BANK OF ENGLAND

Staff Working Paper No. 975

Reducing liquidity mismatch in open-ended funds: a cost-benefit analysis

Benjamin King and Jamie Semark

April 2022

BANK OF ENGLAND

Staff Working Paper No. 975

Reducing liquidity mismatch in open-ended funds: a cost-benefit analysis

Benjamin King[1] and Jamie Semark[2]

Abstract

Macroprudential authorities increasingly find themselves needing to assess, and act on, risks from outside the traditional banking system. How should they think about the costs and benefits of these actions? In this paper we present an approach to cost-benefit analysis for one topical issue related to non-banks – liquidity mismatch in open-ended funds (OEFs). In particular, we analyse the benefits and costs of more extensive use of swing pricing by UK corporate bond OEFs. Using several models, we quantify the impact of liquidity mismatch and swing pricing on corporate bond spreads and expected GDP growth. We estimate that greater use of swing pricing could reduce amplification of investment grade corporate bond spreads by around 8%, and improve the distribution of GDP growth. We discuss qualitatively the impact of swing pricing on fund liquidity buffers, and the possible costs of swing pricing. We conclude that there are likely to be financial stability benefits from more extensive use of swing pricing by UK corporate bond OEFs.

Key words: Cost-benefit analysis, mutual funds, swing pricing, corporate bonds.

JEL classification: D61, G12, G23, G28.

(1) Bank of England. Email: benjamin.king@bankofengland.co.uk
(2) Bank of England. Email: james.semark@bankofengland.co.uk

The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or its committees. We are grateful to Owen Lock, Robert Czech, Arjun Mahalingam, Nicholas Vause, Gerardo Ferrara, Rupal Patel, Yuliya Baranova, Laura Silvestri and Nick Jackson for their analytical contributions and support.

The Bank's working paper series can be found at www.bankofengland.co.uk/working-paper/staff-working-papers

Bank of England, Threadneedle Street, London, EC2R 8AH
Email enquiries@bankofengland.co.uk

ISSN 1749-9135 (on-line)

Contents

1 Introduction

Most open-ended funds (OEFs) offer daily redemptions, meaning that investors can subscribe or redeem from a fund, at its current net asset value (NAV), on any day they choose. But OEFs often invest in assets which take more than one day to sell without a significant price discount. This gives rise to 'liquidity mismatch,' where an OEF's liabilities are more liquid than its assets. As OEFs with a greater degree of liquidity mismatch – such as corporate bond funds – have grown in recent years, policymakers have become concerned about the potential risks to financial stability[1]. In July 2019, the Financial Policy Committee (FPC) commissioned the Bank of England (Bank) and Financial Conduct Authority (FCA) to jointly review liquidity mismatch in OEFs. That review concluded in July 2021 (Box A of Bank & FCA 2021a), with the FPC endorsing a set of proposals to address liquidity mismatch in OEFs by: strengthening OEFs' assessment of the liquidity of their assets, and promoting greater consistency in the use of swing pricing (Box B of Bank of England 2021c).

In this paper we set out one approach to estimating the financial stability benefits and costs of more widespread use of swing pricing by OEFs. We focus on UK corporate bond OEFs, given the size of the corporate bond market, the liquidity mismatch inherent in corporate bond OEFs, and their importance in financing the real economy. Our results suggest that greater use of swing pricing would reduce amplification of shocks to corporate bond spreads, and improve the distribution of GDP growth. We discuss the possible macroeconomic costs of more widespread swing pricing, as well as the impact of different assumptions around OEF asset sales. We conclude that there are likely to be macroeconomic benefits from greater use of swing pricing by UK corporate bond OEFs. Our work also provides an early example of a macroprudential cost-benefit analysis related to non-bank institutions. Such analyses will become increasingly important as macroprudential authorities tackle risks arising from outside the traditional banking system.

2 Background

2.1 Liquidity mismatch and swing pricing

The fact that most OEFs are 'daily dealing' means they offer significant flexibility to investors, who can withdraw their investment on any given day. OEF liabilities are therefore highly liquid, similar to bank deposits[2]. For OEFs investing in highly liquid assets, this is unlikely to be a problem – the liquidity of their assets matches their liabilities. However, OEFs increasingly invest in less liquid assets which cannot be sold immediately without a price discount. This leads to a 'liquidity mismatch,' where the OEF's liabilities are more liquid than its assets. Corporate bond OEFs are an important, and growing, type of OEF in which liquidity mismatch concerns arise. Where OEFs have a liquidity mismatch, there may be an incentive for investors to redeem ahead of others. This is because OEF investors can redeem from the fund on a daily basis at its current net asset value, without taking into account trading costs. This means that redeeming OEF investors do not bear the full cost of their liquidity, which will instead by borne by other investors who remain in the fund. This externality creates an incentive to redeem ahead of others – known as 'first mover advantage' – particularly in situations where financial markets are illiquid, or are expected to become illiquid.

Swing pricing allows an OEF to adjust, or 'swing,' the price at which investors can redeem or subscribe to the fund. This allows the costs of meeting investor flows to be borne by the redeeming/subscribing investors, rather than those remaining in the fund. For example, if an OEF faces net outflows of £100 which would lead to trading costs of £1 (i.e. the sum of bid-ask spreads, commissions, taxes and similar for selling £100 of assets is £1) it can swing its price such that redeeming investors receive £99. Because swing pricing allows fund managers to pass the cost of exiting the OEF on to redeeming investors, it can ensure that redeeming investors internalise the cost of their liquidity. This limits first mover advantage and incentives to redeem early.

[1]For example, the Financial Stability Board published recommendations to address structural vulnerabilities from asset management activities, including liquidity mismatch, in 2017 (Financial Stability Board 2017).

[2]Although importantly OEF shares are redeemable at the fund's net asset value, rather than par.

2.2 Our approach to cost-benefit analysis

This section sets out our approach to this cost-benefit analysis. We do not try to provide a comprehensive analysis of all possible channels, instead focusing on where we expect to see the largest impact on financial stability and the economy.

We start by estimating the impact of liquidity mismatch in UK corporate bond OEFs – that is, how large is the problem which swing pricing might solve? The core channel for us is the impact of liquidity mismatch in driving procyclical redemptions from OEFs – that is, redemptions which increase as asset prices fall. When OEFs face redemptions, they may need to sell assets in order to generate cash with which to pay out investors. If procyclical outflows from OEFs during market stress lead to additional sales of corporate bonds, this will amplify shocks to corporate bond spreads. This in turn feeds through to higher funding costs for corporates, and from there to corporate investment and GDP.

This conceptual framework is illustrated in Figure 1. The three columns in Figure 1 broadly follow the steps in our analysis. First, we quantify the relationship between OEF performance and flows – the 'flow-performance relationship' – empirically. Second, we use a model of the corporate bond market developed by Baranova, Douglas, and Silvestri (2019) (the 'fund-dealer model') to translate these procyclical outflows into corporate bond sales and spreads. Third, we take amplification of corporate bond spreads as an input to 'GDP at risk' estimates as a way to quantify the wider economic impact.

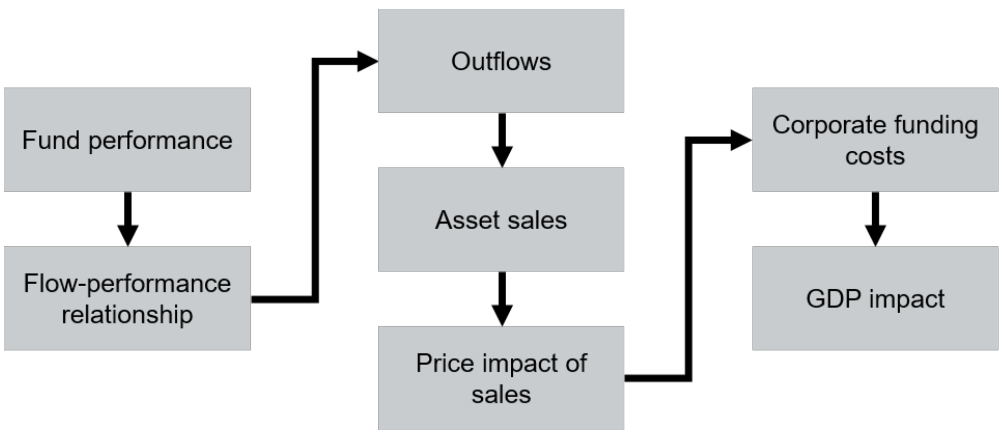

Figure 1: Baseline (cost of status quo)

Next, we consider the potential benefits of swing pricing in this framework. We make use of evidence from Jin et al. (2019) and Lewrick and Schanz (2017) showing that swing pricing can significantly dampen the flow-performance relationship for corporate bond OEFs. We then re-run the rest of our analysis with a reduced flow-performance sensitivity parameter. The effect of less procyclical redemptions flows through to corporate bond spreads and GDP (illustrated in Figure 2), dampening the impact of shocks and allowing us to quantify the economic benefits of swing pricing.

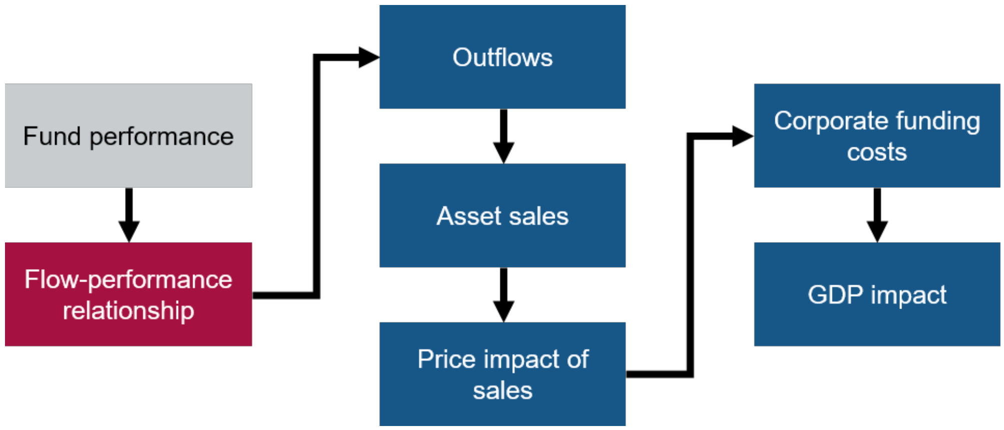

Figure 2: Benefits of reducing liquidity mismatch

Finally, we discuss macroeconomic costs from greater use of swing pricing. If swing pricing were to discourage investment in UK corporate bond OEFs, and therefore in UK corporate bonds, this would represent a key economic cost of the policy. We discuss the potential for such costs to arise by considering the incentives of 'impatient investors,' who benefit from liquidity mismatch, and 'patient investors' who bear the costs (illustrated in Figure 3).

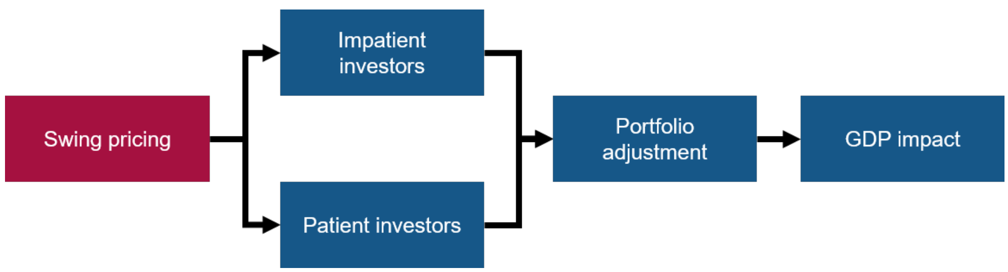

Figure 3: Costs of reducing liquidity mismatch

As with any cost-benefit analysis we make a number of modelling assumptions to derive our results. In particular, our main results assume that OEFs sell a representative portion of their assets (often described as a 'vertical slice') in order to meet redemption requests. Some studies find a more complicated picture – for example, OEFs using cash to meet redemptions in calm markets, and selling closer to a vertical slice in stressed conditions (Jiang, Li, and Wang 2017). We discuss these issues in more detail in Section 3.5. Importantly, we would still expect there to be financial stability benefits from greater usage of swing pricing, although we do not attempt to estimate them quantitatively.

2.3 Related literature

We build on prior work from each of the three strands of our cost-benefit analysis set out in Section 2.2. First, there are studies which investigate the drivers of OEF investor flows. Goldstein, Jiang, and Ng (2017) identify a relationship between OEF returns and outflows, and our regression specification is in the spirit of their work. Second, we use the model of Baranova, Douglas, and Silvestri (2019) to quantify the impact of procyclical OEF flows on corporate bond markets. Models of short-term market stress with similar features have been developed by other central banks. For example, Arora et al. (2019) describe a model of the Canadian bond market featuring OEF asset sales and dealer intermediation, and Sydow et al. (2021) explore how contagion might be propagated from OEFs to the banking sector. Other researchers use empirical approaches to identify price effects of OEF redemption-driven asset sales: Hau and Lai (2013), Lou and Wang

(2018) and Coudert and Salakhova (2020). Third, we rely on the 'GDP at risk' literature, which considers empirically how measures of financial stability relate to future GDP growth, to translate our results into GDP terms. Our GDP at risk specification is drawn from Aikman et al. (2019), and is also in the spirit of Adrian, Boyarchenko, and Giannone (2019).

Beyond the building blocks of our approach, we contribute to an ongoing discussion of the macroeconomic and macroprudential risks arising from OEFs. This dates back at least to the global financial crisis – for example, Manconi, Massa, and Yasuda (2012) document the role of OEFs and other institutional investors in propagating stress in bond markets during that period. More recently, macroprudential authorities have regularly expressed concerns about risks arising from OEFs and the need to develop policy responses: for example, Financial Stability Board (2017), de Guindos (2018), Cetorelli (2021) and Claessens and Lewrick (2021).

We also provide an early example of a macroprudential cost-benefit analysis related to non-bank finance. Approaches to cost-benefit analysis for bank-based macroprudential measures are more developed. For example, Basel Committee on Banking Supervision (2010) analyses the costs and benefits of bank capital using an approach later developed by others, such as Arregui et al. (2013) and Brooke et al. (2015). Karmakar (2016) and Davis, Liadze, and Piggott (2019) carry out their bank-based cost-benefit analysis using a DSGE model and a large-scale econometric model respectively. Looking outside the banking sector, Bank of England (2021b) sets out the FPC's review of its mortgage market recommendations, which considers the costs and benefits of these policies. And regulators of non-banks carry out cost-benefit analysis of their policies as a matter of course – for example see Financial Conduct Authority (2018). However, we are not aware of other cost-benefit analyses that consider issues in non-bank finance from a macroprudential authority's perspective.

3 Benefits

3.1 Baseline: fund flows and corporate bond spreads

3.1.1 Flow-performance relationship

We start by considering the realtionship between OEF returns and investor flows. We follow the literature and assume that fund investors behave procyclically, and redeem shares following fund losses. Goldstein, Jiang, and Ng (2017) show that when returns are negative investors tend to redeem from OEFs, and when they are positive they tend to invest. They further show that the sensitivity of flows to negative returns is greater than to positive returns, and that this is behaviour is exacerbated by liquidity mismatch. This is intuitive – with greater liquidity mismatch there is a larger first mover advantage, which may encourage some investors to redeem ahead of others, particularly in situations where prices are falling. Therefore if liquidity mismatch in OEFs could be reduced, we would expect this to reduce the procyclicality of performance-related flows.

We use monthly data from Morningstar, which covers around 50,000 OEFs from 2005 to 2020. We estimate the regression specification shown in Equation (1), in the spirit of Goldstein, Jiang, and Ng (2017).

$$FF_{i,t} = \beta_1 R_{i,t-1} + \beta_2 I_{(R_{i,t-1}<0)} \cdot R_{i,t-1} + \beta_3 R^2_{i,t-1} + \beta_4 I_{(R_{i,t-1}<0)} \cdot R^2_{i,t-1} + \gamma controls_{i,t-1} + c_i + \epsilon_{i,t} \quad (1)$$

Where: $FF_{i,t}$ is net fund flows (% of net assets) for fund i in month t, $R_{i,t-1}$ is fund returns in month $t-1$, $I_{(R_{i,t-1}<0)}$ is a dummy variable which equals 1 if returns are negative and zero otherwise. $controls_{i,t-1}$ are lagged values of log net assets and the square of log net assets, and c_i are fund fixed effects.

Figure 4 illustrates the results (Annex A provides more detail). The implied flow-performance relationship for corporate bond OEFs is shown in red, with other asset classes provided for reference. We make use of a linear approximation of these results (the impact of -1% returns on expected flows) to update the fund-dealer model parameters. For corporate bond OEFs, the results imply a flow-performance coefficient of 0.15 – i.e. returns in the previous month of -1% of net asset value are associated with additional outflows of 0.15%.

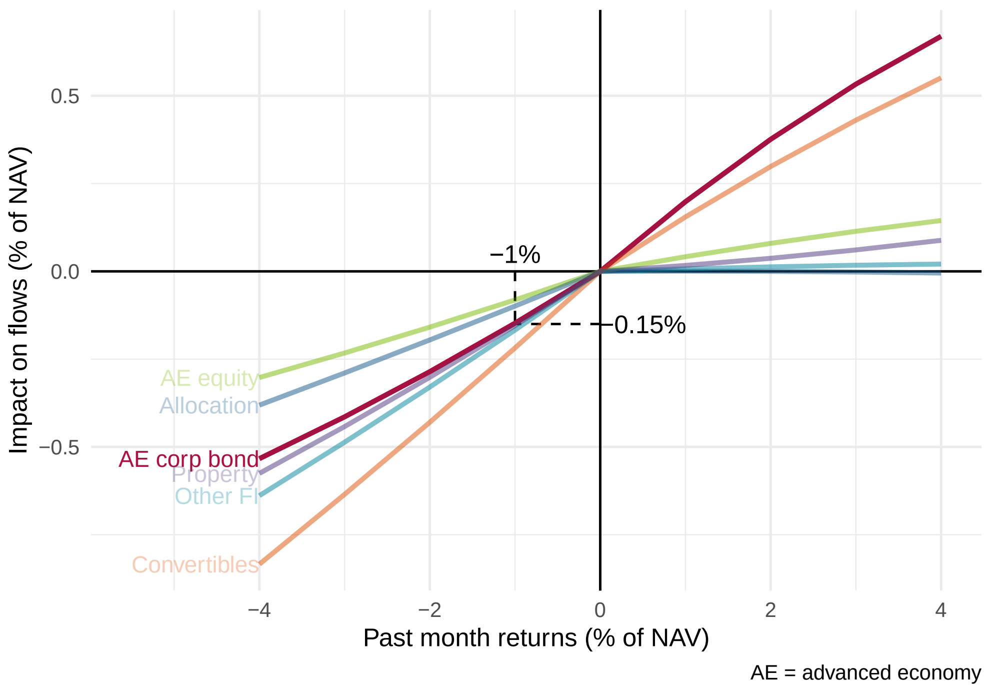

Figure 4: Estimated flow-performance relationship by fund asset class

3.1.2 'Fund-dealer' model approach

We make use of the model of Baranova, Douglas, and Silvestri (2019), the 'fund-dealer' model, to estimate the impact of procyclical redemptions by investors in OEFs on corporate bond spreads. The fund-dealer model includes agents representing buy-side market participants (OEFs, unit-linked funds, insurance companies and pension funds), a leveraged buyer of securities (hedge fund), and a market intermediary (dealer). The model utilises data covering the investment-grade UK corporate bond market.

The data used to parameterise the model capture OEFs domiciled in the UK and those EU jurisdictions with large fund industries, and across a variety of investment strategies. For unit-linked funds, life insurers and pension funds, we capture UK-domiciled entities. By choosing this scope, we capture around two thirds investors in UK investment-grade corporate bonds. For liquidity providers, we focus on largest global dealers and global hedge funds pursuing fixed-income strategies. Given that our focus is on UK investment-grade corporate bonds, as opposed to the global corporate bond market, we adjust the balance sheet capacity that global hedge funds and dealers might be willing to allocate for intermediating this segment of the market.

The model does not attempt to pin down the single most likely type/size of shock and assess its impact. Instead, it models the impact of three types of shock – to the risk-free rate, credit and liquidity risk premia – and we assess the impact of a range of shock sizes.

We assume that fund managers are forced to liquidate assets in order to meet the procyclical redemptions that follow these shocks. We assume they sell assets proportionally to the quantity in which they hold them (i.e. liquidate a 'vertical slice of the portfolio'). The quantity of asset a sold by an OEF following investment strategy i in response to a shock of type k is:

$$Q_{ak}^{OEF_i} = H_a^{OEF_i}(1 - shock_{ak})\sigma^{OEF_i} Losses_k^{OEF_i} \tag{2}$$

where $H_a^{OEF_i}$ is the pre-shock amount of asset a held by an OEF of type i; $shock_{ak}$ is the change in price of asset a for a shock of type k; σ^{OEF_i} is the share of assets that investors of OEF type i will redeem following a loss of 1%; and $Losses_k^{OEF_i}$ are the percentage losses experienced by an OEF of strategy i following a shock of type k. Total losses are computed as the sum of the losses on each asset a held in the portfolio, so $Q_{ak}^{OEF} = \sum_i Q_{ak}^{OEF_i}$.

The other buy-side investors behave similarly, selling assets in response to their constraints[3]. The aggregate behaviour of such investors results in net demand/supply of liquidity for an asset class.

Market intermediaries then provide liquidity to accommodate the sales of assets by other investors. The hedge fund chooses the proportion of the overall quantity of corporate bonds being sold to buy, seeking to maximise its profits by arbitraging as the market-clearing price set by the dealer deviates from the fundamental value.

The dealer clears the corporate bond market (i.e. buys the rest of the assets not purchased by the hedge fund). In doing so, it sets the new market-clearing price at a discount from the primary shock asset price. This discount D is set so that it fully compensates the dealer for the costs of warehousing inventory on its balance sheet and, in nominal terms, can be calculated as:

$$D(Q^D) = Q^D \cdot Cost(Q^D) \cdot HP^D(Q^D) \tag{3}$$

where Q^D is the amount of assets purchased by the dealer; $Cost(Q^D)$ id the cost of holding a unit of inventory on their balance sheet for a unit of time, which is a function of the funding, hedging and regulatory costs incurred in warehousing corporate bonds; and $HP^D(Q^D)$ is the dealer's expected inventory holding period.

This new price, which we call the 'secondary shock price,' is below the 'primary shock price.' Hence, the difference between these two prices effectively quantifies the amplification of shocks resulting from market participants' behavioural responses.

3.1.3 'Fund-dealer' model results

We update the OEF and dealer balance sheets in the fund-dealer model to reflect end-2019 total assets and regulatory constraints (see Annex B for details), before running the model. Notably, while dealer trading assets have grown by about 14% since the model was first parameterised in 2015, OEF assets have grown by nearly 30%.

Results are shown in Figure 5. The degree of amplification varies significantly with the type of underlying shock, driven by the constraints of other agents. Shocks to risk free rates cause the most amplification, while shocks to liquidity risk lead to relatively little[4] – for investment grade bonds liquidity related shocks are not amplified at all. Amplification in the high yield bond market is around ten times larger than for investment grade bonds.

[3]For full details see Section 4 of Baranova, Douglas, and Silvestri (2019).

[4]The model follows Solvency II regulations in allowing insurers to 'look through' shocks to liquidity to some extent, which in turn reduces the degree of amplification in the model.

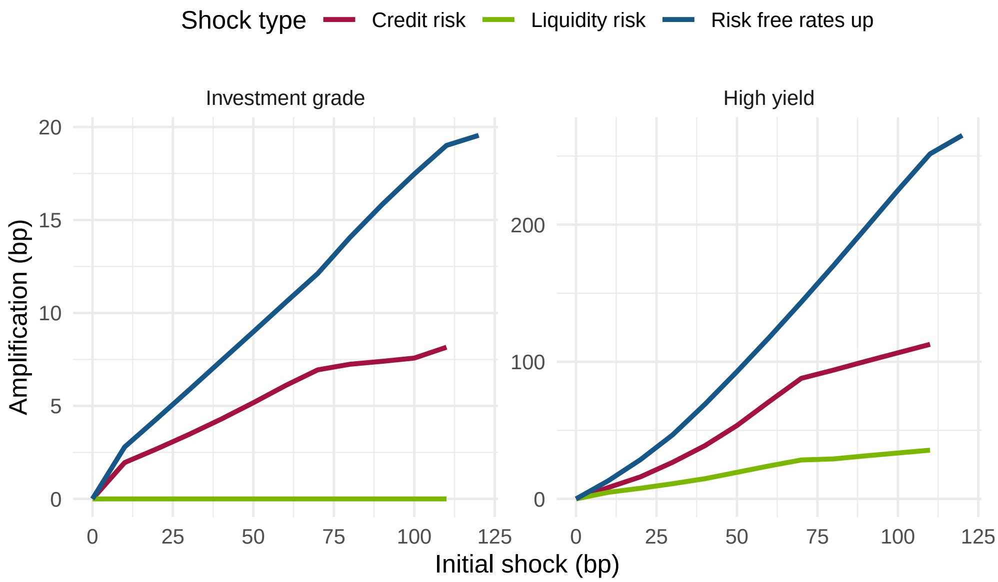

Figure 5: Fund-dealer model implied amplification of shocks to corporate bond spreads

Averaging across the different drivers of a shock, the fund-dealer model suggests that the behaviour of agents, including fund investors, may amplify shocks to UK investment grade corporate bonds by around 9% (with a range depending on the type and size of shock of 0% to 22%).

3.2 How effective is swing pricing?

We then consider whether effective swing pricing might dampen OEF investors' procyclical outflows, and thus reduce the overall impact of shocks to corporate bond spreads. We make use of results in two studies looking at the effect of swing pricing: Jin et al. (2019) and Lewrick and Schanz (2017).

Jin et al. (2019) use data on UK OEFs collected via the FCA. Their data cover 299 corporate bond funds either domiciled or managed in the UK, from January 2006 to December 2016. As part of their analysis they estimate a regression[5] comparing the sensitivity of fund flows to performance for funds which use swing pricing and those that do not. The implied relationship between performance (measured by fund alpha[6]) and flows for the two types of fund is illustrated in the left hand panel of Figure 6.

Their results imply: a) low sensitivity of flows to positive alpha for all funds, b) much higher sensitivity of flows to negative alpha, and importantly c) lower sensitivity to negative flows for swing pricing funds. The impact of performance on expected outflows for swing-pricing funds is 62%-64% lower than for non-swing funds, depending on the particular regression specification.

Lewrick and Schanz (2017) take a different approach, exploiting cross-country differences between OEFs. Their data cover funds domiciled in the USA (1,000 funds) and Luxembourg (719 funds) from January 2012 to May 2016. In the period covered by their data, US funds were not able to use swing pricing, whereas it was widely used by funds in Luxembourg. By controlling for other fund characteristics, comparing the two sets of funds provides an insight into the effect of swing pricing.

The implied flow-performance relationship from their results[7] is shown in the right hand panel of Figure 6. The pattern they find is similar to Jin et al. (2019): fund flows are less sensitive to positive performance, and

[5] Reported in Table 7 of their paper.
[6] Fund returns net of returns on the relevant market benchmark.
[7] Table 2 in their paper.

US funds are more sensitive to negative performance than Luxembourg funds.

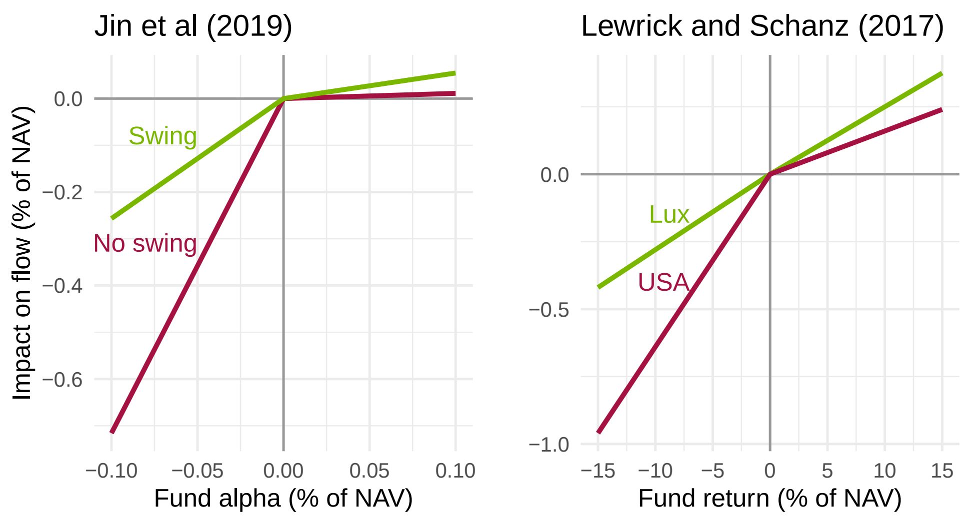

Figure 6: Swing pricing and flow-performance sensitivity from Jin et al (2019) and Lerwick and Shanz (2017)

In this case the sensitivity of outflows from Luxembourg (swing) funds to negative returns is 56% lower than for US (non-swing) funds. Lewrick and Schanz (2017) do find that the impact of swing pricing on flows is more limited during the 'taper tantrum,' the main period of stress in their sample. On the other hand, Jin et al. (2019) find that swing pricing significantly reduces redemptions during stress periods, including the global financial crisis.

Together, we think these results provide good evidence that swing pricing can be effective in softening the effect of poor fund performance on outflows. The average impact from the two papers suggest a 60% reduction in flow-performance sensitivity – we use this value in our analysis.

We then need to consider how this result might apply to the UK corporate bond OEF sector in general. In both cases the studies we rely on compare funds which use swing pricing with those that do not (or in the case of Lewrick and Schanz (2017), funds which generally use swing pricing with a set which definitely do not). However, swing pricing is already used by many UK corporate bond OEFs. In a joint Bank and FCA survey of OEFs (Bank & FCA 2021b), 85% of UK domiciled OEFs surveyed had the option to use swing pricing in some form[8]. However, the survey also showed that the way swing pricing is applied varies widely. Although the number of OEFs using swing pricing increased in 2020 Q1-Q2 – a period which included the March 2020 Covid-19 related stress – 25% of OEFs reported not using swing-pricing at all during this period[9].

For our baseline estimate of the sector-wide impact of swing pricing we therefore scale the 60% figure derived above by the estimated 25% of UK OEFs with no swing pricing usage. This gives us an estimate of a 15% average reduction in flow-performance sensitivity. Arguably this effect could be larger if swing pricing was made more effective across the board, further reducing first mover advantage including for funds which already make use of the tool. The FPC judged that the results of Bank & FCA (2021b) showed that swing pricing was used inconsistently in the March 2020 stress (Bank of England 2021c).

[8]Either swinging their price when redemptions exceed a particular threshold (partial swing) or every day (full swing), or funds which trade with separate bid and offer prices (dual priced). 82% of OEFs in the survey were corporate bond funds, or invested in corporate bonds as part of a mixed portfolio.

[9]Bank & FCA (2021b) report 55 and 121 OEFs using full and partial swing respectively, and 28 dual-priced OEFs, out of a total of 272 surveyed.

3.3 Estimating the impact of swing pricing on fund flows and corporate bond spreads

We then re-run the fund-dealer model with the flow-performance coefficient for corporate bond funds reduced by 15% (from 0.15 to 0.1275). The updated results are shown in Figure 7, alongside the baseline results for comparison.

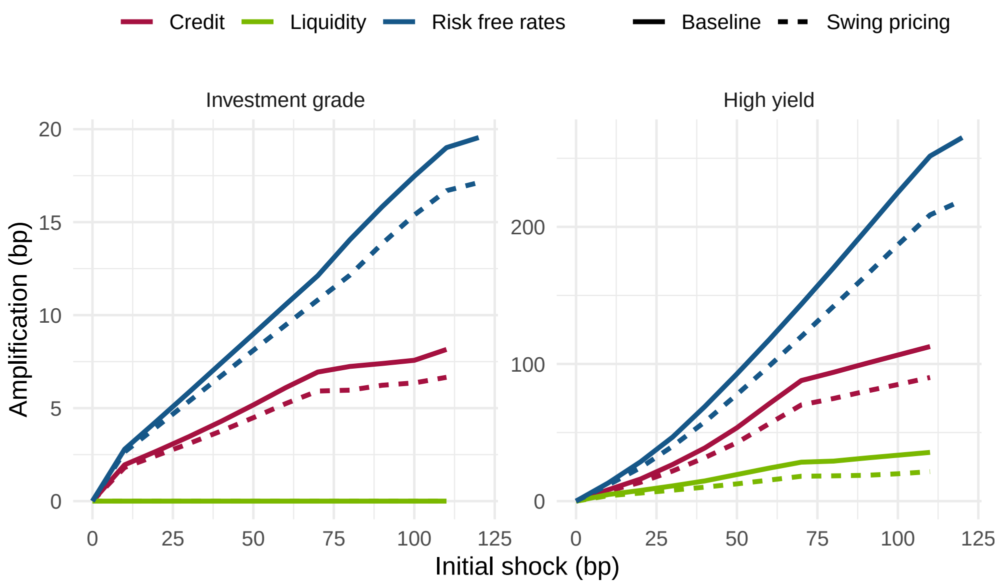

Figure 7: Impact of dampening flow-performance relationship on model results

As expected, by making fund flows less sensitive to performance, swing pricing leads to reduced amplification of shocks to corporate bond spreads in the model. While swing pricing reduces amplification across investment grade, high yield, and the various types of shock, the size of the effect varies (Figure 8). It is larger for high yield bonds and for larger initial shocks – contexts in which wider liquidity conditions may be relatively poor.

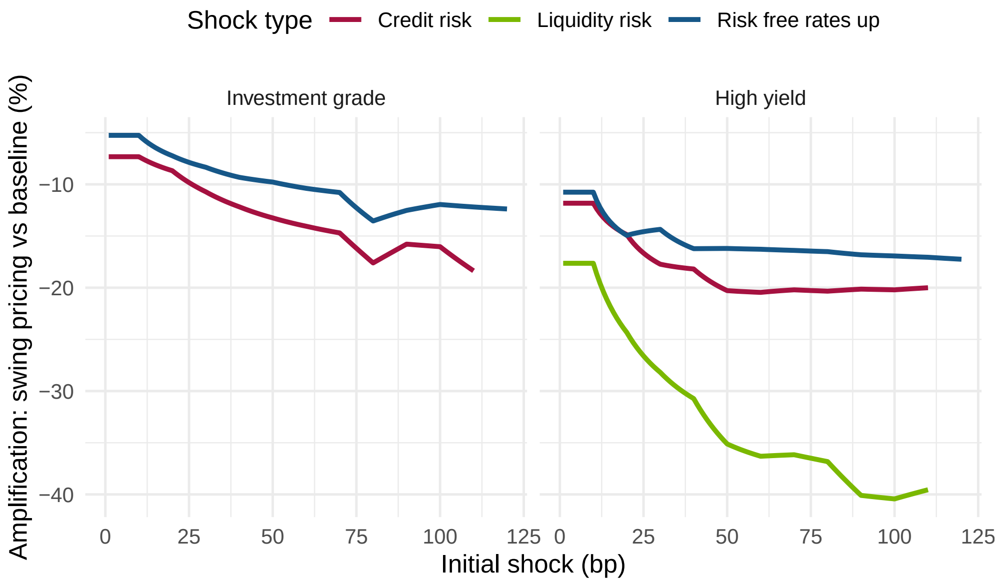

Figure 8: Impact of swing pricing on amplification

Averaging across the different types of shock (including liquidity risk for investment grade bonds, where swing pricing has no impact) and size of initial shock, the fund-dealer model results suggest swing pricing might reduce amplification of investment grade corporate bond spreads by around 8%, and by around 22% for high yield bonds. Table 1 provides the averages by market and type of shock.

Table 1: Reduction in amplification from swing pricing (percent)

	Shock type		
Bond type	Credit risk	Risk free rates up	Liquidity risk
Investment grade	-13	-10	0
High yield	-18	-15	-32

We can also consider the impact on fund flows using the flow-performance regressions from Section 3.1.1. Other things equal, reduced sensitivity to fund performance should make fund outflows less volatile. To illustrate this we calculate expected flows, based on the data and regression results in Section 3.1.1. We then take the monthly mean of expected flows, on the basis that flows across corporate bond OEFs as a whole is more relevant for financial stability than flows for individual funds. We then repeat the process, scaling the effect of returns on flows down by 15%.

Figure 9 plots the results. Expected flows are indeed less volatile – the standard deviation is 0.45 with swing pricing, compared to 0.47 for the baseline estimates. Although the impact on aggregate volatility is relatively small, swing pricing has most effect in thinning the tails of the distribution: the probability of aggregate flows being within -0.5% and +0.5% is about 71% in the baseline, but 74% with swing pricing. Reducing the probability of extreme flows across the OEF sector as a whole should be the main concern of macroprudential authorities, so this is a clear benefit of swing pricing from our perspective.

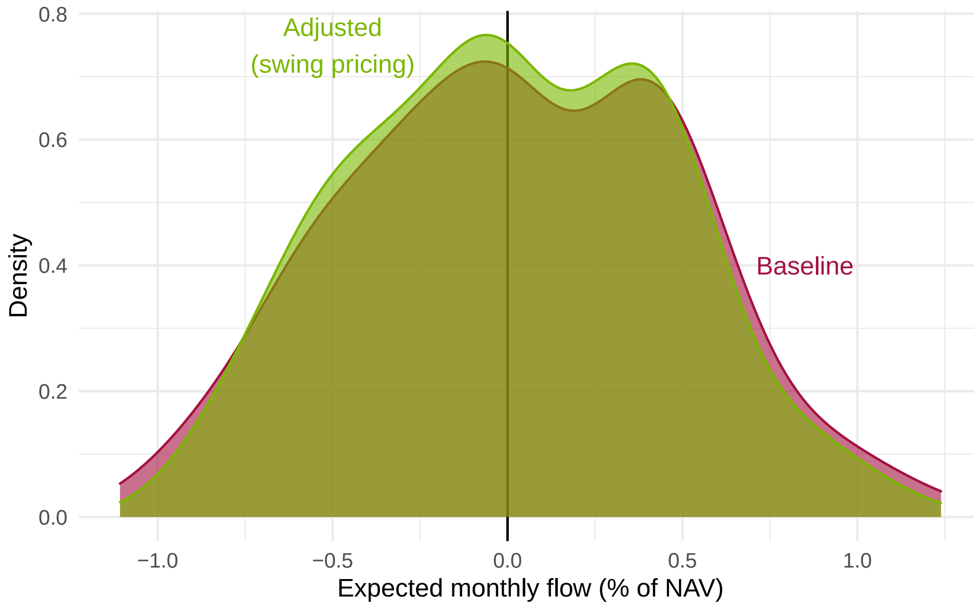

Figure 9: Distribution of expected flows

3.4 Estimating the impact of swing pricing on GDP

In this section we consider a mapping from the financial market benefits identified above (effect on corporate bond spreads and fund flows) into benefits for the economy as a whole.

There is a large literature on the real economic effects of financial markets. This covers the long-standing literature on collateral / financial accelerator mechanisms (Bernanke and Gertler 1986; Kiyotaki and Moore 1997), as well as impacts from a direct increase in the cost of financing for corporates (Lou and Wang 2018) and the potential signalling effect of asset prices for managers (Bond, Edmans, and Goldstein 2012). Important work by Gilchrist and Zakrajšek (2012) shows that the 'excess bond premium' – that is the component of corporate bond spreads not driven by the credit risk of issuers – has strong predictive power for US GDP growth.

One channel by which corporate bond spreads can affect real economic activity is by affecting the cost of financing for firms. Secondary market trading determines the price at which firms can issue new bonds, and therefore the cost of using corporate bonds to finance investment. Corporate bond transaction data[10] provides evidence of the importance of OEFs as buyers of primary issuance of UK corporate bonds. Figure 10 shows that in 2019 and 2020 H1, asset managers bought around 40% of newly issued UK corporate bonds on average. Although not all these purchases can be attributed to OEFs (as purchases by asset managers may include other vehicles such as exchange traded funds (ETFs)), we would expect the bulk of purchases to be related to OEFs given their size relative to other fund vehicles – as of September 2021, global OEFs are around six times larger than ETFs or money market funds (ICI 2021). In addition, OEFs are significant holders of the stock of corporate bonds, owning around 17% of UK-issued corporate bonds (Bank of England 2021a).

[10] Reported under the Market in Financial Instruments Directive (MiFID II).

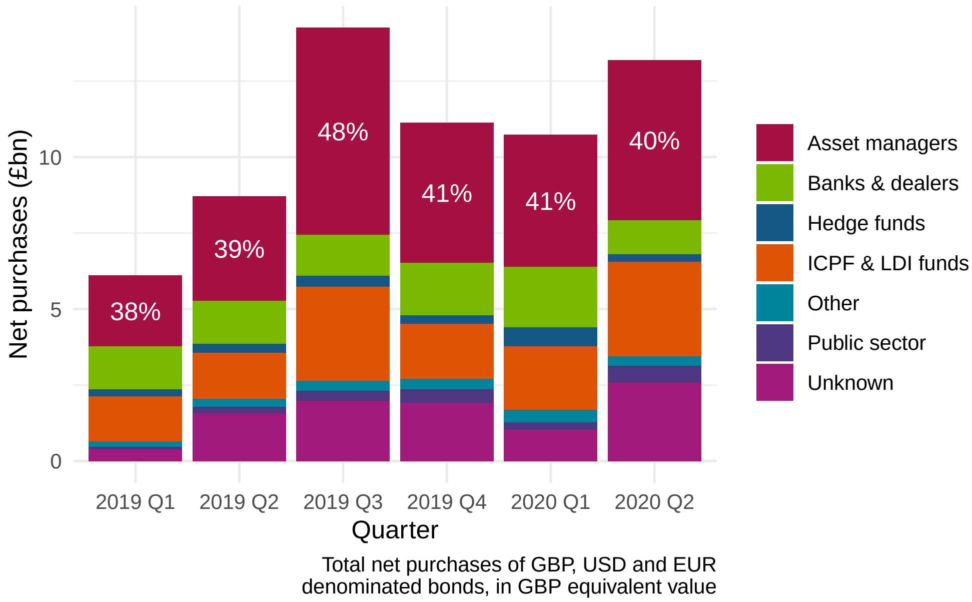

Figure 10: Purchase of newly issued UK corporate bonds by sector

3.4.1 GDP at risk approach

To analyse the possible effects of corporate bond spreads on the wider economy we make use of the 'GDP at risk' framework set out in Aikman et al. (2019). We expand the GDP at risk estimates to include investment grade corporate bond spreads. This allows us to assess the potential impact of shocks to spreads on GDP growth, and therefore what benefit reducing amplification of spreads by OEFs might provide in GDP terms.

Aikman et al. (2019) build on work by Adrian, Boyarchenko, and Giannone (2019), and earlier contributions by Cecchetti and Levin (2008) and Cecchetti and Li (2008), looking at how quantitative indicators affect the distribution of future GDP growth. The core idea is to use quantile regression – linear regressions which estimate a given conditional quantile of the independent variable, rather than the conditional mean as in ordinary linear regression (Koenker and Bassett 1978) – to analyse how changes in financial risks and vulnerabilities affect the distribution of GDP growth. To analyse the impact of changes in variables of interest on the future distribution of GDP growth, GDP at risk uses the local projections technique of Jordà (2005).

GDP at risk estimates start with a panel dataset of countries and relevant macro variables. We make use of the dataset from Aikman et al. (2019), extending it to include investment grade corporate bond spreads. The final dataset covers 14 advanced economies[11]: Belgium, Canada, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, UK and USA. The data are quarterly, and run from 1999 Q3 to 2018 Q4.

In our GDP at risk estimates we include the variables from Aikman et al. (2019)'s baseline specification, with the exception of equity volatility which we substitute for investment grade corporate bond spreads. We have eight independent variables, covering indicators of financial system risk (credit-to-GDP growth, real house price growth, current account and corporate bond spreads), resilience (banking sector capital ratio) and controls (inflation, change in policy rate and lagged GDP growth). Full details of the construction of the dataset and sources are provided in Annex C of Aikman et al. (2019). The data on corporate bond spreads are sourced from ICE BofA. Table 2 summarises our specification.

Having added corporate bond spreads to our dataset, we then proceed with the approach of Aikman et al. (2019). First we estimate country fixed effects, following Canay (2011). We assume that country fixed effects

[11]The macrofinancial dynamics in emerging markets are less likely to be relevant for the UK.

Table 2: GDP at risk specification

Dependent variable	Risk variables	Resilience variables	Controls
xth percentile of cumulative real GDP growth	Credit-to-GDP growth; Real house price growth; Current account; Corporate bond spreads	Banking sector capital ratio	Inflation; Policy rate change; Lagged GDP growth

are identical across quantiles (i.e. the fixed effects shift the whole distribution one direction or another). This means we can use a relatively simple approach to estimate the fixed effects. First we estimate a linear pooled model:

$$y_{i,t+h} = \alpha_i^h + \gamma^h X_{i,t} + \epsilon_{i,t} \tag{4}$$

Where $y_{i,t+h} = \frac{Y_{i,t+h} - Y_{i,t}}{\frac{h}{4}}$. $Y_{i,t+h}$ is the log level of real GDP in country i at time $t+h$ for forecast horizon h. α_i^h is the country fixed effect for country i, and $X_{i,t}$ denotes the indicator variables for country i at time t.

Using the method of Canay (2011) we can then estimate the country fixed effects as:

$$\hat{\alpha}_i^h = \frac{1}{N}(y_{i,t+h} - \hat{\gamma}^h X_{i,t}) \tag{5}$$

Where N is the total number of countries in our dataset.

With our estimated country fixed effects $\hat{\alpha}_i^h$, we can define a final dependent variable $y^*_{i,t+h} = y_{i,t+h} - \hat{\alpha}_i^h$, i.e. $y_{i,t+h}$ without the country fixed effects. We then use quantile regression to estimate the impact of the independent variables (β) for each quantile τ and horizon h:

$$\hat{\beta}_\tau^h = min_{\beta^h} \sum \rho_\tau(y^*_{i,t+h} - X_{i,t}\beta_\tau^h) \tag{6}$$

Where ρ_τ is the quantile regression check (or loss) function. We use local projections (Jordà 2005) to estimate the model from 1 to 20 quarters ahead, although we focus on the impact from 1 to 4 quarters in this analysis. Standard errors are estimated using block bootstrapping (Kapetanios 2008), where the data are resampled in time series blocks. We maintain the approach of Aikman et al. (2019) and use 8 quarter blocks for the bootstrapping.

3.4.2 GDP at risk results

3.4.2.1 Baseline We now turn to the impact of shocks to corporate bond spreads on GDP at risk. The effect of a one standard deviation (around 80 bps) increase in investment grade corporate bond spreads on GDP growth is shown in Figure 11. We show the impact on the left tail of GDP growth (5th percentile), a central estimate (median) and the right tail (95th percentile) on cumulative GDP growth at each horizon. So for example, a one standard deviation shock to corporate bond spreads reduces cumulative expected GDP growth (50th percentile) after one year by 0.78%, and reduces the 5th percentile of the cumulative growth distribution by 1.39%.

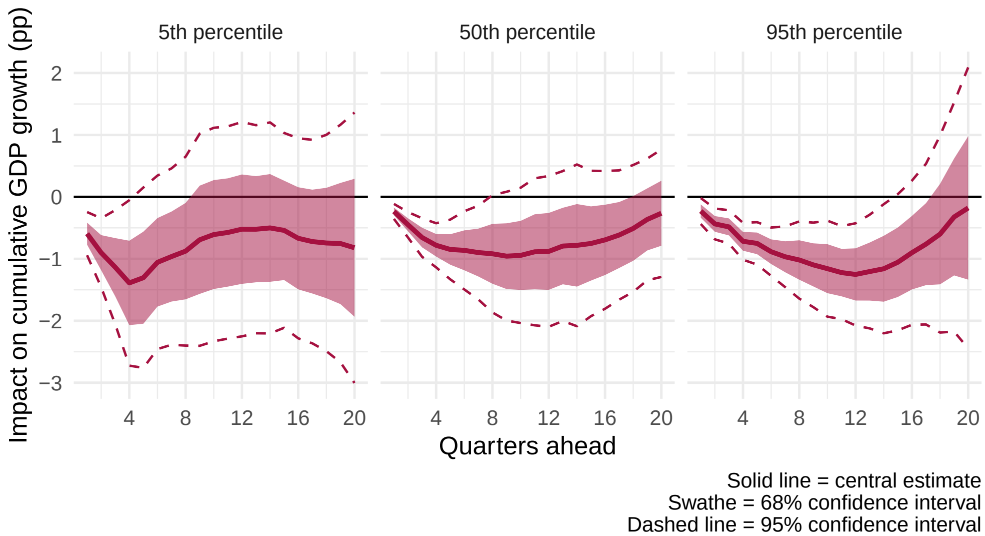

Figure 11: Effect of a one standard deviation shock to corporate bond spreads on GDP growth

Shocks to corporate bond spreads are associated with a negative effect on GDP outcomes across the entire distribution. However, the impact on the 5th percentile of the distribution are larger, particularly in the short term, suggesting that shocks to corporate bond spreads may increase tail risks to GDP growth by more than their effect on expected GDP.

We cannot be certain that all of the impact is driven by a causal relationship. For example, corporate bond spreads are strongly correlated with other measures of financial market stress, and we are not able entirely to separate these other effects due to colinearity among the variables[12]. However, as noted above there is theoretical and empirical evidence for a real economic effect from corporate bond spreads, so it is reasonable to expect that shocks to corporate bond spreads would have a negative effect on GDP growth.

The shock to corporate bond spreads need not be permanent. The GDP at risk regressions use quarterly data, so implicitly the shock must be persistent enough to appear in a quarterly series. This is slightly different from the fund-dealer model, where the action plays out over a month. Although we do not adjust for this mismatch directly, empirical data suggest that shocks to corporate bond spreads can be quite persistent. For example, looking at monthly values of sterling corporate bond spreads, the autocorrelation after three months is about 0.8. This suggests that a shock to bond spreads on the scale of a month is quite likely to persist for at least one quarter.

3.4.2.2 Impact of swing pricing We can now combine our results to estimate the impact of introducing swing pricing on GDP at risk. Rather than focus on a point estimate, we generate a distribution of results based on a range of estimates for the underlying parameters. First, we have our results from the flow-performance regressions and the fund-dealer model, which translate an exogenous shock to corporate bond spreads into a basis point amount of amplification by OEFs. For a one standard deviation (80bp) exogenous shock, our results suggest amplification of 0bp, 7bp and 14bp depending on the underlying driver of the shock. This range effectively incorporates statistical uncertainty in the flow-performance regressions in Section 3.1, as well as the type of underlying shock hitting the financial system.

Second, we incorporate uncertainty in our estimates of how effective swing pricing may be in reducing procyclical flows. Our baseline estimate is a 15% reduction, derived from Jin et al. (2019) and Lewrick and Schanz (2017) who find effects around 60% comparing OEFs with no swing pricing to those mostly or all using it, and evidence from Bank & FCA (2021b) in which around a quarter of surveyed UK OEFs did not

[12] For example, the correlation between corporate bond spreads and equity volatility (as measured by the VIX index) is about 0.5.

use swing pricing during a period of market stress. There are reasons to think the impact of greater use of swing pricing by UK corporate bond OEFs could be larger, or perhaps smaller than our estimate. Enhanced swing pricing might impact flows even for OEFs which already use it, generating a larger impact across the sector as a whole. On the other hand, extending swing pricing in a context where it is already widely used may have a smaller marginal effect than introducing it for the first time, for example if OEFs with the most sensitive investor flows already use swing pricing. To reflect this uncertainty we consider a range of 10pp around our baseline estimate, giving reductions of 5%, 15% and 25% in amplification from swing pricing.

Finally, we use kernel density estimation (Ganbold and Amgalan 2021) to generate a smoothed distribution over the range of each parameter, and draw values from these distributions. We use a linear approximation of the impact of different effects of swing pricing on amplification in the fund-dealer model to account for the fact that the translation between the two is not quite one-for-one[13]. Table 3 and Figure 12 summarise our approach.

Table 3: Approach to generating distributions

Parameter	Description	Values
Degree of amplification by OEFs (bps, baseline)	We use the results from the fund-dealer model for an 80bp initial shock, and take the amplification values for different shock types as the basis for the distribution. The distribution implicitly incorporates uncertainty about the type of shock, as well as the (relatively small) statistical uncertainty around the flow-performance estimates. The coloured rectangles in Figure 12 show the underlying estimate for each shock, along with 95% confidence intervals.	Credit risk = 7.24; Liquidity risk = 0; Risk free rates up = 14.1
Impact of swing pricing on amplification (% reduction)	We centre around our baseline estimate of a 15% effect on the flow-performance relationship, and allow for +-10pp. We take into account the fact that amplification in the fund dealer model is not 1:1 with this reduction.	5%; 15%; 25%

[13] For example, increasing the effect of swing pricing on flow sensitivity by 10pp from -10% to -20% reduces the amplification of a shock to risk free rates by 8.9%.

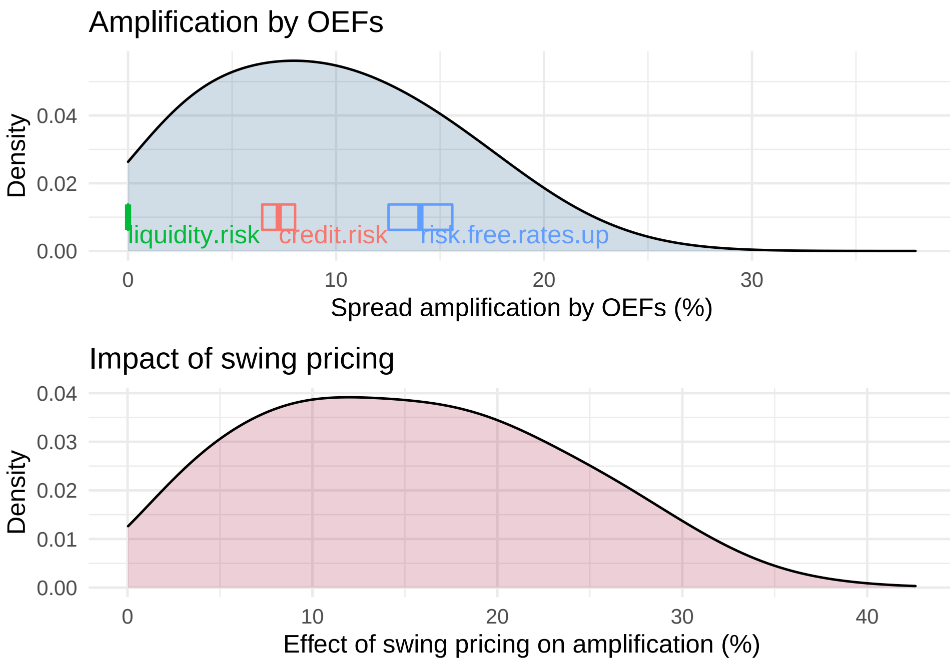

Figure 12: Generated distributions

We then draw from these two distributions describing (1) how much of a one standard deviation shock to spreads is due to amplification by OEFs, and (2) how much this amplification would be reduced by swing pricing, to generate a range of results for the percent reduction in the overall size of shock to corporate bond spreads. We can map this directly onto the GDP at risk regressions to produce a range of improvements in GDP at risk from swing pricing, given a one standard deviation shock to spreads.

Our results are summarised in Figure 13 for one to eight quarters ahead. The red line shows the baseline GDP at risk estimate, corresponding to the central estimate from Figure 11, and the green and yellow swathe shows the distribution of GDP at risk outcomes when swing pricing is applied. Table 4 shows summary results for one year (four quarters) ahead.

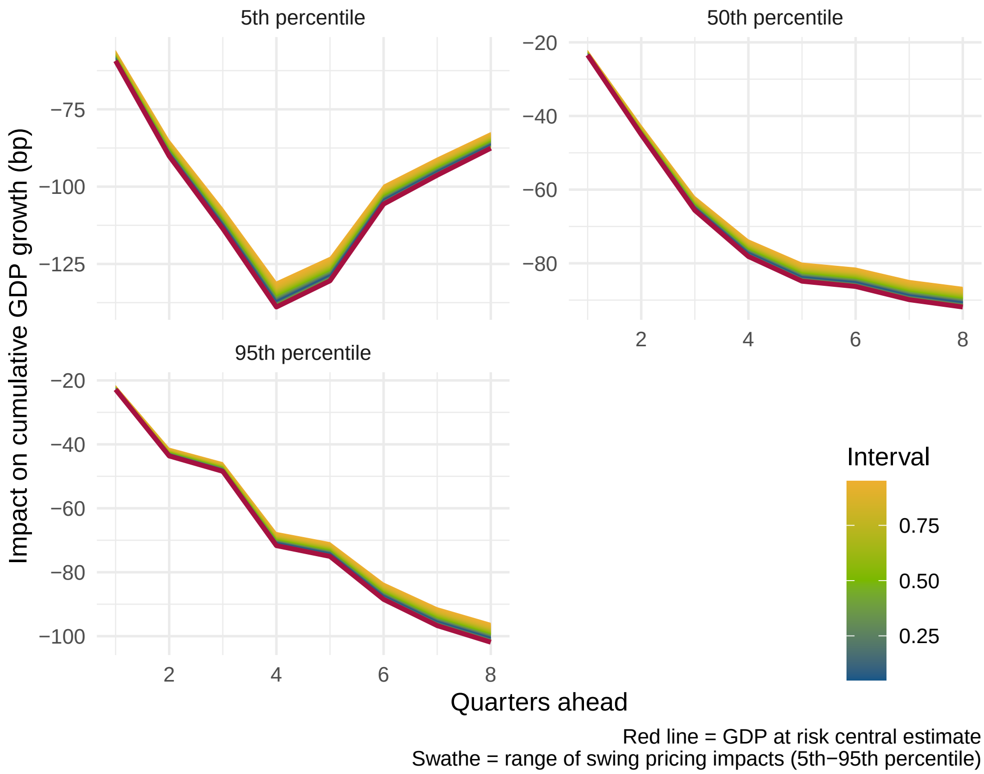

Figure 13: Effect of swing pricing on GDP at risk

Table 4: Effect of swing pricing on GDP growth, 1-year horizon

	Impact of a 1 standard deviation shock to corporate bond spreads (bp cumulative GDP growth)			
		GDP impact with swing pricing		
Percentile of GDP distribution	Baseline	Low	Mid	High
5	-138.9	-138.8	-137.0	-131.9
50	-78.1	-78.1	-77.1	-74.2
95	-71.7	-71.6	-70.7	-68.1

Table 4 summarises our results at a one year horizon. Rows show the impact of a one standard deveviation shock to corporate bond spreads on different points of the GDP at risk distribution: the 5th percentile (left tail), 50th percentile (central case) and 95th percentile (right tail). The 'baseline' column shows the impact of the shock, in basis points of GDP, with no policy intervention. The final three columns show the impact on GDP incorporating the effects of swing pricing, with a range of effects – low, mid and high – corresponding to different percentiles of the results distribution described above (5th, 50th and 95th). Swing pricing reduces the impact of the shock to corporate bond spreads on the 50th percentile of GDP growth by 1.1bps (from -78.1bp to -77.1bp). The estimated range of the effect varies from 0.1bp to 3.9bp. The improvement in GDP tail risks (the 5th percentile of the GDP growth distribution) is somewhat larger: the median estimated reduction is 1.9bp, with a range of 0.1bp to 7bp. Overall our results suggest a modest but relevant potential GDP benefit from enhancing OEFs' use of swing pricing.

We can use the results of Gilchrist and Zakrajšek (2012) to check the magnitude of our GDP at risk estimates. They find that a 100bp increase in the US excess bond premium (EBP) is associated with around a 200bp reduction in GDP growth over the following four quarters. The EBP is the part of corporate bond spreads not driven by changes in underlying credit risk, which should include amplification of shocks within the financial system. If reducing the amplification of shocks by OEFs reduces the EBP one-to-one, then our results (where swing pricing reduces the amplified part of an 80bp shock to spreads from 6.4bp to 5.9bp) imply an improvement in expected GDP of about 1bp. Although Gilchrist and Zakrajšek (2012) use US rather than UK data, the fact that the GDP benefit implied by the EBP is similar to our estimate for median GDP at risk over the same horizon (1.1bp) provides additional comfort that our estimates are broadly reasonable.

3.5 What if funds sell liquid assets?

Our main estimate of the benefits of swing pricing – reducing the risk of redemption driven fire sales – is based on the idea that OEFs need to sell assets, including less liquid ones, to meet redemptions. This is in line with a number of papers which find a price impact on assets held by funds facing net outflows (for example Hau and Lai (2013), Lou and Wang (2018) and Coudert and Salakhova (2020)). If funds sell a representative portion of their portfolios (a 'vertical slice') to meet net outflows, then we would expect sales of less liquid assets to follow from fund outflows. The fund-dealer model described in Section 3.1.2 assumes that funds sell a vertical slice of their assets in response to outflows.

However, other research has reached different conclusions. For example, Jiang, Li, and Wang (2017) find that OEFs use cash and liquid assets to manage redemptions in calm periods, but sell a more representative set of assets during stress – i.e. their reaction to outflows is state contingent. Choi et al. (2020) find limited price impact driven by redemptions from corporate bond OEFs, which they attribute to OEFs' use of liquid asset buffers to meet redemption requests.

In effect, these results suggest OEFs maintain their own private liquidity buffers, and use these to meet outflows in the first instance. This reduces the price impact of meeting redemptions, because funds use their most liquid assets and cash rather than selling more illiquid assets with a larger expected price impact. This liquidity management behaviour would have a positive effect by reducing the impact on corporate bond spreads from procyclical investor behaviour. This in turn would imply a smaller benefit from increasing the use of swing pricing, as measured using the results of the fund-dealer model.

However, using liquid assets to manage flows is unlikely to provide a 'free lunch.' First, corporate bond OEFs would need to maintain larger holdings of liquid assets and cash in order to meet redemptions. If redemptions were less volatile (as discussed in Section 3.3) OEFs would in principle need smaller liquid asset buffers, and could invest more in corporate bonds. OEFs surveyed in Bank & FCA (2021b) reported holding around 8.3% of NAV in liquid assets on average, of which 2.7% was held in cash and 5.6% in other liquid assets (e.g. government bonds). Total assets under management of UK-domiciled corporate bond funds is around £116bn, suggesting nearly £10bn of low return liquid asset might be held across the sector. And that is just the UK – globally fixed income OEFs have assets of nearly $13 trillion[14]. If non-UK funds also maintain liquid asset buffers of around 8%, then fixed income funds may have $1000bn of liquid assets – even small changes to this could represent material levels of investment in corporate bonds. Second, selling more liquid assets first exacerbates first mover advantage: as the fund reduces its liquid asset holdings to meet outflows, the portfolio available for remaining investors becomes relatively more illiquid, increasing the incentive to 'run early.' So although using cash and liquid assets to manage redemptions has the potential to reduce fire sale risks, it a) implies larger liquid asset buffers (with lower returns for investors and reduced investment in corporate bonds), and b) might actually increase first mover advantage.

Although our quantitative results rely on a modelling assumption that OEFs sell a vertical slice of their assets in response to redemptions, our view is that effective swing pricing should provide benefits – smaller required liquid asset holdings, limiting first mover advantage – even if funds sell more liquid assets first to meet redemptions.

[14]Statistics from the Investment Company Institute, see Worldwide Regulated Open-End Fund Assets and Flows First Quarter 2021

4 Costs

In this section we discuss possible macroeconomic costs of reducing liquidity mismatch in OEFs. We think the main way in which macroeconomic costs might arise is if reducing liquidity mismatch were to discourage investment in corporate bonds via OEFs – as noted in Section 3.4, corporate bonds are an important financing source for the real economy, and OEFs are major investors in UK corporate bonds. A policy that discouraged investors from using corporate bond OEFs could increase financing costs for UK companies, if investors rebalanced their portfolios towards other types of asset, or OEFs investing in non-UK corporate bonds.

To think about the possible effect of swing pricing on investment in OEFs, we can imagine two types of OEF investor:

- 'Fast-moving investors.' These investors trade in and out of corporate bond OEFs frequently, and derive a liquidity benefit from the fact that the cost of their trading is borne by remaining investors.
- 'Slow-moving investors.' These investors trade infrequently, and derive no benefit from liquidity mismatch. They do however bear some of the costs by remaining invested in the fund.

Although we are not able to observe directly which category an individual investor falls into, it is likely that most fast-moving investors are institutional. They are more likely to have timely access to relevant information, and trade in quantities such that first-mover advantage could provide a meaningful financial benefit. Jin et al. (2019) find that institutional investors trade in and out of funds more frequently than retail investors – the average flow volatility is five times greater for institutional compared with retail investors in their data. Bank & FCA (2021b) found that funds with a majority of institutional or professionally advised investors saw larger outflows in the March 2020 stress than did funds with mostly retail investors. Institutional investors are a significant source of funds for corporate bond OEFs, making up nearly 50% of overall investment in UK OEFs (Bank & FCA 2021b).

Effective swing pricing reduces the liquidity benefit to fast-moving investors from investing in OEFs, because it means they cannot avoid paying the full cost of their liquidity. Given slow-moving investors trade infrequently, and do not benefit from first mover advantage, the change in OEF liquidity from introducing swing pricing should have no meaningful impact on their investment decisions.

Fast-moving investors may decide to adjust their portfolios in response to the reduced liquidity provided by OEF shares. If we assume that investors choose a diversified portfolio with a level of liquidity and return based on their preferences, a natural response of fast-moving investors would be to reduce their holdings of OEF shares to some extent, and increase their holdings of other more liquid assets. This would move their portfolio towards its previous level of return vs liquidity. In aggregate, this might imply lower demand for corporate bonds and higher demand for liquid assets like government bonds or cash, potentially pushing up corporate bond spreads.

However, reducing liquidity mismatch may also increase the average returns provided by corporate bond OEFs. This is because the costs of trading would now be borne by redeeming investors rather than those remaining in the fund, and potentially because OEFs could hold a smaller proportion of liquid assets (discussed further in Section 3.5). Higher returns are likely to encourage more investment in OEFs from slow-moving investors (who have not lost any liquidity benefit). They may also compensate for some of the lost liquidity for fast-moving investors, depending on their preferences for returns vs liquidity. In addition, OEFs are not the only collective vehicle investors can use to hold corporate bonds. Fast-moving investors could invest in corporate bond ETFs, which provide equity-like liquidity while still offering exposure to corporate bond markets. So even if introducing swing pricing encouraged some fast-moving investors to invest less in OEFs, the impact on corporate bond investment may be more limited.

These effects, summarised in Table 5, mean the direction of the impact on investment in OEFs is ambiguous – reducing liquidity mismatch could lower investment to some extent, or increase it, or have no net effect.

As well as the theoretical argument above suggesting that the macroeconomic costs of introducing swing pricing may be small, there is some empirical evidence from Jin et al. (2019). They find that OEFs using swing pricing see somewhat smaller inflows than other OEFs outside of stress periods, but the results are not

Table 5: Directional impact on OEF investment

	Fund returns up	Fund liquidity down
Patient investors	+	–
Impatient investors	+	No effect

statistically significant. This suggest that the net impact on OEF investment is likely to be limited. Moreover, the data used by Jin et al. (2019) is in a context where similar OEFs with and without swing pricing are available, so investors may switch between the two. If swing pricing were mandated for all corporate bond OEFs this option would not be available, likely reducing the impact even further.

It is important to point out that in the discussion above we assume no 'international leakage,' i.e. we assume that OEFs cannot change their domicile in order to avoid any requirements. Such leakage may not have a significant effect on investment in the UK economy, as a fund could change its domicile and still invest in UK assets. However, it may be undesirable for other reasons, for example because it reduces the degree of regulatory oversight from UK authorities. And given the global nature of the OEF sector, greater benefits could be achieved through coordinated international measures to address liquidity mismatch than by an individual jurisdiction acting alone. This was acknowledged by the FPC in its response to the conclusion of the Bank and FCA's review of liquidity mismatch in OEFs (Bank of England 2021c).

5 Conclusion

Macroprudential authorities have relatively little experience with non-bank financial institutions, compared with the banking sector. But non-bank sectors, and particularly OEFs, are growing rapidly. Macroprudential authorities will likely need to take more action to address risks from non-banks, and will need an approach for weighing up the costs and benefits of such actions. We contribute to this endeavour directly, by analysing the macroeconomic benefits and costs of reducing liquidity mismatch in OEFs, and indirectly by providing an example of how cost-benefit analyses related to non-bank finance might be carried out.

Looking at the benefits of swing pricing, we find that, by reducing the sensitivity of OEF outflows to negative performance, swing pricing reduces the amplification of shocks to investment grade bond spreads by around 8%, and by around 22% for high yield bonds. Using the GDP at risk approach described by Aikman et al. (2019), we show that more widespread swing pricing could improve GDP tail risk in the face of a shock to bond spreads by up to 7bp after one year. This reduction in tail risks is particularly relevant for macroprudential authorities, given their mandates to maintain financial stability.

We also consider, albeit qualitatively, the possible macroeconomic costs of more widespread swing pricing. We argue that the impact on investment in corporate bond OEFs is ambiguous, and could in principle even be positive. Empirical evidence from Jin et al. (2019) suggests a small, statistically insignificant impact on 'normal times' inflows for OEFs using swing pricing, further supporting our view that the macroeconomic costs are likely to be smaller than the benefits.

In our judgement, our results suggest there would be macroeconomic benefits to greater use of swing pricing in the UK, supporting the conclusions drawn by the FPC, Bank and FCA (Bank of England 2021c).

Finally, our work provides an example of how other cost-benefit analyses of non-bank macroprudential issues might be carried out. There are a number of such analyses related to bank capital, but fewer looking at non-bank issues. We hope this paper provides a useful example of how such analyses can be conducted, supporting macroprudential authorities as they tackle risks and issues in non-bank finance.

6 References

Adrian, Tobias, Nina Boyarchenko, and Domenico Giannone. 2019. "Vulnerable Growth." *American Economic Review* 109 (4): 1263–89.

Aikman, David, Jonathan Bridges, Sinem Hacioglu Hoke, Cian O'Neill, and Akash Raja. 2019. "Credit, Capital and Crises: A GDP-at-Risk Approach." Bank of England Staff Working Paper No. 824. https://www.bankofengland.co.uk/working-paper/2019/credit-capital-and-crises-a-gdp-at-risk-approach.

Arora, Rohan, Guillaume Bédard-Pagé, Guillaume Ouellet Leblanc, and Ryan Shotlander. 2019. "Bond Funds and Fixed-Income Market Liquidity: A Stress-Testing Approach." Bank of Canada.

Arregui, Nicolas, Jaromír Bene, Ivo Krznar, Srobona Mitra, and Andre O. Santos. 2013. "Evaluating the Net Benefits of Macroprudential Policy: A Cookbook." International Monetary Fund Working Paper 13/167.

Bank of England. 2021a. "Assessing the Resilience of Market-Based Finance." https://www.bankofengland.co.uk/report/2021/assessing-the-resilience-of-market-based-finance.

———. 2021b. "Financial Stability Report - December 2021." https://www.bankofengland.co.uk/financial-stability-report/2021/december-2021.

———. 2021c. "Financial Stability Report - July 2021." https://www.bankofengland.co.uk/financial-stability-report/2021/july-2021.

Bank of England, and Financial Conduct Authority. 2021a. "Assessing the Resilience of Market-Based Finance (Box A)." https://www.bankofengland.co.uk/report/2021/assessing-the-resilience-of-market-based-finance.

———. 2021b. "Liquidity Management in UK Open-Ended Funds: Report Based on a Joint Bank of England and Financial Conduct Authority Survey." https://www.bankofengland.co.uk/report/2021/liquidity-management-in-uk-open-ended-funds.

Baranova, Yuliya, Graeme Douglas, and Laura Silvestri. 2019. "Simulating Stress in the UK Corporate Bond Market: Investor Behaviour and Asset Fire-Sales." Bank of England Staff Working Paper No. 803. https://www.bankofengland.co.uk/working-paper/2019/simulating-stress-in-the-uk-corporate-bond-market-investor-behaviour-and-asset-fire-sales.

Basel Committee on Banking Supervision. 2010. "An Assessment of the Long-Term Economic Impact of Stronger Capital and Liquidity Requirements." https://www.bis.org/publ/bcbs173.pdf.

Bernanke, Ben S, and Mark Gertler. 1986. "Agency Costs, Collateral, and Business Fluctuations." National Bureau of Economic Research Cambridge, Mass., USA.

Bond, Philip, Alex Edmans, and Itay Goldstein. 2012. "The Real Effects of Financial Markets." *Annu. Rev. Financ. Econ.* 4 (1): 339–60.

Brooke, Martin, Oliver Bush, Robert Edwards, Jas Ellis, Bill Francis, Rashmi Harimohan, Katharine Neiss, and Caspar Siegert. 2015. "Measuring the Macroeconomic Costs and Benefits of Higher UK Bank Capital Requirements." *Bank of England Financial Stability Paper* 35 (35): 1–55.

Canay, Ivan A. 2011. "A Simple Approach to Quantile Regression for Panel Data." *The Econometrics Journal* 14 (3): 368–86.

Cecchetti, Stephen G, and Andrew Levin. 2008. *1. Measuring the Macroeconomic Risks Posed by Asset Price Booms.* University of Chicago Press.

Cecchetti, Stephen G, and Hong Li. 2008. "Measuring the Impact of Asset Price Booms Using Quantile Vector Autoregressions." *Brandeis University, Waltham, MA.*

Cetorelli, Nicola. 2021. "Were Banks Exposed to Sell-Offs by Open-End Funds During the Covid Crisis?" Liberty Street Economics, October 18, 2021. Federal Reserve Bank of New York. https://libertystreeteconomics.newyorkfed.org/2021/10/were-banks-exposed-to-sell-offs-by-open-end-funds-during-the-covid-crisis.

Choi, Jaewon, Saeid Hoseinzade, Sean Seunghun Shin, and Hassan Tehranian. 2020. "Corporate Bond Mutual Funds and Asset Fire Sales." *Journal of Financial Economics* 138 (2): 432–57. https://doi.org/10.1016/j.jfineco.2020.05.006.

Claessens, Stijn, and Ulf Lewrick. 2021. "Open-Ended Bond Funds: Systemic Risks and Policy Implications." *BIS Quarterly Review*, 37.

Coudert, Virginie, and Dilyara Salakhova. 2020. "Do Mutual Fund Flows Affect the French Corporate Bond Market?" *Economic Modelling* 87: 496–510.

Davis, E Philip, Iana Liadze, and Rebecca Piggott. 2019. "Assessing the Macroeconomic Impact of Alternative Macroprudential Policies." *Economic Modelling* 80: 407–28.

de Guindos, Luis. 2018. "Coming to the Forefront: The Rising Role of the Investment Fund Sector for Financial Stability in the Euro Area." Speech at the Opening Conference, 21st Euro Finance Week, Frankfurt AM Main, 12 November 2018. European Central Bank. https://www.ecb.europa.eu/press/key/date/2018/html/ecb.sp181112.en.html.

Financial Conduct Authority. 2018. "How We Analyse the Costs and Benefits of Our Policies." https://www.fca.org.uk/publication/corporate/how-analyse-costs-benefits-policies.pdf.

Financial Stability Board. 2017. "Policy Recommendations to Address Structural Vulnerabilities from Asset Management Activities." https://www.fsb.org/2017/01/policy-recommendations-to-address-structural-vulnerabilities-from-asset-management-activities/.

Ganbold, Makhgal, and Bayarbaatar Amgalan. 2021. *simukde: Simulation with Kernel Density Estimation.* https://CRAN.R-project.org/package=simukde.

Gilchrist, Simon, and Egon Zakrajšek. 2012. "Credit Spreads and Business Cycle Fluctuations." *American Economic Review* 102 (4): 1692–1720.

Goldstein, Itay, Hao Jiang, and David T Ng. 2017. "Investor Flows and Fragility in Corporate Bond Funds." *Journal of Financial Economics* 126 (3): 592–613.

Hau, Harald, and Sandy Lai. 2013. "Real Effects of Stock Underpricing." *Journal of Financial Economics* 108 (2): 392–408.

Investment Company Institute. 2021. "Worldwide Regulated Open-End Fund Assets and Flows Second Quarter 2021." https://www.ici.org/statistical-report/ww_q2_21.

Jiang, Hao, Dan Li, and Ashley Wang. 2017. "Dynamic Liquidity Management by Corporate Bond Mutual Funds." *Available at SSRN 2776829.*

Jin, Dunhong, Marcin Kacperczyk, Bige Kahraman, and Felix Suntheim. 2019. "Swing Pricing and Fragility in Open-End Mutual Funds." International Monetary Fund Working Paper 19/227.

Jordà, Òscar. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review* 95 (1): 161–82.

Kapetanios, George. 2008. "A Bootstrap Procedure for Panel Data Sets with Many Cross-Sectional Units." *The Econometrics Journal* 11 (2): 377–95.

Karmakar, Sudipto. 2016. "Macroprudential Regulation and Macroeconomic Activity." *Journal of Financial Stability* 25: 166–78.

Kiyotaki, Nobuhiro, and John Moore. 1997. "Credit Cycles." *Journal of Political Economy* 105 (2): 211–48.

Koenker, Roger, and Gilbert Bassett. 1978. "Regression Quantiles." *Econometrica: Journal of the Econometric Society*, 33–50.

Lewrick, Ulf, and Jochen F Schanz. 2017. "Is the Price Right? Swing Pricing and Investor Redemptions." BIS Working Paper No 664. https://www.bis.org/publ/work664.pdf.

Lou, Xiaoxia, and Albert Y Wang. 2018. "Flow-Induced Trading Pressure and Corporate Investment." *Journal of Financial and Quantitative Analysis* 53 (1): 171–201.

Manconi, Alberto, Massimo Massa, and Ayako Yasuda. 2012. "The Role of Institutional Investors in Propagating the Crisis of 2007–2008." *Journal of Financial Economics* 104 (3): 491–518.

Sydow, Matthias, Aurore Schilte, Giovanni Covi, Marija Deipenbrock, Leonardo Del Vecchio, Pawel Fiedor, Gábor Fukker, et al. 2021. "Shock Amplification in an Interconnected Financial System of Banks and Investment Funds," European central bank working paper no 2581,.

A Flow-performance regressions

The Table below shows results for corporate bond OEFs, which we use as an input to the fund-dealer model.

Table 6: Flow-performance regression results

	Dependent variable:
	Fund flow (% of net assets)
β_1	0.209^{***}
	(0.010)
β_2	-0.058^{***}
	(0.016)
β_3	-0.010^{***}
	(0.001)
β_4	0.015^{***}
	(0.001)
$log(TNA_{i,t-1})$	0.735^{***}
	(0.064)
$log(TNA_{i,t-1})^2$	-0.043^{***}
	(0.002)
Observations	652,844
R^2	0.011
Adjusted R^2	0.001
F Statistic	$1{,}249.033^{***}$ (df = 6; 645936)
Note:	*p<0.1; **p<0.05; ***p<0.01

B Fund dealer model parameters

Table 7: Updated fund-dealer model parameters

Sector	Parameter	Value
Dealer	capitalRatio	0.12
Dealer	leverageRatio	0.04
Dealer	currentAssets	12511
Dealer	currentRWA	4854
Dealer	currentCapital	713
Funds	Procyclicality estimate: Equity	0.08
Funds	Procyclicality estimate: Allocation	0.1
Funds	Procyclicality estimate: Corporate Bond	0.15
Funds	Procyclicality estimate: Other Fixed Income	0.17
Funds	Procyclicality estimate: Commodities	0.02
Funds	Procyclicality estimate: Convertibles	0.22
Funds	Procyclicality estimate: Property	0.15
Funds	TNA: Equity	2523bn
Funds	TNA: Allocation	1934bn
Funds	TNA: Corporate Bond	1484bn
Funds	TNA: Other Fixed Income	1048bn
Funds	TNA: Commodities	37bn
Funds	TNA: Convertibles	0.81bn
Funds	TNA: Property	234bn

TNA = total net assets