies with the distressed institution. A higher value for the metric means that either the distressed entity has more impact on the system on its own, or that all institutions are strongly correlated when generating losses. In the extreme, if either an entity is driving all the losses in the system, or the entity's losses are fully correlated to those of other players, its $CoES$ will be equal to the $ES$ of the system. From that point of view Rabo, Aegon, and ING Bank respectively have the highest potential to impact the system.

Weighting up and adding up all $NES_{i,j}$ over $i$, i.e. all row entries over a column entry $j$, generates the $CoES$ of institution $j$, as indicated earlier in (19). This allows us to determine the percentage contribution each institution will bring about to systemic losses when one of its peers is in its tail. Formally, we have

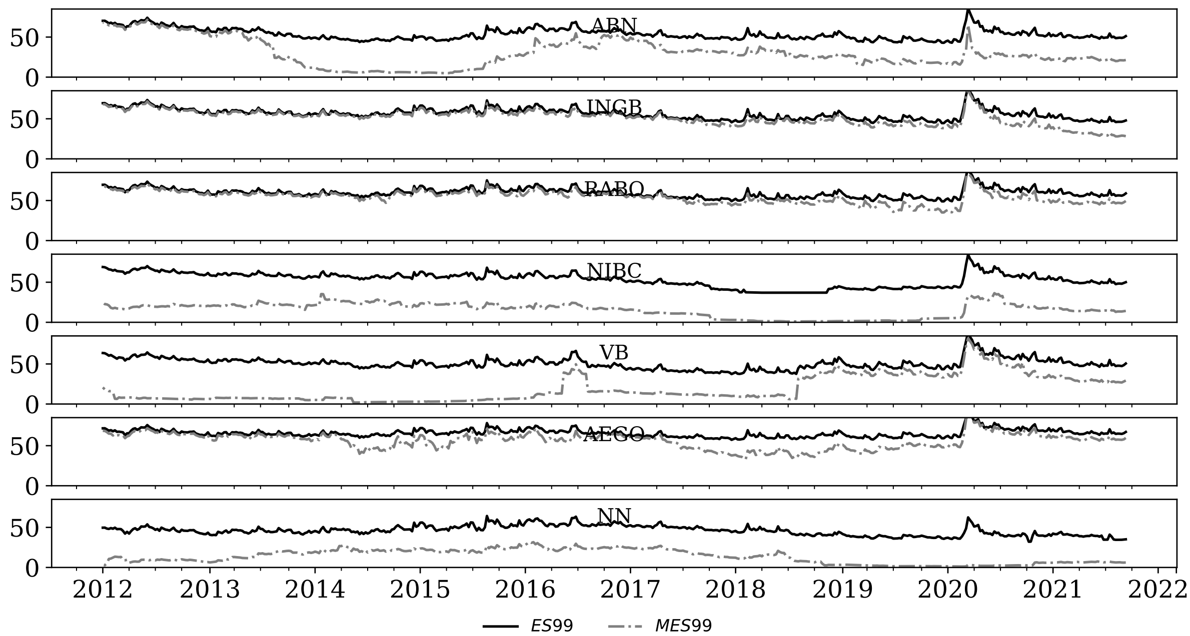
$$\text{Network } PC \text{ to } ES_{i,j} = \frac{\sum_i NES_{i,j}}{CoES_j}$$

The highest systemic loss of 31.1% will occur if Rabo ends up in its tail. If that were to happen, we can see from Figure (7b) that only 44% of the systemic losses will be due to Rabo itself. The rest will be contributed in large part by Aegon (26.2% of the risk), ING (17.9%), and ABN (about 8%).

Figure (8) shows rolling-window $MES$ estimates for each institution. Note that the $ES$, as a measure of standalone risk, is not always moving in conjunction with the systemic contributions ($MES$). Periods, where the two disagree in direction, are indicative of changes in the correlation between the institution and the portfolio.

The Covid impact spike at the beginning of 2020 is a clear systemic event increasing the standalone risk of each company. For some companies, the standalone risk spikes together with the corresponding contribution and reverses a former trend of declining contributions (Rabobank, NIBC, Aegon). For NIBC, in contrast, the spike keeps the firm at an increased level of systemic contribution. For ABN and VB, the shock seems to be largely transient. An interesting case is NN. Even though it experiences an uptick in standalone risk, its contribution does not move.

Figure 8: Backtest, 99% MES



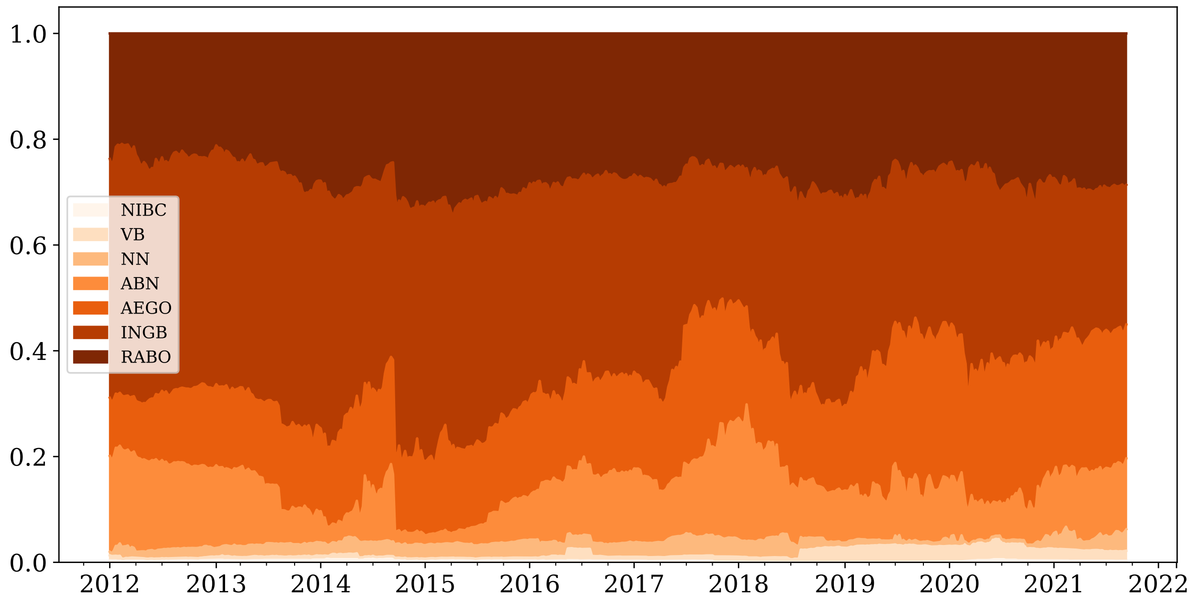

*Note.* This figure shows the MES vs. the ES at $q = .99\%$ for each company. The $MES$ of the institutions sums up to the total $ES$ of the system.

Figure (9) shows the contributions to systemic risk over time as a share of total systemic risk. The companies are ranked on the chart by contribution as of the end of 2021. There is no change in ranking for the top three contributors over time: Rabobank, ING Bank, and Aegon. However, the relative contribution coming from ING Bank has diminished after 2017.

## 6.4 Robustness

Finally, as a robustness chcek, we employ two checks to verify if changing or isolating out some components of the model changes the systemic rankings we estimate. First, we look at whether several other measures of systemic risk sensitivity comply with the rankings established in Section (6.3). Second, we look at the sensitivity of our results relative to the parameter assumption of $\sigma_c$ underlying the RR dynamics in (5).

Figure 9: 99% MES (Percentage Contribution)




This figure shows the MES vs. the ES at $q = .99\%$ respectively for each company. The $MES$ of the institutions sums up to the total $ES$ of the system.

As indicated in Section (2), there is a wide variety of measures in use that imply the systemic risk sensitivity of an institution from market data. Adrian and Brunnermeier (2016) propose the $CoVaR$ to quantify the tail-dependency between an institution and the system it is part of. It is evaluated as the worst $q\%$ losses of the system, given that an institution $i$ is in its worst $q\%$. To align this measure with the concept underlying the $MES$, we invert it to get the Exposure $ECoVaR$, which now also quantifies the sensitivity of the institution's losses to a systemic tail event[17]:

$$\mathbb{P}(L_i \geq ECoVaR_i | L_{sys} \geq VaR_{sys}) = q$$

Both the $MES$ and the $ECoVaR$ measure the institution's losses if the system ends up in the tail of its potential losses over the coming year. However, in contrast to $MES$, which measures the *average* loss once the system is its tail, the $ECoVaR$ zooms in deep in the tail of the potential losses of the institution, measuring the $q$-th quantile not only with respect to the systemic losses but also with respect to the institution's losses.

Next, we relate to another measure, which focuses only on default correlations as presented in Section (6.2). The idea is to compare our results to a measure that is not influenced by the assumptions on how losses are formed and how they correlate between

[17]Note that originally Adrian and Brunnermeier (2016) define $CoVaR$ by conditioning on individual losses being equal to a quantile rather than a region of their distribution as:

$$\mathbb{P}(L_{sys} \geq CoVaR_i | L_i = VaR_i) = q$$

This allows the use of quantile regression for the estimation of the measure. On the negative side, such conditioning can give a misleading tail-risk indication when the loss distribution is fat-tailed, by not capturing the probability mass below the $VaR$ quantile. In our case, systemic losses are strongly non-Gaussian, so we use the modified version of CoVaR, as in Huang et al. (2012), which conditions on $L_i \geq VaR_i$. See also Nolde and Zhou (2021) for the same argument, and the relation to Extreme Value Theory of the modified measure.

companies, as these assumptions will inevitably affect both the $MES$ and the $ECoVaR$ which are driven by the same loss simulations. To measure the sensitivity of individual institutions to distress in the system, Zhou (2010) defines the Vulnerability Index (VI) as the probability that institution $i$ will be in default conditional on more than one default in the system:

$$VI_i = \mathbb{P}(\mathbb{1}_{d_i} = 1 | N_d > 1) \tag{20}$$

Note that Zhou (2010) relies on Extreme Value Theory to estimate the proposed measures. Also, we rely on default as an indication of distress, whereas the original measure is constructed to capture large tail movements in the equity value of the institution. Our approach differs methodologically, but based on the outlined model, the measures can be adapted.[18]

Table (4) summarizes the results. First, we compare the unweighted systemic risk measures to the $MES$ rankings of Table (3). The rank correlations in sub-table (b) indicate strong agreement between the $VI$ measure and the $MES$. The $MES$ and the $ECoVaR$ agree only moderately. Closer inspection indicates that the disagreement is that $ECoVaR$ switches the ranks of NIBC and VB, and of ABN and ING.

Sub-table (c) compares the size-weighted measures and finds strong agreement between them. It is worth noting that only the weighted $MES$ measure (the ranking of which coincides with the presented earlier ranking by $PC$ to $ES$) sums up to total systemic risk. This is due to the additivity property (14). The two other risk measures do not have this property and their weighting can be considered only as a heuristic.[19]Once the measures are weighted, they show a stronger correlation among each other. It is worth noting that size itself correlates strongly to $MES$. It fails however to identify Rabo as the major contributor to systemic risk. Yet, both the $PC$ to $ES$ and the weighted $VI$ find Rabo to be more systemic than ING.

Next, we vary the parameter $\sigma_c$ to verify to what extent the results are driven by the decision to calibrate the parameter to the VSTOXX index. Table (5) shows the resulting percentage difference in the 99% $MES$ estimates when a fixed number of .15 and then to .05 is used in the model, relative to the base figures in which the value of the VSTOXX index was used (at the reference date the index has a value of .2). The parameter choice affects the magnitude of the $MES$ estimates. The new $MES$ figures however do not change the systemic ranking.

Figure (10) shows the $ES$ of the system for each alternative $\sigma_c$ estimate. Again, the magnitude of the tail risk values change, but the overall trends do not. Using VSTOXX also makes the estimates more sensitive to short-term variations. Having a reliable estimate of the individual institutions' asset variance will make a difference in differentiating better between their risk characteristics or in defining the magnitude of the possible losses. In absence of such data, however, using a single number matched to the implied

[18]The VI index is constructed by inverting an earlier measure of conditional default proposed by Segoviano and Goodhart (2009). To evaluate the impact of each institution upon the system, they measure the probability that at least one more institution becomes distressed (PAO) conditional on the distress of one particular institution: $PAO_i = \mathbb{P}(N_d > 1 | \mathbb{1}_{d_i} = 1)$. We do not explore systemic impact measures here, as an initial analysis shows that there is very little difference in rankings between the impact measures (PAO and SII) and the sensitivity measure (SII) for our sample.

[19]To see how the $CoVaR$ can be broken down into components that satisfy the additivity property see Puzanova and Düllmann (2013). For general discussion on the additivity of risk measures see the Euler property in e.g. Chapter 12 of Hull (2018).

Table 4: Systemic Rankings Comparison

| | $ECoVaR$ (%) | | $VI$ (%) | | $w \cdot ECoVaR$ | | $w \cdot VI$ | |
|---|---|---|---|---|---|---|---|---|
| ABN | 64.94 | (4) | 33.81 | (4) | 9.52 | (4) | 4.96 | (4) |
| INGB | 63.65 | (5) | 32.12 | (5) | 22.00 | (1) | 11.10 | (2) |
| RABO | 67.73 | (2) | 57.33 | (2) | 15.74 | (2) | 13.33 | (1) |
| NIBC | 65.39 | (3) | 28.06 | (6) | 0.48 | (7) | 0.21 | (7) |
| VB | 62.41 | (6) | 53.26 | (3) | 1.56 | (6) | 1.33 | (6) |
| AEGO | 73.95 | (1) | 67.00 | (1) | 11.49 | (3) | 10.41 | (3) |
| NN | 56.72 | (7) | 15.41 | (7) | 4.96 | (5) | 1.35 | (5) |

(a) Rankings

| | $MES$ | $ECoVaR$ | $VI$ |
|---|---|---|---|
| MES | | | |
| ECoVaR | 0.64 | | |
| VI | 0.96 | 0.68 | |

(b) Rank Correlations

| | $w$ | $PC$ to $ES$ | $w \cdot ECoVaR$ | $w \cdot VI$ |
|---|---|---|---|---|
| $w$ | | | | |
| $PC$ to $ES$ | 0.93 | | | |
| $w \cdot ECoVaR$ | 1.00 | 0.93 | | |
| $w \cdot VI$ | 0.96 | 0.96 | 0.96 | |

(c) Rank Correlations, Weighted Measures

*Note.* This set of tables shows the systemic risk rankings according to alternative measures and the rank correlations between them.

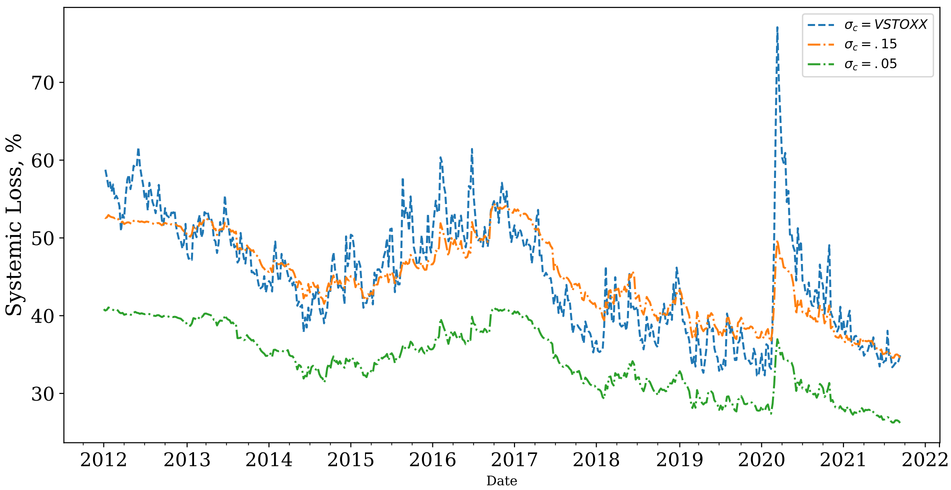
Table 5: Percentage Change in $MES$ when Varying $\sigma_c$

| | $\sigma_c = .15$ | $\sigma_c = .05$ |
|---|---|---|
| ABN | 8.22 | 24.31 |
| INGB | 8.22 | 22.54 |
| RABO | 9.50 | 30.04 |
| NIBC | 7.41 | 21.29 |
| VB | 11.36 | 35.07 |
| AEGO | 6.76 | 20.89 |
| NN | 6.25 | 17.27 |
| Sys | 8.28 | 24.90 |

*Note.* This table shows the percentage difference in $MES$ estimates, relative to the base case from Table (3), when arbitrary fixed values are used to calibrate the $\sigma_c$ parameter.

volatility of European stocks seems an appropriate second-best alternative that does not enforce ranking changes in systemic risk across the observed universe.

Figure 10: Expected Shortfall of the Systemic Portfolio




*Note.* This figure shows ES for the system calculated based on two assumption: $\sigma_c$ is scaled by the implied volatility of the VSTOXX index, and $\sigma_c$ is fixed to 20%. Evaluated at .95 confidence level.

# 7 Policy Relevance

Our results are relevant for the policy framework for systemic risk. For Global Systemically Important Banks (G-SIBs), the Basel Committee on Banking Supervision and the European Banking Authority (EBA) specify in detail the methodology according to which capital surcharges are allocated to institutions that are designated as systemically important. The goal of the surcharges is to improve the resilience of the system by internalizing the systemic risk generated in the financial sector. In addition, the European Union designates banks that it regards to be systemically significant as Other Systemically Important Institutions (O-SIIs), and requires that national authorities, under EBA guidance, decide on identification procedure and on the size of the surcharges for these institutions.

There is currently a large disconnect between the academic approaches used to measure systemic risk and the regulatory approach used to set systemic capital buffers. Section (2) has extensively explored the academic perspective. For European regulators, the general guidance by the EBA is to focus on four criteria of systemic relevance: size, importance, complexity, and interconnectedness (EBA, 2020). Usually, a score is provided in each category and the four categories are equally weighted up to a single O-SII score. The ranked institutions are bucketed based on score ranking, and for each bucket, systemic buffer surcharges are discretionary set through a step-up ladder structure.

As we focus on institutions residing in the Netherlands, we can directly compare the systemic ranking coming out of our model to the ranking based on the O-SII surcharge rate set by the Dutch regulator. In the Netherlands, as of 2021 the following O-SII buffers apply[20]: ING Bank (2.5%), Rabo (2%), ABN (1.5%), Volksbank (1%). As Table (3) indicates, this ranking differs from our ranking by PC to ES, where Rabo comes before ING. Ranking by size, however, we match the O-SII results. It is difficult to generalize based on our small sample, but this could be an indication that the O-SII score is not putting enough weight on the interdependency between the institutions, and is focused more either on size or on standalone risk, where ING ranked on top.

Naturally, the sample that we have is too small to allow us to generalize any conclusions. Yet, we relate to other studies that find a difference between the policy and the academic approaches on measuring systemic risk. For example, Brogi et al. (2021) compare the G-SIB buffer rankings to systemic risk rankings calculated based on a credit portfolio approach similar to ours. They use the DIP measure provided by Huang et al. (2009, 2012) which calculates the average loss (rather than the $ES$) for the regulatory portfolio, where loss is again generated in default. They find significant differences in the two approaches and argue that the regulatory framework would benefit by incorporating also a risk contribution metric into generating systemic rankings.

Bianchi and Sorrentino (2021), on the other hand, explore a small sample consisting of the four Italian banks designated as systemically important and largely find consistency in the ranking based on the CoVaR measure and based on the O-SII buffer rates set by the Italian central bank. Yet, having higher frequency data allows them to link systemic risk estimates to the evolution of bank characteristics and conditions.

Overall, we can conclude that there is no downside to embedding market-based implied measures of systemic risk, as ours, into the policy process. First of all, such measures could provide a way to verify the ranking that policymakers come up with based on EBA's guidelines and using regulatory data. Any discrepancy in the rankings based on the two approaches could raise important questions, the answers of which could improve the regulator's approach to assessing systemic risk. Or even if no discrepancy between the two appears, a market-based measure as the $MES$ can be used to assess risks between annual policy assessments.

# 8 Conclusion

In this paper we examined the systemic linkages and the potential systemic risks arising in the Dutch financial sector. In particular, we look at seven key insurance and banking

[20]See https://www.esrb.europa.eu/national_policy/systemically/html/index.en.html

institutions. To do so we addressed a common challenge in estimating and monitoring the build-up of systemic risks: a regulator cannot resort to equity prices for institutions that are privately or state-held. In these cases, we show how high-frequency data from the CDS market can still be used to imply views on co-dependencies and joint losses. We use the Dutch financial sector as a case study for our approach.

We argue that in contrast to micro-prudential policies, an appropriate macro-prudential view should try to monitor and manage not only the risky positions of an institution on its own, but also the interdependencies between institutions and the potential for several of them to realize large losses at the same time. From that perspective, in the sample that we consider, we confirm that a risk ranking incorporating tail dependence across the institutions is different from a ranking based on standalone tail risk. From a risk management point of view, it is clear that a focus on the former is more important if the goal is to curb risk in the total portfolio. Yet, we find in our sample that the latter is closer to the current ranking based on the O-SII capital surcharges for systemic risk.

In the process, we presented a model, which builds upon the existing academic literature that addresses systemic risk from a structured credit angle (Huang et al., 2012; Puzanova and Düllmann, 2013). The financial institutions in the system are seen as part of a defaultable loan portfolio. Systemic losses occur in the case of default of one or several institutions. The average tail losses of the portfolio (the $ES$ measure) speak for the magnitude of the systemic risk. The average losses of each institution, given that the system is in its tail, speak for the sensitivity of each institution to systemic risk. The share of the portfolio tail risk that can be attributed to each institution speaks for the contribution of the institution to systemic losses. We extend the existing approaches by also incorporating dependency in the size of the losses, and not purely in the default probabilities.

Our research speaks directly to the policy debate around the risk rankings used to set additional buffer charges for systemic risk for banks. We find certain differences in the top three institutions ranked as most systemic by our portfolio-based approach and the regulatory approach. The sample that we consider is too small to draw general conclusions but may indicate a disconnect between how regulators measure systemic importance, and what market co-movements in the price of default protection imply. A natural extension of the current study would be to expand the universe of institutions that are considered and to observe if those rankings systematically differ across European countries. The O-SII buffer rates in Europe are mandated separately by each national regulator, each following its own implementation of the EBA guidelines.

It needs to be acknowledged that there is currently little theoretical backing on determining the size of the capital buffers that institutions need once they are designated as systemic. The policy approach has been to recommend a two-step heuristic, where in the first step institutions are ranked based on a set of criteria associated with systemic importance, and in the second they are bucketed together and surcharges are set in a step-up manner to each bucket. This holds both of O-SIIs and for G-SIIs. Previous studies have found that the approach is very sensitive both to the ranking and bucketing mythologies used (Brogi et al., 2021). In the methodology that we propose, it is natural to link the size of the capital surcharges directly to the possible systemic contributions, measured by the weighted $MES$. Further research is needed to determine what mapping between the two would be socially optimal.

A larger sample would also allow the exploration of additional features in the systemic risk model. In fact, the currently proposed portfolio approach could be considered a basic architecture, which is extendable to incorporate specific observed stylized features of asset prices or of the structure of the examined financial network. Since tail correlations between the institutions are a key driver of systemic contributions, it is worthwhile exploring non-linear structures of these dependencies. The ability to model large multi-dimensional dependencies is key. Oh and Patton (2018) for example suggests the use of a factor Copula approach. Wang (2021) suggest a deep learning approach. Alternatively, network models could be used to mimic the often observed core-periphery structure of the financial sector (Bräuning and Koopman, 2016; Andrieş et al., 2022). Institutions that constitute the core of the network could be dominant drivers of systemic risk (Glasserman and Young, 2016; Jackson and Pernoud, 2021).

To sum up, estimating systemic risk contributions properly is essential for the efficient regulation of the financial system. The additional capital surcharges are a cost that needs to go to the institutions generating the systemic externality, so identifying these institutions is crucial. More research into the methods used to quantify and attribute systemic risk is thus important.

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# Appendices

## A The Merton model of firm value

We present the baseline model of Merton (1974). The value of assets is an exogenous process following a Geometric Brownian Motion

$$dV_t = \mu_v V_t dt + \sigma_v V_t dW_t \tag{21}$$

The company's debt is a zero-coupon bond with maturity $T$ and face value of $D$ and default can occur only at the moment when it matures. If the value of its assets are below the face value of its debt, the owners of the company will prefer to succumb to default. If the value is above the value of debt, the owners retain any residual value.

$$E_T = \max[0, V_T - D]$$

In that case, the value of equity at maturity can be seen as a long European call option on the firm's assets, and before maturity can be evaluated through the Black-Scholes (BS) equation as:

$$E(t, V_t, \sigma_v) = V_t N(d_1) - D^* N(d_2) \tag{22}$$

where $D^* = De^{-r\Delta t}$ is the value of debt, discounted at the risk-free rate $r$, $\Delta t = T - t$ is the time until debt maturity, $N(.)$ stands for the standard normal distribution, and $d_1$ and $d_2$ are given as follows: [21]

$$d_1 = -\frac{\ln\left(\frac{D^*}{V_t}\right)}{\sigma_v\sqrt{\Delta t}} + \frac{1}{2}\sigma_v\sqrt{\Delta t} \tag{23}$$

$$d_2 = d_1 - \sigma_v\sqrt{\Delta t} \tag{24}$$

In the Merton framework under the risk-neutral measure $d_2$ corresponds to Distance to Default (DD), a measure often used to assess the credit risk of a firm. Loosely speaking it measures the number of standard deviations of the asset value of the firm to the default barrier point (?). The risk neutral survival probability in the Merton model can be shown to be $P(V_t > D) = N(d_2)$, and $N(-d_2)$ is the default probability, where $d_2$ is then the risk-neutral Distance-to-Default measure DD.

Both the asset value and the asset volatility are unknown. As $E = E(t, V_t, \sigma_t)$ is a function of the stochastic underlying asset value, applying Ito's rule we can write the default probability as:

$$dE = \left(\frac{\partial E}{\partial t} + \mu_v V \frac{\partial E}{\partial V_t} + \frac{1}{2}\sigma_v^2 V^2 \frac{\partial^2 E^2}{\partial V_t^2}\right) dt + \sigma_v V_t \frac{\partial E}{\partial V_t} dW_t$$

The standard approach in calibrating the model, relying on Ronn and Verma (1986), notes that stock prices $E_t$ are themselves observable on the market and follows a Geometric Brownian motion of the type

$$dE_t = \mu_E E_t dt + \sigma_E E_t dW_t$$

Matching coefficients in the diffusion term with (22) we get,

$$\sigma_E E_t = \sigma_v V_t \frac{\partial E}{\partial V_t} \tag{25}$$

We can then solve the system of two equations and two variables defined by (22) and (25). In Merton's setting, we get that $\frac{\partial E}{\partial V_t} = N(d_1)$, where the derivative is also known as the option delta in option pricing theory.

At any time, the value of assets can be decomposed by sources of financing into debt and equity, so we can write the current market value of its debt as

$$B_t = V_t - E_t \tag{26}$$

which, using (22), can also be written as

$$B(t, V_t, \sigma_v) = V_t N(-d_1) + D^* N(d_2) \tag{27}$$

Equivalently, at maturity bondholders either get back the face value of debt or if the company defaults, they get the residual asset value, such that:

$$B_T = \min[D, V_T] = D - \min[0, D - V_T]$$

As a result, the value of liabilities corresponds to a portfolio of a short put with strike $D$ and a long risk-free bond with the same face value. Valuing liabilities before maturity can again be done through the BS formulas by evaluating: $B_t = De^{-r(T-t)} - P(V_t)$ where $P(.)$ is the corresponding value of a European put option with a strike $D$ written on the asset's underlying.

Using the put-call parity, with $E(.)$ and $P(.)$ the values for a call and a put written on the company assets as an underlying, we have $E(V_t) - P(V_t) = V_t - D\exp\{-r(T-t)\}$ which implies

$$B_t = V_t - E(V_t)$$

At the same time, denoting $y_t$ as the yield on the corporate bond, we have

$$B_t = D^* e^{-(y_t - r)\Delta t}$$

which implies a corporate bond spread:

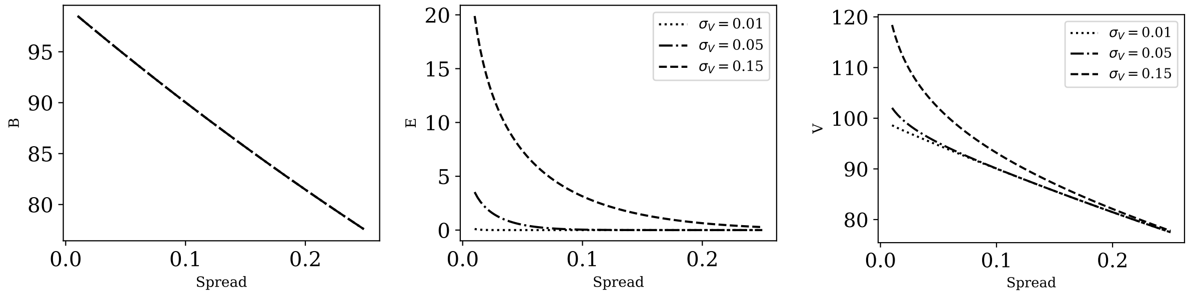
$$s(t, V_t, \sigma_v) = y_t - r = -\frac{1}{\Delta t} \ln \frac{B_t}{D^*} \tag{28}$$

where $B_t$ is given by (27). Note then that:

$$\frac{\partial s_t}{\partial V_t} = -\frac{1}{\Delta t} \frac{N(-d_1)}{B_t} \tag{29}$$

where we make use of the fact that $\frac{\partial B_t}{\partial V_t} = \frac{\partial (V_t - E_t)}{\partial V_t} = 1 - N(d_1) = N(-d_1)$.

Figure 11: Merton Model




(a) (b) (c)

This figure shows the results of using the spread level to imply through the Merton model (a) the firm's liabilities (b) the firm's Equity value and (c) the asset value of the company. The company's debt is fixed at 100.

# B Latent Factor Model Estimation

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 $\Sigma$ 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 $\boldsymbol{F}^i$.

# C Charts and Graphs

Figure 12: CDS Prices (bps)

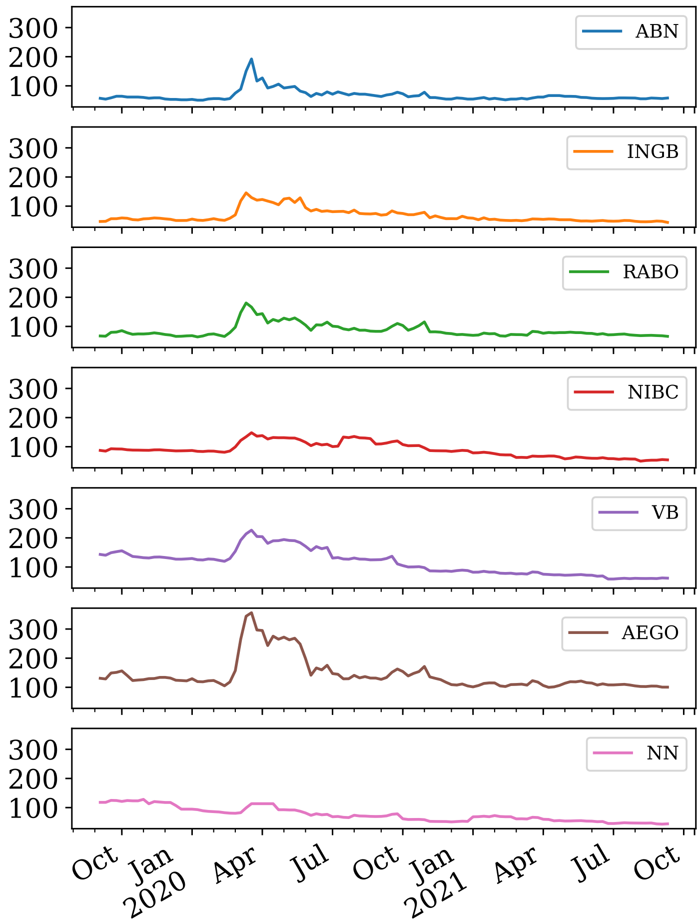


Figure 13: CDS Prices Log Changes

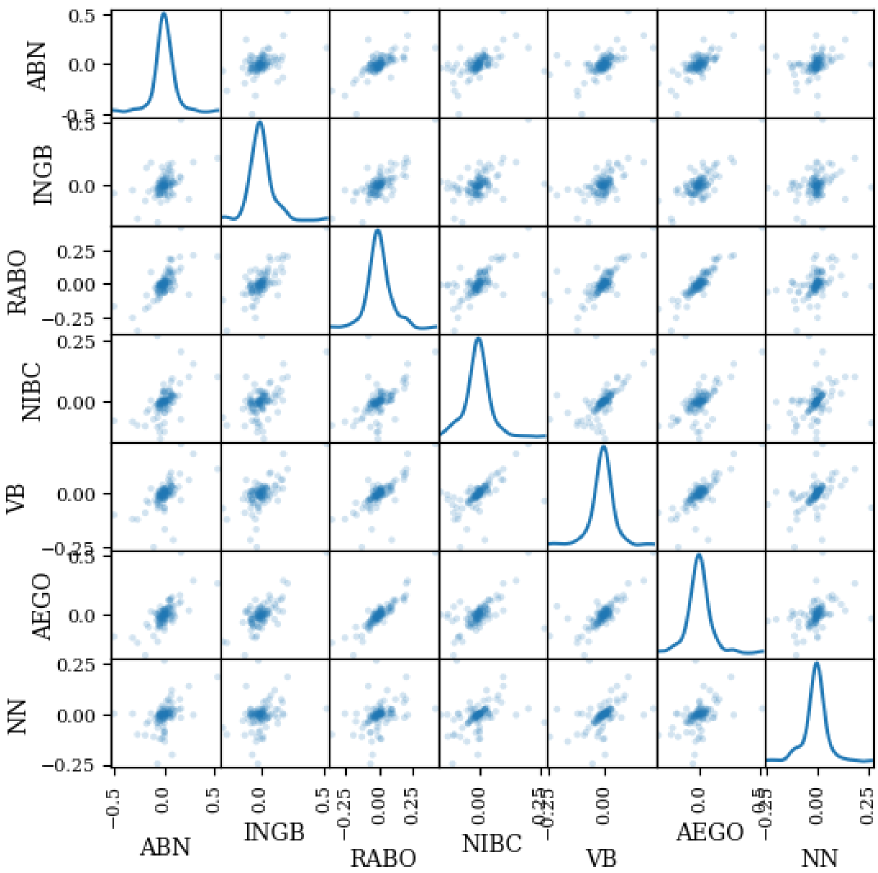



Figure 14: VSTOXX

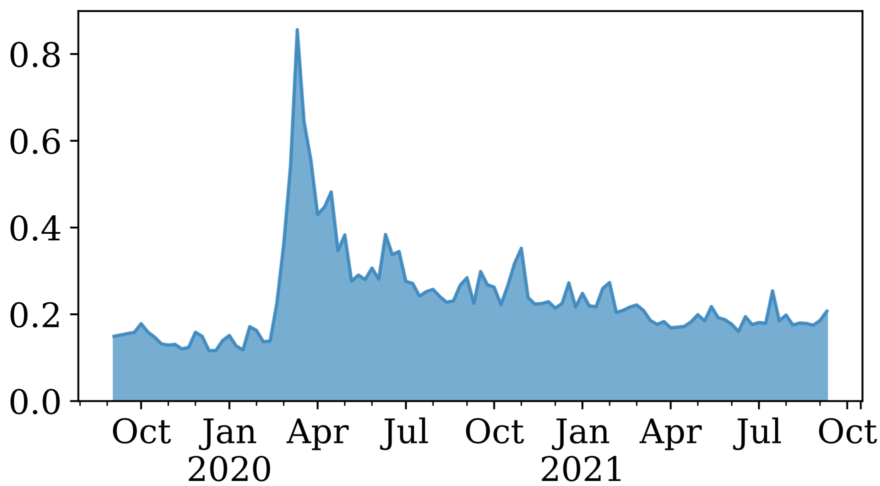


Figure 15: Liability Weights

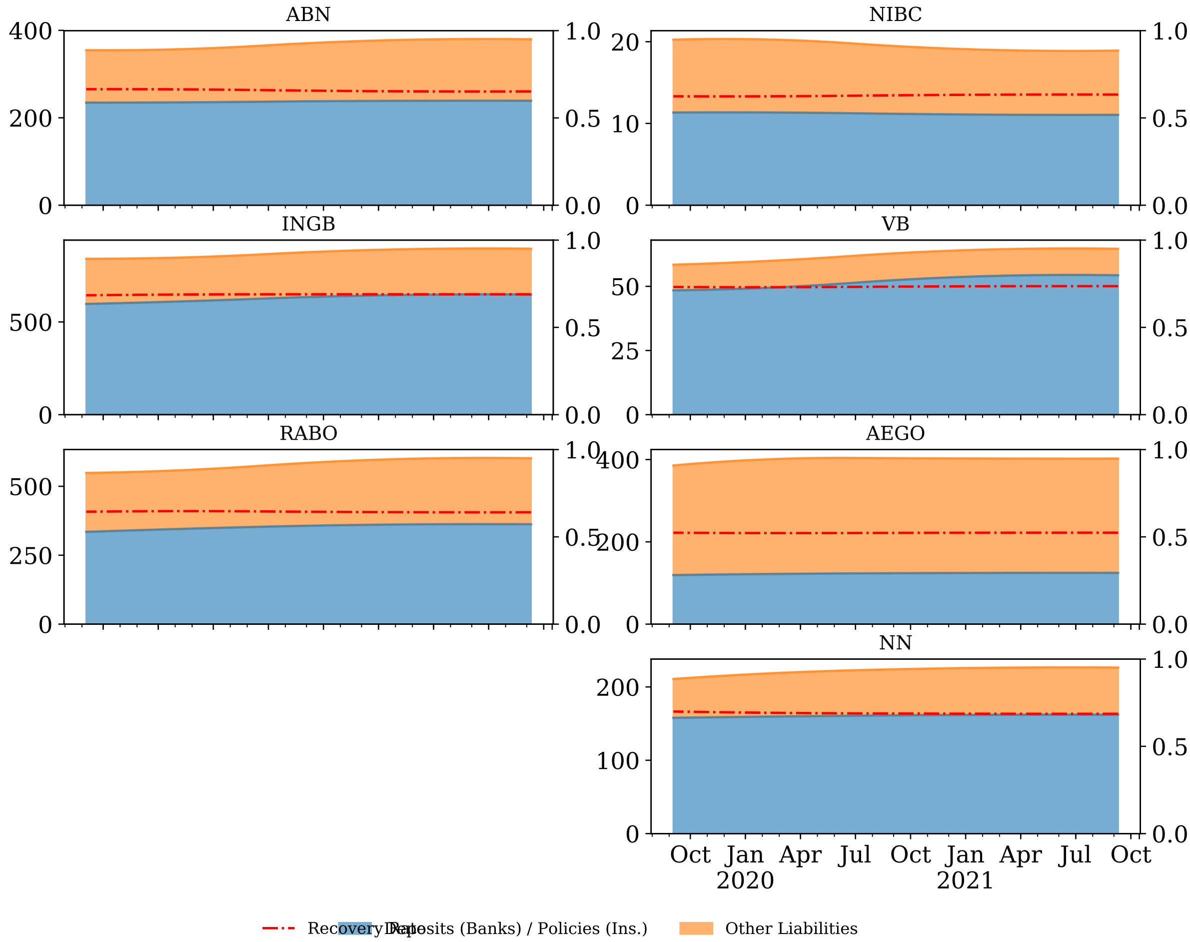


Figure 16: Simulations, Scatter Matrix

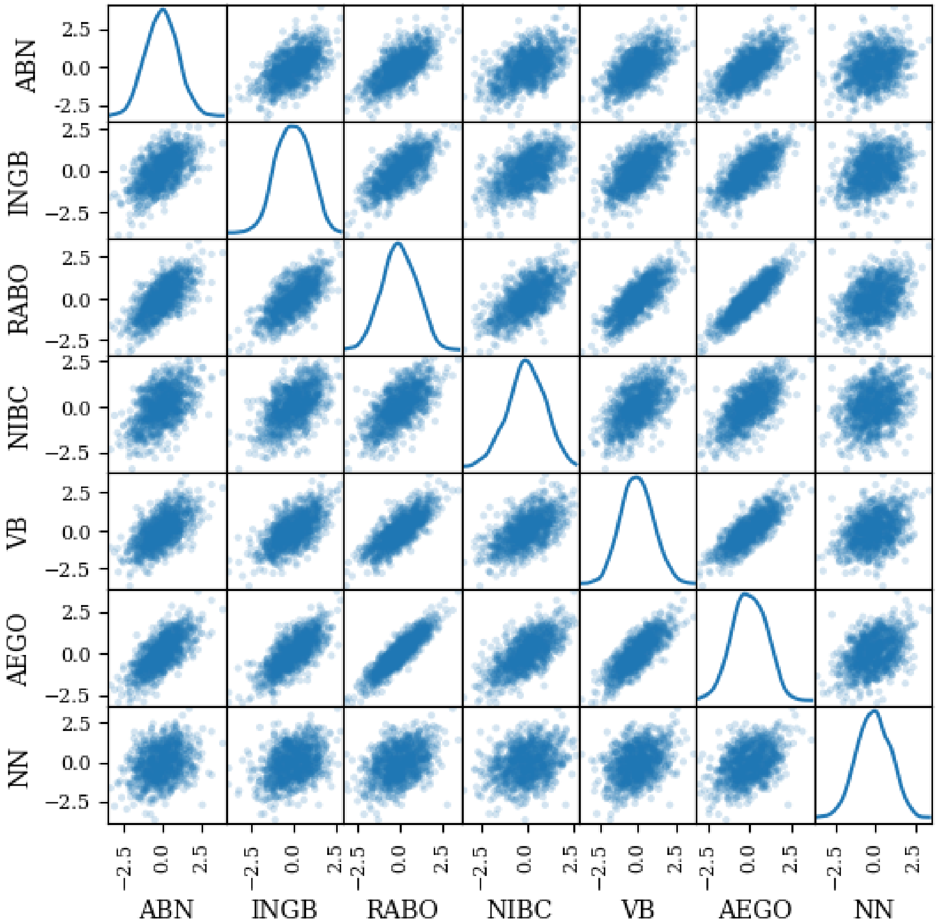
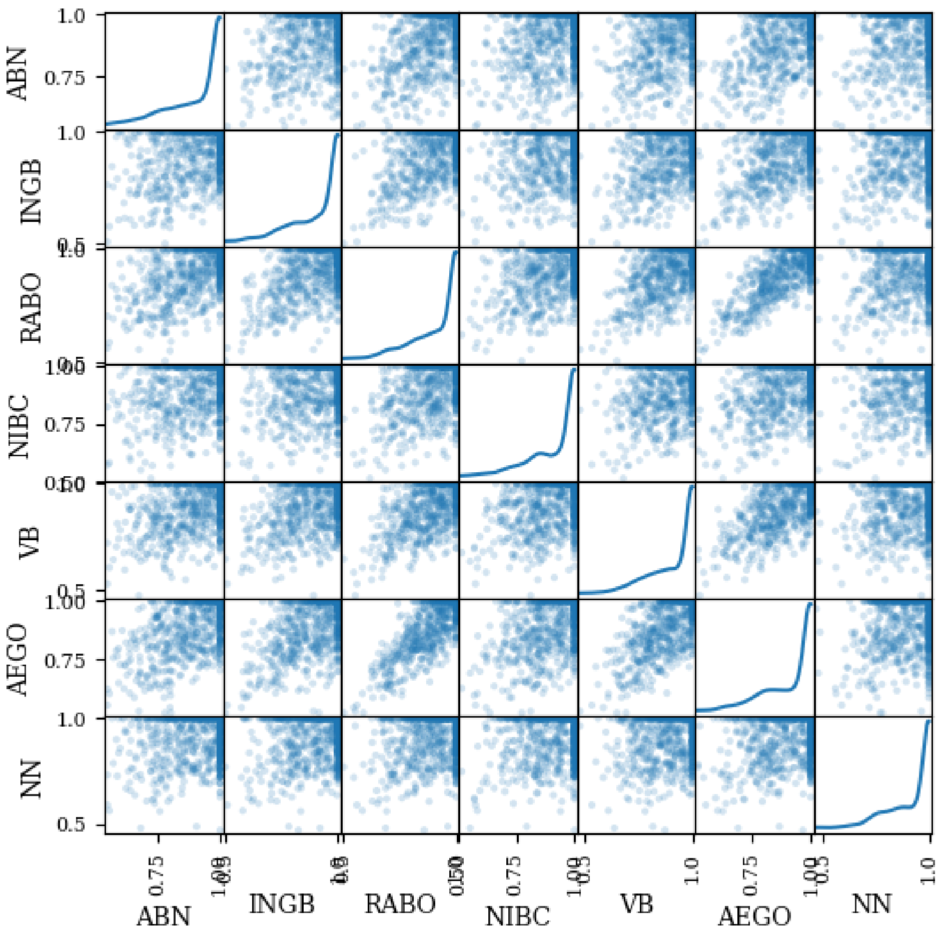



Figure 17: Asset Simulation

Figure 18: Recovery Rate Simulations



# D Glossary

**CoVaR** Codependet VaR. Tail loss of the system given a tail loss in one particular institution

**CDS** Credit Default Swap

**DD** Distance to Default in Merton's firm model

**EBA** European Banking Authority

**ECoVaR** Exposure CoVaR. Tail loss of a particular institution given a tail loss in the system

**ES** Expected Shortfall. The average loss if the variable is in its tail

**G-SIB** Global Systemically Important Banks

**MES** Marginal Expected Shortfall. The average loss of an institution if the system is in its tail

**O-SII** Other Systemically Important Institutions

**PC to ES** Percentage Contribution to Expected Shortfall

**PAO** Probability of Additional Default if one particular institution defaults

**RR** Recovery Rate in case of default

**SII** Systemic Impact Index. Expected number of defaults, if one particular institution defaults

**SIFI** Systemically Important Financial Insinuation

**VaR** Value at Risk. The $q$-th quantile of worst losses; defines the tail of the loss distribution

**VI** Vulnerability Index. The probability that a particular institution will default, given that there are more than one defaults