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David Murphy⁽¹⁾ and Nicholas Vause⁽²⁾

Abstract

Following a period of relative calm, many derivative users received large margin calls as financial market volatility spiked amid the onset of the Covid-19 global pandemic in March 2020. This reinvigorated the policy debate about dampening such 'procyclicality' of margin requirements. In this paper, we suggest how margin setters and policymakers might measure procyclicality and target particular levels of it. This procyclicality management involves recalibrating margin model parameters or applying anti-procyclicality (APC) tools. Different options reduce procyclicality by varying amounts, and do so at different costs, which we measure using the average additional margin required over the cycle. Thus, we perform a cost-benefit analysis (CBA) of the different options. We illustrate our approach using a popular type of margin model – filtered historical simulation value-at-risk – on simple portfolios, presenting the costs and benefits of varying a key model parameter and applying a number of different APC tools, including those in European legislation.

Key words: Central counterparty, cost-benefit analysis, derivatives clearing, initial margin models, mandatory clearing, procyclicality.

JEL classification: G17.

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1. Introduction

After losses cascaded between derivative counterparties during the 2007-08 global financial crisis, international regulators required most derivative exposures to be backed by collateral. Not only did that require *variation margin* (VM) to be posted against the current value of exposures, but also *initial margin* (IM) to be posted against their potential future value, both for centrally cleared (CPSS-IOSCO, 2012) and non-centrally cleared (BCBS-IOSCO, 2013) derivatives. Those rules mandated practices that were already ubiquitous for exchange-traded derivatives to over-the-counter (OTC) derivatives, and led to more than US\$1 trillion of additional collateral supporting derivative positions (FSB, 2017).

While mandating collateralisation has reduced counterparty credit risk, it has increased liquidity risk. This is because changes in more derivative exposures now necessarily lead to margin calls, all of which must be settled in cash or, where acceptable, other liquid assets. This likely effect was known when the post-2008 Global Financial Crisis (GFC) standards were introduced, and policy makers sought to mitigate it. While there is little that can be done to reduce VM calls, which are driven by observable changes in market prices, the standards called on margin setters to avoid sharp increases in IM requirements, notably in periods of market stress:

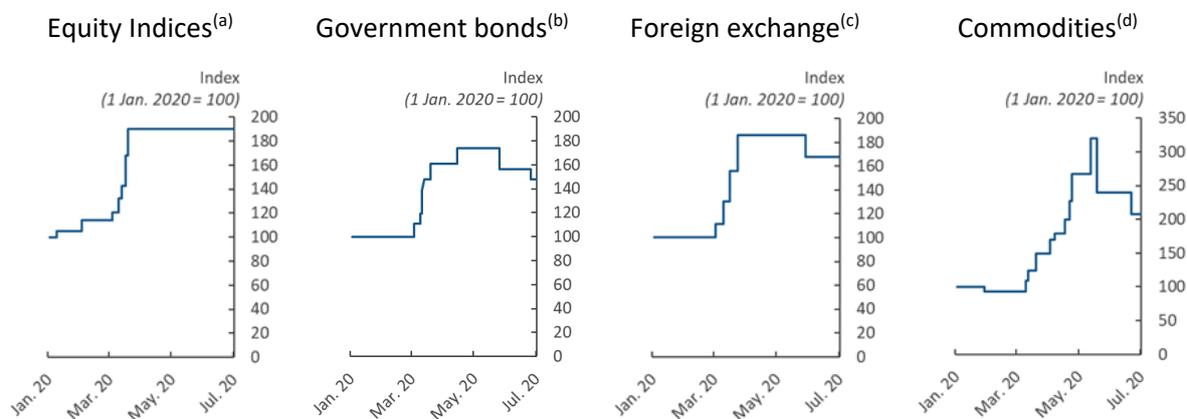
“To the extent practicable and prudent, a [central counterparty (CCP)] should adopt forward-looking and relatively stable and conservative margin requirements that are specifically designed to limit the need for destabilising, procyclical changes.” – CPSS-IOSCO (2012).

“The build-up of additional initial margin should be gradual so that it can be managed over time. Moreover, margin levels should be sufficiently conservative, even during periods of low market volatility, to avoid procyclicality.” – BCBS-IOSCO (2013).

1.1 Insights from the Covid stress

Financial market volatility in March 2020 related to Covid-19 provided a real-life stress-test of the new derivatives collateralisation regime. In contrast to the GFC, the stress did not result in widespread concern about counterparty risk. Given the sharp moves in asset prices, however, VM calls naturally increased to multiples of typical values in the prior period. Moreover, IM requirements for centrally cleared derivatives increased sharply, more than doubling for some exchange-traded derivatives, as Figure 1 illustrates.

Figure 1: Initial margin requirements for selected exchange-traded futures in 2020 H1



Sources: CME Group and Bank calculations.

(a) S&P 500 future, (b) 10-year US Treasury note future, (c) USD/JPY future, (d) WTI oil future.

This behaviour prompted both market participants and regulators to ask whether the procyclicality of IM models should be further reduced:

“[The FIA] urges all stakeholders in the global clearing system to consider what steps can be taken to mitigate the procyclicality of margin models ...” – Futures Industry Association (FIA, 2020).

“We need to be sure that derivatives clearing and margining can adjust to sharp price changes as efficiently and smoothly as possible. We need also to dampen down as far as possible procyclical effects without reducing appropriate protection against counterparty credit risk.” – Sir Jon Cunliffe, Deputy Governor of the Bank of England and Chair of the Committee on Payments and Market Infrastructures (‘CPMI’) (Cunliffe, 2020).

1.2 Our contribution

In this paper, we develop a framework which quantifies the benefits and costs of alternative approaches to mitigating the procyclicality of IM models, allowing them to be compared.

Less procyclical margin requirements can bring two benefits. First, it can reduce the size of large margin calls at times of stress, which, other things equal, would make them easier to fund. Second, it can lower the range of margin requirements over the financial cycle, reducing the scope for derivative users to establish high levels of leverage when margin requirements were low, only to be forced to deleverage when they are relatively high. Drawing on earlier work (Murphy et al. 2014), we respectively define a *large-call* (LC) and a *peak-to-trough* (PT) metric to help quantify these benefits. These provide simple measures of the two aspects of procyclicality, allowing different models to be compared.

These two aspects of procyclicality are reflected in the quotes from the post-GFC standards above.¹ The intention that IM models should “limit the need for destabilising, procyclical changes” and that “the build-up of additional IM should be gradual” helps to motivate our LC measure. Similarly, the desire that IM requirements should be “relatively stable” and “sufficiently conservative, even during periods of low market volatility” helps to motivate our PT measure.

Different approaches to procyclicality mitigation often have the effect of boosting margin requirements during normal times, as then they do not have to jump as much to reach appropriate levels in stress times. Higher average margin requirements are costly, however, as they require derivative users to hold more collateral-eligible assets than otherwise. These assets tend to be relatively liquid but low yielding. Hence, we use an *average cost* (AC) metric to record average margin requirements over the financial cycle.² This cost dimension has sometimes been missing from the procyclicality debate.

We use this framework to assess the benefits and costs of several alternative approaches to procyclicality mitigation. These include the anti-procyclicality (APC) tools in European Market Infrastructure Regulation (EMIR), as well as some other APC tools of our design. These are all applied as add-ons to a baseline margin model. One other approach to procyclicality mitigation that we consider is to vary parameters in the baseline model, without any add-on.

¹ See also CPSS-IOSCO (2017) and ESMA (2018).

² The cost of funding a given margin requirement will depend on the individual poster’s funding cost. As this is not known, we use the total dollar amount to be funded as a proxy for the actual cost.

These different approaches result in different margin requirements in normal and, especially, stress times. While there is no unequivocal notion of the correct level of margin, we require a certain level of confidence that margins should cover the derivative user's value-at-risk (VaR). Hence, we require that all approaches should pass backtesting.

Our framework could be used by CCPs and policymakers to assess alternative approaches to procyclicality mitigation and choose those with the best cost-benefit trade-offs. One possible way in which this could work is that policymakers could set a target level of procyclicality (i.e. a target for LC or PT) and CCPs could use the framework to find the least cost (i.e. lowest AC) approach that delivers it.

1.3 Related work on margin procyclicality

This paper builds on earlier work on margin procyclicality, including by the authors. Murphy et al. (2014) propose the LC and PT procyclicality measures and show that their values can differ substantially across different types of IM model. Murphy et al. (2016) then investigate how different APC tools trade-off reduced procyclicality for IM requirements that are less close to the portfolio value-at-risk (VaR). That paper assumes the process generating portfolio returns is known, so IM requirements from the baseline model cover the true portfolio risk perfectly and the APC tools generate over-margining (or sometimes under-margining) relative to that. This paper adds realism by relaxing that assumption, reflecting the inability to precisely estimate risk in practice.³ This means we lose the ability to compare IM with the 'true' requirement. Instead, we ensure our IM models are sufficiently accurate by requiring them to pass backtesting, and we then trade off procyclicality and *average* IM requirements rather than procyclicality and *inaccurate* IM requirements.

Glasserman and Wu (2018) show that the cost-benefit trade-off is generally an expensive one because the conditional distribution of portfolio VaRs typically has a long right tail, so high buffers are needed in calm market conditions to cover the difference between current risk and tail risk, and thus reduce procyclicality. Relatedly, O'Neill & Vause (2018) study how derivative users are incentivised to set their liquid-asset buffers, finding that they choose to hold sufficient liquid assets to cover most potential margin calls but not the most-extreme ones. However, a releasable margin buffer could force them to hold more liquid assets than otherwise, reducing the likelihood of liquidity shortages and hence the scale of an associated fire-sale externality. Bakoush et al. (2018) and Cont & Schaanning (2017) also study the mechanism through which margin calls generate stressful liquidity demands and, potentially, a systemic crisis, while Lewandowska & Glaser (2017) analyse the evidence for this mechanism in practice.

Our perspective on procyclicality in this paper is that a model that passes (a suitable selection of) backtests is acceptable. Both Raykov (2018) and Goldman & Shen (2020) go further by studying a trade-off between risk sensitivity and procyclicality. This could be taken forward in practice by allowing margin in stress to be lower than that suggested by the model, and capturing the deficiency in the CCP's default fund. This might, of course, imply using a model that failed some aspects of backtesting. Raykov shows when this mutualisation of risk via the default fund creates harmful side effects due to moral hazard and when it improves market liquidity, while Goldman & Shen show which IM models perform best for a given trade-off function.

³ See Danielsson et al. (2016) for a discussion of this issue.

In work similar in concerns to ours, Maruyama & Cerezetti (2019) propose an outcome-based approach to procyclicality, i.e. one guided by procyclicality measures, and use it to examine the behaviour of the EU APC tools in the oil market. Like us, they also advocate enhanced disclosure of margining practices. Relatedly, Gurrola-Perez (2020) examines the behaviour of margin models during the Covid stress, arguing for a holistic approach to procyclicality including both IM and VM, and – unlike Goldman & Shen (2020) and Raykov (2018) – arguing that margin should keep the CCP adequately collateralised at all times, while ensuring that central clearing is economically efficient.

1.4 Related work on cost-benefit analysis of financial regulation

Compared to areas such as environmental policy, cost-benefit analysis has come relatively late to financial regulation: see Coates (2015) and Posner & Weyl (2014) for a discussion. As these authors describe, this is partly due to the difficulty of quantifying the benefits of taking measures which reduce the probability of events like financial crises, which are already unlikely but severe if they occur.⁴ Nevertheless, CBA often offers an effective way of “organising and communicating the pros and cons”⁵ of a particular regulation, as we illustrate here.

Indeed, in the US, the Administrative Procedures Act allows regulatory (and some other) decisions to be set aside if they are “arbitrary, capricious, an abuse of discretion, or otherwise not in accordance with law.”⁶ Since the advent of this Act, cost-benefit analysis has become a popular tool for demonstrating that regulation is not arbitrary or capricious. This has been further strengthened by the requirement to demonstrate the proportionality of action by the European Union⁷ and by the perceptions that US Courts are more likely to strike down regulation which has not been justified by cost-benefit analysis.⁸

2. Methodology

This section presents our methodology for conducting a cost-benefit analysis of methods of reducing initial margin procyclicality. Specifically, ways to reduce procyclicality are compared based on their benefits as measured by their effects on the LC and PT measures, and their costs in terms of the AC metric.

Our approach is primarily illustrated using a single-derivative portfolio comprised of a JPY/USD foreign exchange (FX) futures contract, for which a long history of price data is readily available. However, results for additional portfolios with rather different return distributions (but still only a small number of derivatives) are also presented. In practice, clearing members would have much more complicated portfolios than these, but the same methodological approach could be applied.

The methodology has four steps. First, using daily data on the JPY/USD FX rate, we derive a time series of IM requirements for our futures contract using an industry standard filtered historical simulation (FHS) value-at-risk model. Initial margin in these models depends on a parameter, the decay constant, which controls how much information about past returns is used in current risk estimation. Hence, in the second step, we vary the value of this parameter and keep only those values for which the IM model still passes a backtest. In the third step, we show how varying the parameter within this

⁴ See in particular the discussion in Coates (2015) of the SEC's CBA of its cross-border swaps rule at 978.

⁵ *Ibid* at 1009.

⁶ 5 U.S.C. § 706(2)(A).

⁷ §4, Article 5, Treaty on European Union. All of the regulations discussed in this paper are implemented at the EU level, and hence are covered by this Article.

⁸ See Sunstein (2017) for a discussion.

retained range affects the trade-off between procyclicality and average cost. In case they can do better, a fourth step applies different APC tools to the baseline IM model (i.e. with the original decay parameter setting) and shows how they affect the trade-off between procyclicality and average cost. Each of these steps is discussed briefly below, while Annex 1 contains the technical details.

2.1 Baseline initial margin model

We set IM requirements equal to the one-day 99.5% FHS VaR of the portfolio, which we derive from historical data. For this, we collect daily data on the JPY/USD FX rate. After cleaning, we obtain 9,300 end-of-business-day observations from January 1984 to October 2020. We compute exponentially weighted moving average (EWMA) volatilities using a decay constant, λ , and ‘devolatilise’ the returns by dividing them by the EWMA volatility. We use a 500-day historical simulation window, so the 99.5% FHS VaR for a day t is the third-worst devolatilised return in the 500 days going back from t , multiplied by the EWMA volatility at t .⁹ This procedure gives a time series of FHS VaRs starting in January 1986 (i.e. 500 days after the start of the returns series).

2.2 Backtesting

The VaR estimate is strongly dependent on the choice of λ in the EWMA volatility estimation. In order to ensure that all the models studied are acceptably accurate, we confine attention to those which cannot be rejected by the Kupiec (1995) Proportion of Failures backtest at the 99% significance level.¹⁰ This is a popular test both in the literature and in practice, although sophisticated model designers would typically also combine it with other tests.¹¹

2.3 Cost and benefit measures

As introduced above, we use two procyclicality metrics to quantify the benefits of procyclicality mitigation:

- A *large-call* (LC) measure captures a plausible very large increase in margin requirements over a 20 business-day window for the portfolio under analysis.¹² This is inspired by the Basel III Liquidity Coverage Ratio, which requires banks to hold sufficient liquid assets to meet net outflows over 30 calendar days of stress. This measure focusses on increases in margin requirements over short periods of intensifying stress.
- Longer-term procyclicality is captured by a *peak-to-trough* (PT) measure. This is the ratio of (close to) the highest to lowest IM requirements over the financial cycle for the portfolio.¹³ Low IM requirements when markets are placid can allow derivative users to establish relatively large positions. As the cycle turns and IM requirements increase, however, those collateral requirements may cause funding stress. In extremis, they might no longer be affordable, and some leverage-sensitive derivative users might be forced to unwind some of their positions. The PT measure captures the potential size of this effect. For instance, if the derivative user had a portfolio with a PT measure of 2, it may have to liquidate up to 50% of that portfolio in stressed

⁹ One could argue for an average of the second and third worst returns, but the choice makes little difference in practice.

¹⁰ See Gurrola Perez (2018) for a discussion of the validation of FHS VaR models like the one used in this paper.

¹¹ The effect of using more stringent backtests would be to reduce the range of acceptable λ s. However, there is good evidence that FHS VaR models are robust performers, so there will likely be some values of λ which are acceptable. See Buczyński & Chlebus (2020) for a discussion of these models and their competitors.

¹² Specifically, we pick the 99.7th percentile of the distribution of increases in margin over a 20 business-day period. This is used rather than the maximum to reduce the effects of statistical ‘noise’ in the very far tail of observations and, hence, to make the measure more stable for different observation windows.

¹³ Here we use the ratio of the 99.7th percentile of margin requirements to the 0.3rd percentile, again to reduce statistical ‘noise’ from the far tail. One could alternatively use averages in the far tails, similar to an expected shortfall measure.

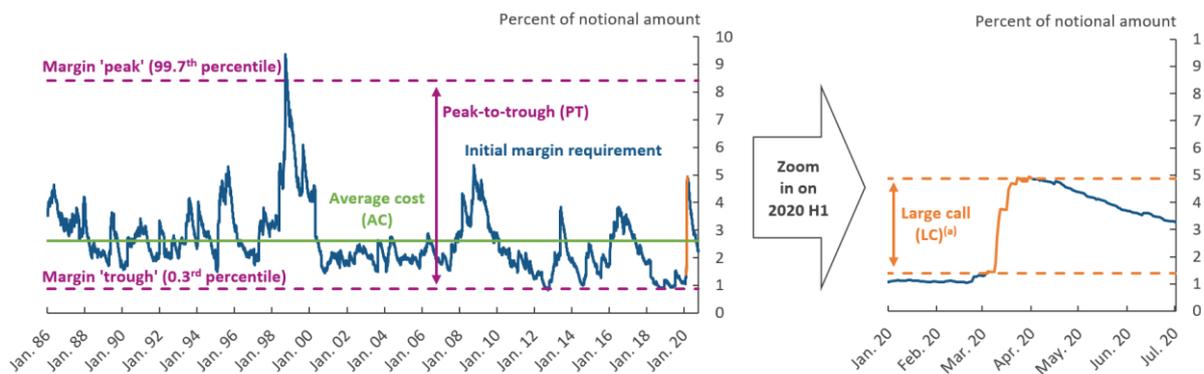
market conditions (assuming an otherwise unchanged financial position and that no extra liquidity was available).

We also have a single cost metric:

- *Average cost (AC)* is the average margin requirement for the portfolio over the financial cycle. If derivative users did not have to post a share of their assets as initial margin collateral, they would not have to hold this share in liquid but low-yielding investments. The precise opportunity cost to a particular derivative user also depends on the additional yield available to it on alternative investments. However, in the absence of that information, we focus solely on the quantity of collateral that derivative users must post.

These three metrics are illustrated in Figure 2, which plots the time series of initial margin requirements for our JPY/USD futures contract using a benchmark FHS VaR model with $\lambda = 0.98$.¹⁴

Figure 2: Large-call procyclicality, peak-to-trough procyclicality and average cost of an IM model^(a)



Sources: Federal Reserve Economic Data and Bank calculations.

(a) Each daily IM requirement is equal to the third-worst volatility-scaled USD/JPY return from the past 500 days rescaled by conditional volatility, which is estimated using a EWMA model with a decay parameter of 0.98. (b) Large-call procyclicality is the 99.7th percentile of increases in IM requirements within a 20 business-day period.

We first investigate the effects on LC, PT and AC of varying the decay parameter (within a range such that the model still passes backtesting) in our baseline model.

2.4 Antiprocyclicality tools

We next investigate the effects of APC tools, beginning with the three in EMIR.¹⁵ These are:

- (i) a *floor* level set at the 10-year unweighted VaR;
- (ii) a 25% *buffer* on top of IM requirements that is drawn down in stress;
- (iii) a 25% weight given to *stressed* periods in calibrating IM requirements.

In addition, two further tools are studied:

- (iv) an *adaptive* variant of (iii) introduced in Murphy et al. (2016) in which the weight given to stressed observations increases when IM requirements are low and decreases when they are high; and
- (v) a model that *caps* IM requirements at a high level.

¹⁴ The $\lambda = 0.98$ FHS VaR model passes all the relevant backtests and is a common choice in practice.

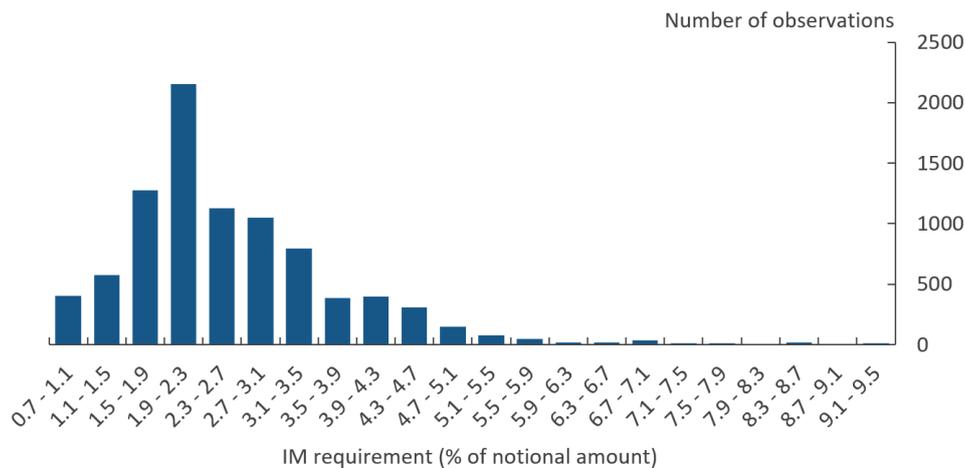
¹⁵ These tools also remain in operation in the UK in 2021, following its departure from the European Union.

In each case, we compute the LC, PT and AC metrics and study the benefits and costs of using the tools, for given values of λ . Further details on the specification of the five APC tools is available in Annex 1.

3. Results

This section presents results for the JPY/USD FX futures contract. In particular, we will plot LC or PT against AC for the range procyclicality mitigation techniques. Before that, however, the distribution of IM requirements for the baseline (pre-mitigation) model is presented in Figure 3, as this helps to explain much of the following material.

Figure 3: Historical distribution of IM requirements for the baseline model^(a)



Sources: Federal Reserve Economic Data and Bank calculations.

(a) IM requirements as in Figure 2.

Three features of this distribution are notable for our purposes:

1. The most common situation is margin of around 2.5% of notional amount, with margin in the relatively tight interval of [1.9%, 3.1%] about half the time;¹⁶
2. The distribution of margin has a very fat right tail. This is because stressed episodes are unlikely, but when they do occur, they generate significantly higher risk estimates – and hence margin requirements – than ordinary conditions. Average margin is 2.6% of notional amount, but margin of more than three times this amount occurs on 43 days out of the total of 8,874, or 0.48% of the time;
3. Very placid periods in the left tail also occur. Margin is less than half the average on 699 days out of the total, or 7.9% of the time.

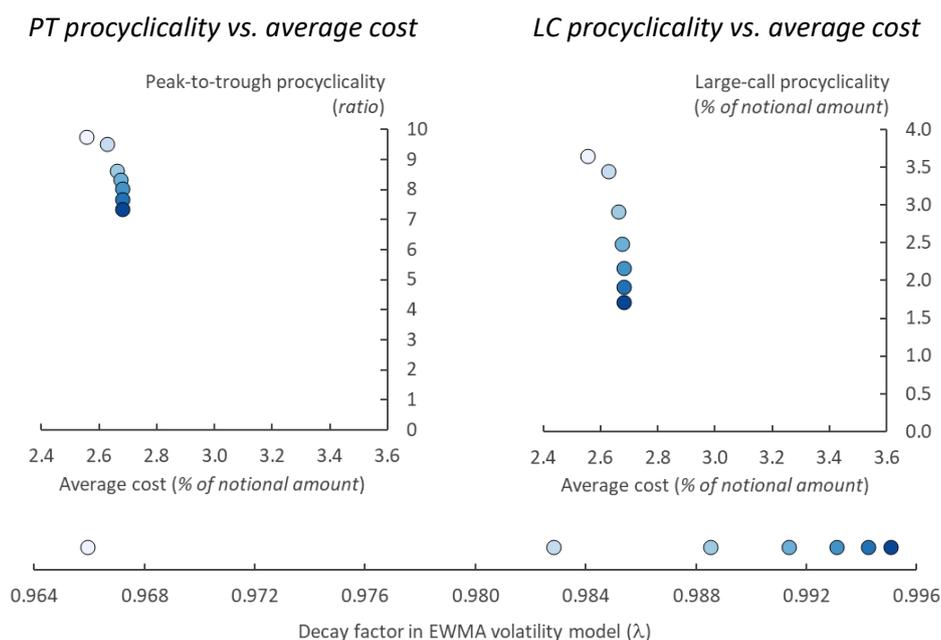
Transitions from the placid periods (noted in point 3) to ordinary or, especially, stressed conditions generate the most common situations where there is a danger of deleveraging, while the stressed conditions (identified in point 2) tend to create the largest short-term margin calls.

¹⁶ CCPs may prefer more procyclical margin models, especially when there is competition in clearing a product, because such models allow them to offer lower levels of margin during these extended placid periods. The question for public policy is whether the impact of such incentives should be constrained by regulation.

3.1 Unmitigated models

Figure 4 presents the results for the unmitigated FHS model with decay constants ranging from 0.96 to 0.995. As the decay constant increases, procyclicality – on both the PT and LC measures – goes down. This is intuitive: models with λ closer to 1 react relatively slowly to new data, and hence the margin requirements they produce are less variable. The average cost of higher λ models goes up at first and then levels off, but the variation is not large compared with using some of the procyclicality mitigation tools (see below). For this single-derivative portfolio, procyclicality mitigation can be achieved at low cost by turning up the model’s decay constant.

Figure 4: Procyclicality-cost trade-off for IM model with different λ values^(a)



Sources: Federal Reserve Economic Data and Bank calculations.

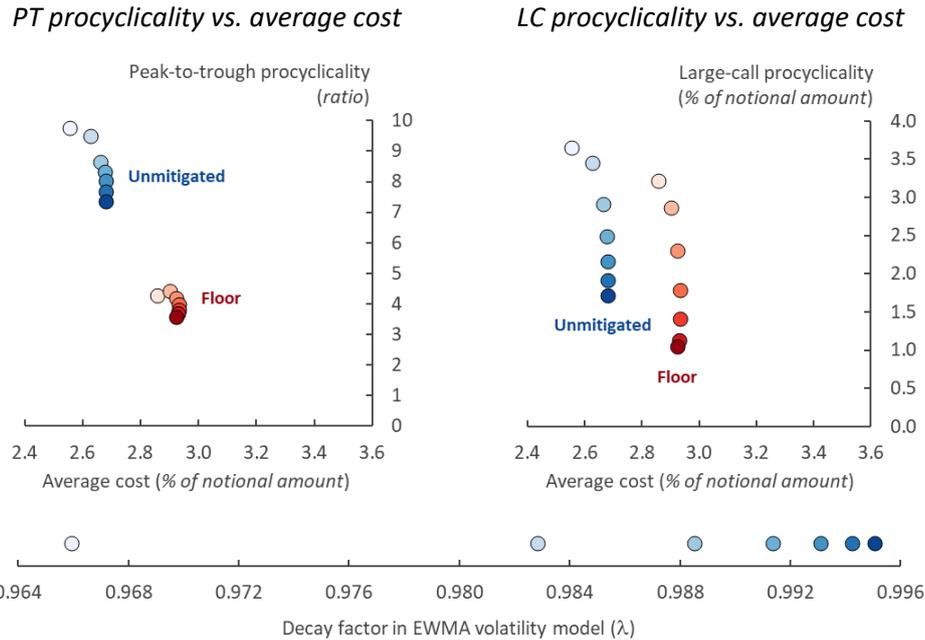
(a) IM model is a filtered historical simulation value-at-risk model applied to a USD/JPY FX futures contract.

3.2 Floored models

Figure 5 compares the results for the unmitigated model with those generated by applying the first EMIR APC tools – the floor – to that model. The same range of values for λ is used for the comparisons. All of the models still pass backtesting, as the floor never decreases margin requirements.

The floor tool prevents margin requirements falling to low levels in placid times, so is effective at reducing PT procyclicality. However, this increases margin requirements during those times, raising average margin requirements (i.e. the AC metric) by about 0.3% of notional amount. LC procyclicality only falls modestly, as large margin calls are often generated by transitions from normal or slightly elevated levels of volatility or to stress levels (i.e. from the near to the far right tail in Figure 3) and the floor tool essentially only raises margin requirements in placid times.

Figure 5: Procyclicality-cost trade-off for IM model with floor APC tool^(a)



Sources: Federal Reserve Economic Data and Bank calculations.

(a) IM model is a filtered historical simulation value-at-risk model applied to a USD/JPY FX futures contract.

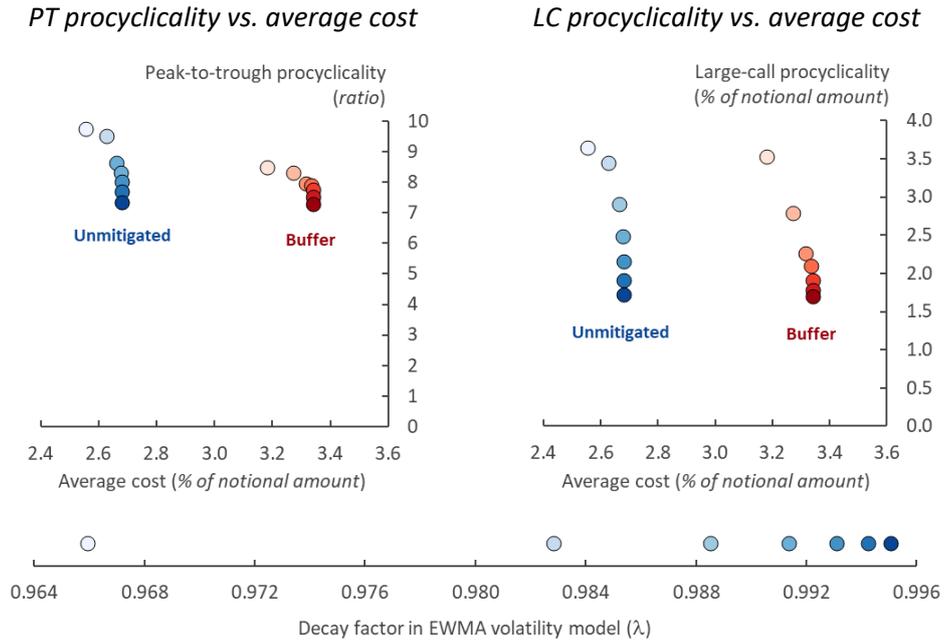
3.3 Buffered models

As noted in Murphy et al. (2016), a key issue in the use of the buffer tool is the release rule for the buffer. This can be based on the shape of the distribution in Figure 3. The buffer is 25% of the unmitigated margin requirement, so if we want it to be just exhausted when unmitigated margin hits its 99.7th percentile, y (meaning that only margin calls in very high stress exhaust the buffer), then it should be released from the percentile of unmitigated margin requirements which is $y/1.25$. For our portfolio, the 99.7th percentile of unmitigated margin is 8.4% of notional amount, $8.4\%/1.25$ is 6.7% of notional amount, and that corresponds to the 98.9th percentile of unmitigated margin requirements. We round off and release the buffer when unmitigated margin hits the 99th percentile of its historical distribution.¹⁷

Figure 6 compares the procyclicality and cost of the unmitigated model with margin requirements after application of the second EMIR APC tool – the buffer. As for the floor tool, these margin requirements still pass backtesting because the buffer never decreases margins. Comparing the results in Figure 6 with those in Figure 5 shows that the buffered model has a higher cost than the floored model and lower benefits. The cost of the buffered model is almost 25% higher than the unmitigated model. This is because a 25% buffer is added to unmitigated margin requirements and is not drawn down 99% of the time. Moreover, when it is drawn, it is not necessarily fully drawn. This is why the procyclicality metrics are less than 25% lower than in the unmitigated model. The effects of the buffer on LC procyclicality are particularly muted as margin requirements can increase sharply without crossing into the top 1% of the distribution, which would at least partially release the buffer.

¹⁷ This implicitly demonstrates the difficulty of calibrating the buffer release rule consistently for multiple portfolios, as different portfolios have different distributions of margin requirements.

Figure 6: Procyclicality-cost trade-off for IM model with buffer APC tool^(a)



Sources: Federal Reserve Economic Data and Bank calculations.

(a) IM model is a filtered historical simulation value-at-risk model applied to a USD/JPY FX futures contract.

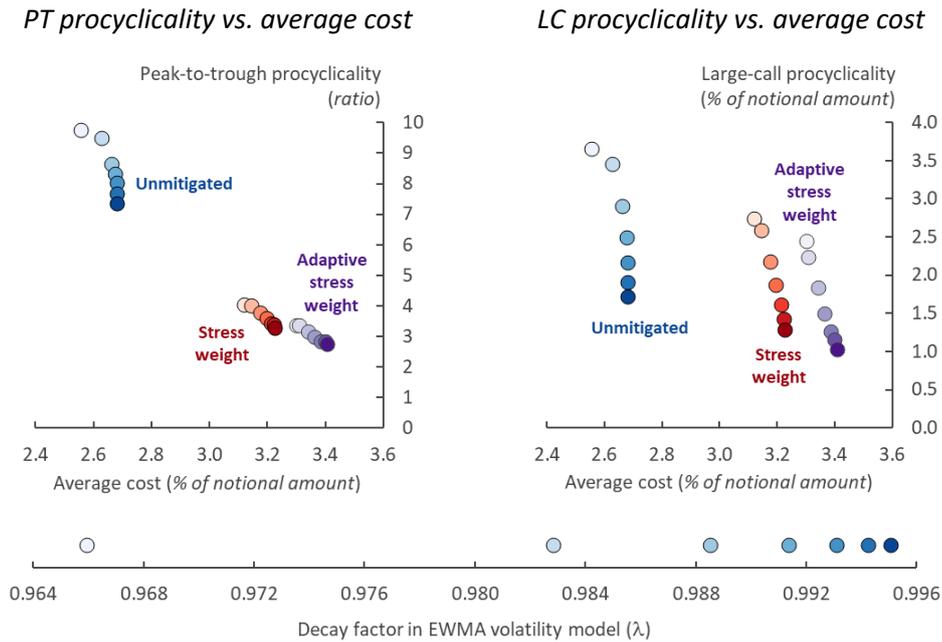
3.4 Stressed VaR models

Figure 7 shows similar results for the third EMIR APC tool, which gives some weight to margin requirements from a historical period of stress in calculating current requirements. Occasionally, current IM requirements are higher than the stress requirements, which means the stress-weight tool can pull margin requirements below those of the unmitigated model. Nevertheless, the stress-weight tool still passes our backtest for all values of λ from 0.96 to 0.995. Usually, however, current IM requirements are lower than the stress requirements, so giving weight to the latter increases margin requirements. As that weight is material, the stress-weight tool increases the AC metric quite significantly. However, having a constant component in margin requirements significantly reduces PT procyclicality and because that constant component has a relatively high value it noticeably lowers LC procyclicality too.

3.5 Adaptive stressed models

The adaptive stressed model was proposed to address the problem with the basic stress-weight tool that if current conditions are more stressed than the ones used to calibrate the stressed component, the model with APC mitigation can pull margin requirements below the current value-at-risk. Hence, the adaptive stressed model applies a higher weight to the stressed component in placid conditions (in the left of the distribution in Figure 3) and a lower weight in stressed conditions (in the right of the distribution in Figure 3).

Figure 7: Procyclicality-cost trade-off for IM model with stress-weight APC tools^(a)



Sources: Federal Reserve Economic Data and Bank calculations.

(a) IM model is a filtered historical simulation value-at-risk model applied to a USD/JPY FX futures contract.

As can be seen in Figure 7, the adaptive stress-weight tool has similar but slightly larger effects – both in terms of costs and the two procyclicality measures – than the EMIR stress-weight tool. The model again passes our backtest for all values of λ from 0.96 to 0.995.

3.6 Capped models

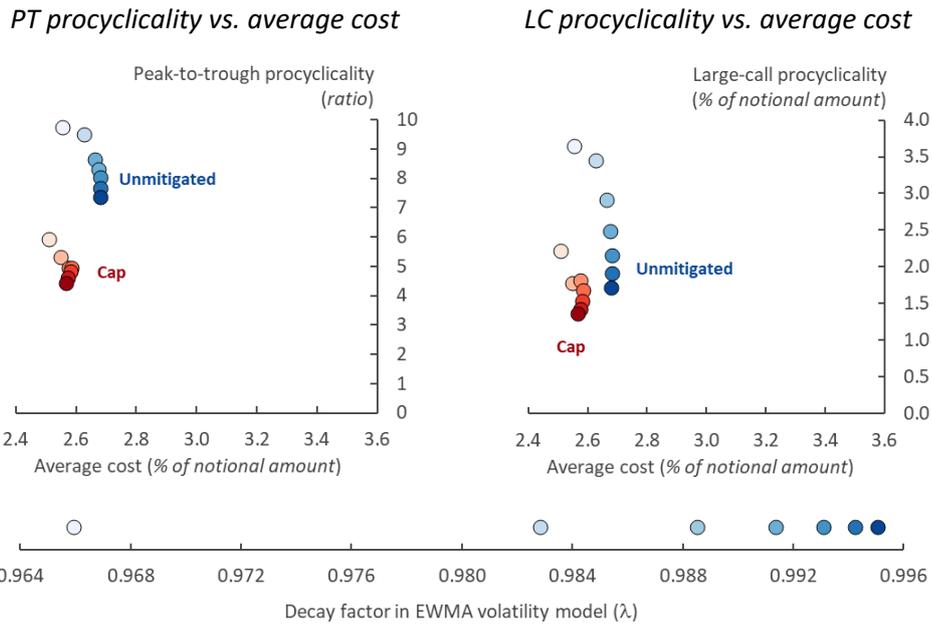
The insights of Raykov (2018) and Goldman & Shen (2020) motivate the introduction of a model that caps margin at a high level. Should losses exceed that high level, they would fall to the post-margin layers of the CCP’s default management ‘waterfall’, notably the default fund, which mutualises risk since all clearing members contribute to it.¹⁸

Figure 8 presents the results for this model. As the cap stops margin requirements reaching the highest levels, it reduces PT and LC procyclicality while (slightly) reducing margin requirements on average and still (just) passing our backtest.¹⁹ Of course, this comes at the cost of increased mutualisation of tail risks, so any consideration of a cap tool would require further work on the benefits of liquidity risk reduction in high stress versus the extra risk to the default fund.

¹⁸ The effectiveness of mutualisation in reducing total liquidity demands depend on the distribution of cleared risk between accounts at the CCP: see Murphy (2017).

¹⁹ This is because backtest exceptions are often caused by a large negative return at the start of stress, and the cap only acts after margin has spiked in response to this return, so it stops margin over-reacting to it. The cap only increases backtest exceptions in the presence of significant autocorrelation of large negative returns.

Figure 8: Procyclicality-cost trade-off for IM model with cap APC tool^(a)



Sources: Federal Reserve Economic Data and Bank calculations.

(a) IM model is a filtered historical simulation value-at-risk model applied to a USD/JPY FX futures contract.

4. Tool selection and stability of results

In this section, we assess the relative costs and benefits of the alternative approaches to procyclicality mitigation and investigate whether these appear to be stable over time and across portfolios.

4.1 Comparing different approaches to APC mitigation

Figure 9 puts the six approaches to reducing procyclicality on the same graphs: the three EMIR tools (in different shades of blue), the adaptive stress-weight tool (light purple), the cap tool (dark purple), and the simple approach of choosing a model with a different decay constant, $\lambda = 0.995$ (pink). As before, the unmitigated model with $\lambda = 0.98$ is used as a benchmark (yellow) and the portfolio is the single JPY/USD FX futures contract.

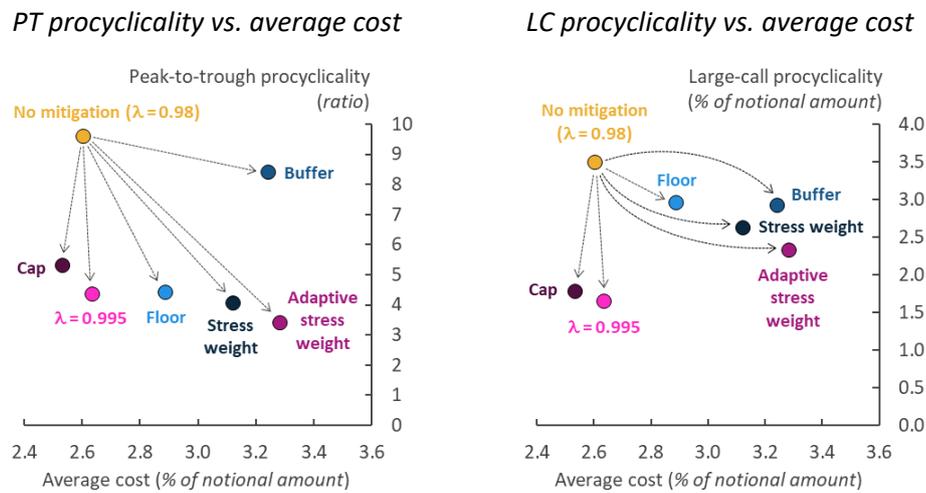
Most of the tools reduce PT and LC procyclicality at the cost of a higher AC metric. Hence, whether they are net beneficial depends on the value of procyclicality reductions to the financial system relative to the cost of higher average margin requirements, which remains an open issue.²⁰ However, the cap tool reduces both (PT and LC) procyclicality and average margin requirements, so is net beneficial in terms of this trade-off. But, as noted above, this particular tool may have extra costs for the CCP's default fund, which would need to be taken into account in a full assessment.

Comparing the different procyclicality mitigation techniques against each other, the buffer tool is inferior to several of the alternatives for the portfolio under consideration as it reduces both PT and LC procyclicality by relatively little and increases costs by more. In contrast, simply raising the value of λ dominates several other strategies when focusing on LC procyclicality, as it reduces this metric by more than the floor, buffer, stress-weight and adaptive stress-weight tools, while raising the cost by

²⁰ Although see O'Neill and Vause (2016), which maps at least some of the costs and benefits to the risk-adjusted expected returns of derivative users.

relatively little. Although it does not reduce PT procyclicality by as much as some of these alternatives, the differences are not large.

Figure 9: Comparison of procyclicality-cost trade-off across procyclicality mitigation techniques^(a)



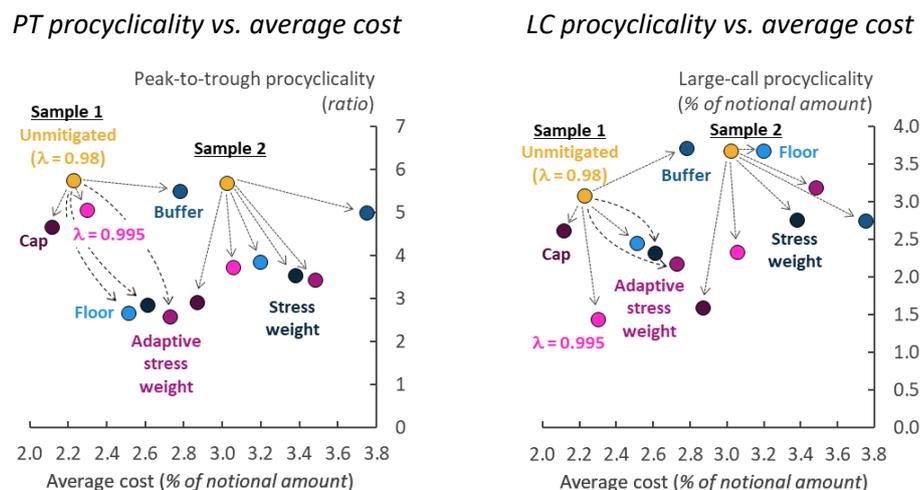
Sources: Federal Reserve Economic Data and Bank calculations.

(a) IM model is a filtered historical simulation value-at-risk model applied to a USD/JPY FX futures contract.

4.2 Time stability

In order to investigate the time stability of these results, the whole dataset was split into a number of segments. Figure 10 reports the results for a split in two.²¹ The relative changes in procyclicality and costs are fairly consistent across time periods, suggesting they are somewhat intrinsic to the specification of the different tools. However, there are some exceptions. Notably, the floor reduces LC procyclicality by more than the cap and buffer tools in Sample 1, but it does not reduce LC procyclicality in Sample 2, which is the worst performance of all the tools. This is because some of the large increases in margin requirements started below the floor in Sample 1, but not in Sample 2.

Figure 10: Comparison of procyclicality-cost trade-off across sub-samples^(a)



Sources: Federal Reserve Economic Data and Bank calculations.

(a) IM model is a filtered historical simulation value-at-risk model applied to a USD/JPY FX futures contract.

²¹ The results were similar for a split into three, but are more difficult to present visually, so not reported.

4.3 Portfolio stability

Ideally, any given margin models should not be excessively procyclical for a wide range of portfolios, not just for an outright position in a single risk factor, as considered so far. In order to investigate the stability of our results across portfolios, the tool comparison in Figure 9 was repeated for two additional portfolios:

1. A FX portfolio comprised of USD/JPY, USD/GBP and USD/CHF futures in equal weight;
2. A WTI/Brent spread portfolio formed by buying one WTI oil futures contract and selling one Brent oil futures contract, as commonly used by commodity market participants.

These two portfolios have very different return distributions. Table 1 compares their descriptive statistics with those of the original USD/JPY FX portfolio studied above. These three portfolios therefore offer insight into the behaviour of the APC tools for a range of return distributions, as might be found in practice.

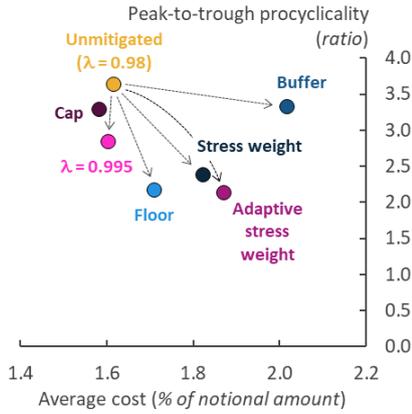
Table 1: Descriptive statistics for the three portfolios studied

	USD/JPY	FX portfolio	WTI/Brent spread
Number of returns	9,373	7,806	8,258
Mean return	-0.009%	-0.011%	-0.052%
Standard deviation(σ)	0.66%	0.48%	154%
Skewness	0.42	1.22	-1.10
Kurtosis	5.05	2.58	176
Unconditional VaRs:			
99%	2.91 σ	2.57 σ	2.67 σ
99.5%	3.50 σ	3.03 σ	3.24 σ
99.9%	5.20 σ	4.56 σ	4.91 σ

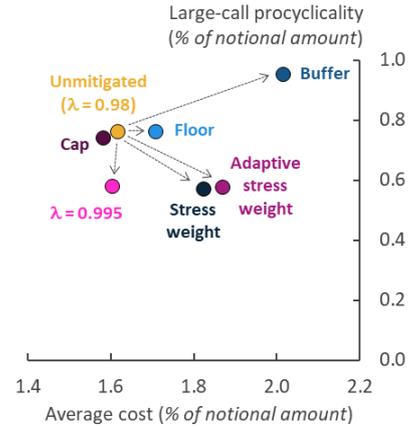
Figure 11 shows the summary cost-benefit analysis for the APC tools for the FX portfolio. For the most part, the results are qualitatively similar to those in Figure 9, but there are some significant differences in magnitudes. Even without mitigation, both measures of procyclicity are significantly lower in this more-diversified and, hence, less-risky portfolio. One striking result in terms of the mitigation tools, is that the buffer – which we continue to release when unmitigated margin requirements exceed their 99th percentile – increases LC procyclicity for this portfolio, which is the opposite of its intended purpose. Also, the floor tool no longer reduces LC procyclicity, and could be made more effective by raising the level of the floor in its calibration. The cap still reduces (both PT and LC) procyclicity without increasing costs, but to a much lesser degree than for the single FX futures portfolio. Again, we have calibrated the cap as previously, setting it at the 95th percentile of unmitigated margin requirements. The results for the stress-weight tool, and adaptive stress-weight tool and the higher- λ model are more similar to those of the single FX futures portfolio. The main issue these results raise, then, is the difficulty of simultaneously calibrating some of the tools for use across different portfolios.

Figure 11: Comparison of procyclicality-cost trade-off for FX overlay portfolio^(a)

PT procyclicality vs. average cost



LC procyclicality vs. average cost



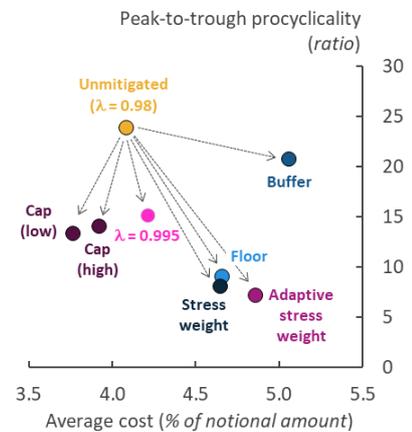
Sources: Federal Reserve Economic Data and Bank calculations.

(a) IM model is a filtered historical simulation value-at-risk model applied to a (static) portfolio comprised of USD/JPY, USD/GBP and USD/CHF FX futures in equal weights.

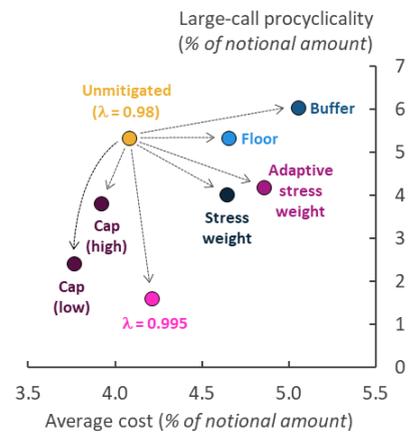
The WTI-Brent spread portfolio, as Table 1 shows, has a very different return distribution to the previous two. This also raises the question of tool recalibration. One specific issue here is that the cap tool as calibrated previously no longer passes our backtest. For this reason, we show results for two caps: one set at a higher level (98th percentile of unmitigated margin requirements) that still passes backtesting, and a second at a lower level (94th percentile of unmitigated margin requirements) that reduces procyclicality more effectively but which may be considered unsatisfactory because of its backtest failure. These different caps do not make much difference to PT procyclicality, but do have a significant effect on LC procyclicality. The buffer and floor tools again increase or do not decrease LC procyclicality for this portfolio, suggesting they could do better if they were recalibrated across portfolios. But the stress-weight tool, adaptive stress-weight tool and the higher- λ model all continue to have tangible beneficial effects on procyclicality, albeit at varying costs, without any recalibration. The results are presented in Figure 12.

Figure 12: Comparison of procyclicality-cost trade-off for WTI-Brent spread portfolio^(a)

PT procyclicality vs. average cost



LC procyclicality vs. average cost

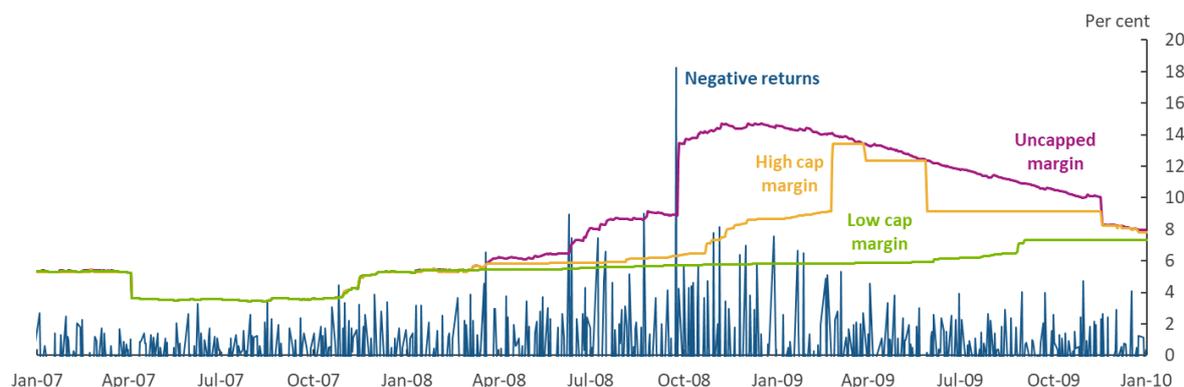


Sources: Federal Reserve Economic Data and Bank calculations.

(a) IM model is a filtered historical simulation value-at-risk model applied to a portfolio of long WTI oil futures and short Brent oil futures in equal notional amounts.

The period around the 2008 financial crisis illustrates well the effect of different caps. This is shown in Figure 13. It can be seen that the lower cap reduces the margin increase following the Lehman default to a greater degree and for longer than the higher one. What saves the higher cap from a backtest fail is its increase in October 2008, which avoids three negative-return exceedances.

Figure 13: Capped IM requirements for WTI-Brent spread portfolio and their backtest exceptions^(a)



Sources: Federal Reserve Economic Data and Bank calculations.

(a) IM model is a filtered historical simulation value-at-risk model applied to a portfolio of long WTI and short Brent oil future contracts.

5. Conclusions

The size of margin calls experienced by derivatives market participants in March 2020 has reinvigorated the debate about dampening the procyclicality of CCP margin requirements. To help assess alternative approaches to procyclicality mitigation we have proposed a particular cost-benefit framework. This quantifies reductions in procyclicality along two dimensions: the PT measure reflects changes in margin requirements between the peaks and troughs of the financial cycle, which can force deleveraging; and the LC measure reflects the potential for large margin calls over a short horizon, which can lead to liquidity strains. It also quantifies the cost of mitigation strategies, which is measured as the increase in margin requirements on average over the cycle. We illustrated our framework by applying it to a selection of simple derivative portfolios with different return characteristics.

Comparison of the results across these simple portfolios showed that the inherent level of procyclicality can vary significantly, especially across asset classes. Thus, it may be more important to dampen procyclicality for some types of portfolio than for others. The comparison also showed that the relative benefits and costs of alternative mitigation strategies can vary across portfolios, notably for strategies with parameters relating to different percentiles of the distribution of historic volatility, where a particular specification can work relatively well for one portfolio but less well for another. Thus, widespread use of a particular mitigation strategy across different portfolios could deliver mixed results. These two insights suggest an alternative approach that may merit further research: regulators could set targets for levels of procyclicality (e.g. $PT \leq x$ or $LC \leq y$) and, in cases where reductions were necessary, CCPs could seek the least-cost strategy for achieving those targets given the asset types that they clear.

One particular issue that would warrant further consideration under such an approach is the levels at which to set targets for PT and LC procyclicality. It may be, for instance, that different targets would be appropriate for different clearing services depending on their membership. Some services

predominantly clear trades between dealer-banks, which have sophisticated liquidity management systems and access to central bank lending; while other services also cater to non-financial derivative users, with fewer liquid assets and less access to contingent liquidity. The systemic benefits of procyclicality targets may be greater in the latter case than the former. Moreover, once calculated, the same procyclicality metrics could be reported to these institutions to help with their leverage and liquidity planning.

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Annex 1: Technical Definitions

A.1 Baseline initial margin model

We set IM requirements equal to the one-day 99.5% FHS VaR of the portfolio, which we derive from historical data. For this, we collect daily data on the JPY/USD FX rate from the Federal Reserve Economic Data (FRED) database maintained by the Federal Reserve Bank of St Louis. The data series code is DEXJPUS. After data cleaning, this gives us 9,300 end-of-business-day observations from the beginning of 1984 to October 2020. Denoting the FX rate on day t as S_t , we compute logarithmic returns as $r_t = \ln(S_t/S_{t-1})$. Next, we estimate conditional return volatilities (σ_t) using an Exponentially Weighted Moving Average (EWMA) model. Thus, we set

$$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1 - \lambda)r_t^2, \text{ where } \sigma_1 = \sigma = \frac{1}{T}\sum_{t=1}^T r_t^2$$

where λ is the decay parameter. We use these EWMA volatilities to compute filtered returns, $\rho_t = r_t/\sigma_t$. We then take the time series of filtered returns and divide it into 500-day overlapping windows. The 99.5% FHS VaR for a given day t , $m_t(\lambda)$, is the third worst (i.e. most negative) return in the 500-day window ending on that day, multiplied by σ_t .²²

A.2 Backtesting

The time decay or λ parameter determines how quickly the model reacts to changing market conditions. We narrow down its range of acceptable values by requiring that the IM model, $m_t(\lambda)$, pass a backtest. In particular, we require that it pass the Kupiec (1995) Proportion of Failures (PoF) test with 99% confidence. This test assesses whether the proportion of days with margin exceedances ($-r_{t+1} > m_t$) in a sample of historical data is the same as that intended by the model, which is one minus the VaR confidence level (α_{VaR}), i.e. 0.5% in our case. Denoting x as the number of exceedances in the backtest sample and N as the total number of observations, the PoF (likelihood ratio) test statistic is

$$LR = -2 \ln \left(\frac{\alpha_{VaR}^{N-x} (1 - \alpha_{VaR})^x}{(1 - x/N)^{N-x} (x/N)^x} \right).$$

For large values of N , this statistic follows a $\chi^2(1)$ distribution under the null hypothesis that the backtest proportion of exceedances is equal to the model-intended proportion. We reject that hypothesis if the backtest value of LR falls in the top 1% of the $\chi^2(1)$ distribution.

We use non-overlapping three-year windows, and demand a Kupiec POF pass in each of the 11 available windows in order to pass the model, with the exception that we pass a model that has zero exceptions, where this would otherwise fail.

A.3 Procyclicality measures

We define LC procyclicality as the 99.7th percentile of increases in IM requirements within 20 business days. This roughly corresponds to 30 calendar days, as used in the Basel III Liquidity Coverage Ratio. This large call could cumulate between day 1 and day 20 of the window or anything in between, and in any window. Formally, the large call in the 20 days up to t is

$$LC_t = \max_{w,W} (m_{t-w} - m_{t-w}) \quad \forall \{0 \leq W \leq 20, 1 \leq w < W\}$$

The LC measure up to T is the 99.7th percentile of $\{LC_t | t < T\}$.

²² See Gurrola Perez and Murphy (2015) for a more detailed discussion of FHS VaR models.

We define PT procyclicality as the difference between the 99.7th percentile and the 0.3rd percentile of IM requirements. Writing m_t^α for the α percentile of the distribution of margins before t , the PT ratio for the period up to T is:

$$PT = \frac{m_T^{99.7}}{m_T^{0.3}}.$$

Finally, we define the AC metric as the time-series mean of IM requirements, i.e.

$$AC = \frac{1}{T} \sum_{t=1}^T m_t.$$

A.4 APC tools

We study five anti-procyclicality (APC) tools:

1. *Buffer*. Based on Article 28(1)(a) of EU (2013), we add a 25% buffer to baseline IM requirements. We release this buffer when the resulting IM requirements exceed the 99th percentile of their historical distribution up to that point. Formally,

$$m_t^B = \max\{\min\{1.25m_t, 1.25m_t^{99}\}, m_t\}.$$

2. *Stress weighting*. Based on Article 28(1)(b) of EU(2013), we assign 75% weight to baseline IM requirements and 25% to IM requirements consistent with stressed market conditions. For the latter, we use the 95th percentile of the historical distribution of baseline IM requirements up to that point. Formally,

$$m_t^{SW} = 0.75m_t + 0.25m_t^{95}.$$

3. *Floor*. Based on Article 28(1)(c) of EU (2013), we set a floor on IM requirements at the unfiltered VaR for the prior ten years, m_t^{10y} . The post APC requirements are then

$$m_t^F = \max\{m_t, m_t^{10y}\}.$$

4. *Adaptive stress weighting*. This is an adaptation of the stress-weighting tool motivated by the fact that blending current and stressed VaRs to form IM requirements is only conservative if the current VaR is lower than the stressed VaR. So, instead of giving the stressed VaR a fixed weight of 25%, we vary it smoothly using an exponential weighting scheme such that a higher percentage of stressed VaR is blended in at lower levels of margin in the baseline model. Specifically, we set

$$m_t^{ASW} = (1 - w_t)m_t + w_t m_t^{95},$$

with $\alpha = 0.4$ (i.e. 40% weight to stressed VaR at $m_t = 0$), $\beta = 0.25$ and

$$w_t = \alpha \exp\left(\frac{m_t}{m_t^{95}} \ln \beta\right).$$

5. *Cap*. We place an upper limit on the margin as a percentile of the distribution of prior margins. Specifically, we set the cap at the 95th percentile of this distribution:

$$m_t^{cap} = \begin{cases} m_t & \text{if } m_t < m_t^{95} \\ m_t^{95} & \text{otherwise.} \end{cases}$$