Big Data and Graph Theoretic Models: Simulating the Impact of Collateralization on a Financial System

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Abstract. In this paper, we simulate and analyze the impact of financial regulations concerning the collateralization of derivative trades on systemic risk. We represent a financial system using a weighted directed graph model. We enhance a novel open source risk engine to automatically classify a financial regulation for its impact on systemic risk. The analysis finds that introducing collateralization does reduce the costs of resolving a financial system in crisis. It does not, however, change the distribution of risk in the system. The analysis also highlights the importance of scenario based testing using hands on metrics to quantify the notion of system risk.

Index Terms– big data, graph theoretic models, stochastic Linear Gauss-Markov model, Monte Carlo simulation, financial risk analytics, systemic risk, collateralizations, variation margin, initial margin, open source risk engine

I. Introduction

Counterparty Credit Risk (CCR) is the risk of suffering a loss when a contracting party defaults before satisfying its obligations. While banks and financial institutions have been well aware of the CCR in classical business lines like loans for centuries, the credit risk component in derivative trades has gained recent attention. Since the 2008 crisis, markets can no longer assume that the credit risk in a derivative with a bank – even if it is AAA rated – is zero. As the volume of the Over-the-Counter (OTC) derivatives business alone exceeds \$20,701 billions of U.S. dollars,[1] it has been suggested that the inherent credit risk now poses a significant threat to the system. Indeed, a number of financial regulations have been enacted aimed at reducing the potential adverse effects of credit risk on the financial system. A key feature of these regulations is that they provide strong incentives (and increasingly the obligation) to collateralize–post and receive capital in reserve–derivative trades.

It is obvious that a counterparty that receives collateral for its derivative trades has a lower CCR exposure than a counterparty that does not. However, it is less obvious to show that the introduction of collateralization reduces the systemic risk in a financial system as a whole. It is the aim of this article to define under what conditions this conjecture is in fact true. In doing so, we develop a framework to predict how financial regulations impact systemic risk. Building off graph theoretical methods, where the nodes are individual banks, we define the system as a weighted graph.[2] Two steps are required to predict the impact of financial regulations on systemic risk. First, we define different regulatory regimes. Here we will focus on the rules governing the collateralization of derivative trades. Second, we evaluate the impact these regulation have on systemic risk by simulating a financial system over time, thereby allowing us to compare the regimes by the total costs to resolve a system once it has failed and the distribution of these costs.[3]

The next section provides a brief review of the state of the art of alternative systemic risk metrics. We next describe our approach for modeling a financial system that builds on a graph theoretical framework. We then present a measure of systemic risk, relying on the existing risk metrics that banks already report as regulated entities. The next section demonstrates how we technically implement the model to create a financial system using a weighted directed graph model. We follow with a simulation of systemic changes under various regulatory regimes. The analysis validates that collateralization does indeed reduce systemic risk; it does not, however, change the distribution of risk in a system. The analysis also illustrates that validation depends on the metric chosen to quantify systemic risk. The last section provides conclusions and discusses next steps in developing additional measures and further research.

[1]The corresponding outstanding notional amounts of all contracts in 2016 was \$544,052 billions of U.S. dollars. See Bank of International Settlements, Global OTC Derivatives Market Semi-Annual Statistics, March 6, 2017. http://stats.bis.org/statx/srs/table/d5.1.

[2]Graph theoretic methods produce networks that are generally large, sparse, and complex, and share common global topological properties and structure, much like a financial system.

[3]One of the key challenges is to quantify and define the notion of systemic risk. Although many economic metrics have been suggested, see [7] for an overview, we introduce a notion that is based on enterprise-level metrics commonly used. The risk metrics are derived from an underlying Linear Gauss-Markov model and numerically solved using Monte Carlo simulations. The analysis is detailed in [11].

ASONAM '17, July 31 - August 03, 2017, Sydney, Australia

ACM ISBN 978-1-4503-4993-2/17/07?/\$15.00
https://doi.org/10.1145/3110025.3120989

II. State of the Art

There are numerous metrics of systemic risk in the literature, see [7] for an overview. Most of these metrics focus on the analysis of market data like housing prices or government bonds and their correlations. For instance, a popular metric of systemic market risk is CoVaR, which relies on a quantile of correlated asset losses, see [1]. Similarly, [6] use Principal Components Analysis (PCA) and Granger Causality to study the correlations between the returns of banks, asset managers and insurances.

Cont et al. adopt a graph model to describe the interconnectedness of Brazilian banking system based on Central Bank data from 2007/08. They estimate the impact that an increase in capital requirements has on interbank exposures, see [8].

In general, these analyses rely on macro-level data of aggregate interbank exposures. Therefore, they cannot predict the impact of financial regulations on systemic risk in detail because their impact depends on a banks' individual trades. As the trade data is not publicly available, we use simulated data instead.

III. Method and Approach

We construct a predictive graph model of the financial system and simulate the impact of regulatory interventions on systemic risk. The analysis studies a proto-typical example of a financial system not because it is realistic, but because it is simple enough to capture the mechanics of a change in financial regulations. As all the simulated data is available to us, this change can be studied at all levels in a fully transparent manner: individual trades, portfolios, interbank exposures and the system as a whole. We illustrate this technique to examine the impact of collateralization on systemic counterparty credit risk in the derivatives business.

To obtain the exposures in the simulated system, we use a novel open source risk engine, which was originally built to compute the risk in the portfolio of a single bank. Using Python, we enhance this technology not only to compute the systemic risk in a financial system, but also to automatically classify if a regulation makes a financial system safer or not.

This is the first of the usual two steps to tackle a problem with big data techniques. If we consider a financial system as a single data point, we can automatically process that point. The second step applies this classification problem to a large randomized sample of financial systems and explores to what extent this simulation scales to a large number of data points. As this is already a non-trivial problem, we focus on the first step in the present paper.

IV. Collateralization of Netting Sets

The credit risk component in derivatives trades stems from highly valuable contracts that are not yet settled. For example, assume that a bank A buys an FX Forward EUR/USD from a bank B at fair value zero at $t = 0$ that matures in 1Y for a notional of N = USD 1mn and some strike rate FX_K. This contract obliges A to pay the difference between the EUR value of the USD 1mn converted using the strike rate FX_K and the actual rate FX_{1Y} prevailing in 1Y from now, i.e. to a payment of $N(FX_K - FX_{1Y})$ at $t = 1Y$. (Notice that this payment can have both signs, i.e. this triggers a cashflow that can go in either direction.) Assume that after 6 months the EUR/USD FX rate has changed such that this FX Forward is deep in the money, i.e. it is worth a lot for bank A. The value from this trade stems entirely from the fact that A expects to receive a big payoff at maturity from bank B. However, the value of this contract is reduced to zero in case B defaults before the trade matures. Therefore, the two counterparties are fully exposed to each others' credit risk during the lifetime of the trade. This problem is not specific to the example of the FX Forward discussed above, but a general problem that affects all derivative trades. A solution to this problem is collateralization. We will discuss the various types of collateralization, which will define our regulatory regimes.

A. VM Collateralization

To mitigate this risk, the two counterparties A and B can agree at inception to collateralize this trade. That means that the two counterparties proceed as follows: On the day after A has bought the FX Forward from B, the value of the FX Forward will have changed by some amount Δ because the markets will have moved. This amount Δ is then paid out as collateral (depending on the sign either from A to B or vice versa). Such a payment is called *variation margin (VM)* and the process of asking a counterparty to make that payment is called a *margin call*. The same procedure is repeated every day until the maturity of the trade.

While such a VM collateralization greatly reduces the exposure, such a collateral agreement does not come without caveats. One obvious drawback is the administrative overhead of managing the VM on both sides, see Fig. 1 vs Fig. 2 for a schematic visualization of the cashflows.

In practice there are multiple mechanisms in place to reduce this administrative overhead. We briefly discuss three very common practices: *Netting Sets (NS)*, *Thresholds (TH)* and *Minimum Transfer Amounts (MTA)*.

Netting Sets: Typically, the two banks A and B have more

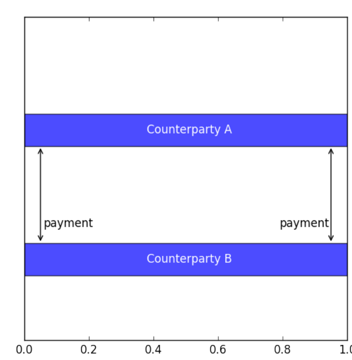

Fig. 1. Cashflows for uncollateralized netting sets

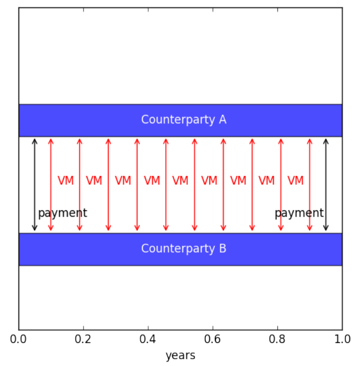

Fig. 2. Cashflows for VM collateralized netting sets

than just one trade together. As soon as they have at least two, one can in principle choose to exchange collateral for each trade separately, i.e. if trade $i = 1$ moves into A's favor and trade $i = 2$ moves into B's favor, then A posts the corresponding variation margin to B in one payment and B posts its variation margin to A in another payment. If the two banks have k trades, this would cause k payments every day (it is not uncommon that k is in the order of hundreds or thousands). Alternatively, A and B can agree that the trades form a *netting set*. In that case, the counterparties compute the Δ of the sum of the value of all the trades in the netting set and then exchange only one payment each day covering all the trades. This practice is very common.

Thresholds: Just because two banks have a large number of trades, this does not necessarily mean that the exposure stemming from these trades is high. To simplify the collateral management process, the counterparties can agree to call for variation margin only, if the exposure of their netting set breaches a certain *threshold* TH, for instance USD 1mn.

Minimum Transfer Amounts: Even if the exposure of a netting set is above a certain threshold, the daily difference Δ of its value might be quite small on many business days. Therefore, the counterparties can agree to issue a margin call only if Δ is itself bigger than a certain *minimum transfer amount* MTA, for instance USD 100k.

If TH and MTA are large, the administrative overhead of the VM collateral management is small as less margin calls are triggered. But on the other hand, this means that if the markets move the netting set can be undercollateralized (within limits determined by TH and MTA), hence the benefit in exposure reduction that stems from the VM collateralization is smaller then too. While some counterparties choose to optimize this trade-off between minimizing the administrative overhead and maximizing the benefits of VM collateralization by setting non-trivial TH and MTA, others choose to waive that option and simply set TH=MTA=0.

B. VM & IM Collateralization

In the standard case MTA=TH=0, a VM collateralized netting set has always zero exposure in theory under the following assumptions:

- Defaults can only happen instantaneously after VM margin calls are paid.
- The defaulting counterparty notifies the surviving counterparty about its default instantaneously after it has defaulted.
- The surviving counterparty is able to instantaneously enter into the exact same derivative contracts it had with the defaulting counterparty with a third counterparty under the exact same conditions using the VM it has collected. This process is called *close-out*, so the assumption is that the default date is identical to the close-out date.

The problem is that in practice none of these assumptions are satisfied. Defaults can happen any time and detecting whether or not a counterparty has defaulted and incorporating default times realistically into a CCR exposure engine is not so easy. Due to the events during the financial crisis it is known for a fact that the close-out date can be significantly later than the default date. This gap is called *Margin Period of Risk (MPOR)*. It is also known that the VM might not be enough to enter into new derivative contracts at the close-out date because during the turmoil following a default the markets can move quite adversely. To mitigate this gap risk over the MPOR, posting *Initial Margin (IM)* on top of the VM is recommended and increasingly mandatory.

Although the term "Initial Margin" suggests otherwise, IM is actually not only posted at inception of the trades, but also re-adjusted according to market conditions just like the VM. Theoretically, it corresponds to a 99% quantile of the change in value of the trades over the MPOR. In practice it is given by a method that depends on the business line of the derivative (bilateral, cleared or exchange traded). For bilateral business, there is a standardized method called *SIMM* to compute the IM published by ISDA, see [10]. IM must not be netted with VM and be posted into segregated accounts, which makes the administrative overhead even bigger, see Fig. 3 for an illustration. For cleared and exchange trades derivatives the precise margin methodologies are set by the various clearing houses respectively the exchanges.

We identify four regulatory regimes: Uncollateralized trading, VM collateralized with TH and MTAs, VM collateralized without TH or MTAs and IM & VM collateralized. The next step is to calculate the risk metrics in each regime.

V. Risk Metrics

A. Enterprise-level metrics of Counterparty Credit Risk

Banks can quantify their Counterparty Credit Risk as follows: For any derivative trade i, denote by $\mathrm{NPV}(i,t)$ the *net present value* of the trade i at time t. By definition the value of a *netting set* of trades $1,\dots,k$ is given as $\mathrm{NS}(t) := \sum_{i=1}^{k} \mathrm{NPV}(i,t)$. There are legal restrictions on whether or not two trades can be in the same netting set.

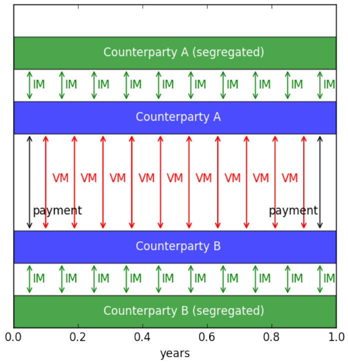

Fig. 3. Cashflows for IM and VM collateralized netting sets

Trades with different counterparties for example must not be netted. The quantity[4]

$$V(t) := \mathrm{NS}(t + MPOR) - \mathrm{VM}(t) - \mathrm{IM}(t) \qquad (1)$$

represents the loss suffered by the bank in case of a default of the counterparty at time t. Notice that $V(t)$ can have both signs and has to be modeled as a random variable. In case of an uncollateralized netting set, we set $VM(t) = 0$ respectively $IM(t) = 0$. As random variables are not very easy to report, one quantifies the exposure in simpler terms using the Basel III metrics.

Definition 1 (Basel III metrics): Let $V(t)$ be as in Eq. (1) above.

- The *Expected Exposure* $\mathrm{EE}(t) := \mathbb{E}[V(t)]$ represents the average loss from the collateralized netting set if a default occurs at t. It can be positive or negative.
- The *Expected Positive Exposure* $\mathrm{EPE}(t) := \mathbb{E}[\max(V(t), 0)]$ represents the loss averaged only over those scenarios where the markets move in the banks favor. It is always non-negative and is a metric of what the bank expects to loose if the counterparty defaults.
- The *Expected Negative Exposure* $\mathrm{ENE}(t) := \mathbb{E}[\min(V(t), 0)]$ represents the value of the netting set averaged only over scenarios where the markets move against the banks' favor. It is always non-positive and is a metric of what the bank expects to gain if the counterparty defaults.
- The *Potential Future Exposure* $\mathrm{PFE}_\tau(t) := \max(q_\tau(V(t)), 0)$, where $q_\tau(V(t))$ denotes the τ-quantile of the random variable $V(t)$, is a worst case loss suffered by the bank on counterparty default at confidence level τ (a typical value is $\tau = 95\%$).
- The *Effective Expected (positive) Exposure* $\mathrm{EEE}(t) := \max_{s\in[0,t]}(\mathrm{EPE}(s))$ at t is simply the maximum $\mathrm{EPE}(s)$ till time t.

[4]In Eq. (1) we ignore the problem of unpaid cashflows over the MPOR, see [2] for a detailed discussion of that issue.

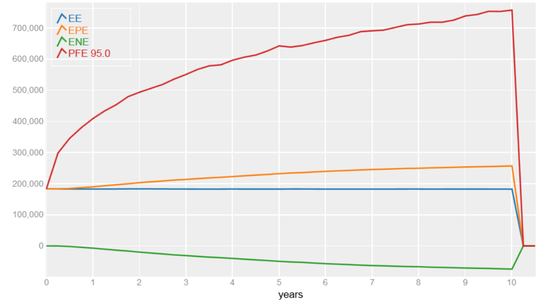

Fig. 4. Basel III exposure metrics for an FX Forward

- The *Effectivized Expected Positive Exposure* $\mathrm{EEPE}(t) := \frac{1}{t}\int_0^t \mathrm{EEE}(s)ds$ averages the EEE over time. In practice, the value $\mathrm{EEPE}(t = 1Y)$ is called *the* EEPE. It is a single number that quantifies the losses suffered by the bank in case of the default of the counterparty over the next year.

Some of the metrics from Definition 1 are visualized for an example in Fig. 4. Notice that none of these metrics incorporate a default probability of the counterparty. They are a quantification of losses given that a default occurs. A banks' EEPE is of particular importance as it aggregates the CCR received from a netting set into a single number. Summing the EEPE over all netting sets measures a banks' total CCR it receives from all its counterparties. Banks have to report their total EEPE to the regulator and it is an important quantity in the computation of a banks' *Risk Weighted Assets (RWA)*.[5] The relationship between a banks RWA, its *core capital* CC and its *capital adequacy ratio* CR is given by

$$\mathrm{CR} = \frac{\mathrm{CC}}{\mathrm{RWA}}. \qquad (2)$$

Regulators typically impose thresholds onto this quantity, for instance $\mathrm{CR} \geq 10\%$. That means that banks with higher CCR in terms of EEPE, hence higher RWA, need more core capital in order to hold this thresholds. A failure to hold this threshold can put a bank and a whole system into default.

B. Metrics of Systemic Risk

We have outlined how an individual bank quantifies the Counterparty Credit Risk it receives from all its counterparties. We now tend to the financial system as a whole and start with the following mathematical formalization.

Definition 2 (financial system): A *financial system* is a weighted digraph $G = (B, A, w)$,[6] where

- B is the set of nodes in the graph representing the banks.
- A is the set of arrows in the graph. We add an arrow from a bank $b_1 \in B$ to a bank $b_2 \in B$ if b_2 is exposed to CCR from b_1 as a consequence of their trades.

[5]The precise relationship between EEPE and RWA is complicated, but as a rule of thumb, the higher the EEPE, the higher the RWA.

[6]See [5] for an overview of graph theoretic modeling of large-scale networks.

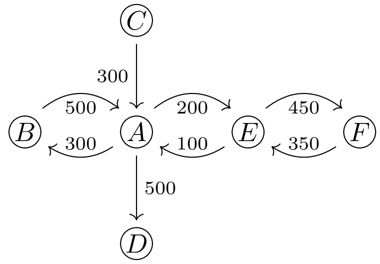

Fig. 5. An example of a financial system.

- $w : A \to \mathbb{R}$ is a weight function on the arrows quantifying the risk attached to each arrow in some metric.

An example of a financially meaningful weight function is $w(a) := \mathrm{EEPE}(a)$, i.e. if $a = (b_1, b_2)$, then $w(a)$ denotes the EEPE that b_2 receives from b_1. Another example could be the PFE over a certain time horizon at a fixed quantile τ (analogous to US stress testing).

An example of a financial system of six banks trading bilaterally with each other is shown in Fig. 5.

Here, the banks are labeled A - F. Notice that there are trades like Interest Rate Swaps that induce risk from one counterparty to another and vice versa. In this case we see two arrows between the counterparties that go in opposite directions (for example between A and B). There are also trades like FX Options where risk is induced only in one direction, for instance between A and D.

A financial system modeled as a graph contains the Counterparty Credit Risk each bank is exposed to from any other bank. To obtain a notion of the risk in the system as a whole, we aggregate this information as follows.

Definition 3: Let $G = (B, A, w)$ be a financial system as above. For each bank $b \in B$, we define

$$w^+(b) := \sum_{\substack{a \in A \\ a \text{ starts at } b}} w(a), \quad w^-(b) := \sum_{\substack{a \in A \\ a \text{ ends at } b}} w(a), \tag{3}$$

i.e. the total weight of outgoing respectively incoming arrows. Formally, this corresponds to a weighted analogue of an outdegree $\deg^+(b)$ respectively indegree $\deg^-(b)$.[7] Intuitively, $w^\pm(b)$ corresponds to the total weight (for instance EEPE) imposed by respectively received from b. Setting $w(G) := \sum_{a \in A} w(a)$ to be the total weight in the system, these quantities can also be expressed in relative terms by

$$\rho^+(b) := \frac{w^+(b)}{w(G)}, \qquad \rho^-(b) := \frac{w^-(b)}{w(G)},$$

i.e. $\rho^\pm(b)$ is the relative weight imposed/received by b.

Any of the quantities

$$w(G), \qquad \max_{b \in B} w^+(b), \qquad \max_{b \in B} \rho^+(b)$$

[7]Notice that $\deg^\pm(b) = w^\pm(b)$ for the weight function $w \equiv 1$.

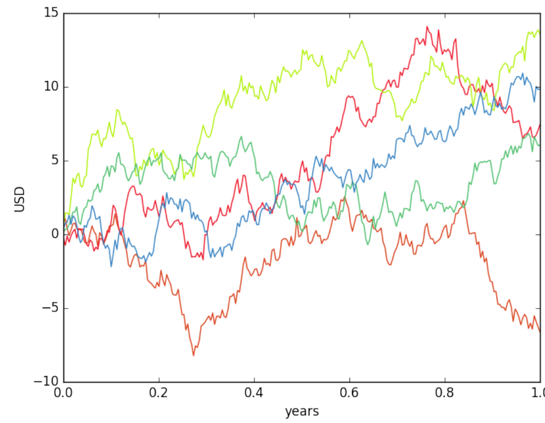

Fig. 6. A MonteCarlo simulation with $N = 5$ possible futures for the value of a trade.

could be considered a measure of systemic risk. In case $w = \mathrm{EEPE}$, the quantity $\mathrm{EEPE}^+(b)$ can be thought of as the cost of resolution if b defaults like a loss given failure (but not a probability of failure). The quantities $\rho^+(b)$ are a metric that quantifies the concentration of these costs of resolution in the system.[8]

VI. Simulation via ORE

We want to compute the systemic risk metrics for an example of a financial system like Fig. 5. While the system itself is only an example and the trades are made up, we want to compute the risk metrics as realistically as possible. To that end we use the *Open Source Risk Engine (ORE)*, an open-source software, which performs risk management computations like a production system in a bank. It has been released by Quaternion Risk Management in 2015 as part of the Open Source Risk initiative, see [12].

ORE models the risk in a derivative trade from the perspective of a single bank. Given the banks' portfolio, market data and some additional configuration files, it projects the value of the trades into the future using a *MonteCarlo simulation* based on complex stochastic modeling of the risk factors. In its current version 1.8.0.7 only IR/FX products are supported and for these a cross currency Linear Gauss-Markov model[9] is used, see Eq. (4).

[8]Our measure takes a ground up view of systemic risk, focusing on credit losses incurred and imposed by each bank on a system, and aggregating those losses across the entire system. What is clear from the analysis is that liquidity and leverage are the flip slide to losses and linkages and therefore a full understanding of systemic risk must also take into account these effects. We discuss this possibility in the concluding remarks.

[9]Notice that calibrating such a model is similar to training a supervised machine learning AI. The technicalities of this modeling are extensive and beyond the scope of this article, but can be found in detail in [11].

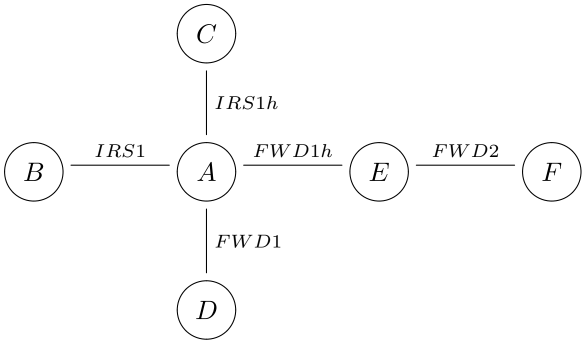

Fig. 7. Trade Relations in the Example

$$
\begin{aligned}
dz_0 &= \alpha_0 dW_0^z \\
dz_i &= \gamma_i dt + \alpha_i dW_i^z, i > 0 \\
\frac{dx_i}{x_i} &= \mu_i dt + \sigma_i dW_i^x, i > 0
\end{aligned}
\tag{4}
$$

The basic principle is as follows: In its core, a MonteCarlo simulation uses a pseudo-random number generator to compute N representative possible futures, called *paths* or *samples*, for the value of each trade, see Fig. 6 for an example with $N = 5$ (in practice typical values for N are $N = 5,000$). Here, "representative" means that the distribution of the samples approaches the mathematical distribution of the value of the trades according to the stochastic modeling as N gets larger and larger. Technically, a main output of the simulation is the NPV *cube* of the portfolio. That is for each trade i, each date t and each sample ω, it computes $\mathrm{NPV}(i, t, \omega)$, the *simulated net present value* of trade i at a point t on a pre-specified time grid in path ω. The value of a netting set of k trades can then be computed by $\mathrm{NS}(t, \omega) = \sum_{i=1}^{k} \mathrm{NPV}(i, t, \omega)$. The expectations in Definition 1 are then approximated by taking the average over the samples, for instance $\mathrm{EE}(t) = \frac{1}{N} \sum_{\omega=1}^{N} \mathrm{NS}(t, \omega)$ for an uncollateralized netting set.

In case of a collateralized netting set, ORE also consumes parameters that specify the details of a netting agreement and simulates the value of the VM and IM collateral onto each future point on a time grid. It should be pointed out that the simulation of the collateral is also a non-trivial matter. In particular forecasting the IM is still subject to current research. We use a second order multi-factor regression technique that is based on the model proposed in [4] and further evaluated in [9] as ORE 1.8.0.7 has an implementation of that model available. The MPOR is set to two weeks here. Using these simulations, ORE computes NPV, VM and IM for a fixed set of default times t. Using Eq. (1) it finally computes all the risk metrics from Definition 1.

VII. Results

We define an example of a financial system with a similar structure as in Fig. 5 and the only derivative trades are Interest Rate Swaps and FX Forwards. We consider the proto-typical business case that some of these counterparties sell a derivative to another counterparty and then hedge this trade, i.e. they buy a derivative from a third counterparty that offsets the former.

More precisely, we assume the system has six banks, again labeled A-F, and that they have done the following business:

- A has sold an Interest Rate Swap IRS1 to B and hedged it with a reversed Interest Rate Swap IRS1h with C. The swap has a notional of GBP 40mn maturing in 12Y and swaps the 6M GBP-LIBOR versus the fixed swap rate such that it is at the money at inception.
- A has also sold an FX Forward FWD1 to D and hedged it with a reversed FX Forward FWD1h with E. This FX Forward has a maturity in 10Y a notional of USD 10mn vs EUR at a strike rate such that it is at the money at inception.
- E has an FX Forward FWD2 with F and no hedge. This FX Forward has a 10Y maturity and a notional of USD 5mn vs EUR at a strike rate such that this is at the money at inception.

A graphical representation of the trades in the system is shown in Fig. 7.

On that financial system we test the following hypothesis:

(H) Collateralization reduces systemic risk.

In order to test this hypothesis, we use ORE to perform the following four simulations of the system that correspond to the following four regulatory regimes:

1) All derivative trades are uncollateralized, see Fig. 8;
2) All derivative trades are VM collateralized with a threshold of TH = EUR 1mn and a minimum transfer amount of MTA = EUR 100k set globally for all counterparties, see Fig. 9;
3) All derivative trades are VM collateralized with TH = MTA = 0, see Fig. 10; and
4) All derivative trades are VM collateralized with TH = MTA = 0 and also IM collateralized, see Fig. 11.

In Figs. 8 to 11 the arrows between any two banks b_1 and b_2 show the $\mathrm{EEPE}(b_1, b_2)$ that arises from the trades shown in Fig. 7 and the percentage values in the nodes show the ρ^+ of each bank.

Comparing the results of the regimes one to four we can draw the following conclusions:

1) In terms of total EEPE, see Fig. 12, we can clearly validate the hypothesis (H) in this metric. It is worth noticing that in the VM collateralized cases, there is still a significant EEPE present even if TH=MTA=0 resulting from the gap risk over the MPOR. However, in the presence of VM and IM collateral, the EEPE is close to zero.
2) We can also validate the hypothesis (H) not only in terms of total EEPE, but also in terms of EEPE^+ and

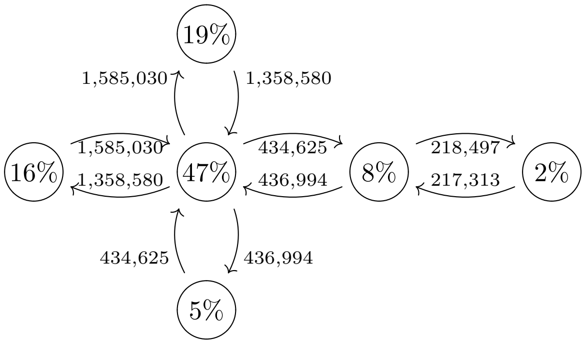

Fig. 8. Simulation 1: Uncollateralized, Total EEPE: 8,066,268

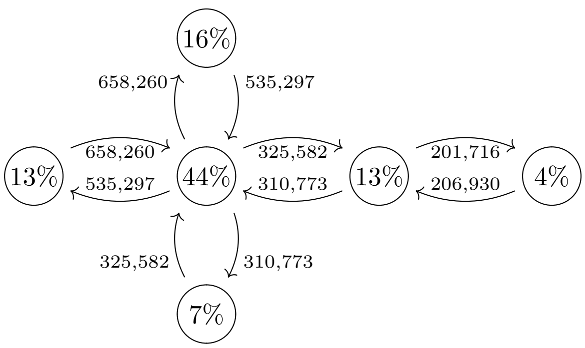

Fig. 9. Simulation 2: VM Collateralized with TH=1mn and MTA=100k, Total EEPE = 4,068,470

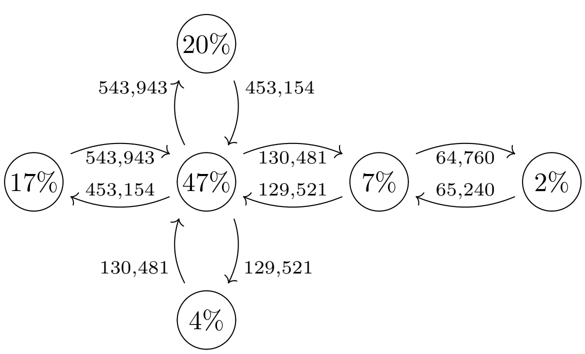

Fig. 10. Simulation 3: VM Collateralized with TH=MTA=0, Total EEPE = 2,644,199

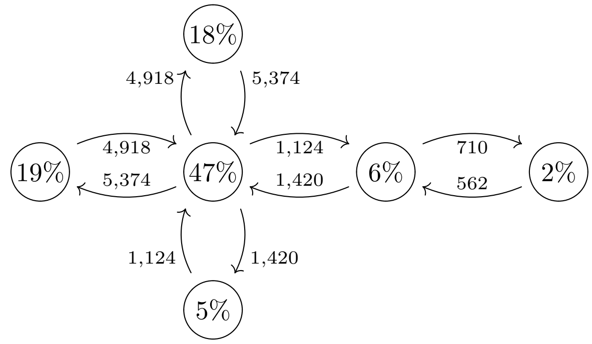

Fig. 11. Simulation 4: VM & IM collateralized , Total EEPE = 26,949

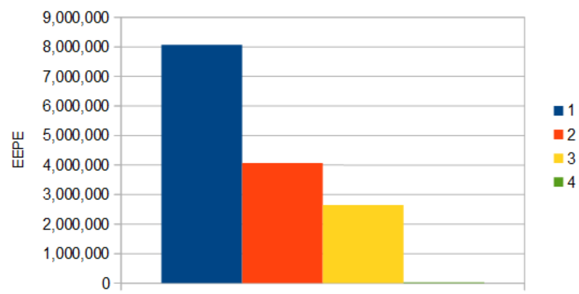

Fig. 12. Comparison of total EEPE between regimes 1-4

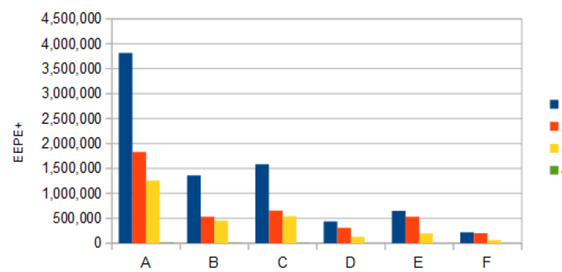

Fig. 13. Comparison of $EEPE^+$ between regimes 1-4

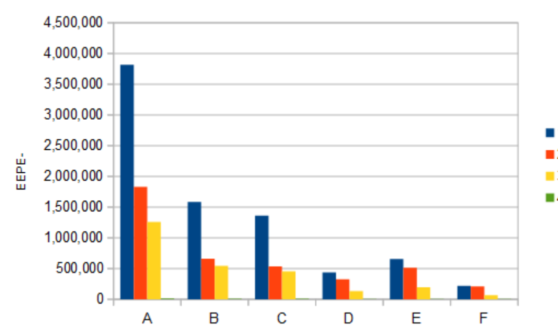

Fig. 14. Comparison of total $EEPE^-$ between regimes 1-4

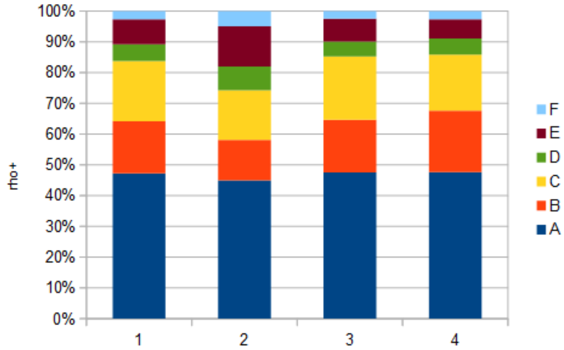

Fig. 15. Comparison of total ρ^+ between regimes 1-4

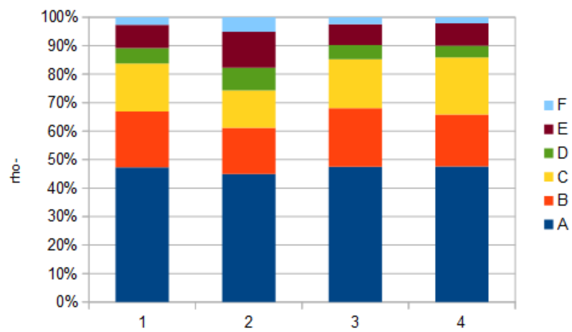

Fig. 16. Comparison of total ρ^- between regimes 1-4

EEPE$^-$ for each counterparty individually, see Fig. 13 and Fig. 14, respectively.

3) In terms of ρ^+ and ρ^-, see Fig. 15 and Fig. 16, respectively, we see that (H) is not valid at all. The concentration of risk among the various counterparties is almost unaffected by the regulatory regime.

VIII. Synopsis

It has always been assumed that collateralization reduces systemic risk. What we have found is that it does indeed reduce the costs of resolution drastically[10], see Fig. 12, but it does not change the distribution of these costs in the system, see Fig. 15. However, both components are seen as essential features of systemic risk.

Regarding practical applicability of this research, any bank b knows its own $\mathrm{EEPE}^-(b)$ and has to report this quantity to the regulator. It is reasonable to assume that it also knows its $\mathrm{EEPE}(b, b')$ for any other counterparty b' it does business with. (Especially for large complex banks it is reasonable to assume that they can compute their own $\mathrm{EEPE}^+(b)$ as well.) A regulator who would collect this information from all banks in the system could actually compute a graph like Fig. 5 representing the real financial system as of today.

The research outlined in this paper can be expanded into several directions.

Capitalization and Central Clearing. The $\mathrm{EEPE}^+(b)$ of a bank b should be thought of as a measure of loss given failure, not a probability of failure. A bank with a large $\mathrm{EEPE}^+(b)$ can actually still be very safe, if it has also large capital reserves. The key to take this into account is Eq. (2). Given a financial system $G = (B, A, w = \mathrm{EEPE})$ one has to enrich it by a function $\mathrm{RWA} : B \to \mathbb{R}$, which computes the RWA of each bank from its EEPE (and some other inputs) and also a capital adequacy ratio function $\mathrm{CR} : B \to \mathbb{R}$ as an additional input. The core capital of each bank can then be computed from Eq. (2). This allows us to model a bank failure due to market risk, for instance by using the criterion

$$\mathrm{CC}(b) < \mathrm{VaR}_q(b), \tag{5}$$

where VaR_q is the *Value at Risk* at some confidence level q. It also allows us to model a bank failure due to credit risk, for instance using the criterion

$$\mathrm{CC}(b_1) < \mathrm{EEPE}((b_1, b_2)). \tag{6}$$

By increasing the confidence level q further and further and labeling a bank as defaulted if either Eq. (5) or Eq. (6) is satisfied, one can study the collapse of the whole system. In particular, one can study how a default of one counterparty causes chain reaction of defaults. The values of q at which default events occur can be interpreted as p-values of the hypothesis that the system is safe. We believe this framework to be particularly suited to study the regulation around central clearing in a similar fashion.

Statistical robustness. We validated the hypothesis (H) that collateralization reduces systemic risk an example of a financial system shown in Fig. 7. Although our results are in line with expert intuition, we cannot yet claim that this is a statistically robust validation. It may be tempting to think that it is better to test the hypothesis on the one and only real financial system by making the regulators collect the necessary data from the banks. Apart from the practical and legal challenges of such an approach one should consider that this is not necessarily future proof. Between the point where a decision has to be made whether or not to implement a regulation and the point where it gets enforced on the real financial system for the first time, many years can pass.[11] Therefore, it is not enough to test the hypothesis on one financial system as of today even if someone had all the data. In order to show that the findings are statistically robust, one has to produce a large number of financial systems - preferably close to the real current one and realistically expected future ones - and repeat the analysis for all of them. However, producing a good set of samples of financial systems for such

[10]The question to what extent exactly Initial Margin reduces exposure to CCR is subject to debate even when considering only one counterparty. In [3], the authors argue that when taking time lags between trade payments and margin re-posting into account, the reduction is much smaller.

[11]Notice that as a result of the 2007/08 crises Initial Margin was introduced. The last phase-in date which makes Initial Margin mandatory even for smaller counterparties is currently set to 2020.

an analysis remains a non-trivial challenge.

Derivative Market vs. Money Market. In the current example, only the derivative business is considered. However, there is also an inherent credit risk in the classical money market. The financial regulation on collateralization has a significant impact on the interplay between the two: Unlike Variation Margin, the Initial Margin cannot usually be rehypothecated (that means you cannot reuse the Initial Margin you receive from one counterparty to post your Initial Margin to another). Raising the necessary funds to post Initial Margin will increase the business in the money markets and it would be interesting to test the hypothesis that this increases the systemic credit risk in the money market in a similar fashion. In that case the trade-off between the reduction of credit risk in the derivative market and the increase of credit risk in the money market should be further examined. Imagine a situation where where a counterparty A hedges a trade it has sold to counterparty B by buying a reversed trade from counterparty C (recall Fig. 7). Although A has zero market risk, it has to post Initial Margin twice, namely to B and C. If A borrows this Initial Margin directly or indirectly from B or C, the reduction in overall credit risk across both markets will be a lot lower.

Initial Margin and Funding Costs. The reduction in EEPE in the derivative business comes at the cost of funding the collateral (MVA), in particular the Initial Margin. It is to be expected that these costs will be significant. Therefore, it would be interesting to study the funding costs by simulating the total amount of Initial Margin in the system in a similar fashion. Comparing the distribution of imposed credit risk, see Fig. 15, by an analogous distribution of paid funding costs would enable an evaluation of the trade-off.

Credit Risk vs. Liquidity Risk vs. Market Risk. While the reduction of credit risk in Fig. 12 is very convincing, one should keep in mind that EEPE, the metric we use to quantify systemic risk, is a metric that captures Counterparty Credit Risk only. However, this is not the only source of risk in a financial system. Therefore, it would be more precise to say that collateralization reduces systemic credit risk. It is very reasonable to assume that pulling large amounts of money out of a financial system due to Initial Margin increases the liquidity risk in that system. Therefore, testing the hypothesis that collateralization increases systemic liquidity risk in a similar fashion and again study the trade-off between the two would be enlightening. While quantifying liquidity risk is difficult, it should be pointed out that Value at Risk (VaR), a standard metric to measure market risk - the most obvious source of risk - has a systemic analogue, namely CoVaR, see [1]. It would be prudent to have a comprehensive simulation that studies the impact of collateralization on all these sources of risk and systemic risk.

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