Towards a Macroprudential Framework for Investment Funds: Swing Pricing and Investor Redemptions*

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How effective are available policy tools in managing systemic liquidity risks in the mutual fund industry? We assess one such tool—swing pricing—which allows funds to adjust their settlement price in response to large flows. A global game guides our empirical analysis. Consistent with its predictions, we show that during normal market conditions swing pricing dampens outflows in reaction to weak fund performance by mitigating investor first-mover advantages. Yet during episodes of market stress, swing pricing fails to contain redemption pressures despite supporting fund returns. This calls for adjusting swing pricing rules to achieve macroprudential objectives.

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1. Introduction

The outbreak of the COVID-19 crisis laid bare the systemic risks that can emanate from the shadow-banking sector. In March 2020, open-end bond funds experienced rapidly accelerating outflows amid bouts of market illiquidity (e.g., Falato, Goldstein, and Hortaçsu 2021). U.S. bond funds, for example, suffered monthly outflows of more than 5 percent of total net assets (TNA), twice the amount observed during the peak of the Great Financial Crisis (GFC) of 2007/08.[1] Central banks intervened at unprecedented scale to stabilize markets and to prevent runs on funds, reminiscent of the safety net they had provided during the GFC.

Fund managers are equipped with a variety of tools to manage the risk of large-scale redemptions (International Organization of Securities Commissions (IOSCO) 2015). Yet despite the GFC experience, risk-management tools in the fund industry remain largely predicated on a microprudential approach. Relatively little is known about the effectiveness of these tools in supporting financial stability, highlighting the need for policy review (e.g., Financial Stability Board 2020).

Systemic concerns focus on the risks associated with open-end bond funds' liquidity mismatch: these funds invest in assets, such as corporate bonds, that often become illiquid under stressed market conditions, while granting fund investors the right to redeem their shares for cash daily. Concerted investor redemptions can thus force these funds to fire-sell assets. This can trigger adverse spillovers on the valuations and functioning of the underlying bond markets (e.g., Jiang, Li, and Wang 2021; Ma, Xiao, and Zeng 2020) and, given the growing role of bonds as a source of corporate funding, weigh on firms' funding conditions.

In this paper, we assess the effectiveness of swing pricing through the lens of a macroprudential perspective.[2] Swing pricing has several

[1]European bond funds, by comparison, experienced outflows equivalent to 4.9 percent of TNA in March 2020, slightly above the 4.6 percent recorded during the height of the GFC.

[2]Liquidity buffers, redemption gates, or suspensions as well as supervisory stress tests (if accompanied by corrective supervisory action) could potentially also serve as macroprudential tools to avoid fire sales and preserve investor confidence during episodes of market stress (Cominetta et al. 2018).

features that are conducive to supporting financial stability. It allows the fund manager to adjust by the "swing factor" the fund's net asset value (NAV) per share to reflect the estimated costs associated with investor redemptions and subscriptions, such as selling or buying assets in order to meet redemption requests or invest cash inflows. Importantly, these costs can suddenly spike during episodes of market stress (e.g., Friewald, Jankowitsch, and Subrahmanyam 2012; Kargar et al. 2021; O'Hara and Zhou 2021). It is often during these times that fund investors redeem their shares to meet their liquidity needs. Absent swing pricing or other redemption charges that are credited to the fund, the cost of liquidating assets to satisfy redemptions will only be borne by those investors that stay with the fund. Anticipating this dilution of the NAV, investors have a first-mover advantage in withdrawing from the fund—creating the breeding ground for a run on the fund and destabilizing fire sales.

We present a global game that formalizes how swing pricing affects investor behavior. We illustrate how the fund can mitigate the first-mover advantage by passing the dilution costs on to withdrawing investors. However, we also show that swing factors which reflect the liquidity costs that prevail during normal market conditions fail to offset the first-mover advantage during periods of market stress. This is despite the fact that swing pricing raises measured fund returns by reducing fund dilution.

We empirically test the predictions from the global game based on a comparative analysis of nearly 2,000 open-end bond funds. We exploit the fact that swing pricing was available to funds domiciled in Luxembourg during our period of observation (2012–17), whereas U.S. funds were not yet permitted to apply swing pricing.[3]

Consistent with the predictions derived from the global game, but in contrast to previous research, we show that swing pricing did not curb outflows during the 2013 U.S. "taper tantrum." This episode represents an ideal test case since it was characterized by a sharp but short-lived decline in fund returns that was largely contained to funds investing in fixed-income instruments. It thus did

[3]U.S. open-end funds are allowed to apply swing pricing since November 2018. However, the institutional structure of the U.S. market and operational challenges have prevented the adoption of swing pricing by U.S. funds to date (Kashyap, Kohn, and Wessel 2021).

not prompt market intervention by the public sector at any scale comparable to the one observed during the GFC or COVID-19 crisis that would blur the assessment.

We argue that swing pricing rules, which tend to be based on applying a constant swing factor once outflows exceed a certain threshold, fail to offset investor first-mover advantages in stressed markets. Because the cost that funds charge investors for their liquidity provision rises only modestly, the funds remain prone to runs in the advent of aggregate liquidity shocks. Even so, swing pricing funds exhibited higher returns during the taper tantrum. Their market-adjusted returns exceeded those of their peers by about 17 to 36 basis points (annualized) on average, at a time when the average fund return fell to −19 basis points below the funds' benchmark returns. This tallies with our model's prediction that swing pricing contains the dilution of the fund value.

Swing pricing does benefit funds when shocks are idiosyncratic. Flows of swing pricing funds are less sensitive to negative returns during normal times—as predicted by the impact of swing pricing on investor incentives. Specifically, outflows are reduced by about 0.07 percent of TNA for every percentage-point decline in returns. A swing pricing fund that exhibits a one-standard-deviation decline in (negative) returns thus benefits from a reduction in outflows of roughly 1 percent of TNA, equivalent to about half the cash holdings of the median U.S. fund in our sample. This difference arises only if returns are negative. By contrast, positive returns do not stimulate meaningful inflows into either swing pricing funds or their peer funds. The difference is most pronounced for funds investing in relatively illiquid assets, whereas it dissipates when comparing funds that invest in highly liquid securities.

Our results prove robust to testing a variety of different return measures, accounting for differences in investors' units of account and benchmark returns, as well as to considering changes in funds' market shares as an alternative approximation of fund flows.

Overall, swing pricing could provide a useful macroprudential tool to bolster the resilience of funds. However, adjustments to swing pricing rules appear necessary to ensure that investor first-mover advantages are mitigated during episodes of stress. In addition, macroprudential authorities may wish to consider topping up swing factors of large funds or those with common exposures to make these funds internalize the adverse price impact of asset liquidations in response to large redemptions.

The rest of the paper is organized in four sections. In Section 2, we discuss the related literature. Section 3 presents the rationale for swing pricing and develops a global game allowing us to derive a number of testable predictions. We apply these predictions to the data in Section 4, where we assess the impact of swing pricing on several fund performance measures, highlighting the differences between the impact under normal market conditions and during the 2013 taper tantrum. Section 5 concludes.

2. Related Literature

Our paper is related to a growing strand of the literature that studies financial stability risks arising from mutual funds and the tools to manage such risks. Jin et al. (2022) study the role of alternative pricing schemes, such as dual pricing and swing pricing, in dampening fund outflows. Based on data for about 230 U.K.-oriented funds, they find that alternative pricing schemes can dampen investor outflows including during periods of stress. This stands in contrast to our finding for a much larger sample of Luxembourg funds during the taper tantrum. One possible reason for this discrepancy is the steep downward adjustment of the NAV observed for U.K.-oriented funds during the GFC in the analysis of Jin et al. (2022), which has likely contributed to dampening fund outflows during this episode. For Luxembourg funds—similar to the approach taken in the United States—regulation limits funds' discretion to lower the NAV. This implies that first-mover advantages can surface during episodes of market stress, as also suggested by Malik and Lindner (2017), who analyze samples of up to six individual funds.[4]

Capponi, Glasserman, and Weber (2020) propose a model in which informed fund investors can anticipate redemptions and the resulting dilution of the fund value, creating a first-mover advantage. Swing pricing can offset this advantage in their model by accounting

[4]A notable feature of the data set in Jin et al. (2022) is the availability of confidential supervisory information on the funds' swing pricing activity. Our analysis, by comparison, relies on assessing investor behavior based on information that is available to investors at the point of deciding whether to redeem their shares.

for the dilution in the settlement price. This requires the swing factor to increase for larger redemptions. Modest swing factors may thus fail to contain outflows during stress episodes, consistent with our empirical findings.

Lewrick and Schanz (2017) derive welfare-optimal swing pricing policies in a general equilibrium framework. They show that trading frictions and investors' liquidity needs determine the fund manager's ability to swing the settlement price in the presence of no-arbitrage conditions. Less liquid markets would thus allow for a more active use of swing pricing. This resonates with our finding that funds investing in illiquid bonds benefit relatively more from swing pricing than those investing in more liquid bonds.

Our work also builds on that of Chen, Goldstein, and Jiang (2010), who develop a model showing how costly redemptions dilute a fund's NAV per share, creating an incentive for investors to run on the fund. They provide evidence that equity funds investing in less liquid assets experience greater outflows in response to poor performance. Goldstein, Jiang, and Ng (2017) show that this effect is even more pronounced for corporate bond funds, given the higher cost of liquidating the underlying assets.[5] Furthermore, their results imply a concave shape of the flow-to-performance relation for corporate bond funds: bond fund outflows are more sensitive to bad performance than inflows are to good performance—in contrast to the case of equity funds. This relation points to the risk of self-reinforcing redemptions during periods of weak fund performance. Our findings confirm the concave flow-to-performance relation for U.S. bond funds, while suggesting that flows for swing pricing funds are less susceptible to bad performance.

Aramonte, Scotti, and Zer (2020) study the liquidity profile of funds based on the sensitivity of fund returns to aggregate liquidity shocks. They show that less liquid funds are more exposed to redemptions in response to adverse macroeconomic news. This result tallies with our finding that funds with less liquid portfolios benefit

[5]A few empirical studies consider the dilution of fund value that arises from fund flows. Edelen (1999) finds that liquidity-motivated trading has a significant adverse effect on open-end U.S. equity fund performance. Greene and Hodges (2002) confirm this result for international funds but find no significant effect for other fund categories.

more from the dampening effect of swing pricing on fund outflows at least during normal market conditions.

3. How Does Swing Pricing Affect Investors' Behavior?

3.1 Swing Pricing in Practice

Flows in and out of an investment fund dilute the fund's value whenever they prompt the fund manager to trade securities. This is due to liquidation costs, which comprise direct transaction costs (e.g., commissions, fees) and, if the transactions are large enough, the cost due to the adverse impact on market prices.

The dilution of the fund's value creates an externality that makes funds vulnerable to the risk of runs. When investors redeem their shares, they receive the value of the fund's NAV per share. The NAV is fixed on the day the order is placed and does not incorporate the cost of fulfilling the investors' orders. Since this cost is exclusively borne by the investors that remain with the fund, there is an advantage in being among the first investors to redeem.

Swing pricing aims to reduce this externality. In principle, the externality could be eliminated by allocating to the orders the costs of their fulfillment. However, in practice, fund managers do not know these costs when fixing the NAV. Instead, fund managers adjust the NAV per share (p) by the *swing factor* (s), which approximates these costs. The "swung" NAV per share, $\tilde{p}$, at which all orders are subsequently settled, is then equal to $\tilde{p} = (1 - s)\, p$.

Various implementations of swing pricing trade off the desire to reduce the dilution of the fund's value with the need for operationally efficient and transparent rules of application. Funds typically set the swing factor equal to the approximate cost of selling securities under normal market conditions. While these factors are periodically reviewed and adjusted, there are limits to how quickly and by how much they can be raised in crisis times.[6] In addition, most

[6]According to the Association of the Luxembourg Fund Industry (ALFI) (2015), around half of the fixed-income funds cap the swing factor at a maximum of 2 percent and around half of all funds review their swing factor only at a quarterly frequency. This tallies with the description of the swing pricing policy in the prospectus of several major fund-management companies studied in our analysis. U.S. regulation, effective November 2018, applies a maximum swing factor of 2 percent of a fund's NAV per share.

funds apply a *partial* swing pricing policy, in which the swing factor is positive (negative) only if total net outflows (inflows) exceed a specified threshold (ALFI 2015).

3.2 A Model of the Effect of Swing Pricing on Investors

We present a global game to develop three testable hypotheses on how swing pricing affects investor behavior. Our model builds on the one developed in Chen, Goldstein, and Jiang (2010). We assume there is one fund and a continuum of risk-neutral investors, $[0, 1]$. Each investor initially holds one share of the fund. We normalize the total amount invested to 1. There are two periods: 1 and 2. In period 1, a fraction $\bar{X}$ of the investors decide whether to redeem their shares or whether to stay invested in the fund until period 2, when the fund is closed. All other investors remain with the fund and there are no inflows. To service redemptions, the fund needs to sell $(1+\lambda)$ worth of securities to raise one unit of cash, with $\lambda > 0$ representing the liquidation costs. Following Chen, Goldstein, and Jiang (2010), we assume the fraction $\bar{X}$ is sufficiently small to rule out that the fund has to pay out more than the amount of available funds.

Investors' actions give rise to strategic complementarities, which can bring about multiple equilibria. Each investor compares the return from withdrawing in period 1 with that from remaining invested until period 2. If she withdraws, she receives the NAV per share R_1 but will be charged the swing factor $s > 0$.[7] We assume without loss of generality that $R_1 = 1$ such that her payoff is equal to $(1 - s)$. If she stays with the fund, her payoff depends on the return of the portfolio in period 2, R_2, and the share of redeeming investors, x. The larger the redemptions, the higher the dilution and hence the lower the return from remaining with the fund, and the more optimistic about R_2 the investor has to be to stay.

To ensure a unique equilibrium, we follow the global games literature and make additional assumptions about the fund's return and investors' information.[8] We assume that R_2 increases in the random fund fundamental θ, drawn from a uniform distribution on the real

[7]This is in line with the fact that the vast majority of funds in Luxembourg only use a simple swing pricing rule, according to which a single swing factor is applied once net flows exceed the threshold.

[8]See Morris and Shin (2003) and the literature reviewed therein.

line. Each investor i receives a private signal $\theta_i = \theta + \sigma\,\varepsilon_i$ in period 1 about the unobserved fund fundamental. ε_i is an idiosyncratic noise term drawn from the distribution $g(\cdot)$, with cumulative distribution function $G(\cdot)$. The parameter $\sigma > 0$, in turn, indicates the noisiness of the signal.

In the resulting equilibrium, all investors apply a threshold strategy. If the private signal is below the threshold θ^*, the investor withdraws from the fund, whereas she remains invested if her signal is above θ^*. Morris and Shin (2003) present the proof for the general case of a symmetric binary action global game like the one presented here. For the sake of brevity, we do not restate their proof but apply their result to our case.[9]

The threshold signal θ^* is given by

$$R_2(\theta^*) = (1-s)\left[\int_{x=0}^{\bar{X}} \frac{1-(1+\lambda)\,(1-s)\,x}{1-x}dx\right]^{-1}. \qquad (1)$$

To see this, notice that the investor is indifferent between remaining invested in the fund and withdrawing in period 1 if the expected return on her fund share is equal to the return she yields from redeeming her share:

$$ER_2\frac{1-(1+\lambda)\,(1-s)\,x}{1-x} = 1-s. \qquad (2)$$

Rewriting the indifference condition in (2) in terms of the investor's expected payoff gain, it must hold that for the investor receiving signal $\theta_i = \theta^*$:

$$\pi(x,\theta^*) = \int_{\theta=-\infty}^{\infty} \frac{1-(1+\lambda)(1-s)x}{1-x}R_2(\theta)\frac{1}{\sigma}g\left(\frac{\theta^*-\theta}{\sigma}\right)d\,\theta - (1-s) = 0. \qquad (3)$$

[9]Ensuring uniqueness of the equilibrium requires some restrictions on the swing pricing rule, $s(\cdot)$, if we allow the rule to depend on investor outflows. In particular, the rule needs to preserve action monotonicity so that the investor's expected payoff gain from remaining invested as opposed to withdrawing, $\pi(x, \theta_i)$, is non-increasing in x. The incentive to withdraw from the fund thus (weakly) increases with the share of investors that also decide to withdraw. This ensures that the rule does not reverse the first-mover advantage, which is implied by the effect of dilution, by making it more profitable for an investor to remain with the fund when an increasing share of investors decides to withdraw.

Here, $(1/\sigma)g\left((\theta^{*}-\theta)/\sigma\right)$ is the posterior distribution of θ conditional on having received the signal θ^{*}, that is, the signal of the investor who is exactly indifferent between withdrawing and remaining with the fund. Since $x = G((\theta^{*}-\theta)/\sigma)\bar{X}$ is the proportion of investors who withdraw, the above indifference constraint can be written as

$$\pi(x,\theta^{*}) = \int_{x=0}^{\bar{X}} \frac{1-(1+\lambda)(1-s)x}{1-x} R_2\left(\theta^{*}-\sigma\, G^{-1}\left(\frac{x}{\bar{X}}\right)\right) dx - (1-s) = 0, \tag{4}$$

which implicitly characterizes the threshold signal θ^{*}. In the limiting case when the investor signal becomes increasingly precise, (4) converges to (1). Equation (1) motivates three hypotheses that we test in our empirical analysis.

First, we consider how swing pricing affects the sensitivity of investor redemptions to weak fund performance. In equilibrium, all investors with signals below θ^{*} redeem their shares. A positive swing factor (i.e., a downward adjustment of the NAV) reduces the cutoff signal and, as a result, reduces the fraction of investors who withdraw from the fund (i.e., lowers x). This is due to the decline in the payout to redeeming investors and the increase in the expected payoff for those who remain invested.

Past returns provide a useful proxy of investor signals. Individual investor signals (θ_i) are generally not observable in practice. However, both theoretical (e.g., Berk and Green 2004; Franzoni and Schmalz 2017) and empirical research (e.g., Ben-David et al. 2022; Ben-Rephael 2017) have underscored the role of past returns in predicting investor behavior. Our analysis thus builds on using past fund returns as a gauge of investors' return expectations, in line with the literature studying the relation of fund flows and past returns.[10] Applied to our setup, we conjecture the following:

HYPOTHESIS 1. *Swing pricing reduces fund outflows in response to weak fund performance.*

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[10]See Chevalier and Ellison (1997) or Sirri and Tufano (1998) for early contributions to this literature.

For our empirical analysis, this implies that swing pricing funds exhibit lower outflows than comparable U.S. funds if the investors receive a moderately weak signal. For sufficiently strong signals, by contrast, the flow-to-performance relation would be expected to be comparable across swing pricing funds and their peers, given that the expected returns of remaining invested would exceed those from withdrawing for most investors regardless of whether the fund applies swing pricing.

Our second hypothesis is concerned with the effectiveness of swing pricing as a financial stability tool given its current application. Since liquidation costs (λ) rise under stressed market conditions, funds would need to raise their swing factors in response to rising liquidation costs and increasing outflows to offset the first-mover advantage.[11]

In practice, however, swing pricing rules tend to be simple, with swing factors confined to relatively low values, subject to an upper bound and reviewed only periodically. This has important consequences for the usefulness of swing pricing as a financial stability tool. We thus conjecture the following:

HYPOTHESIS 2. *Swing factors that are calibrated to normal market conditions fail to offset investor first-mover advantages during periods of market stress.*

In this context, a key consideration relates to the link between asset sales and liquidation costs. For large funds or concerted sales by funds with common exposures, the liquidation of assets risks raising endogenously the associated liquidation costs (i.e., turning λ into an increasing function of x). This would rationalize a macroprudential top-up of the swing factor in order to account for the negative externality that the funds' sales impose on market conditions.

Our third prediction relates to the effect of swing pricing on the fund's returns:

HYPOTHESIS 3. *Swing pricing raises measured fund returns by reducing fund dilution, particularly during periods of large fund outflows.*

[11] Specifically, the fund would need to set the swing factor to $s = \lambda x/(1 + \lambda x)$ such that $\theta^* = R_2^{-1}(1)$ to ensure that investors remain invested unless they expect R_2 to drop below R_1.

This is due to two effects. First, for a given amount of outflows, the fund reduces the payout to redeeming investors by adjusting the NAV downwards (preserving sx in the fund). In addition, the fund incurs lower liquidation costs since it needs to sell fewer securities to service redemptions (preserving $sx\lambda$).[12] While we expect swing pricing to support fund returns whenever the fund swings the NAV, the effect should be strongest when liquidation costs are high such as during stressed periods.

4. Empirical Analysis

4.1 Data

Our analysis builds on 1,878 mutual bond funds for which we gather monthly data from Refinitiv Lipper and daily data on funds' NAV from Bloomberg. To construct our sample, we first select all actively managed open-end mutual bond funds available from Refinitiv Lipper that are registered in the United States or Luxembourg. These countries host the two largest mutual fund industries worldwide. Since swing pricing is applied at the level of the fund, we perform our analysis based on fund-level data, rather than using data at the level of individual fund share classes. Data coverage for Luxembourg funds improves significantly as of 2012, which is why we base our analysis on the period from January 2012 to April 2017. U.S. funds were allowed to use swing pricing only as of November 2018. Their fund-flow relationship is thus not affected by swing pricing during the period of observation.

The funds in the sample need to meet three criteria. First, based on the Refinitiv Lipper fund classification (henceforth referred to as the fund *style*), we keep only funds that can be allocated to a style for which we observe both U.S. and Luxembourg funds. This is to ensure that we are comparing funds with similar investment focus. Second, for each Luxembourg fund, we manually screen the management company's prospectus to include only those funds that have the

[12]The results in BlackRock (2016) indicate that such effects can be sizable. For the year 2015, the study finds an increase in annual emerging market fund returns by up to 77 basis points with funds swinging on up to 46 days.

ability to apply swing pricing.[13] Finally, we exclude all funds that invest mainly in advanced-economy sovereign debt. For these funds liquidation costs are low and, as a result, the first-mover advantage is small, as we will show in our analysis. Overall, our survivorship bias-free sample consists of 1,233 U.S. funds and 645 Luxembourg funds, split across 10 different styles such as *Bond USD Corporates* or *Bond USD High Yield*.

Throughout our empirical analysis, we control for time-varying characteristics of U.S. and Luxembourg funds as reported in Table 1. We consider several different measures of fund returns. This includes the funds' nominal returns and the funds' *alpha*, which for comparability we estimate based on a two-factor model as in Goldstein, Jiang, and Ng (2017).[14] About 60 percent of the funds report a benchmark index to evaluate their performance. These funds tightly manage their performance against the benchmark, as is evident from the low standard deviation and small range of the reported *market-adjusted returns*, which are given by the difference between the funds' returns and those of the benchmark. We will exploit this fact when comparing the performance of funds during the taper tantrum (see Section 4.5 below).

We measure funds' liquidity by benchmarking their cash ratio against the corresponding value of comparable funds. Specifically, we calculate an indicator variable, which is equal to one (zero otherwise) for funds with a cash ratio below the median of all funds allocated to the same style. This takes into account that funds' use of derivatives (Vivar, Wedow, and Weistroffer 2020) and holdings

[13] While the majority of Luxembourg bond funds can apply swing pricing, some funds do not apply this tool. This could reflect a preference to cater to investors that trade more frequently or diminishing marginal returns to switching to swing pricing when a large number of funds has already introduced it (e.g., Capponi, Glasserman, and Weber 2020; Jin et al. 2022). We note that the exclusion of these funds does not materially affect our main results.

[14] To estimate the fund alphas, we regress daily fund excess returns on excess aggregate bond market and aggregate stock market returns, using the Vanguard Total Bond Market Index Fund return and the Center for Research in Security Prices (CRSP) value-weighted market return as proxies, respectively. Fund alphas are then calculated as the average of the intercepts of rolling-window regressions for each fund over the past year. Our results prove robust to selecting alternative estimates of alpha, such as those resulting from a standard Fama-French three-factor model.

Table 1. Summary Statistics

	N	P10	P25	P50	P75	P90	St. Dev.	Mean
U.S. Funds								
Flow (%)	62,459	−3.48	−1.33	−0.04	1.42	4.32	6.27	0.41
Total Net Assets (Log US$ Million)	62,459	3.45	4.65	6.04	7.32	8.47	1.94	5.99
Age (Log Years)	62,459	1.10	1.79	2.64	3.09	3.33	0.86	2.41
Expense Ratio (%)	62,459	0.30	0.50	0.72	0.94	1.15	0.35	0.74
Three-Month Return (%)	62,459	−7.33	−0.58	3.22	8.58	14.59	10.04	3.82
Two-Factor Alpha (%)	48,277	−5.14	−2.31	−0.94	0.32	3.43	4.16	−0.84
Market-Adjusted Return (%)	51,691	−0.47	−0.15	0.02	0.21	0.56	0.66	0.03
Cash Relative to Peers (Binary)	47,656	0	0	1	1	1	0.50	0.52
Liquidity Beta	61,466	−0.20	−0.08	−0.01	0.04	0.15	0.20	−0.02
Redemption Charges (Binary)	62,459	0	0	0	0	1	0.31	0.11
Retail (Binary)	56,862	0	0	1	1	1	0.49	0.60
Luxembourg Funds								
Flow (%)	26,040	−4.96	−1.94	−0.02	2.08	7.21	8.44	0.87
Total Net Assets (Log US$ Million)	26,040	2.88	3.98	5.13	6.28	7.51	1.96	5.10
Age (Log Years)	26,040	0.69	1.10	1.79	2.48	3.04	0.87	1.83
Expense Ratio (%)	26,040	0.58	0.95	1.25	1.53	1.83	0.55	1.25
Three-Month Return (%)	26,040	−16.52	−6.24	2.19	9.98	19.73	14.89	2.12
Two-Factor Alpha (%)	17,109	−8.35	−3.72	−0.52	2.24	6.72	6.32	−0.68
Market-Adjusted Return (%)	12,878	−0.78	−0.30	−0.03	0.25	0.73	0.92	−0.04
Cash Relative to Peers (Binary)	16,079	0	0	0	1	1	0.50	0.47
Liquidity Beta	24,492	−0.34	−0.13	0.00	0.13	0.32	0.32	−0.01
Redemption Charges (Binary)	26,040	0	0	0	0	0	0.21	0.04
Retail (Binary)	25,238	0	1	1	1	1	0.35	0.86

Note: Unbalanced sample comprising 1,233 U.S. and 645 Luxembourg mutual open-end bond funds for the period from January 2012 to April 2017 with up to 88,499 month-fund observations per variable. The table reports the number of observations (N), the 10th (P10), 25th (P25), 50th (P50), 75th (P75), and 90th (P90) percentile as well as the standard deviation (St. Dev.) and the mean (Mean) by fund domicile. Flow: monthly net fund inflows as a percentage of total net assets (TNA); Total Net Assets: natural log of TNA in millions of U.S. dollars (USD) at the fund level; Age: natural log of years since launch of the fund; Expense Ratio: monthly expense ratio as a percentage of TNA (annualized); Three-Month Return: compound return over past three months in USD terms, in percent (annualized); Two-Factor Alpha: fund alpha, in percent, estimated over the past 12 months using a two-factor model which adds excess aggregate bond market returns to the standard Fama-French one-factor model; Market-Adjusted Returns: difference between monthly returns and the corresponding return of the fund's benchmark, in percent (annualized); Cash Relative to Peers: indicator variable that is equal to one (zero otherwise) if the fund reports cash holdings below the median of funds in the same fund style category; Liquidity Beta: Monthly average of the estimated sensitivity of the funds' net asset value per share to changes in aggregate liquidity conditions. A higher beta indicates a more sensitive liquidity profile. See footnote 15 for details; Redemption Charges: indicator variable equal to one (zero otherwise) if redemption charges apply to the fund's main share class; Retail: indicator variable that equals one (zero otherwise) if the fund's main share class has a minimum subscription amount of less than or equal to 50,000 USD.

of cash-like substitutes (Chernenko and Sunderam 2016, 2020) can blur measured cash positions.

We also estimate the funds' sensitivity to changes in aggregate liquidity conditions ("liquidity beta"), building on the approach outlined in Aramonte, Scotti, and Zer (2020).[15] This approach provides an approximation of changes in funds' liquidity risk profile at higher frequency than what can typically be constructed from reported fund holdings and is available for a large number of funds. By relying on aggregate factors, the estimates are also more robust to noisy or stale liquidity measures of infrequently traded securities, a salient feature of corporate bonds (e.g., Goldstein and Hotchkiss 2020).

Only about 1 out of 10 U.S. funds applies redemption charges, which is consistent with the results in Chernenko and Sunderam (2016) or Goldstein, Jiang, and Ng (2017). Luxembourg funds make even less use of redemption charges. This is not surprising, given that swing pricing already provides these funds with a means of levying liquidation costs on redeeming investors.

Fund flows and other fund characteristics are similar for the U.S. and Luxembourg funds, given the similarity of their investment strategies and investor basis. Figure 1A depicts the aggregate fund flows as a percentage of TNA, and Figure 1B shows TNA by country. At this level, fund flows of U.S. and Luxembourg funds as well as their TNA are highly correlated, with correlation coefficients of 0.72 and 0.85, respectively.[16]

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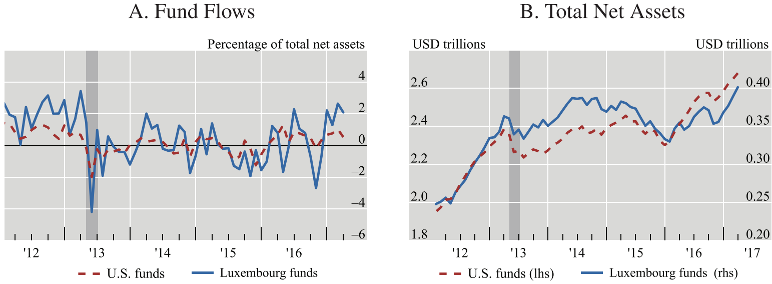
[15]We estimate the liquidity profile for each fund individually based on a rolling regression over 90-day windows for funds with at least 30 observations per window: $Ret_{i,t} = \alpha_i + \beta_{Li} Liq_t + \gamma_{Zi} Z_t + \gamma_{Xi} X_{i,t} + \delta_y + \varepsilon_{i,t}$, where $Ret_{i,t}$ is the daily return of fund i, measured as the daily NAV log-changes, in excess of the return on three-month U.S. Treasury bills, our proxy of the risk-free rate. Liq_t is the negative of the noise measure proposed by Hu, Pan, and Wang (2013), such that higher values imply better aggregate liquidity conditions in bond markets. Funds with a higher liquidity beta (β_{Li}) are more sensitive to changes in aggregate liquidity risk and thus have a more risky liquidity profile. As in Aramonte, Scotti, and Zer (2020), we include in Z_t controls for changes in the level and slope of the U.S. yield curve as well as the investment grade and high-yield Markit CDX spreads, respectively. $X_{i,t}$ controls for the fund's log net asset value and log age (in years plus 1), whereas α_i and δ_y represent the constant term and year fixed effects.

[16]Flows are calculated in the standard way: $Flow_{i,t} = [TNA_{i,t} - TNA_{i,t-1} (1 + R_{i,t})]/TNA_{i,t-1}$, with $R_{i,t}$ equal to fund i's nominal return in month t. We winsorize flows at 1 percent.

Figure 1. Aggregate Fund Flows and Net Assets by Country



Note: Unbalanced sample comprising 1,233 U.S. funds and 645 Luxembourg funds. The gray-shaded region indicates the period from May 2 to July 5, 2013, when yields on longer-term U.S. Treasury securities rose sharply in reaction to policy statements by the U.S. Federal Reserve (U.S. "taper tantrum").

The period from May to early July 2013, highlighted by the gray-shaded region, marks a clear break in the flow patterns for both countries. This period was characterized by a sharp increase in bond yields, following signs of a possible tapering of the U.S. Federal Reserve's monetary policy accommodation. During this "taper tantrum," credit spreads on corporate bonds and emerging market economy debt increased significantly, resulting in sizable valuation losses for the type of funds in our sample (Bank for International Settlements 2013).

This episode coincided with a marked decline in broker-dealers' commitment of capital to support liquidity in corporate bond markets (e.g., Bessembinder et al. 2018), which amplifies illiquidity in times of stress (e.g., Bao, O'Hara, and Zhou 2018). This decline also implies an increase in search costs, particularly for larger trades, and in the implicit costs of desired trades that could not be executed. Conventional measures of liquidity, such as bid-ask spreads or the cost of executed trades, may fail to take account of this shift in broker-dealers' business models and thus overstate bond liquidity (Goldstein and Hotchkiss 2020), particularly for larger redemption-induced trades of bond funds. While, for instance, average bid-ask spreads in U.S. corporate bond markets ticked up only modestly during the taper tantrum, Dannhauser and Hoseinzade (2022) document a steep increase in the discount on the price of less liquid bond exchange traded funds, indicative of strains on dealers' intermediation capacity and tight liquidity conditions at the time.

Unlike the GFC or the COVID-19 crisis, the taper tantrum did not result in massive public sector intervention. This episode thus provides an ideal test case of the ability of swing pricing to mitigate redemption pressures absent a public sector backstop.

4.2 Methodological Approach

Our methodological approach builds on the premise that investors subscribe to funds or redeem their shares based on the information they have about a fund at any given point in time. In this sense, we presume that investors in Luxembourg funds are aware of the risk of the NAV being swung and adjust their trading behavior accordingly. This information, often supplemented by a commitment to a maximum swing factor, is available from the fund's prospectus. However, funds do not disclose the threshold nor whether they swung the NAV. For the evaluation of the impact of swing pricing on investor incentives and the corresponding investment decisions, the fact that the fund *can* swing thus appears more relevant than whether the fund *actually* swung the NAV in any given period.

Our empirical analysis is also based on the fact that, with the exception of swing pricing, U.S. and Luxembourg fund managers could resort to the same set of policy tools to address redemption pressures during the period of observation (IOSCO 2015).[17] At the same time, it appears unlikely that the ability to swing prices has any meaningful impact on the fund company's decision whether to register a fund in the United States or in Luxembourg. Other considerations, such as having established a renowned brand name in the region, are likely to dominate. Thus, we can consider the ability of the fund to swing as largely exogenous. Controlling for other fund characteristics, we can therefore gauge whether differences in the fund performance of U.S. and Luxembourg funds are consistent with the predictions from the model.

[17] We note that Luxembourg funds are, in principle, also allowed to charge anti-dilution levies on an individual transaction basis. These levies are applied to large orders of individual clients. They are thus less relevant for the investor coordination problem studied in our paper.

4.3 Differences in the Flow-to-Performance Relation of Swing Pricing Funds and Their Peers

We start with testing Hypothesis 1 by analyzing whether the flows of funds that can apply swing pricing are less sensitive to weak performance than those of their peers. We run the following regression to estimate the flow-to-performance relation:

$$\begin{aligned} Flow_{i,t} = \alpha_i &+ \beta_1 R_{i,t-1} + \beta_2 NegR_{i,t-1} + \beta_3 (SP_i \times R_{i,t-1}) \\ &+ \beta_4 (SP_i \times NegR_{i,t-1}) + \gamma_1 X_{i,t-1} \\ &+ \gamma_2 (SP_i \times X_{i,t-1}) + \delta_{sct} + \varepsilon_{i,t} , \end{aligned} \tag{5}$$

where $Flow_{i,t}$ represents the value of fund i's net inflows as a percentage of TNA in month t. α_i controls for time-invariant individual fund effects.

$R_{i,t-1}$ is the fund's lagged performance. $NegR_{i,t-1}$, in turn, is equal to R_{it-1} times an indicator variable, which is equal to one (zero otherwise) if the fund's return is negative. This accounts for potential non-linearity in the flow-to-performance relation, i.e., that investor flows respond differently to weak returns than to strong ones as motivated by our model.[18]

SP_i is a binary variable with value one if the fund applies swing pricing (i.e., is domiciled in Luxembourg) and is otherwise equal to zero. Importantly, we allow for the coefficients on all observable fund characteristics to differ between U.S. and Luxembourg funds in order to account for any underlying differences in the two groups.

We consider lagged fund controls, $X_{i,t-1}$, comprising the first lag of fund flows, log TNA, log age, and the expense ratio. We also include the indicator variable that identifies funds for which cash holdings in the previous month were below the median of those reported by all funds allocated to the same style.

We saturate the regression with fund style-country-month fixed effects, captured by δ_{sct}. This is to account for, e.g., differences in investor clienteles across fund styles or tax-loss selling before year-end, which is more prevalent for U.S. funds than for those

[18]Similar parametric regressions have been considered in the literature by, for example, Goldstein, Jiang, and Ng (2017) or Vivar, Wedow, and Weistroffer (2020).

domiciled in Luxembourg. While this conservative choice of fixed effects captures a significant share of variation across funds, it provides additional confidence in the robustness of the estimated flow-to-performance relation. $\varepsilon_{i,t}$, finally, is the error term.

Our main results are based on the first lag of compound three-month returns. This performance metric is readily available to investors when taking their decision whether to sell or buy shares. It also addresses potential endogeneity concerns that would be associated with using current returns. Furthermore, relying on nominal returns is consistent with the findings in, e.g., Ben-David et al. (2022) and Fulkerson, Jordan, and Riley (2013), who make the case that investors focus on simple return measures or composite ratings, largely neglecting any risk adjustment. All that said, we consider a variety of alternative return measures to confirm the robustness of our results.

As a reference point, we run a fund fixed-effect regression based on using all funds in the sample.[19] We report the slope coefficients on returns and negative returns in column 1 of Table 2, while also depicting the results for less saturated versions of the regression in columns 2 and 3.[20] The estimates accord with previous findings in the literature of a concave flow-to-performance relation (e.g., Goldstein, Jiang, and Ng 2017), as indicated by the much larger coefficient on negative returns than the one on (all) returns for U.S. funds.

Based on column 1, an increase in a representative U.S. fund's annualized returns by 10 percentage points in the preceding three-month period (roughly equivalent to one standard deviation of the U.S. funds' returns in our sample) would lead to additional inflows of only 0.2 percent of TNA in the current month. Had the fund,

[19] Alternative estimation procedures, such as ordinary least squares (OLS) or the widely applied GMM estimator proposed by Arellano and Bond (1991), do not appear preferable to the fixed-effect regression for our purposes. The OLS estimation is expected to be biased in a dynamic panel setup, as is confirmed by a much higher coefficient estimate for lagged flows (not reported) compared with the estimate of the fixed-effect regressions. The GMM estimator, in turn, may overidentify the model given the large number of instruments that result from using a sample with up to 54 monthly observations per fund. Indeed, the length of the sample argues in favor of using the fixed-effect regression in our case.

[20] For brevity, we only report the slope coefficients on returns. All other estimates are available upon request from the authors.

Table 2. Flow-to-Performance Relation: Funds With vs. Funds Without Swing Pricing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
R_{t-1}	0.023*	0.020*	0.022*	0.014	0.062**	0.140**	0.042
	(0.012)	(0.009)	(0.010)	(0.015)	(0.027)	(0.061)	(0.046)
$NegR_{t-1}$	0.092***	0.062***	0.041**	0.128***	0.109***	0.166	0.142
	(0.020)	(0.009)	(0.014)	(0.020)	(0.033)	(0.104)	(0.094)
$R_{t-1} \times SP$	0.012	0.016*	0.016	0.019	0.051	0.085	0.084
	(0.012)	(0.008)	(0.010)	(0.014)	(0.035)	(0.076)	(0.059)
$NegR_{t-1} \times SP$	–0.075***	–0.065***	–0.053***	–0.091***	–0.159**	–0.371**	–0.144
	(0.010)	(0.009)	(0.009)	(0.013)	(0.064)	(0.118)	(0.101)
R-squared	0.108	0.075	0.060	0.125	0.127	0.127	0.131
Number of Funds	1,878	1,878	1,878	1,479	1,467	1,442	1,128
Observations	88,499	88,499	88,499	54,965	54,785	53,886	42,735
Return Measure	3m	3m	3m	3m	6m	12m	Alpha
Cash Holdings	No	No	No	Yes	Yes	Yes	Yes
Fund Fixed Effects (FE)	Yes	No	Yes	Yes	Yes	Yes	Yes
Style × Country × Month FE	Yes	No	No	Yes	Yes	Yes	Yes
Excluding Funds with Redemption Charges	No	No	No	Yes	Yes	Yes	Yes

Note: *p < 0.1; **p < 0.05; ***p < 0.01. Estimates based on Equation (5) with robust standard errors, clustered by fund style, in parentheses. Dependent variable: net inflows as a percentage of total net assets (TNA). All regressions control for lagged returns, lagged negative returns, lagged log TNA, log age, and the lagged expense ratio; regressions (4) to (7) also include an indicator of cash holdings, which is equal to one if the fund's cash holdings in the previous month were above the median of corresponding cash holdings of funds with the same style. For each control variable, we include the base effect and an interaction term for swing pricing funds (SP) to allow for a different elasticity for these funds and their peer funds. Return measure (R): annualized returns (in percent) over the past 3 months (regressions (1) to (4)), 6 months (5), and 12 months (6) as well as fund alpha (7), which is based on a two-factor model, estimated as the average of the intercepts of rolling-window regressions for each fund over the past year. Negative returns (NegR): returns interacted with an indicator variable, which is equal to one (zero otherwise) if returns are negative.

by comparison, experienced a decline in returns from 0 percent to -10 percent, it would have been subject to additional net outflows of 1.2 percent of TNA $(10 \times (0.023 + 0.092))$. To put these numbers into perspective, we note that median cash holdings of U.S. funds in our sample were 2 percent of TNA.

The relation of fund flows and past returns differs for swing pricing funds and their peers, supporting Hypothesis 1. To see this, we move to the slope coefficients that result from interacting returns and the indicator for swing pricing funds (SP, column 1 of Table 2). What stands out is these funds' lower sensitivity to negative returns. The reduction in outflows that can be linked to swing pricing follows from the sum of the slope coefficients on returns and negative returns of swing pricing funds $(0.012 - 0.075)$. Conditional on returns being negative, outflows are reduced by roughly 0.06 percent of TNA for every percentage-point decline in returns. A swing pricing fund with a negative three-month return dropping by 10 percentage points would thus have witnessed additional net outflows of 0.5 percent of TNA $(-10 \times (0.023 + 0.092 + 0.012 - 0.075))$ in the next month, less than half of its U.S. counterparts. Positive returns, by comparison, do not seem to stimulate meaningful inflows into either U.S. or swing pricing funds.

Controlling for additional fund characteristics that may affect investor redemptions reinforces our findings. First, we exclude funds that apply redemption charges, since such charges, similar to swing pricing, should discourage investor redemptions. Second, we account for differences in the funds' cash holdings in order to control for anticipated dilution costs. We recall from the model that higher liquidation costs increase the dilution effect of investor redemptions, reducing investor incentives to stay with the fund. Cash holdings serve as a useful gauge of liquidation costs. As a direct effect, lower (higher) cash holdings raise (reduce) the average costs of liquidating the fund portfolio. In addition, funds with lower cash holdings may have to respond more promptly to net outflows, suggesting that they have less leeway in timing their sales and may need to make higher price concessions when liquidating securities.

The effect on swing pricing funds is reinforced by applying these additional controls (column 4 of Table 2). Specifically, the marginal effect of negative returns on outflows is lowered by roughly 0.07 percent of TNA (0.019–0.091) per percentage-point of return when comparing swing pricing funds with U.S. funds. A swing pricing fund that exhibits a one-standard-deviation decline in (negative) returns thus benefits from a reduction in outflows equivalent to about 1 percent of TNA.

As an additional robustness check, we regress fund flows on the same set of predictors as before, but vary the measure of fund returns. Specifically, we consider the impact of using cumulative returns over the preceding 6 months, 12 months, and the estimated two-factor fund alpha, respectively. This adjustment assumes that investors not only factor in the recent returns to assess future fund performance, but also consider the fund's medium-term performance in their assessment. One rationale for such an approach is the presumption that skilled fund managers perform well on average, but may nevertheless fail to generate returns in individual months (Kacperczyk, van Nieuwerbaugh, and Veldkamp 2014).

The results shown in columns 5 to 7 of Table 2 lend further support to Hypothesis 1. Negative returns induce fewer outflows from swing pricing funds than from their peers. Intuitively, the difference becomes larger as we lengthen the range of returns that we assume investors are factoring into their decisions. Comparing a U.S. and swing pricing fund with negative returns over the past six months, the latter benefits from reduced outflows of about 0.11 percent of TNA (0.051–0.159) per percentage-point change in negative returns (column 5). If the return of both funds was negative over the past 12 months, the benefit amounts to as much as 0.29 percent of TNA (0.085–0.371; column 6). The results are qualitatively similar for regressions based on fund alpha, although the coefficient estimates are statistically insignificant at the usual confidence levels (column 7).

4.4 Discussion of Alternative Drivers

We assess to what extent alternative factors could be driving cross-country differences in the flow-to-performance relation. First, we assess whether differences in the flow-to-performance relation persist if we compare funds that face no meaningful dilution risks. Absent such risks, there would be no first-mover advantage and any observed differences between swing pricing funds and their peers would need to be driven by other factors.

To test this, we estimate the flow-to-performance relation for subsamples of funds with different liquidity profiles. Following Aramonte, Scotti, and Zer (2020), we measure these profiles based on the sensitivity of the funds' daily returns to aggregate liquidity factors. We expect the swing pricing effect to be strongest for funds that are most sensitive, i.e., those with the highest liquidity betas. The price of these funds declines the most when aggregate liquidity conditions worsen, consistent with their portfolio being the least liquid. Accordingly, we group the funds based on their monthly average liquidity betas, distinguishing between the most sensitive ones with betas above the 75th percentile of the sample (column 1 of Table 3), the sensitive ones with betas above the sample median (column 2), and the least sensitive ones with betas below the 25th percentile (column 3).

Differences between swing pricing funds and their peers dissipate as the liquidity risk profile of the funds improves (Table 3). The dampening effect of swing pricing on redemptions from funds with negative returns is strongest for those funds that exhibit the highest sensitivity to changes in aggregate liquidity conditions, whereas we find a much weaker and statistically insignificant effect for funds with the least sensitive profiles.

We also consider subsample regressions based on categorizing funds by their style as suggested by Chen, Goldstein, and Jiang (2010). The advantage of this approach is that it is based on a feature that is disclosed at the inception of the fund. The style is thus known to investors and is exogenous to fund flows. We estimate the flow-to-performance relation for a subsample of funds that invest in particularly illiquid bonds, e.g., emerging market bonds, high-yield bonds (column 4 of Table 3), one composed of funds investing in relatively more liquid bonds, e.g., USD short- and medium-term bonds (column 5), and a control group comprising funds that exclusively invest in the most liquid bonds, i.e., advanced-economy sovereign bonds (column 6).[21]

[21] The sample of sovereign bond funds comprises 151 U.S. funds and 94 Luxembourg funds which are not included in the main sample presented in Table 1. To ensure that the results are representative, the regression in column 3 of Table 3 does not include funds' cash holdings, for which data are missing for many funds. For this type of fund, cash holdings are likely to be less relevant given the high liquidity of the fund portfolio. Accordingly, differences in the flow-to-performance relation remain insignificant if cash holdings are accounted for in the regression.

Table 3. Flow-to-Performance Relation: The Effect of Portfolio Liquidity

	Portfolio by Liquidity Risk Profile			Portfolio by Fund Style		
	(1)	(2)	(3)	(4)	(5)	(6)
R_{t-1}	–0.010	0.020	0.016	0.014	0.018	0.010
	(0.024)	(0.024)	(0.017)	(0.024)	(0.019)	(0.019)
$NegR_{t-1}$	0.201***	0.133***	0.111**	0.162**	0.106***	0.004
	(0.061)	(0.037)	(0.038)	(0.041)	(0.016)	(0.041)
$R_{t-1} \times SP$	0.040	0.009	0.038	0.014	0.016	–0.014
	(0.030)	(0.025)	(0.032)	(0.015)	(0.016)	(0.068)
$NegR_{t-1} \times SP$	–0.205***	–0.141***	–0.059	–0.107**	–0.082***	0.061
	(0.051)	(0.040)	(0.043)	(0.023)	(0.008)	(0.103)
R-squared	0.196	0.158	0.171	0.178	0.089	0.147
Number of Funds	1,307	1,435	1,241	436	982	245
Observations	12,895	26,939	12,821	15,587	36,849	12,626
Portfolio Liquidity	Most Sensitive	Sensitive	Least Sensitive	Illiquid	Liquid	Most Liquid
Return Measure	3m	3m	3m	3m	3m	3m
Cash Holdings	Yes	Yes	Yes	Yes	Yes	No
Fund Fixed Effects (FE)	Yes	Yes	Yes	Yes	Yes	Yes
Style × Country × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Excluding Funds with Redemption Charges	Yes	Yes	Yes	Yes	Yes	Yes

Note: *p < 0.1; **p < 0.05; ***p < 0.01. Estimates based on Equation (5) with robust standard errors, clustered by fund style, in parentheses. Dependent variable: net inflows as a percentage of total net assets (TNA). Funds categorized by liquidity risk profile: (1) funds for which the monthly liquidity beta (estimated sensitivity to changes in aggregated liquidity conditions) is above the 75th percentile of the sample; (2) funds with monthly liquidity beta above the sample median; (3) funds with monthly liquidity beta below the 25th percentile. Funds categorized by liquidity of fund style: (4) funds investing in relatively illiquid assets (e.g., emerging market bonds, high-yield bonds); (5) funds investing in relatively liquid assets (e.g., USD short- and medium-term bonds, global bonds), (6) control sample of 245 funds investing predominantly in the most liquid assets, i.e., advanced-economy sovereign bonds. All regressions control for lagged returns, lagged negative returns, lagged log TNA, log age, and the lagged expense ratio; regressions (1) to (5) also include an indicator of cash holdings, which is equal to one if the fund's cash holdings in the previous month are above the median of corresponding cash holdings of funds with the same style. This variable is excluded in (6) given that funds in this subsample focus on most liquid assets. For each control variable, we include the base effect and an interaction term for swing pricing funds (SP) to allow for a different elasticity for these funds and their peer funds. Return measure (R): annualized returns (in percent) over the past three months. Negative returns (NegR): returns interacted with an indicator variable, which is equal to one (zero otherwise) if returns are negative.

Sovereign bond funds exhibit no notable cross-country difference in their flow-to-performance relation. For funds investing in illiquid bonds, by contrast, the difference is significant and somewhat more pronounced than for the intermediate case of funds invested in relatively more liquid bonds. These findings lend support to our interpretation that by reducing the risk of dilution, swing pricing dampens the funds' sensitivity of flows to weak performance.

Second, we test whether potential differences in investors' currency of account and opportunity costs affect our results. One concern with the above regressions could be that investors from different regions evaluate fund performance based on their local currency. Since an appreciation (depreciation) of the USD against the investor's local currency raises (reduces) the fund's return in local-currency terms, investors using different currencies of account could respond differently to past fund returns. While information on investors' currency of account is generally not available, a rough approximation is that investors are more likely to evaluate U.S. fund performance in USD terms and Luxembourg fund performance in euros (EUR), for example, because investors are biased towards investing in funds domiciled in their home region.

Another concern relates to measuring investors' opportunity costs. Thus far, we have implicitly assumed that investors respond differently to negative returns than to positive returns because a natural alternative to investing in funds—at least in the short term—is to hold cash, which yields zero nominal return. We alter this assumption and consider how our results change if we assume that investors benchmark fund returns against the corresponding risk-free rates. Specifically, we replace our identifier of negative returns in Equation (5) with one that indicates whether the fund returns fell below the risk-free rate ($BelowRF_{i,t-1}$). For Luxembourg funds, our approximation of the risk-free rates is given by the euro-currency market interest rates with the corresponding term. For U.S. funds, we use the corresponding yields on the U.S. Treasury bills.[22]

[22]Differences in the funds' investor base could influence the flow-to-performance relation. Studying equity funds, Ferreira et al. (2012) relate cross-country variation in this relation to differences in investor sophistication and participation costs. Yet such differences are small for the United States and Luxembourg, as gauged from the proxies used in their study, such as average education levels or the quality of the judicial system.

Our results prove robust to varying investors' currency of account and opportunity costs. In columns 1 and 2 of Table 4, we show the slope coefficients of interest based on measuring U.S. fund returns in USD (as throughout the paper), but swapping Luxembourg fund returns into EUR terms based on spot exchange rates. In both cases, we control for returns falling below the risk-free rate with the corresponding term. We note that the estimated effect of swing pricing is little changed when compared with the corresponding estimates in Table 2 (columns 4 and 5).

Finally, we inspect changes in funds' market shares as an alternative measure of fund flows. Spiegel and Zhang (2013) question the validity of the standard flow-to-performance specification. They argue that measuring flows as a percentage of TNA yields biased results and propose using changes in market shares to obtain robust estimates of the flow-to-performance relation. To consider this, we repeat the above analysis based on using this alternative measure of flows. Following Spiegel and Zhang (2013), we calculate the change in fund i's market share, $\Delta m_{i,t}$ as

$$\Delta m_{i,t} = \frac{TNA_{i,t}}{\sum_{j \in \Omega_{t-1}} TNA_{j,t}} - \frac{TNA_{i,t-1}}{\sum_{j \in \Omega_{t-1}} TNA_{j,t-1}}, \tag{6}$$

where Ω_{t-1} comprises all the funds with the same style as fund i that were in existence in period $t-1$. We measure changes in market share in basis points and, as for fund flows, winsorize at 1 percent.

Our finding of swing pricing funds' lower sensitivity to poor performance is robust to using this alternative measure of fund flows. Columns 3 to 5 of Table 4 report the corresponding results for different specifications, taking into account the role of cash holdings, varying investors' currency of account, and opportunity costs. In each case, we find a statistically significant reduction in the response of market shares to negative performance for swing pricing funds.

4.5 Fund Performance During the Taper Tantrum

We now turn to assessing differences in fund performance between swing pricing funds and their peers during the taper tantrum. Overall, we detect little evidence of systematic differences in net fund

Table 4. Flow-to-Performance Relation: Accounting for Exchange Rates, Opportunity Costs, and Alternative Measures of Fund Flows

	Fund Flows		Change in Market Share		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
R_{t-1}	0.014	0.062**	–0.007	–0.007	–0.007
	(0.015)	(0.026)	(0.008)	(0.008)	(0.008)
BelowRF_{t-1}	0.128***	0.109***	0.018	0.026**	0.026**
	(0.020)	(0.033)	(0.011)	(0.010)	(0.010)
$R_{t-1} \times \text{SP}$	0.019	0.051	0.011	0.016	0.016
	(0.014)	(0.034)	(0.009)	(0.011)	(0.011)
$\text{BelowRF}_{t-1} \times \text{SP}$	–0.094***	–0.161**	–0.016**	–0.027***	–0.028***
	(0.013)	(0.058)	(0.006)	(0.008)	(0.008)
R-squared	0.125	0.127	0.131	0.145	0.145
Number of Funds	1,479	1,467	1,577	1,479	1,479
Observations	54,965	54,965	75,210	54,965	54,965
Return Measure	3m	6m	3m	3m	3m
Risk-Free Rate	3m	6m	0	0	3m
Currency	Local	Local	USD	USD	Local
Cash Holdings	Yes	Yes	No	Yes	Yes
Fund Fixed Effects (FE)	Yes	Yes	Yes	Yes	Yes
Style × Country × Month FE	Yes	Yes	Yes	Yes	Yes
Excluding Funds with Redemption Charges	Yes	Yes	Yes	Yes	Yes

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Estimates based on Equation (5) with robust standard errors, clustered by fund style, in parentheses. Dependent variable in (1) and (2): net inflows as a percentage of total net assets (TNA); in (3) to (5): monthly change in the fund's market share in basis points as defined in Equation (6). All regressions control for lagged returns, lagged negative returns (or returns below the risk-free rate with the corresponding tenor), lagged log TNA, log age, and the lagged expense ratio; regressions (1), (2), (4), and (5) also include an indicator of cash holdings, which is equal to one if the fund's cash holdings in the previous month are above the median of corresponding cash holdings of funds with the same style. For each control variable, we include the base effect and an interaction term for swing pricing funds (SP) to allow for a different elasticity for these funds and their peer funds. Return measure (R): returns are measured as the three-month (3m) or six-month (6m) return, annualized in percent. BelowRF: returns interacted with an indicator variable, which is equal to one (zero otherwise) if returns are below the risk-free rate indicated in the respective column. For U.S. funds, risk-free rates are approximated by the yield on U.S. Treasury bills. For Luxembourg funds, risk-free rates are approximated by euro-currency market interest rates. Currency: In regressions (1), (2), and (5), Luxembourg fund returns are converted from USD into local currency (EUR) based on monthly USD/EUR spot exchange rates.

flows of these two groups of funds during this episode. This finding tallies with Hypothesis 2, which suggests that swing pricing, given its current design, is unlikely to offset investor first-mover advantages if markets are under stress. That said, our results suggest that swing pricing funds which were subject to outflows benefitted from higher market-adjusted returns than their U.S. peers. This is consistent with the anti-dilution effect of swing pricing conjectured in Hypothesis 3.

We start with Hypothesis 2 and test for systematic differences in the flow-to-performance relation of funds during the taper tantrum. We run the following regression, which considers the triple interaction of the effect of returns, swing pricing (SP), and observations during the taper tantrum ($Stress$):

$$\begin{aligned}
Flow_{i,t} = \alpha_i &+ \beta_1\, R_{i,t-1} + \beta_2\, BelowRF_{i,t-1} \\
&+ \beta_3\,(R_{i,t-1} \times Stress_t) + \beta_4\,(BelowRF_{i,t-1} \times Stress_t) \\
&+ \beta_5\,(R_{i,t-1} \times SP_i) + \beta_6\,(BelowRF_{i,t-1} \times SP_i) \\
&+ \beta_7\,(R_{i,t-1} \times SP_i \times Stress_t) \\
&+ \beta_8\,(BelowRF_{i,t-1} \times SP_i \times Stress_t) \\
&+ \gamma_1\, X_{i,t-1} + \gamma_2\,(X_{i,t-1} \times Stress_t) \\
&+ \gamma_3\,(X_{i,t-1} \times SP_i) + \gamma_4\,(X_{i,t-1} \times SP_i \times Stress_t) \\
&+ \delta_{sct} + \varepsilon_{i,t},
\end{aligned} \tag{7}$$

where we control for the possibility that the elasticity of flows with respect to all other fund characteristics ($X_{i,t-1}$) may have also varied for U.S. and Luxembourg funds during the taper tantrum. Table 5 reports each of the eight β coefficients in Equation (7) for different specifications.

In line with the above analysis, we find that swing pricing dampens the net flows of funds with returns below the risk-free rate during normal market conditions ($\beta_5 + \beta_6$) for each specification. The magnitude of the effect is also comparable to our previous results.

However, consistent with Hypothesis 2, we find no systematic difference between swing pricing funds and U.S. funds during the taper tantrum. The sum of the four coefficients (β_5 to β_8) that are interacted with the swing pricing indicator (SP) is near zero

Table 5. Flow-to-Performance Relation: Swing Pricing during Stress Episodes

	(1)	(2)	(3)	(4)	(5)
R_{t-1}	0.012	0.012	–0.007	0.020	0.068**
	(0.016)	(0.016)	(0.008)	(0.016)	(0.027)
$BelowRF_{t-1}$	0.127***	0.127***	0.025**	0.092**	0.094***
	(0.023)	(0.023)	(0.011)	(0.022)	(0.024)
$R_{t-1} \times$ Stess	0.047	0.047	0.013	–0.000	0.062
	(0.071)	(0.071)	(0.013)	(0.059)	(0.066)
$BelowRF_{t-1} \times$ Stress	0.073	0.073	0.013	0.095	–0.073
	(0.221)	(0.221)	(0.045)	(0.177)	(0.113)
$R_{t-1} \times SP(\beta_5)$	0.022	0.022	0.017	0.016	0.016
	(0.014)	(0.014)	(0.011)	(0.016)	(0.030)
$BelowRF_{t-1} \times SP$ (β_6)	–0.099***	–0.102***	–0.029**	–0.076***	–0.112**
	(0.017)	(0.017)	(0.010)	(0.018)	(0.036)
$R_{t-1} \times$ SP $\times$ Stress (β_7)	0.085	0.079	–0.023	–0.224	–0.083
	(0.338)	(0.350)	(0.046)	(0.209)	(0.118)
$BelowRF_{t-1} \times$ SP $\times$ Stress(β_8)	0.005	0.017	0.048	0.314	0.270
	(0.492)	(0.500)	(0.081)	(0.323)	(0.183)
Swing Pricing Effect:					
Normal Conditions ($\beta_5 + \beta_6$)	–0.077***	–0.079***	–0.012*	–0.060***	–0.096**
Stress ($\beta_5 + \beta_6 + \beta_7 + \beta_8$)	0.013	0.017	0.012	0.029	0.091
R-squared	0.214	0.214	0.301	0.202	0.201
Number of Funds	1,472	1,472	1,472	1,532	1,513
Observations	54,915	54,915	54,944	73,451	73,045
Dependent Variable	Flows	Flows	ΔMarket Share	Flows	Flows
Return Measure	3m	3m	3m	3m	6m
Risk-Free Rate	0	3m	3m	3m	6m
Currency	USD	Local	Local	Local	Local
Liquidity Measure	Cash	Cash	Cash	Liq. Beta	Liq. Beta
Fund Fixed Effects (FE)	Yes	Yes	Yes	Yes	Yes
Style $\times$ Country $\times$ Month FE	Yes	Yes	Yes	Yes	Yes
Excluding Funds with Redemption Charges	Yes	Yes	Yes	Yes	Yes

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Estimates based on Equation (7) with robust standard errors, clustered by fund style, in parentheses. Dependent variable in (1), (2), (4), and (5): net inflows as a percentage of total net assets (TNA); in (3): monthly change in the fund's market share in basis points as defined in Equation (6). All regressions control for lagged returns, lagged negative returns (or returns below the risk-free rate with the corresponding tenor), lagged log TNA, log age, and the lagged expense ratio. In regressions (1) to (3), the control variables also comprise an indicator of cash holdings as a measure of liquidity, which is equal to one if the fund's cash holdings in the previous month are above the median of corresponding cash holdings of funds with the same style. In regressions (4) and (5), cash holdings are replaced by the lagged liquidity beta. Stress is an indicator variable, which is equal to one (zero otherwise) for observations in May and June 2013 (taper tantrum). For each control variable, we include the base effect, an interaction term for swing pricing funds (SP), an interaction term for the taper tantrum (Stress), and the triple interaction with Stress and SP to allow for different elasticities for U.S. funds and swing pricing funds during normal times and the taper tantrum, respectively. Return measure (R): returns are measured as the three-month (3m) or six-month (6m) return, annualized in percent. BelowRF: returns interacted with an indicator variable, which is equal to one (zero otherwise) if returns are below the risk-free rate indicated in the respective column (see line "Risk-Free Rate"). For U.S. funds, risk-free rates are approximated by the yield on U.S. Treasury bills. For Luxembourg funds, risk-free rates are approximated by euro-currency market interest rates. Currency: In regressions (2) to (5), Luxembourg fund returns are converted from USD into local currency (EUR) based on monthly USD/EUR spot exchange rates.

for returns measured over a three-month horizon (columns 1 to 4). It is also statistically insignificant for funds for which returns fell below the risk-free rate if measured over a six-month horizon (column 5). The increased sensitivity of fund flows to weak performance of swing pricing funds relative to U.S. funds during the taper tantrum, as captured by the coefficient β_8 on the triple interaction of $BelowRF_{i,t-1} \times SP_i \times Stress_t$, contributes to counterbalancing the dampening effect of swing pricing on investor redemptions. This tallies with the model's prediction that it would take a large swing factor to fully offset the investor first-mover advantage during stressed market conditions.

To sharpen the previous analysis, we match individual swing pricing funds with U.S. funds (excluding those that impose redemption charges) based on a variety of fund characteristics available to investors in the run-up to the taper tantrum. We estimate the average treatment effect of swing pricing funds, the *treated* funds (ATET). We consider the ATET of several different measures. The top rows of Table 6 present results for the cumulative net fund flows from May to June 2013, winsorized at 1 percent to account for outliers. The next row reports estimates for market-adjusted returns. These are calculated as the difference between each fund's annualized returns and those of the fund's benchmark from May to June 2013. We use this measure, rather than nominal returns, to account for differences in the riskiness of fund portfolios. We recall that the funds in our sample deviate little from their benchmarks (see also Table 1), suggesting that this adjustment provides a powerful control for differences across fund returns that are not related to swing pricing. Because we expect funds to swing most frequently if they experience large outflows during this period, we report in the third row the results based on considering only those funds that experience net outflows.

We apply several alternative matching algorithms to evaluate the effect of swing pricing. Columns 1 and 2 of Table 6 report the ATET using nearest-neighbor matching. We match each swing pricing fund with four U.S. funds, using the number of neighbors recommended in Abadie and Imbens (2011). For the results in column 1, we match funds based on their log age, log TNA, nominal returns, net flows, and cash ratio relative to peers in April 2013, i.e., the month preceding the taper tantrum. We also include an indicator variable for

Table 6. Average Treatment Effect of Swing Pricing Funds during the Taper Tantrum

	(1)	(2)	(3)	(4)
Net Fund Flows	–1.656	–0.430	–0.781	0.511
	(1.324)	(1.229)	(0.845)	(0.803)
Matched Swing Pricing Funds	150	135	286	277
Market-Adjusted Returns:	0.113	0.166*	0.223***	0.222***
All Funds	(0.077)	(0.088)	(0.073)	(0.062)
Matched Swing Pricing Funds	147	135	154	140
Market-Adjusted Returns:	0.253***	0.268***	0.358***	0.246***
Funds with Net Outflows	(0.094)	(0.100)	(0.102)	(0.071)
Matched Swing Pricing Funds	100	88	97	80
Matching	Nearest Neighbor	Nearest Neighbor	ρ of Daily Returns	ρ of Daily Returns

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Robust standard errors in parentheses. The table reports the average treatment effect of swing pricing funds. Net fund flows are measured as the cumulative net flows in May and June 2013 (taper tantrum); as a percentage of total net assets (TNA). Market-adjusted returns are given by the compound nominal fund return less the return of the fund's benchmark for the period from May to June 2013, annualized in percent. Funds with net outflows comprises all funds with net outflows during the period from May to June 2013. Matching: (1) Nearest-neighbor matching with four neighbors; (2) nearest-neighbor matching with four neighbors within the same fund style category. Funds are matched on April 2013 observations (i.e., the month preceding the taper tantrum) of net fund flows, (log) TNA, (log) age, and one-month returns (all normalized by their cross-sectional standard deviation) as well as an indicator variable of whether the fund had cash holdings above or below the median of those of other funds using the same benchmark in April 2013 and an indicator variable for retail funds; (3) each swing pricing fund is matched with the U.S. fund in the same fund style category with the highest pairwise correlation based on daily returns over the three months preceding the taper tantrum; (4) each swing pricing fund is matched with the four U.S. counterparts exhibiting the highest correlation; to calculate potential outcomes for swing pricing funds, we weigh the observations for the four U.S. funds by the relative value of their correlation coefficients.

retail funds to take account of potential differences in funds' investor base. All variables are normalized by their cross-sectional standard deviation. For the results in column 2, we impose as an additional constraint that funds are only matched with funds of the same style.

Swing pricing funds do not appear to have experienced smaller outflows than their U.S. counterparts during the taper tantrum. The top row of columns 1 and 2 depicts the ATET for cumulative net fund flows during the taper tantrum. If swing pricing was effective in dampening fund outflows during the taper tantrum, we would expect to observe positive coefficient estimates. Yet, consistent with Hypothesis 2, we find no statistically significant difference between the outflows of the two groups of funds.

To gain further insights, we develop an alternative matching algorithm based on the correlation of daily fund returns. This approach builds on the presumption that funds with similar portfolios should be characterized by a high correlation of their returns.

For each swing pricing fund, we calculate the pairwise correlation coefficient of daily returns with each individual U.S. fund within the same style category over the three months preceding the taper tantrum. Since funds experienced relatively steady inflows during these months (see also Figure 1A), we do not expect their measured returns to be much affected by swing pricing activity. To further increase the precision of our comparison, we keep only correlation coefficients that are based on at least 30 non-zero observations per fund during this period. Next, we match each swing pricing fund with the U.S. fund for which we observe the highest correlation. Column 3 of Table 6 presents the corresponding ATET. For robustness, we also estimate the ATET that follows from matching each swing pricing fund with the four U.S. funds of the same style that exhibit the highest correlation with this fund in column 4.[23]

Overall, the ATET for the funds' net inflows provides no evidence of a dampening effect of swing pricing fund outflows during the taper tantrum. Seen through the lens of funds' liquidity management, this suggests that swing pricing policies were too timid to offset first-mover advantages during this episode of elevated market uncertainty.

[23]The correlation coefficients for the (fourth) closest match between swing pricing funds and U.S. funds have a median value of (0.69) 0.74.

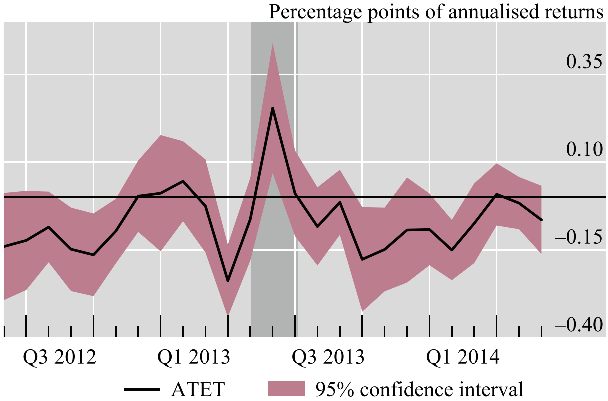
We now turn to the assessment of market-adjusted returns to test whether swing pricing funds managed to mitigate the dilution implied by fund outflows. In line with Hypothesis 3, we find evidence that swing pricing funds generated higher returns than their peers. Columns 1 and 2 report the ATET based on using nearest-neighbor matching, whereas columns 3 and 4 depict the estimates based on matching daily returns (see above). We report results based on matching all funds (middle row) and based on matching only those funds that exhibited net outflows during the taper tantrum (bottom row).

The estimates based on all funds point to additional returns in a range of about 17 to 22 basis points on an annualized basis—a sizable effect, given that the average market-adjusted return dropped to about –19 basis points during the taper tantrum (unadjusted returns averaged –21 percent) and hovered around zero when considering the entire period of observation (see Table 1). With swing pricing funds facing average net outflows of about 2.85 percent of TNA during the taper tantrum, these additional returns imply an average swing factor of about 1 percent to 1.3 percent—consistent with the values reported by the industry (ALFI 2015).

Intuitively, we find a larger effect—up to 36 basis points—if we constrain the sample to funds exhibiting outflows (Table 6, bottom row). These funds were under greater pressure to liquidate assets in order to accommodate investor redemptions. Thus, they are more likely to have incurred high liquidation costs, with only the swing pricing funds benefiting from the reduction in payouts to investors by swinging their NAV. This finding accords with Jin et al. (2022), who document that U.K.-oriented funds with alternative pricing schemes suffer less dilution due to outflows than other funds.

We test whether the difference in market-adjusted returns is not an artefact of matching generally more profitable swing pricing funds with less profitable U.S. funds. To do so, we estimate the ATET for the matched funds for each month over a two-year window centered on the taper tantrum based on comparing (annualized) market-adjusted returns for the latest two months. Figure 2 depicts the corresponding ATET and its 95 percent confidence interval using the matching approach applied for the results in column 1 of Table 6

Figure 2. Monthly ATET Estimates for Swing Pricing Funds' Market-Adjusted Return



Note: Average treatment effect of 100 matched swing pricing funds based on the regression in Table 6, column 1. Market-adjusted returns are calculated as the difference between two-month compound returns and the corresponding return on the fund's benchmark, annualized in percent. The gray-shaded region indicates the period from May 2 to July 5, 2013 (taper tantrum).

for the 100 swing pricing funds subject to net outflows during the taper tantrum. The ATET tends to hover around or slightly below zero but spikes during the taper tantrum (highlighted by the gray-shaded region), consistent with swing pricing helping these funds to contain dilution relative to their peers during this stress episode.

5. Conclusion

The COVID-19 crisis has revived concerns about systemic risks in the shadow-banking sector. The crisis thus provides a timely reminder of the need to expand the macroprudential framework to non-banks, such as open-end mutual funds. In this paper, we intend to make a first step towards developing such a framework by exploring the effects of swing pricing—a candidate tool to mitigate the risk of runs on funds and fire sales.

Based on a global game, we develop several predictions to guide our empirical analysis of how swing pricing affects investor behavior.

Our identification strategy is based on comparing Luxembourg funds that were allowed to apply swing pricing with similar funds from the United States, where swing pricing was not available to fund managers during the period of observation.

Consistent with the predictions from the conceptual framework, we observe that negative returns prompt larger outflows from funds that cannot swing than from their swing pricing counterparts. This observation holds during normal market conditions. Yet during the 2013 U.S. taper tantrum, a period of sharp declines in bond prices, funds appear to have been equally exposed to investor redemptions regardless of whether they applied swing pricing. Even so, swing pricing funds generated higher returns during this episode. This tallies with the predicted anti-dilution effect of swing pricing, which is based on the redistribution of liquidation costs from remaining investors to those deciding to redeem their shares.

We conclude that current swing pricing rules, which tend to apply only a modest swing factor if outflows exceed a certain threshold, fail to offset investor first-mover advantages in stressed markets.

Regulatory responses to address vulnerabilities in the mutual fund industry can thus be enhanced by allowing funds more flexibility in setting swing factors, provided that sound governance policies ensure a transparent and fair treatment of investors. Specifically, swing factors should be an increasing function of liquidity costs and redemptions to offset investor first-mover advantages during episodes of stress. For large funds or groups of funds with common exposures, topping up swing factors to account for the adverse price impact of asset liquidations could further enhance the effectiveness of this tool for macroprudential purposes.

Swing pricing is likely to be most effective if combined with other tools to address first-mover advantages. While swing pricing seeks to mitigate such advantages by reducing the dilution of the NAV, countercyclical liquidity requirements and liquidity stress testing could lower funds' liquidity mismatch and thereby help to further support fund resilience. That said, more research is needed to assess the underlying risks in this industry and the interaction of liquidity-management tools in order to inform the design of a macroprudential framework for the fund-management industry.

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