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Simulating liquidity stress in the derivatives market

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Michael Yoganayagam[4]

Abstract

We investigate whether margin calls on derivative counterparties could exceed their available liquid assets and, by preventing immediate payment of those calls, spread such liquidity shortfalls through the market. Using trade repository data on derivative portfolios, we simulate variation margin calls in a stress scenario and compare them with the liquid-asset buffers of the institutions facing the calls. Where buffers are insufficient we assume institutions borrow additional liquidity to cover the shortfalls, but only after waiting as long as possible to receive payments before making their own. Such delays can force recipients to borrow more than otherwise, and so liquidity shortfalls can grow in aggregate as they spread through the network. However, we find an aggregate liquidity shortfall equivalent to only a modest fraction of average daily cash borrowing in international repo markets. Moreover, we find that only a small part of this aggregate shortfall could be avoided if partial payments were allowed and co-ordinated by an external authority.

Key words: Financial networks, systemic risk, derivatives, central counterparties.

JEL classification: C60, G29.

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1 Introduction

Regulatory reforms following the 2007-08 global financial crisis resulted in the vast majority of derivative exposures in the core of the financial system being backed by collateral. Firstly, mandates have been introduced in major jurisdictions requiring financial institutions to clear new trades in many of the most popular over-the-counter (OTC) derivatives with central counterparties (CCPs). CCPs then collect collateral to cover both the current and potential future value of derivative exposures with their counterparties, the former being known as variation margin (VM) and the latter as initial margin (IM). As a result, the state of OTC derivatives clearing is steadily shifting towards that of exchange-traded derivatives, which are cleared only with CCPs. Secondly, major jurisdictions have also introduced requirements for financial counterparties to exchange both VM and IM on any new OTC derivative trades that are not centrally cleared.

However, greater collateralisation of derivative exposures means that financial institutions can expect to face larger margin calls when prices change or become more volatile. With few exceptions, these institutions already have to post VM to their financial counterparties whenever the value of their derivatives moves against them, reducing their unencumbered liquid-asset buffers (LABs).[1] If margin calls exceeded an institution's LAB, it would have to take some form of defensive action to bolster it (e.g. borrowing in the repo market, selling less liquid assets, or drawing on liquidity lines). Such defensive actions could impose costs not only on that institution but also on other market participants. For example, borrowing cash in the repo market could push up the repo rate faced by all market participants if the borrowing required was large enough.

In this paper we simulate margin calls on most interest rate and foreign exchange (FX)

[1] For centrally cleared derivatives, VM typically must be paid in cash, while IM may alternatively be settled in high-quality liquid securities. In practice, market participants use these two types of collateral in roughly equal measure for IM calls (ISDA, 2015). For non-centrally cleared derivatives, international rules allow VM and IM to be settled in cash or liquid securities (BCBS and IOSCO, 2015)), though in practice VM is usually settled in cash and IM in securities (ISDA, 2017).

derivative positions between a set of institutions comprising London Clearing House Limited (LCH.Ltd) and members of its SwapClear and ForexClear clearing services. Margin calls originate from the changes in risk factors implied by the Severely Adverse scenario used in the 2018 Comprehensive Capital Analysis and Review (CCAR) stress test of US banks.[2] In this scenario, some of the trading book shocks move asset prices more sharply than ever before, including during the 2007-08 global financial crisis. Where LABs are insufficient to meet these margin calls we record a liquidity shortfall. While this would require some kind of defensive action, we do not explicitly model such actions and the consequences they might have. However, to put our simulated shortfalls into context, we compare them to daily volumes of cash borrowing in international repo markets. In our worst-case analysis, where we make intentionally conservative assumptions about the liquid assets available to meet margin calls (e.g. we allow for LABs being depleted by non-derivatives business activity during a stress), liquidity shortfalls amount to about 10% of daily repo volumes.

To avoid miscalculating shortfalls, care must be taken to avoid unrealistic assumptions that can affect VM payments. Our methodological contribution addresses two potential sources of such miscalculation, which have not previously been accounted for in the literature.

First, we model the sequencing of VM payments in a realistic way and discuss its implications for potential liquidity shortfalls in the financial system. CCPs typically require clearing members facing VM calls to make payment early the next day. Shortly after receiving all of these incoming payments, CCPs then make outgoing payments to clearing members to whom they have a VM obligation. VM payments between different

[2] Although we do not simulate IM calls, we suspect these would be quite small compared with VM calls. This is because, according to CCPs' Public Quantitative Disclosures, the largest aggregate VM calls across clearing members are typically several times those of IM calls. For instance, the largest daily aggregate VM call made by SwapClear in 2017 Q4 was 5.3 times its largest IM call. That said, IM requirements can additionally contribute to liquidity strains when they are settled in securities, as more securities are required when their values fall or their haircuts increase.

clearing members on their non-centrally cleared derivatives are normally made later in the day. Neglecting this sequencing would allow clearing members to use incoming payments from other clearing members to pay CCPs, whereas in reality they would not yet have received those funds. Using the realistic sequencing, we find that firms would need to borrow an additional $62.8 billion in our scenario (under our most conservative LAB definition).

Second, we address the behaviour of institutions with insufficient LABs to pay their VM obligations in full. Most of the literature on payment networks is based on Eisenberg and Noe (2001). However, using this would allow institutions to make partial (pro rata) payments to their counterparties in cases where they had insufficient LABs to pay in full. While partial payments might seem reasonable for insolvent firms paying as much of their debts as they could afford, they are less suited to still-solvent firms with a liquidity shortfall, which is the case we consider. Instead, we assume that institutions with insufficient LABs to pay their VM obligations in full initially wait for any incoming payments from institutions with sufficient LABs, including those who only have sufficient LABs because they were paid by others. If institutions still have a LAB shortfall after receiving any such payments, they must take the last resort of borrowing in the repo market in order to pay in full. In our scenario (under our most conservative LAB definition), the aggregate shortfall is $42.6 billion larger when institutions do not make partial payments.

This approach to settling payment obligations fits well with the description of the 1987 stock market crash by now Federal Reserve Chair Jerome Powell when he was then a Federal Reserve Governor (Powell, 2017). He noted that the sequencing of VM payments did not matter on 'normal' days, but during the crash market participants waited to receive incoming payments before making their own outgoing payments.

We also decompose liquidity shortfalls into different components, one of which could be addressed by policymakers. First, we split contributions into 'fundamental' and 'domino' components. The fundamental component of an institution's shortfall is the amount it would have to borrow even if all incoming payments were received before it had to go to the repo market. In contrast, the domino component is the amount it has to borrow because its incoming payments were delayed by counterparties in an effort to avoid borrowing themselves. Subsequently, we split the domino component into 'avoidable' and 'unavoidable' portions. The avoidable portion is that which an authority could eliminate by acting on self-fulfilling payment chains, e.g. if A paid B, B could pay C and C could pay A, which would give A the liquidity it needs to make the initial payment to B. The action needed is to direct simultaneous payments along such chains, some of which may be partial payments, with borrowing necessary to make up the difference.

Finally, we compute contributions of individual institutions to the aggregate liquidity shortfall. Institutions contribute more than their own shortfalls to the aggregate when their delayed payments to counterparties cause those institutions to also delay payments. Authorities considering emergency liquidity assistance in crises should focus on reaching institutions with the largest aggregate shortfall contributions.

Empirical studies on contagion in the derivative market are relatively few, due mostly to limited data availability. The vast majority of early works focused on credit default swaps (CDSs). Brunnermeier et al. (2013) find that the CDS market is concentrated and, by using a simple algorithm based on default cascades, point out that several banks have exposures that exceed 30% of their equity bases. Similarly, Clerc et al. (2014) find that so-called "super-spreaders" of contagion are mostly banks with exposures larger than their equity. Additionally, Cetina et al. (2018) show that second-round effects can be larger than first-round effects, thus highlighting the importance of taking the full network into account. Cont and Minca (2016) and Duffie et al. (2015) look specifically at the role of central clearing in reshaping the counterparty network and find, respectively, that it reduces the chance of a systemic illiquidity crisis and the system-wide demand for collateral.[3]

Data availability has improved since 2013, when European Market Infrastructure Regulation (EMIR) started to require EU institutions to report their derivative transactions to trade repositories, from which we extract individual portfolios for our analysis. To the best of our knowledge, only Abad et al. (2016) and Bardoscia et al. (2019a) used such data to cover interest rate, foreign exchange, and CDS markets at the same time with the former providing descriptive statistics of those markets in isolation and the latter linking the vulnerability of individual institutions to specific centrality measures.

Our paper is most closely related to Paddrik et al. (2020), which also simulates margin calls and liquidity shortfalls in the derivatives market. There are, however, some differences in scope and methodology between the two papers. First, Paddrik et al. (2020) focus on the US CDS market, which they cover in its entirety (around 900 institutions). In contrast, we cover several types of interest rate and foreign exchange derivatives for around 100 of the largest participants in these markets. Second, due to the difficulty of sourcing data on LABs, Paddrik et al. (2020) estimate these as high percentiles of potential VM calls, whereas we compile this information from various sources, including regulatory reports. Finally, the consequences of liquidity shortfalls differ between the two papers. Paddrik et al. (2020) study a range of alternatives that, at one extreme, put counterparties into default (with initial margin collateral seized to mitigate payment shortfalls) and, at the other, allow counterparties to pay the maximum fraction of obligations they can afford. In contrast, we assume that liquidity shortfalls leave institutions solvent and result in actions to raise new liquidity. Hence, we require that whenever payments are made they are made in full.

The algorithms that determine payments between counterparties in this paper and in Paddrik et al. (2020) are both variations of the model developed by Eisenberg and Noe

[3]For a broad overview of the relationship between systemic risk and central clearing, see Pirrong (2011, 2012).

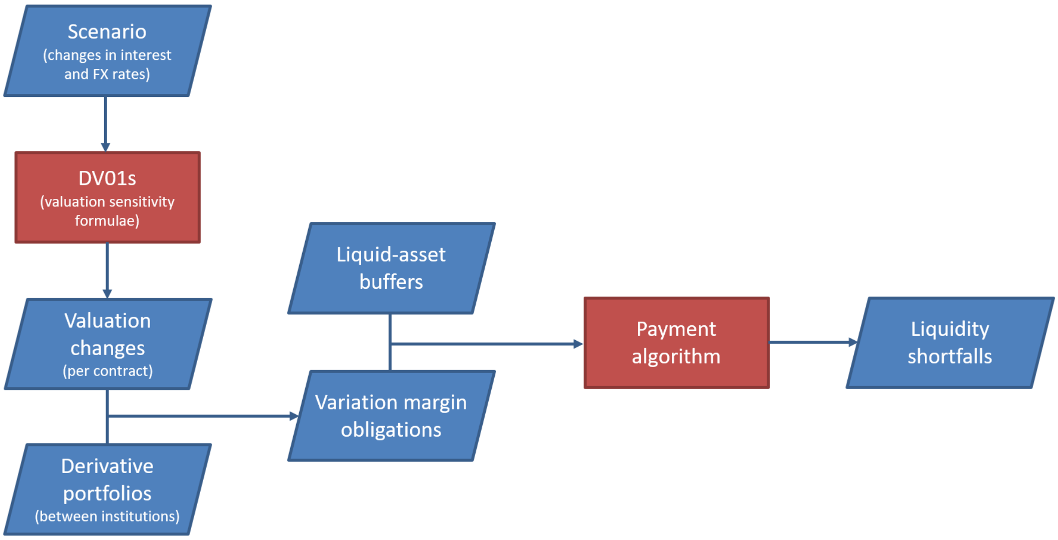


Figure 1: Schematic overview of simulation framework.

(2001), which finds mutually consistent 'clearing' payments. Bardoscia et al. (2019b) discuss the construction of an algorithm that does not allow partial payments to be made and compares the resulting payments with those deriving from the classic Eisenberg and Noe model.

The remainder of the paper is organised as follows: in Section 2 we describe our simulation framework, including the data it employs, in Section 3 we discuss our results regarding liquidity shortfalls and contributions to them, and we conclude in Section 4.

2 Model and data

Our stress testing framework consists of a few steps, which are summarised in Figure 1. First, we compute changes in derivative values implied by a stress scenario. Next, we combine these per-contract valuation changes with data on the composition of bilateral derivative portfolios to compute profits and losses for each market participant. For each portfolio, the party suffering a loss owes VM in equal amount to the party with a gain. Payments made by each market participant depend on their VM obligations and their

LABs, but can also vary substantially depending on the sequencing of due payments in the counterparty network. Here we introduce a novel payment algorithm that properly accounts for the sequencing of payments between centrally cleared and non-centrally cleared VM obligations and that does not rely on market participants making partial payments. In the final step, we use the payment algorithm to compute payments and therefore shortfalls for each market participant. Where shortfalls are greater than zero, we assume VM obligations will still be met but only after borrowing to cover the shortfall. Hence, we do not capture any defaults in our simulation; only liquidity strains. This is consistent with the very short time scale, a day or less (see Section 2.6), over which market participants are expected to meet their VM calls.

2.1 Scenario

As mentioned above, for our stress scenario we adopt changes in interest and exchange rates from the trading book component of the 2018 US CCAR Severely Adverse scenario. Tables 1 and 2 show the most important interest and exchange rate shocks in this scenario. These apply to over 90% of the interest rate derivatives and more than 85% of the FX derivatives in our bilateral portfolios by notional amount. The values of interest and exchange rate shocks not reported in Tables 1 and 2 are available in the CCAR scenario documentation (Board of Governors of the Federal Reserve System, 2018a). These shocks, which we implement as instantaneous shocks (as institutions are required to do for the CCAR itself (Board of Governors of the Federal Reserve System, 2018b)), are in several cases larger than any single-day moves in history, including during the 2007-08 global financial crisis.

	Residual maturity (months)												
Currency	1	3	6	9	12	24	36	60	84	120	180	240	360
EUR	-16	-18	-19	-21	-22	-24	-24	-22	-19	-16	-13	-12	-11
USD	28	39	54	71	85	115	141	175	187	191	193	194	196
GBP	-24	-23	-22	-22	-21	-20	-20	-19	-17	-14	-13	-11	-6
AUD	-18	-21	-25	-29	-31	-38	-40	-40	-37	-36	-36	-37	-39
JPY	-9	-10	-11	-11	-12	-15	-16	-16	-16	-17	-17	-18	-20
CAD	42	44	52	57	60	65	72	87	92	92	87	82	76

Table 1: Changes in most important swap rates in the scenario (in basis points).

	Quote currency					
Base currency	EUR	USD	GBP	AUD	JPY	CAD
EUR						
USD	2.2					
GBP	-1.6	15.0				
AUD	-9.8	5.3	-8.4			
JPY	14.1	13.8	-1.1	7.5		
CAD	-5.4	10.5	-3.9	4.7	-2.9	

Table 2: Changes in most important exchange rates in the scenario (appreciation of quote currency against base currency in per cent).

2.2 Valuation of derivatives

In order to compute changes in derivative valuations consistent with our scenario we use first-order approximations, also known as 'DV01s'.[4] This economises on data requirements and does not affect our results materially.[5] In the class of interest rate derivatives we cover forward rate agreements (FRAs) and interest rate swaps (IRS), while in the class of FX derivatives we cover forwards and swaps.[6] In both derivative classes, we cover spot-starting as well as forward-starting contracts.

2.2.1 Forward rate agreements

In a FRA, counterparties agree to exchange on a future date, T, a single interest payment at a fixed rate, r, of the contract's notional amount, N, for a payment at the then-prevailing value of a floating rate. The fixed rate is known as the forward rate, while the floating rate is usually an interbank offered rate (IBOR) or an overnight rate (ONIA) of specified maturity, m. The value of a long (i.e. pay-fixed) position in a FRA would fall following a rise in the forward rate by approximately the size of that increase, Δr_t, multiplied by the FRA's duration, D_t:

$$\Delta V_t^{\mathrm{FRA}} \approx -ND_t\Delta r_t = -N\left[me^{-i_{t,T-t}(T-t)}\right]\Delta r_t\,. \tag{1}$$

The duration, in turn, depends on the risk-free rate of interest with maturity $T-t$, $i_{t,T-t}$, where t is the scenario date. We approximate risk-free interest rates with OIS rates, interpolating for missing maturities where necessary.[7]

[4]DV01 formulae give the change in value of a derivative consistent with a one-basis-point change in an underlying.

[5]For instance, across interest rate swaps with a wide range of swap rates and maturities, as observed in our portfolios, the difference between valuation changes computed using comprehensive and DV01 formulae is no more than 3%.

[6]Specifically, for interest rate swaps we cover single-currency fixed-for-floating swaps. We do not cover cross-currency swaps and single-currency floating-for-floating swaps (i.e. basis swaps).

[7]Where ONIA rates are not available, we use IBORs or, occasionally, government bond yields.

2.2.2 Interest rate swaps

In an interest rate swap, counterparties agree to exchange regular interest payments at a fixed rate, ρ, of the contract's notional amount, N, for payments at a floating rate. The fixed rate is known as the swap rate and, as for FRAs, the floating rate is usually an IBOR or overnight rate (ONIA) of specified maturity. However, to simplify our calculations, while hardly affecting our results, we assume the maturity of the floating rate is always six months and that interest payments are exchanged twice a year. Similarly, we round the maturity date of the swap, T, to the nearest half-year. Similar to FRAs, the value of a long (i.e. pay-fixed) position in an IRS would fall following a rise in the swap rate by approximately the size of that increase, $\Delta\rho_t$, multiplied by the swap's duration, D_t:

$$\Delta V_t^{\mathrm{IRS}}(T) \approx -ND_t\Delta\rho_t = -N\left[\frac{1}{2}\sum_{c=1}^{2T} e^{-i_{t,\frac{c}{2}}\frac{c}{2}}\right]\Delta\rho_t\,. \tag{2}$$

The duration, in turn, depends on risk-free rates of interest with maturities $c/2$, $i_{t,\frac{c}{2}}$, where t is the scenario date. We calculate durations for swaps of all maturities based on same-maturity OIS rates, interpolating for missing maturities where necessary.

In a forward-starting IRS, the exchange of payments does not begin until an agreed future date, T_1, after which they continue to the maturity date, T_2. Thus, a long (i.e. pay-fixed) position in a forward-starting IRS is equivalent to a long position in a spot-starting IRS maturing at T_2 and a short position in a spot-starting IRS maturing at T_1:

$$\Delta V_t^{\mathrm{FSIRS}}(T_1, T_2) = \Delta V_t^{\mathrm{IRS}}(T_2) - \Delta V_t^{\mathrm{IRS}}(T_1)\,. \tag{3}$$

2.2.3 FX forwards

In an FX forward, counterparties agree to exchange on a future date, T, a fixed amount, F, of a quote currency (Q) for each of the contract's N units of a base currency (B).

Thus, F is known as the forward exchange rate, in contrast to the rate for immediate exchange, which is known as the spot rate, S. [8] The value of a long (i.e. buy base currency) position in an FX forward would increase following a rise in the spot rate, ΔS_t, by approximately that amount multiplied by a discount factor, d_t^B:

$$\Delta V_t^{\mathrm{FXF}}(T) \approx N d_t^B \Delta S_t = N \left[e^{-i_{t,T-t}^B (T-t)} \right] \Delta S_t \, . \tag{4}$$

The discount factor has the same maturity as the forward and depends on the risk-free interest rate in the base currency with maturity $T-t$, $i_{t,T-t}^B$, where t is the scenario date. We approximate risk-free interest rates with base-currency OIS rates, interpolating for missing maturities where necessary.

2.2.4 FX swaps

In an FX swap, counterparties immediately exchange base and quote currencies at the prevailing spot rate, S, as with a spot FX trade, and agree to exchange them back on a future date, T, at a fixed rate, F, as with an FX forward. As the first of these two legs is completed immediately, the remaining leg of the FX swaps in our portfolio data is equivalent to an FX forward:

$$\Delta V_t^{\mathrm{FXS}}(T) = \Delta V_t^{\mathrm{FXF}}(T) \, . \tag{5}$$

However, this is not the case for forward-starting FX swaps that have not yet started. For this type of contract, the initial exchange of currencies is for a relatively near future date, T_1, and the reverse exchange for a later future date, T_2. The two currency exchanges are at agreed fixed rates F_1 and F_2 respectively. Thus, the contract is equivalent to a

[8] Exchange rates, whether spot or forward, are quoted as BBB/QQQ, where BBB denotes the currency code for the base currency and QQQ denotes the code for the quote currency. For instance, a quote of 110 for USD/JPY would be to trade 110 Japanese yen (JPY) for one US dollar (USD).

position in an FX forward maturing at T_2 and an equal-size but opposite-direction position in an FX forward maturing at T_1. Thus, the DV01 for a forward-starting FX swap is the difference between those of two FX forwards:

$$\Delta V_t^{\text{FSFXS}}(T_1, T_2) = \Delta V_t^{\text{FXF}}(T_2) - \Delta V_t^{\text{FXF}}(T_1)\,. \tag{6}$$

2.3 Portfolio data

We use our DV01 formulae to revalue and, thus, determine VM calls on bilateral derivative portfolios. These portfolios comprise net long positions, x_{ijk}, of counterparty i with j in contract k on 29 September 2017. We use close to 8000 portfolios in our analysis: 103 centrally cleared portfolios, which are held between one CCP, LCH.Ltd, and its clearing members, and almost 7900 non-centrally cleared portfolios, which are held between pairs of clearing members.[9] A complete list of the institutions covered is available in Appendix A.

Our portfolio data comes from EU derivative trade repositories, to which the Bank of England has constrained access. Since 2013, EMIR has required EU institutions to report their derivative transactions to trade repositories. Eight of these were in operation at the time of writing. We extracted data from two: Unavista, to which LCH.Ltd reports, and DTCC, to which many of the largest derivative dealers and other LCH.Ltd clearing members report. The Bank of England cannot access data on all trades in these repositories; only those referencing sterling financial instruments or with at least one UK counterparty. Each trade is reported to repositories by both of its counterparties, so as long as one counterparty reported to Unavista or DTCC we capture the trade in our analysis. Where trades are reported by both counterparties, we remove duplicate records.

[9]The centrally cleared portfolios include derivative trades cleared on behalf of clients as well as proprietary trades of clearing members. Nevertheless, clearing members are responsible for meeting margin calls across these portfolios. To help with this, they would normally pass on margin calls to the relevant clients.

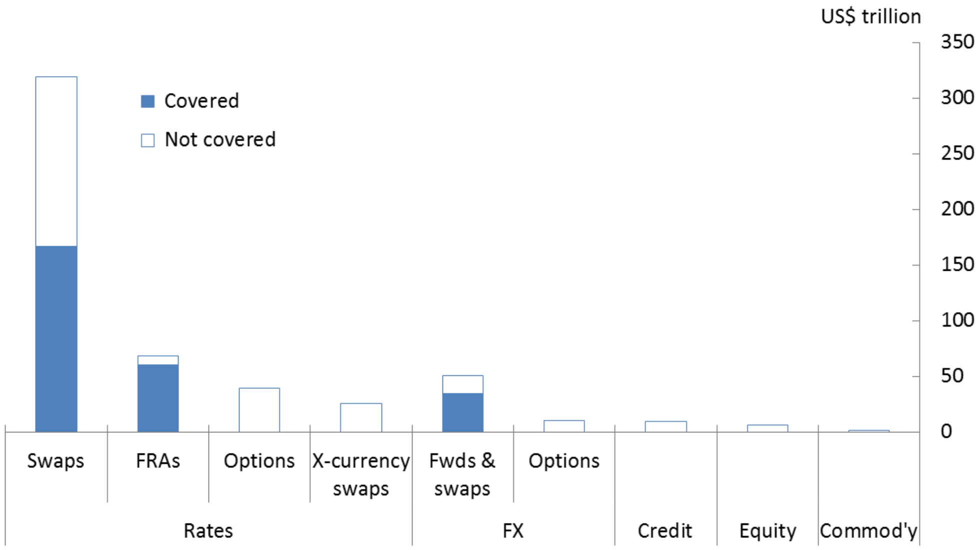


Figure 2: Notional amounts of derivatives in our portfolio data compared with global totals.

Reflecting our limited coverage of institutions and derivative types as well as our restricted access to data, we only capture a fraction of the global derivatives market in our analysis. Overall, we capture about 50% of outstanding global derivatives as reported in the 2017 H2 Bank for International Settlements' OTC derivative statistics (BIS, 2018), based on notional amounts. Figure 2 shows how this coverage varies by derivative type.

2.4 Margin calls

Given the composition of bilateral portfolios and valuation changes for their constituents, VM calls are straightforward to compute. First, we compute profits for institution i on its portfolio with counterparty j consistent with the scenario:

$$\pi_{ij} = \sum_k \Delta V_{ijk}\,, \tag{7}$$

where ΔV_{ijk} is the change in value of contract k held between i and j, which is computed according to the contract classes discussed in Section 2.2. Then, since counterparties make VM calls to protect their gains, i would face calls from j of:

$$m_{ij} = \max(-\pi_{ij}, 0)\,. \tag{8}$$

Note that LCH.Ltd does not net profits and losses with clearing members across its SwapClear and ForexClear services or across derivatives settled in different currencies within either of these services when calculating VM calls. Hence, we initially treat these various portfolios separately, in order to calculate portfolio-specific VM calls. As a consequence, clearing members can have at the same time both inward and outward VM payments from and to the CCP.

2.5 Liquid assets

Alongside margin calls, the other key input to our payment algorithm is a set of LABs. Hence, we compile LAB data for each of the institutions in our simulation, except for the CCP. The CCP's clearing services collect VMs before paying them and we assume that clearing members are always able to source the cash needed to pay the CCP (see Section 2.6), so the CCP never dips into its LAB. Hence, we do not need this data. For the remaining institutions, we collect LAB data for as close as possible to our scenario date from regulatory returns and public financial statements.[10] From these data, we compile three increasingly conservative LAB metrics.

Our first LAB metric, denoted by a_i^1 for institution i, is total cash holdings. This is defined as central bank reserves and commercial bank demand deposits. We focus on cash holdings because VMs on centrally cleared trades have to be paid in cash and, even

[10]For seven institutions in our sample, neither regulatory returns nor public financial statements were available. For each of these seven institutions (which were all non-deposit taking institutions) we estimated their cash buffers by taking the sum of the cash buffers of the non-deposit taking institutions for which public financial statements were available and scaling this down by the relative size of the derivatives portfolio of the institution for which cash buffer data was missing.

though it is typically not a requirement, they are usually also settled this way for non-centrally cleared trades (ISDA, 2017). Hence, we exclude high-quality liquid securities from this and our other LAB metrics. After we have run our payment algorithm and we know what payments can be made in the counterparty network without borrowing, those with liquidity shortfalls remaining may use high-quality liquid securities as collateral to borrow in the repo market and finally meet their margin obligations.

Our second LAB metric, denoted by a_i^2 for institution i, recognises that clearing members usually pursue several other business activities that require liquidity buffers beside derivatives trading. Hence, for this metric, we apportion a_i^1 to a part dedicated exclusively to derivatives trading and a residual part for all the other business activities. We do this based on UK regulatory returns relating to the Liquidity Coverage Ratio (LCR). These returns show the liquid assets that banks must hold to cover potential cash outflows over 30 days due to different business activities. Potential outflows related to derivative holdings are primarily to cover VM obligations. Hence, for UK banks, we apportion using the ratio of potential derivative outflows to total potential outflows. For non-UK banks, where we do not have LCR returns, we apportion using the average ratio for UK deposit-taking banks or broker-dealers, depending on whether the non-UK bank is itself a deposit-taker or broker-dealer. These average ratios were 10% and 60% respectively.

Our third and most conservative LAB metric, denoted by a_i^3 for institution i, recognises that banks may prefer to keep their liquidity above regulatory requirements, even though it is permissible to use all available liquidity to meet outflows in a stress. Indeed, we might expect such behaviour if the cost of funding liquidity shortfalls is smaller than the cost of any stigma associated with falling below a regulatory threshold. Hence, our third LAB metric is a_i^2 scaled by the ratio of each bank's liquid assets in excess of LCR requirements to its total liquid assets, where the excess is defined as the difference between

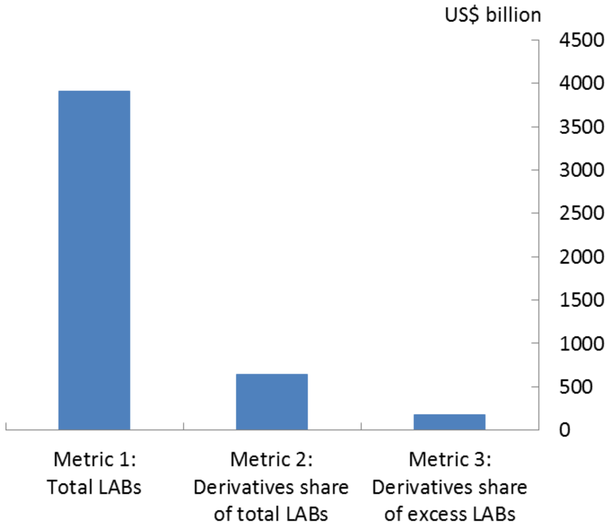


Figure 3: Aggregate liquid asset buffers.

total liquid assets and the regulatory requirement. Arnould and Lallour (2020) explain why banks that give more detailed information to the public may be wary of disclosing a lower LCR ratio because they fear it could trigger a withdrawal of their investors and/or depositors. This is especially true for liquidity disclosures, as underlined by Praet and Herzberg (2008). This concern led the Basel Committee to only request the disclosure of simple averages of daily LCR of the previous quarter (BCBS, 2014).

These three metrics produce very different LABs. Figure 3 shows their aggregate values across clearing members. In the results section below, we will initially show liquidity shortfalls for all three LAB metrics, but then focus on a_i^3. This makes our estimates of liquidity shortfalls conservative. If the derivatives market is resilient to margin calls using a_i^3 as the LAB metric, it must be resilient in the other cases.

2.6 Payment algorithm

Institutions use their LABs to make VM payments. The payment algorithm specifies the details of how payments between institutions are made. We will see that those details matter and that changing the payment algorithms can have a substantial impact on the aggregate shortfalls. Our set-up is conceptually similar to Eisenberg and Noe (2001), with two key differences that reflect market protocols. First, payments are not all simultaneous, but they are made in three stages: from clearing members to the CCP, from the CCP to clearing members, and finally (on non-centrally cleared derivatives) between clearing members. Second, clearing members do not make partial pro rata payments when their LABs are not sufficient to cover their outward VM obligations. Instead, they wait for inward payment and make their outward payments only when they can pay them in full. We stress that institutions do not have complete information on the full network of VM obligations, but they only know their direct inward and outward VM payment. This means that they cannot internalize the indirect consequences of the payments they make. For example, while partial payments made by one institution might enable a chain of downstream payments that would eventually come back to it, that institution cannot anticipate it. Institutions that immediately before close of business cannot pay their VM obligations in full record their shortfall. At this point they need take some defensive action, such as borrowing on the repo market. Institutions prefer to wait rather than taking any defensive action earlier in the day precisely because if they received an inward payment they might not need to take any defensive action at all.

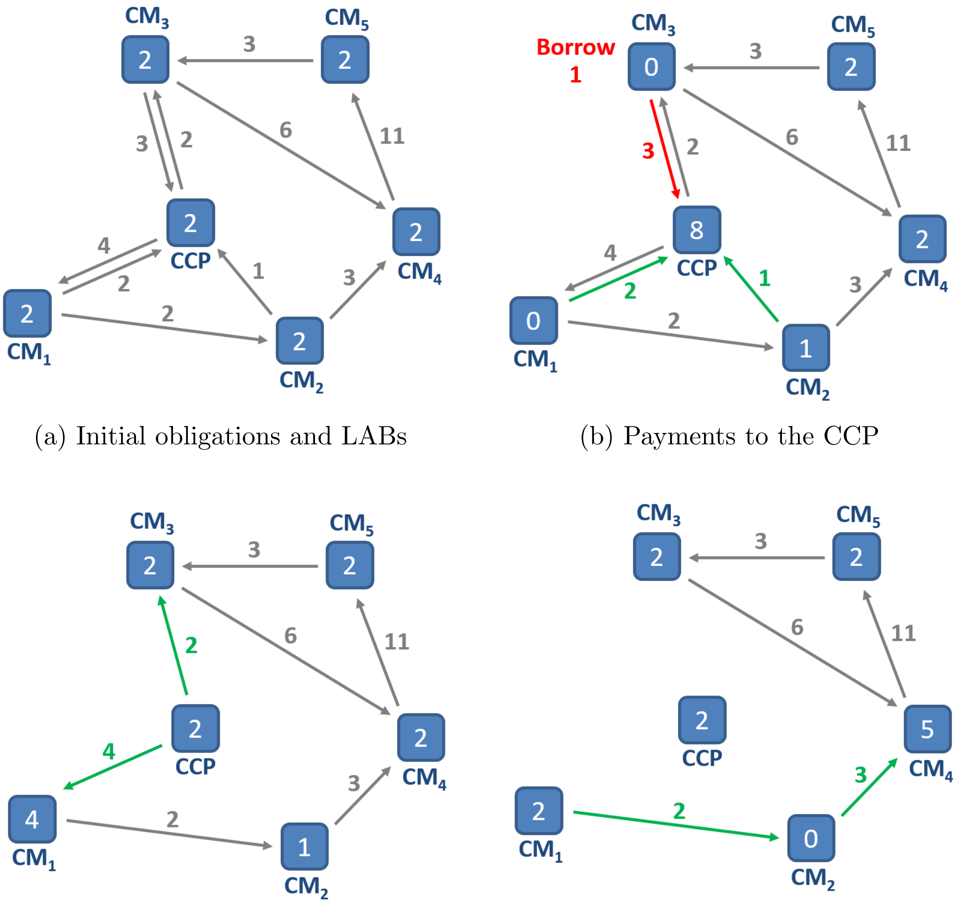
Our framework fits well with the description of the 1987 stock market crash in Powell (2017) where the now Chair of the Federal Reserve (then a Federal Reserve Governor) explains that the sequencing of VM payments did not matter on 'normal' days since counterparties would extend intraday credit to each other while they awaited payment of margin calls, confident that these would arrive later in the day. However, such credit dried up on 20 October 1987. This forced many margin obligations to be paid sequentially, with market participants waiting to receive payments before making their own.

The top-left panel of Figure 4 shows a small network of VM obligations at the start of a particular day (grey arrows) and the LABs held by market participants (blue boxes) to help meet them.[11] The obligations reflect prices movements of the previous day. In some cases, the figure shows multiple arrows between the CCP and clearing members (CMs). These reflect VM obligations in different currencies or across different clearing services offered by the CCP. This is because the CCP only nets obligations in the same currency and in the same clearing service. In contrast, there are only single arrows between clearing members, as we assume VM obligations on non-centrally cleared trades that are in different currencies are converted into a common currency and netted. This reflects common market practice.

We denote the VM payment obligation from i to j with $\bar{p}_{ij}$, the corresponding payment made without borrowing with p_{ij}, and the LAB of i with e_i. We reserve the index zero for the CCP, so that $\bar{p}_{0j}$ is the payment obligation from the CCP to j and $\bar{p}_{i0}$ is the payment obligation from i to the CCP. Moreover, we use the superscript (k) to denote quantities at the beginning of the k-th stage of the algorithm. At the beginning of the first stage, VM payment obligations are set equal to VM margin calls: $\bar{p}_{ij}^{(1)} = m_{ij}$, while the LAB $e_i^{(1)}$ is set to one of the three metrics in Section 2.5.

The first stage of the algorithm considers the obligations of clearing members to the CCP, which are the first obligations to be settled during the day. The other obligations, and therefore the corresponding payments, are zero at this stage: $\bar{p}_{ij}^{(1)} = p_{ij}^{(1)} = 0$, for $j \neq 0$. Obligations are met from LABs wherever they are sufficient, otherwise each institution with a LAB shortfall borrows just enough additional liquidity to make its due

[11]Ideally, these LABs would be split into different currencies and we would track whether VM obligations in particular currencies could be met from same-currency buffers. However, this data is not available to us for the majority of institutions in our simulation.



(a) Initial obligations and LABs

(b) Payments to the CCP

(c) Payments from the CCP

(d) Non-centrally cleared payments

Figure 4: Illustrative example of the different rounds of our payment algorithm.

payment. Therefore, payments and shortfalls are equal to:

$$p_{i0}^{(1)} = \max(\bar{p}_{i0}^{(1)}, e_i^{(1)}) \tag{9a}$$

$$s_i^{(1)} = \bar{p}_{i0} - p_{i0}^{(1)} . \tag{9b}$$

In the example (top-right panel of Figure 4), CM1 and CM2 meet their obligations to the CCP solely from their LABs, while CM3 borrows one unit of cash to help meet its obligations and records the amount borrowed as a shortfall. Receipt of such payments boosts the CCP's LAB and depletes the clearing members ones. In fact, at the beginning of the second stage we have: $e_0^{(2)} = \sum_i \bar{p}_{i0}^{(1)}$, while $e_i^{(2)} = e_i^{(1)} - p_i^{(1)}$.

In the second stage, the CCP makes its payments to clearing members. At this stage the obligations and payments of clearing members are equal to zero: $\bar{p}_{ji}^{(1)} = p_{ji}^{(1)} = 0$, for $j \neq 0$. As it holds a 'matched book', with long positions equal to short positions in every derivative that it clears, the CCP's total VM obligations is equal to the sum of all the VM payments it received in the first stage of the algorithm, i.e. $\sum_i \bar{p}_{0i}^{(2)} = \sum_i \bar{p}_{i0}^{(1)} = e_0^{(2)}$. Hence, the CCP always meets its obligations without borrowing, i.e. $p_{0i}^{(2)} = \bar{p}_{0i}^{(2)}$, for all i and no shortfall is recorded at this stage. In the example (bottom-left panel of Figure 4), the CCP pays CM1 and CM3 without needing to borrow. These payments boost the clearing members' LABs.

Finally, in the third stage VM obligations on non-cleared derivatives are settled. In this stage payments are made in subsequent iterations t. We denote with $\bar{p}_{ij}^{(3)}(t)$, $p_{ij}^{(3)}(t)$, and $e_i^{(3)}(t)$ respectively the payment obligation of i to j, the realised payment (before borrowing) from i to j, and the LAB of i at iteration t. We further denote with $\bar{p}_i^{(3)}(t) = \sum_j \bar{p}_{ij}^{(3)}(t)$ and with $p_i^{(3)}(t) = \sum_j p_{ij}^{(3)}(t)$ the total obligation and the total payment (before borrowing) of i at iteration t. At $t = 0$, payment obligations between clearing members correspond to VM margins: $\bar{p}_{ij}^{(3)}(0) = m_{ij}$. All obligations and payments involving the CCP are equal to zero: $\bar{p}_{i0}^{(3)}(0) = p_{i0}^{(3)}(0) = \bar{p}_{0i}^{(3)}(0) = p_{0i}^{(3)}(0) = 0$, for all i as they have been cleared in the two previous stages. LABs are those at the end of the second stage: $e_i^{(3)}(0) = e_i^{(2)} + p_{0i}^{(2)} = e_i^{(2)} + \bar{p}_{0i}^{(2)}$. At a given iteration t, clearing members that can afford to pay their VM obligations in full only by drawing on their current LABs (i.e. without borrowing) will make those payments. Clearing members that cannot make full payments instead do not make any payment and wait until the next iteration:

$$p_i^{(3)}(t) = \begin{cases} \bar{p}_i^{(3)}(t) & \text{if } e_i^{(3)}(t) \geq \bar{p}_i^{(3)}(t) \\ 0 & \text{if } e_i^{(3)}(t) < \bar{p}_i^{(3)}(t) \,. \end{cases} \tag{10}$$

At iteration $t+1$ payments obligations are updated:

$$\bar{p}_i^{(3)}(t+1) = \bar{p}_i^{(3)}(t) - p_i^{(3)}(t) = \begin{cases} 0 & \text{if } e_i^{(3)}(t) \geq \bar{p}_i^{(3)}(t) \\ \bar{p}_i^{(3)}(t) & \text{if } e_i^{(3)}(t) < \bar{p}_i^{(3)}(t) \,, \end{cases} \tag{11}$$

and payments made at iteration t are incorporated into LABs:

$$e_i^{(3)}(t+1) = e_i^{(3)}(t) + \sum_j p_{ji}^{(3)}(t) - p_i^{(3)}(t) \tag{12}$$

and can be potentially be used to make payments by evaluating (10) at iteration $t+1$. Eqs. (10), (11), and (12) are iterated until convergence to the steady state. When the steady state is reached, those institutions that have residual obligations record a shortfall equal to the difference between those residual obligations and their LABs:

$$s_i^{(3)} = \bar{p}_i^{(3)}(\infty) - e_i^{(3)}(\infty) \,, \tag{13}$$

where with $\bar{p}_i^{(3)}(\infty)$ and $e_i^{(3)}(\infty)$ we denote respectively the residual obligation and the LAB of i in the steady state. In the example (see the bottom-right panel of Figure 4) CM1 pays CM2 in the first iteration. After having received this payment, CM2 pays CM4 in the second iteration. Any remaining obligations are then met by institutions borrowing the difference between their residual obligations and updated LABs. In the example, CM3 borrows 4 to help meet its obligation of 6 to CM4, CM4 borrows 6 to help meet its obligation of 11 to CM5, and CM5 borrows 1 to meet its obligation of 3 to CM4. As at the end of the first stage, we record the total shortfalls that necessitated borrowing.

The total shortfall of i is the sum of the shortfalls recorded in the first and the third stage:

$$s_i = s_i^{(1)} + s_i^{(3)} \,. \tag{14}$$

Finally, in order to gauge whether the sequencing of payments has an impact on liquidity shortfalls, one can compare the shortfalls computed with (14) with the shortfalls obtained when all institutions (both clearing members and the CCP) make their payments simultaneously. Those can be computed by removing the first and second stage in the payment algorithm and by treating the CCP like all the other institutions in the third stage.

2.7 Decomposition of liquidity shortfalls

We now decompose liquidity shortfalls – or equivalently borrowing amounts – at each stage of the payment algorithm into two main components: a 'fundamental' part and a 'domino' part. The fundamental part of the shortfall is the shortfall that one institution would face if it received all its expected inward payments. The domino component is the difference between the total shortfall and fundamental component. Therefore, it isolates the network contribution to shortfalls, as it can only exceed zero if an institution fails to receive timely payment of at least one inward obligation.

In the first stage there are only obligations towards the CCP and no payments due to clearing members. As a consequence, any shortfall recorded on centrally cleared trades must be fundamental. Shortfalls on obligations to other clearing members, which are cleared in the third stage of the payment algorithm, can have both a fundamental and a domino component.[12] The fundamental shortfall that i faces in the third stage is computed simply as the positive excess of its net VM obligations towards other clearing members over its LAB, i.e. $\max\left(\bar{p}_i^{(3)}(0) - \sum_j \bar{p}_{ji}^{(3)}(0) - e_i^{(3)}(0), 0\right)$.

[12]We recall that no shortfalls occurs in the second stage of the algorithm, in which the CCP pays its VM obligations.

There are cases of both fundamental and domino shortfalls in Figure 4. For instance, CM3 has a fundamental shortfall in the top-right panel, as its net obligation to the CCP at that stage of the payment algorithm is 3 but it only has 2 units of LABs. Note that the CCP's obligation of 2 to CM3 does not net against CM3's obligation to the CCP because this is not due until later. Indeed, as clearing members must pay the CCP before it pays them, and since they have no other counterparties for their centrally cleared trades, any shortfalls on these trades must be fundamental shortfalls. As already observed, shortfalls on obligations to other clearing members could be fundamental or domino in nature. For instance, CM3 has a fundamental shortfall of 1 in the bottom-right panel. This is because it would still have to borrow 1 unit of liquid assets to help meet its obligation to CM4 even if CM5 immediately paid its obligation of 3 to CM3. However, CM5 will not meet this obligation immediately, so CM3 has a domino shortfall of 3 on top if its fundamental shortfall of 1. This is because CM5 prefers to wait for an inward payment from CM4 before making its outward payment to CM3, as it would then be able to make the payment without borrowing. Indeed, CM5 is in a chain with CM3 and CM4, where each institution prefers to wait for inward payments before making outward payments, as receipt of the inward payment would reduce or eliminate their need to borrow. However, since they all wait, all obligations end up being met at the last moment. This involves CM3 borrowing 4 (3 domino and 1 fundamental) and CM4 and CM5 borrowing 6 and 1 (both domino shortfalls).

Finally, we further decompose domino shortfalls into 'avoidable' and 'unavoidable' components. Some domino shortfalls could possibly be avoided if institutions with insufficient LABs to meet their obligations in full without waiting for incoming payments at least made partial payments by drawing on their currently available LABs. In particular, if a set of such institutions, coordinated by an authority, made some additional partial payments that facilitated new payments by the recipient institutions, and these eventually fed back to the original institutions as incoming payments, then domino shortfalls would have been reduced. This is because some additional obligations would have been met, at least partially, without any additional borrowing. Bardoscia et al. (2019b) show that the solution to the Eisenberg and Noe (2001) (EN) model precisely identifies payments that have this effect.[13] Unavoidable domino shortfalls are the residual domino shortfalls after implementing these payments.

In the example shown in Figure 4, a central authority could have directed some self-financing payments between CM3, CM4 and CM5 in the bottom-right panel, thereby reducing the volume of domino borrowing. In particular, by computing payments implied by the solution of EN, we find that CM3 could have paid 5 to CM4, which is 3 more than its LAB. This would have allowed CM4 to pay 10 to CM5, which would have allowed it to pay 3 to CM3. CM3's receipt of this amount would complete the payment loop, which is therefore self-financing. Thus, all but 2 of the domino borrowing (1 for CM3 and 1 for CM4) could have been avoided through coordination of payments. Such coordination would, however, be difficult to implement in practice. It would require a central authority to have data on the counterparty network of obligations, to calculate the solution to the EN model and then to direct the necessary payments.

3 Results

In this section we present our results on liquidity shortfalls. First, we report the size of variation margin calls. Second, we discuss aggregate liquidity shortfalls, their decomposition and their distribution. Next, we report contributions of individual institutions to aggregate liquidity shortfalls. Finally, we show how these two metrics vary with a structural change: the effect of introducing netting of VMs in different currencies by the CCP.

[13] In particular, the least solution of the multiple possible solutions to the model.

3.1 Variation margin calls

For centrally cleared derivatives, LCH.Ltd both calls and pays \$96 billion of VM on interest rate derivatives and \$1 billion on FX derivatives in our scenario. The former compares with about \$16 billion (£12 billion) on 24 June 2016, which was the day after the Brexit referendum.[14] On that day, ten-year swap rates fell by nearly 30 basis points for GBP contracts and almost 20 basis points for USD contracts. In our scenario, the USD swap rate rises by over 190 basis points (see Table 1), which is why our VM calls on centrally cleared interest rate derivatives are so much larger than on 24 June 2016. VM calls on centrally cleared FX derivatives are much smaller than for centrally cleared interest rate derivatives, reflecting the small size of LCH.Ltd's ForexClear service compared with SwapClear. ForexClear only clears non-deliverable forwards, which are just a small part of the FX derivatives market. Its largest daily VM calls and payments in the latest quarter for which data were available at the time of writing (2017 Q4) were \$0.5 billion. This is less than in our (very severe) scenario, but still the same order of magnitude.

For non-centrally cleared derivatives, VM calls in our scenario are \$46 billion for interest rate derivatives and \$177 billion for FX derivatives. Due to netting of VMs across asset classes for non-centrally cleared derivatives, total VM calls are less than the sum of these two amounts at \$201 billion. The figure for FX derivatives may appear high, given that the notional amount of FX derivatives in our analysis is just one-fifth of that of interest rate derivatives. However, in many cases their values change by much more than those of interest rate derivatives in our scenario. For instance, the value of several major currency-pairs changes by double-digit percentages (see Table 2). In contrast, only longer-dated USD swaps, representing around 5% of the interest rate derivatives in our analysis, move this sharply.[15]

[14] The reported data (LCH, 2016) is for the day in 2016 Q2 with the largest VM calls. We presume this was the day after the referendum based on the large movements in swap rates that occurred.

[15] The percentage change in value of an interest rate swap can be approximated by multiplying its

3.2 Liquidity shortfalls: Aggregate

Turning to our main results, we begin by reporting individual liquidity shortfalls as computed by our payment algorithm. Table 3 shows the aggregate value of these shortfalls across our three LAB metrics, breaking it down into fundamental shortfalls on centrally cleared and non-centrally cleared VM obligations and into avoidable and unavoidable domino shortfalls on non-centrally cleared VM obligations. It also shows how this aggregate shortfall varies with the relationship between institutions in a common group. In our most conservative case, institutions in the same group must exchange VMs with each other, just as they would with any other counterparty. However, this is not a requirement in the major jurisdictions and it is not common practice[16] We therefore stress that this should be considered as a worst case scenario. Hence, we also compute aggregate liquidity shortfalls for the case in which institutions do not exchange VMs with group affiliates. As a final case, we treat institutions in a common group as a single consolidated entity.[17] This pools their LABs, recognising that group members experiencing a shortfall may source additional liquidity from elsewhere in the group in preference to borrowing. Of course, VM obligations are also consolidated in this case.

Unsurprisingly, aggregate shortfalls are generally larger when LABs are smaller and when group members operate on a standalone basis and have to exchange VMs between themselves. The aggregate shortfall exceeds \$150 billion in our most conservative case, in which institutions exchange VMs with all counterparties, including other group members, and they use only the derivatives share of their liquid assets in excess of regulatory requirements. However, even this amount is less than 10% of the cash borrowed in

maturity by the change in swap rate (as shown in Table 1) and subtracting one.

[16] For instance, affiliates can be exempted by regulators from requirements to exchange VM in the European Union (EBA, EIOPA and ESMA (2016)) and the United States (Commodity Futures Trading Commission (2016)).

[17] These entities are not necessarily the consolidated groups found in practice, as we do not have all of the subsidiaries of all groups represented in our sample.

	Component of shortfall	Liquid-asset buffers		
		Total cash	Derivatives share of total	Derivatives share of excess over LCR
Institution level (with intra-group margin payments)	Centrally cleared: fundamental	0.0	3.1	22.9
	Non-centrally cleared: fundamental	4.4	18.4	74.9
	Non-centrally cleared: domino unavoidable	0.0	0.2	13.0
	Non-centrally cleared: domino avoidable	0.0	1.7	42.6
	Total	4.4	23.5	153.1
Institution level (without intra-group margin payments)	Centrally cleared: fundamental	0.0	3.1	22.9
	Non-centrally cleared: fundamental	10.8	24.5	51.0
	Non-centrally cleared: domino unavoidable	0.1	0.6	7.6
	Non-centrally cleared: domino avoidable	0.3	1.3	35.8
	Total	11.2	29.5	117.2
Grouped entities (without intra-group margin payments and pooling LABs)	Centrally cleared: fundamental	0.0	2.5	13.5
	Non-centrally cleared: fundamental	0.0	6.8	35.8
	Non-centrally cleared: domino unavoidable	0.0	0.1	2.0
	Non-centrally cleared: domino avoidable	0.0	0.3	3.0
	Total	0.0	9.7	54.2

Table 3: Aggregate liquidity shortfalls in USD billions.

international repo markets on an average day.[18]

The aggregate shortfall falls to zero in our least conservative case, in which group members are treated as consolidated entities and those entities draw on all of their liquid assets to help meet their VM obligations. Treating group members as consolidated entities more than halves the aggregate shortfall, regardless of the LAB metric, as this pools some broker-dealers (facing relatively large VM calls) with some commercial banks (with relatively large LABs).

Reflecting the relative size of VM obligations in our scenario, non-centrally cleared shortfalls contribute more than centrally cleared ones to aggregate liquidity shortfalls. These shortfalls are mainly fundamental in nature. In both simulations at institution level, domino shortfalls become economically significant, especially for the avoidable component. We recall that the avoidable component corresponds to the shortfall that could be avoided if institutions made partial payments.

[18]See e.g. Harris and Taylor (2018) for the sterling repo market, European Central Bank (2015) for euro repo market, and SIFMA (2019) for the US dollar repo market.

Interestingly, non-centrally cleared shortfalls can be larger when individual institutions do not have to post VM to other group members than when they do. This is because payment of intra-group margins happens to move some liquidity to where it is needed, given the margin calls in our scenario. Consistent with that, non-centrally cleared shortfalls decline when individual institutions (not transferring intra-group margins) are consolidated, as this allows them to share liquidity.

3.3 The importance of payment sequencing

In reality, payments to the CCP are made before the CCP pays out, and payments between clearing members on non-centrally cleared derivatives are usually made after these other two types of payment (see Section 2.6). Here we check whether aggregate shortfalls depend on this specific sequencing of payments. To this extent, here we treat the CCP as any other clearing member. In practice, this means that we do not distinguish between centrally cleared and non-centrally cleared VMs. Therefore, the payment algorithm is reduced to the third stage in the payment algorithm described in Section 2.6. We point out that, a priori, shortfalls in this case could be either larger or smaller than shortfalls when payments are sequenced. On the one hand, they could be larger because, being treated as any other clearing member, the CCP can now face a non-zero shortfall. In fact, while inward and outward VM obligations perfectly net out for the CCP, realised inward and outward payments might not offset anymore and the CCP's qualifying liquid resources[19] might not be sufficient to bridge that gap. Moreover, if the CCP fails to make its outward VM payments, clearing members will see their inward payments reduced, further reducing their capability to meet their own VM obligations. On the other hand, they could be smaller because clearing members can now use inward payments made by other clearing members to pay the CCP.

[19] Cash deposited at a central bank of issue of the currency concerned, cash deposited at other central banks, secured cash deposited at commercial banks, and unsecured cash deposited at commercial banks.

	Component of shortfall	Liquid-asset buffers		
		Total cash	Derivatives share of total	Derivatives share of excess over LCR
Institution level (with intra-group margin payments)	Fundamental	4.4	20.5	92.5
	Domino unavoidable	0.0	0.2	12.2
	Domino avoidable	0.0	2.0	111.3
	Total	4.4	22.7	216.0
	Extra shortfall	**0**	**-0.8**	**62.8**
Institution level (without intra-group margin payments)	Fundamental	10.8	26.6	67.6
	Domino unavoidable	0.1	0.5	8.6
	Domino avoidable	0.3	1.6	89.7
	Total	11.2	28.7	166.0
	Extra shortfall	**0**	**-0.8**	**48.8**
Grouped entities (without intra-group margin payments and pooling LABs)	Fundamental	0.0	8.8	45.5
	Domino unavoidable	0.0	0.0	1.9
	Domino avoidable	0.0	0.3	3.5
	Total	0.0	9.1	50.9
	Extra shortfall	**0**	**-0.6**	**-3.3**

Table 4: Aggregate liquidity shortfalls in USD billions. The extra shortfalls generated by neglecting sequencing of payments between clearing members and the CCP are obtained by comparing totals with the results in Table 3.

Table 4 shows the shortfalls for different LABs when the CCP is meeting its obligations as any other market participant. We also show the difference with shortfalls in the case in which payments are sequenced (see Table 3). We can see that neglecting the normal functioning of the market protocols may either increase or decrease the aggregate shortfall in the system. Not surprisingly, the largest differences occur using our most restrictive LAB metric. In the two cases in which entities are not grouped differences are particularly large and driven mostly by the change in domino avoidable shortfalls.

3.4 Liquidity shortfalls: Distribution

Looking within aggregate liquidity shortfalls, the top panel of Figure 5 shows shortfalls at grouped entities when using only the derivatives share of their excess liquid assets to meet VM obligations. Almost one-third of our grouped entities have non-zero shortfalls,

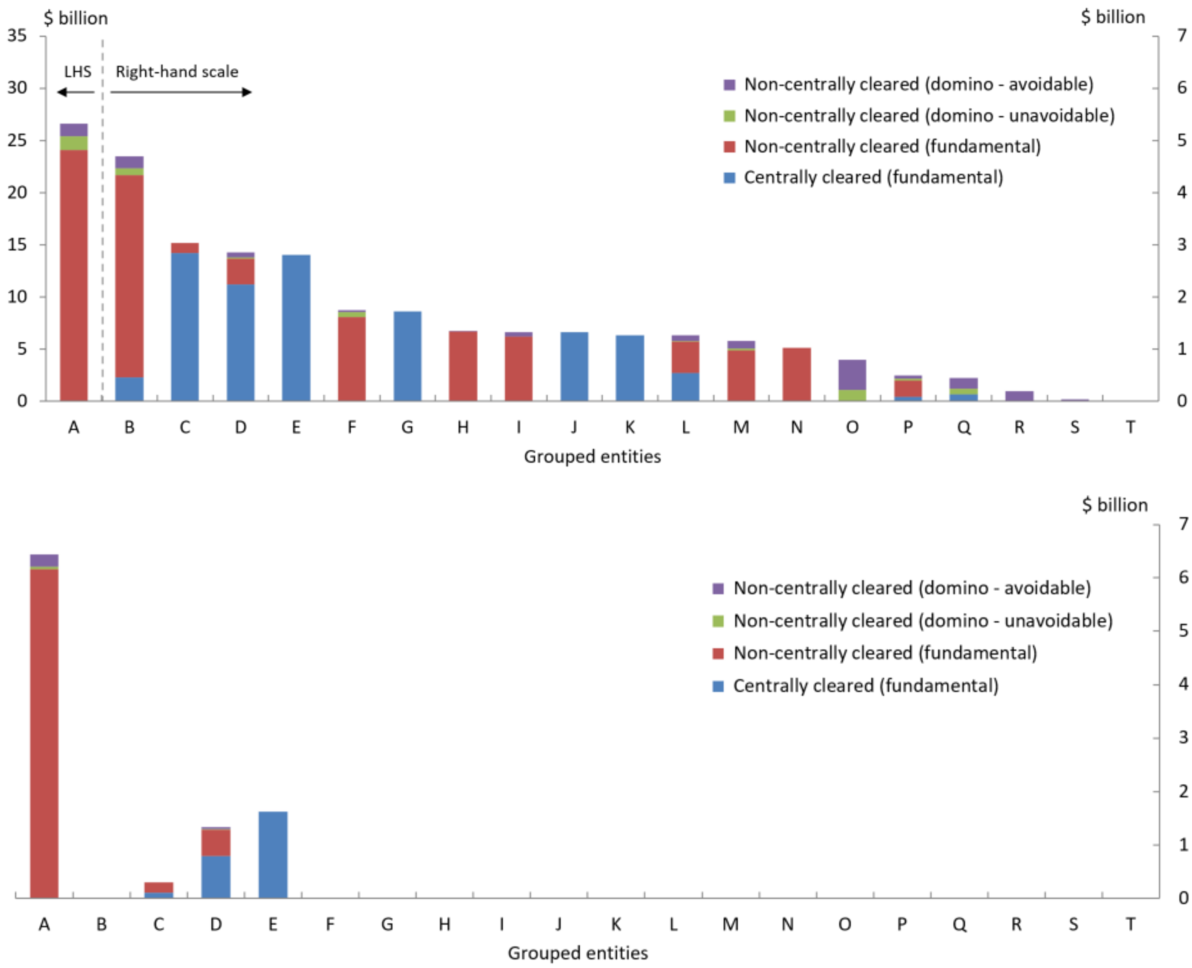


Figure 5: Liquidity shortfalls at grouped entities, using either the derivatives share of excess liquid assets over LCR requirements (top panel) or the derivatives share of total liquid assets (bottom panel) to help meet VM calls. Note that the left scale of the top panel only refers to grouped entity A.

with one group having a significantly larger shortfall than the others. For most of these groups, fundamental liquid-asset shortfalls – whether relating to centrally cleared or non-centrally cleared VM payments – are the main contributors to the overall shortfalls. Only in a few cases are domino shortfalls more important.

The effect of larger LABs can be seen by comparing these results with the bottom panel of Figure 5, which shows liquidity shortfalls at grouped entities when they use the derivatives share of their total (rather than excess) liquid assets to help meet VM obligations. In this figure, shortfalls are reduced at every group, such that only four still have a non-zero shortfall. Furthermore, all shortfalls are eliminated when grouped entities use their entire liquid-asset holdings to help meet VM calls (as shown in the bottom-left cells in Table 3).

The effect of consolidating group members can be seen by comparing the top panel of Figure 5 with the top panels of Figures 6 and 7, which shows shortfalls at individual institutions using only the derivatives share of their excess liquid assets to help meet VM obligations. We can see the consolidation of the LABs facilitates timely payments by a number of groups, avoiding many of the non-centrally cleared domino shortfalls (shown in green and purple in Figures 6 and 7). From the bottom panels of Figures 6 and 7 it is clear that, similarly to the case of grouped entities, for larger LABs only a handful of institutions face shortfalls.

3.5 Contributions to aggregate liquidity shortfalls

Next, we show contributions to the aggregate liquidity shortfall. We define the contribution of one institution as the amount by which the aggregate shortfall would be reduced if that institution had a large enough LAB to make all its payments in full. This can be interpreted simply as the amount of aggregate shortfall that institution is responsible for. To compute these, we run counterfactual experiments. In particular, for each of our grouped entities, i, we run our payment algorithm on the same data as previously except that we supplement i's LAB such that it can just meet all its VM obligations without borrowing. We then compute i's contribution to the aggregate liquidity shortfall as the difference between the aggregate shortfall when i has its real LAB and the aggregate shortfall when it has its counterfactual LAB.[20] As i is just able to meet its VM obligations without borrowing in the experiment, its contribution to the aggregate shortfall is

[20] This is similar to 'net financial centrality' as in Jackson and Pernoud (2019), which captures aggregate portfolio losses in excess of institution i's direct loss that stem from that latter loss.

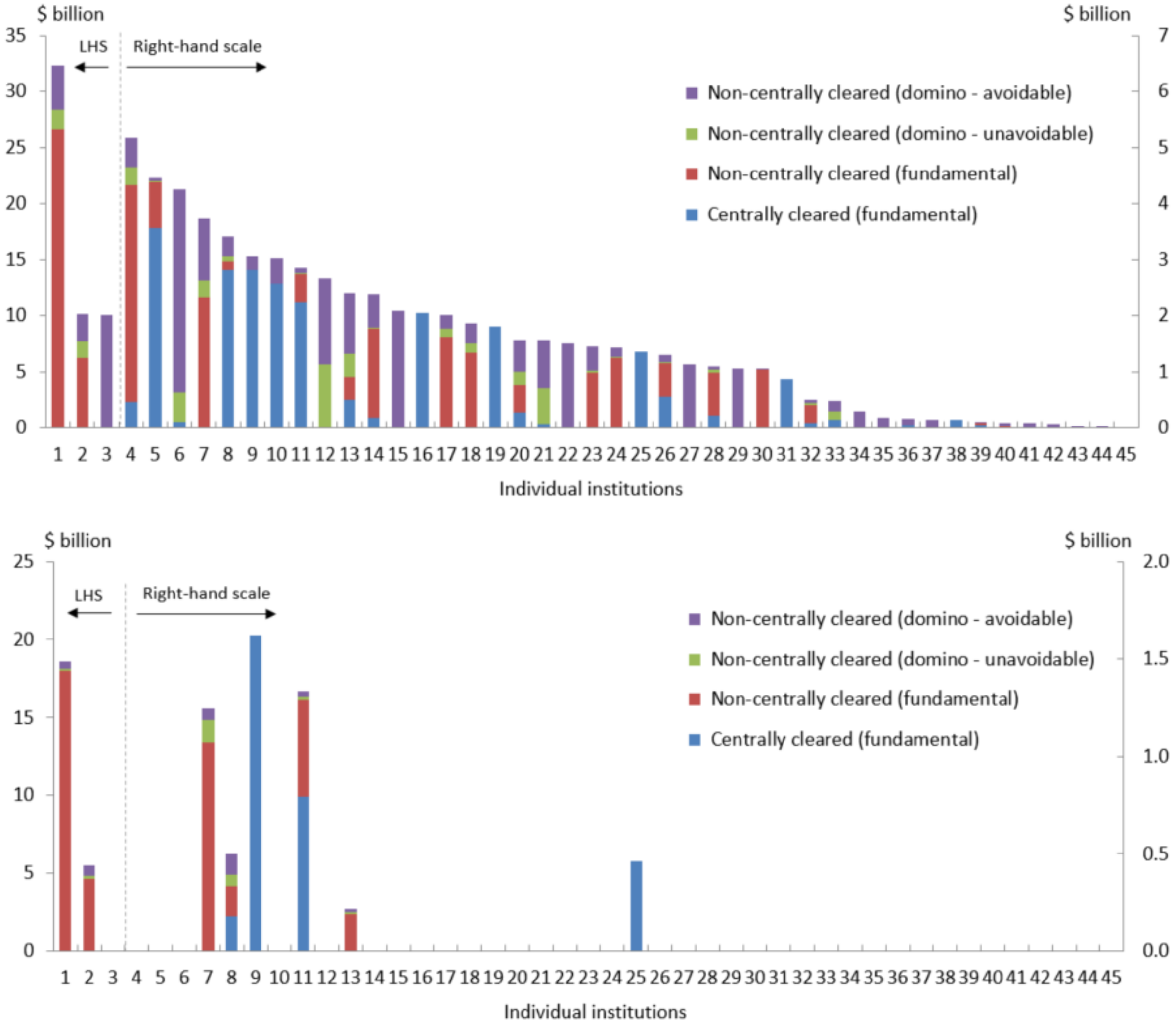


Figure 6: Liquidity shortfalls at individual institutions, using either the derivatives share of excess liquid assets over LCR requirements (top panel) or the derivatives share of total liquid assets (bottom panel) to help meet VM calls and assuming no intra-group VM obligations. Note that the left scale only refers to individual institutions 1, 2, and 3.

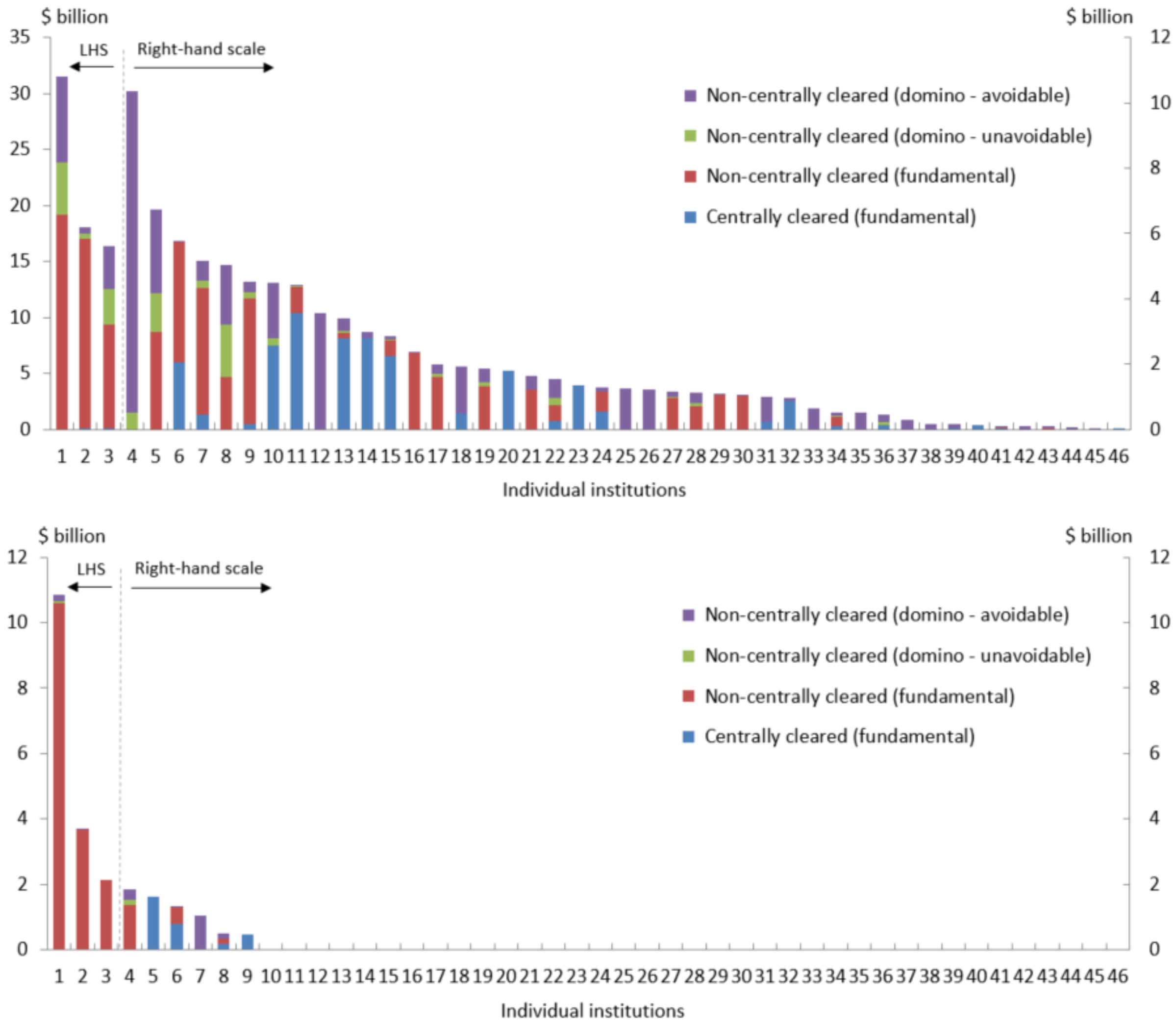


Figure 7: Liquidity shortfalls at individual institutions, using either the derivatives share of excess liquid assets over LCR requirements (top panel) or the derivatives share of total liquid assets (bottom panel) to help meet VM calls and assuming intra-group VM obligations. Note that the left scale only refers to individual institutions 1, 2, and 3.

at least its individual shortfall. It is more than this if receipt of payments from i additionally allows downstream counterparties to meet more of their VM obligations without borrowing.[21] Of course, if i can meet all of its VM obligations from its real LAB without borrowing, its individual shortfall and contribution to the aggregate shortfall are both zero.

Figure 8 shows contributions of our grouped entities to the aggregate shortfall alongside their individual liquidity shortfalls. Where these are equal, the shortfall at the group has no consequences for downstream counterparties. That is, failure of the group to meet its VM obligations prior to borrowing at the end of the day does not stop any of its counterparties from meeting their VM obligations on a timely basis. In contrast, where the amounts differ, counterparties are prevented from making timely payments. Potentially, this can spread to counterparties of counterparties, and so on. For instance, the top panel shows that, when using only the derivatives share of their excess liquid assets to meet VM obligations, Group A's individual shortfall of \$26.6 billion leaves other institutions short of cash to the extent that they need to borrow \$1.8 billion to help meet their VM obligations. Hence, A's contribution to the aggregate shortfall is \$28.4 billion.

The contribution to the aggregate shortfall of i can be interpreted as the reduction in the aggregate shortfall that would result from injecting additional liquidity in this entity such that it can just meet its VM obligations without borrowing. The cost of achieving this reduction is the amount of additional liquidity needed, which is equal to the individual shortfall of i. We define the 'bang-for-buck' ratio for i as the quotient of its contribution to the aggregate shortfall and its individual shortfall. This measures how many dollars the aggregate shortfall is reduced on average for each dollar of liquidity injected into i. The bang-for-buck ratios for our grouped entities are shown in Figure

[21] Hence, the sum of contributions to the aggregate liquidity shortfall generally exceeds the aggregate shortfall itself. Nevertheless, the relative size of these contributions remains valuable as it identifies institutions that spread the most liquidity stress.

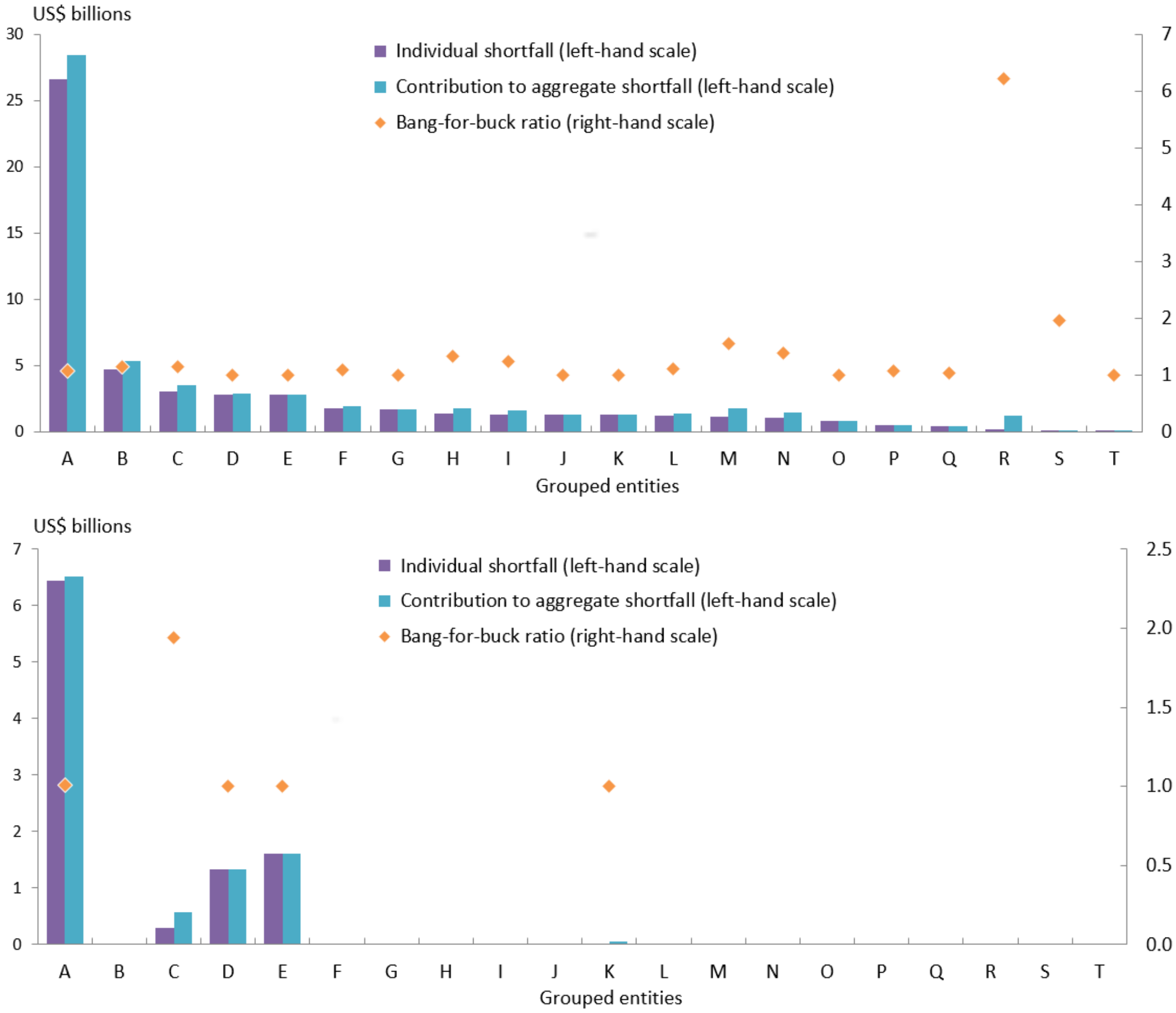


Figure 8: Contributions and 'bang-for-buck' ratio of grouped entities to aggregate shortfall vs their individual shortfalls using either the derivatives share of excess liquid assets over LCR requirements (top panel) or the derivatives share of total liquid assets (bottom panel) to help meet VM calls.

8. A regulator concerned with systemic liquidity risk might wish to focus any bolstering of LABs on entities with larger bang-for-buck ratios.[22] We can see that, for both LAB metrics, many institutions have a bang-for-buck ratio larger than one. This means that the effects of liquidity injections targeting those institutions are positively amplified, yielding a reduction in the aggregate shortfall that is larger than the injection itself.

4 Conclusion

Drawing on granular data on institutions' derivatives holdings and liquid assets, we have developed a model for computing liquidity shortfalls in a stress scenario. As institutions address these shortfalls by taking defensive actions that could impose costs not only on themselves but also on other market participants, the shortfalls themselves are the source of an externality. For example, when institutions address liquidity shortfalls by borrowing on the repo market, this could push up the repo rate not only for themselves but for other borrowers too if liquidity shortfalls are large enough. Moreover, a component of these shortfalls, which we compute, reflects a coordination failure, at least some of which is avoidable. We also compute contributions of individual entities (or grouped entities) to the aggregate shortfall and suggest the ratio of this measure to individual shortfalls as a useful metric for regulators wanting to inject liquidity into the system where it is most needed.

We apply our model to the 2018 US CCAR 'Severely Adverse' scenario. In this scenario, some of the trading book shocks move asset prices more sharply than ever before, including during the 2007-08 global financial crisis. For this scenario, we find that, even in aggregate, simulated liquidity shortfalls would be only a modest fraction of average daily cash borrowing in the repo market, even when using the most conservative

[22] It would be wise to do this for entities with high bang-for-buck ratios across many scenarios, rather than for a single scenario, as shown here.

assumptions about the liquid assets available to meet margin calls. This suggests that VM calls seem unlikely to be a source of significant liquidity stress at present. However, this may reflect the historically high cash buffers of many institutions following an extended period of low interest rates and quantitative easing in the major jurisdictions. Hence, it would be prudent to update our simulations on a regular basis to monitor the evolution of liquidity risk in the derivatives market.

Our model could also be extended along a number of dimensions. First, more institutions could be added, including the financial clients of clearing members. Second, more types of derivatives could be added, including those linked to credit, equities and commodities. Finally, more scenarios could be considered. Ideally, the model would be run for many fixed scenarios, with results aggregated over them on each update.

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A List of entities

Table A.1 lists the institutions covered in our analysis. The shading in the table distinguishes the entities that we consolidate into groups.

Abbey National Treasury Services PLC	Credit Suisse (Switzerland) Ltd	MUFG Securities EMEA PLC
Banco Santander SA	Credit Suisse AG	National Australia Bank Ltd
ABN AMRO Bank NV	Credit Suisse International	National Bank of Canada
ABN AMRO Clearing Bank NV	Credit Suisse Securities (USA) LLC	Natixis SA
Australia and New Zealand Banking Group Ltd.	Danske Bank A/S	Nomura Financial Products & Services Inc.
Banca IMI SpA	DekaBank Deutsche Girozentrale	Nomura Global Financial Products Inc.
Banco Bilbao Vizcaya Argentaria SA	Deutsche Bank AG	Nomura International PLC
Bank of America NA	Deutsche Postbank AG	Norddeutsche Landesbank Girozentrale
Merrill Lynch Capital Services Inc.	Dexia Credit Local	Nordea Bank AB
Merrill Lynch International	DNB Bank ASA	RBC Capital Markets LLC
Merrill Lynch, Pierce, Fenner & Smith Inc.	DZ Bank AG	Royal Bank of Canada
Bank of Montreal	FirstRand Securities Ltd	SG Americas Securities LLC
Bank of New Zealand	Goldman Sachs & Co. LLC	Societe Generale International Limited
Bankia SA	Goldman Sachs Bank USA	Société Générale SA
Banque Palatine SA	Goldman Sachs Financial Markets Pty Ltd.	Skandinaviska Enskilda Banken AB
Credit Foncier de France	Goldman Sachs International	SMBC Capital Markets Inc
Barclays Bank PLC	HBSC Ltd.	Standard Chartered Bank
Barclays Capital Inc.	HSBC Bank PLC	Swedbank AB
Bayerische Landesbank	HSBC Bank USA NA	The Bank of New York Mellon
Belfius Bank SA/NV	HSBC France	The Bank of Nova Scotia
BNP Paribas	HSBC Securities (USA) Inc.	The Royal Bank of Scotland PLC
BNP Paribas Fortis SA/NV	ING Bank NV	The Toronto-Dominion Bank
BNP Paribas Securities Corp.	ING Bank Slaski SA	UBS AG
CACEIS Bank SA	ING-DiBa AG	UBS Ltd.
Credit Agricole Corporate and Investment Bank	J.P. Morgan AG	UBS Securities, LLC
CaixaBank SA	J.P. Morgan Securities LLC	UniCredit Bank AG
Canadian Imperial Bank of Commerce	JPMorgan Chase Bank NA	UniCredit Bank Austria AG
Citadel Securities (Europe) Ltd.	KBC Bank NV	UniCredit SpA
Citadel Securities Swap Dealer LLC	Landesbank Baden-Württemberg	Wells Fargo Bank NA
Citibank NA	Landesbank Hessen-Thüringen Girozentrale	Wells Fargo Securities LLC
Citigroup Global Markets Inc.	Lloyds Bank PLC	Westpac Banking Corporation
Citigroup Global Markets Ltd.	Mizuho Capital Markets LLC	Zurcher Kantonalbank
Commerzbank AG	Mizuho International PLC	LCH Ltd.
Commonwealth Bank of Australia	Morgan Stanley & Co. International PLC	
Coöperatieve Rabobank UA	Morgan Stanley & Co. LLC	
	Morgan Stanley Capital Services LLC	

Table A.1: List of entities.