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Does Swing Pricing Reduce Investment Funds' Liquidity Risk in Times of Market Stress? – Evidence from the March-2020 Episode

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Abstract

The March-2020 episode has raised questions on whether the post-GFC reforms on the liquidity management of open-ended funds' (OEFs) adequately contain their liquidity risk in times of market stress. Using an extensive dataset that covers this episode, our study shows that swing pricing could help to mitigate OEFs' redemption pressures in times of market stress. However, the mitigating effect may be limited by several factors. First, the swing pricing-led volatility of OEF returns would lead to a larger volatility of OEFs' flows. Secondly, swing pricing would encourage OEFs to raise leverage during normal periods, which may lead to substantial losses and amplify the redemption pressures in a stressful episode. Thirdly, some OEFs may not disclose the usage of swing pricing, but such non-disclosure practice could weaken the effectiveness of swing pricing. Our findings have two policy implications. First, while the results suggest that swing pricing would be one effective tool for liquidity management of OEFs, it may come with "side effects", including larger flow volatility and higher leverage. A proper design and combination with other risk management tools may be warranted for swing pricing to work in a more effective way. Second, policies to promote a higher level of relevant disclosures may also enhance the effectiveness of swing pricing.

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1. Introduction

The COVID-19 pandemic caused an unprecedented shock to the global financial system in March 2020. The shock resulted in a sharp increase in the demand for liquidity in both the financial and non-financial sectors, which spread through the system and morphed into a "dash for cash" (FSB, 2020). For instance, some open-ended funds (OEFs) experienced large redemptions due to liquidity demand from their investors. The associated outflows were more pronounced for OEFs holding more illiquid underlying assets, for example fixed-income funds, despite having less negative returns than their equity counterparts during the March-2020 episode (Figure 1). OEFs that held extremely illiquid assets, such as leverage loan funds, have recorded even greater outflows.

Apart from investors' liquidity demand, the significant outflows could also be driven by investors' incentive to take first-mover advantage (FMA)[3] and redeem earlier than others to avoid dilution of their investments due to redemptions by other investors (Chen et al., 2010). The FMA mainly exists in OEFs adopting the traditional pricing rule, where the costs of investors' redemptions (e.g. the transaction costs of asset sales) are priced in the OEF shares held by the remaining investors.

Since the GFC, an alternative pricing rule called "swing pricing" is being increasingly employed by OEFs to reduce investors' FMA and manage liquidity risk. Swing pricing allows OEF managers to adjust ("swing") the fund's NAV per share to charge the estimated redemption costs on the redeeming investors.[4] Given its potential usefulness, a survey by the Investment Company Institute (2020) finds that swing pricing was the most popular liquidity management tool (LMT) used by European OEFs during the March-2020 episode (Figure 2).

Despite some favourable evidence of the usefulness of swing pricing in literature (e.g, Jin et al., 2021; Lewrick and Schanz, 2017b), there are several concerns over its effectiveness in times of market stress. First, it is widely recognised that swing pricing will increase the accounting volatility of the fund price due to its design (i.e., the price would be swung "up" on inflows and "down" on outflows). Given the positive flow-return relationships in OEFs (e.g. Coval et al., 2007; Chen et al., 2010 and Goldstein et al., 2017), the increased return volatility could raise the flow volatility of OEFs at the same time and, therefore, destabilise OEF flows. This issue could be more pronounced in times of market stress, as OEFs' prices could be "swung" by a much greater degree amid large OEF flows and heightened transaction costs due to market illiquidity.

Secondly, the perceived usefulness of swing pricing could reduce fund managers' incentive to insure against liquidity risk and encourage larger risk-taking. In addition to the lower cash buffer documented in Lewrick and Schanz (2017b),[5] swing pricing may also induce a higher leverage by OEFs. With the lower expected redemption pressures, OEFs may be tempted to take higher leverage to boost their returns, as they tend to receive less inflows during normal periods than those that do not use swing pricing (Jin et al., 2021). In times of market stress,

[3] The FMA was one of the major drivers of investors' runs on OEFs during the GFC. Since then, market regulators have implemented reforms to mitigate the liquidity risk. See IOSCO (2013, 2015 and 2018)

[4] Annex A describes the mechanism in more detail and Annex B provides a numerical example.

[5] Lewrick and Schanz (2017b) document that fixed-income OEFs in Luxembourg could reduce their cash buffer, the primary tool for OEFs' liquidity management compared to their US counterparts, given the lower redemption pressures.

the high leverage could amplify OEFs' losses and trigger large redemption pressure (Vivar et al, 2020).

Finally, it is observed that some OEFs may opt not to disclose much information about their use of swing pricing. OEFs are required to disclose the range of liquidity management tools (such as swing pricing) available in most cases; but the level of details disclosed on how these tools are operated vary across OEFs. In the case of swing pricing, OEFs may opt not to disclose too many details of swing pricing adoption, such as swing threshold or the actual usage of swing pricing, as they concern about the "gaming behaviour" by investors.[6,7]

However, the lack of ex-post disclosure on implementation may result in investors not fully realising the anti-dilution benefits of swing pricing and how implementation could penalise large redemptions (Malik and Lindner, 2019), particularly in times of market fear, thus reducing the mitigating effects of swing pricing.

Therefore, it is important to examine how significant these concerns are. To this end, our paper explores several questions of particular interest:

1. Does swing pricing mitigate OEFs' redemption pressures by reducing investors' FMA?
2. Does the swing pricing-led return volatility lead to a larger volatility of OEF's flows?
3. Does swing pricing encourage a higher leverage by OEFs?
4. Does the OEFs' practice of non-disclosure reduce the effectiveness of swing pricing?

To summarise our findings, this study confirms that swing pricing could be effective in times of market stress, specifically the March-2020 episode. However, the observed effectiveness may have been limited by the concerns raised above. First, the swing pricing-led volatility of OEF returns will lead to larger volatility of OEFs flows. Secondly, swing pricing will encourage OEFs to raise leverage during normal periods, which may lead to substantial losses and amplify the redemption pressures in a stressful episode. Thirdly, some OEFs may not disclose the usage of swing pricing, but such non-disclosure practice could weaken the effectiveness of swing pricing.

This paper contributes to the literature on three aspects. To our best knowledge, we are the first to provide a systematic empirical study on the effectiveness of swing pricing. We use an extensive dataset that covers the March-2020 episode – an episode of immense redemption pressure in OEFs (Figure 1), providing an excellent scenario of market stress. More importantly, we employ a unique dataset that contains granular data of OEFs, particularly in the use of swing pricing, thus allowing us to quantify the reduction in FMA by swing pricing and how it helps to mitigate the redemption pressures of OEFs. Secondly, this study is one of the few in literature that discusses the potential limitations of swing pricing. As such, it offers a more balanced view for market participants, academics, and financial regulators to understand the risks behind this liquidity management tool (LMT), especially for regulators

[6] For swing threshold (i.e., the amount of net redemptions to trigger partial swing pricing), it is argued that disclosing the information to investors could prompt them to make large-scale redemptions but at the same time avoid hitting the swing threshold, such that they can maximise the benefits of FMA.

[7] A survey conducted jointly by the Bank of England and the UK Financial Conduct Authority on OEFs indicated that the actual use of these tools ex post was only disclosed to investors in some cases (Bank of England, 2021). One possible reason for OEFs' reluctance to disclose usage of swing pricing could be that OEF managers concern about the leak of proprietary information such as the OEF manager's trading patterns or broker arrangements, thereby allowing investors to build up a pattern of trading strategies and processes that could be used unfavourably against the OEF (Funds Europe, 2016).

(such as those in emerging markets) looking to add swing pricing to their regulatory framework.[8] Finally, studying the role of disclosure contributes to the debate on whether effective operation of swing pricing necessitates a higher level of disclosure. These contributions provide important information to policy makers and standard-setting bodies, such as the International Organization of Securities Commissions (IOSCO), as they review OEFs' LMTs following the March-2020 episode.

This paper is organised as follows. The next section reviews the related literature. Section 3 describes the methodology and data, while Section 4 discusses our findings. The final section concludes.

2. *Literature review*

This study relates to two strands of literature. One strand focuses on why investment funds are prone to run risks. Previous studies have effectively documented the origins of runs in the asset management sector. Chen et al. (2010) outlines the pricing rule of mutual funds that leads to run risks. Under this rule, investors redeem their shares at the daily-close net asset value (NAV), but the corresponding portfolio adjustment typically takes place the next day. Therefore, any transaction costs incurred by the portfolio adjustment are not reflected in the transaction price on the day of redemption. As a result, the share value of the remaining investors will be diluted, creating incentives to run on funds. Other studies assess the extent to which different fund types are vulnerable to runs, including equity mutual funds (Coval et al., 2007), fixed-income mutual funds (Goldstein et al., 2017) and money market funds (Schmidt et al., 2016). For exchange-traded funds (ETFs), Converse et al. (2020) finds that ETF flows are more sensitive to global financial conditions than flows of mutual funds. Leung et al. (2021) also studies run risks of ETFs by redemption types and find that runs on ETFs are conspicuous if redeemable in cash.

Another strand is related to the adoption of LMTs by investment funds and their impact on fund and market risks. Several studies cover swing pricing, which is the focus of this study. From a theoretical perspective, models by Lewrick and Schanz (2017a) and Capponi et al. (2020) show that swing pricing can mitigate runs on funds by reducing investors' FMA. On the empirical side, Jin et al. (2021) provide empirical evidence that swing pricing can eliminate the first-mover advantage arising from the traditional pricing rule and significantly reduces outflows from the UK corporate fixed-income OEFs during market stress. Lewrick and Schanz (2017b) show that swing pricing can make fixed-income OEFs in Luxembourg less sensitive to bad fund performance during normal times. However, in the "Taper Tantrum" case they find that the effect of swing pricing vanishes during periods of market stress, possibly due to the inadequate usage of swing pricing to discourage redemptions by investors.

Other earlier studies on LMTs mostly centre on the effectiveness of redemption fees and gates. On the redemption fee, Chordia (1996) and Nanda et al. (2000) show that it can dissuade redemptions by short-term investors, but Chordia (1996) also shows that funds would hold less liquid assets as a result of lower short-term redemption pressures. On redemption gates, Teo (2011) finds that the LMT helps to avoid the deleterious effects of asset fire-sales in hedge funds, but it could also encourage hedge funds to take on greater liquidity risks and exacerbate the asset-liability mismatch. Together these suggest that LMTs could backfire by inducing funds to take a larger liquidity risk. This is further supported by the theoretical model in Cipriani et al. (2014), which shows that imposing a redemption fee or redemption gate in a crisis can

[8] Regulators would also have to consider some practical challenges in adopting swing pricing, such as the collection customer order information and estimation of transaction costs for an accurate calibration of the swing factor.

lead to pre-emptive runs by investors. More recently, Agarwal et al. (2020) show that funds reserving their right to exercise redemption in kind will experience less redemption after a poor performance, with the liquidation costs being passed on to redeeming investors because they need to liquidate the assets on their own. Grill et al. (2021) suggest that while outright suspension of redemptions can prevent stress at the fund level during the March-2020 episode, it impairs the ability of the economic sector to obtain liquidity, with repercussions for various sectors of the real economy and the wider financial system.

While the availability of LMTs to OEFs may be subject to regulations in individual markets, some studies investigate how OEFs use cash, arguably as a "universally" available LMT, to manage their liquidity risk. On one hand, Chernenko and Sunderam (2016, 2018) find that investment funds hold cash to accommodate outflows, but the holdings are not large enough to fully mitigate price impact externalities created by the liquidity transformation. On the other hand, however, Morris et al. (2017), give an opposite view by suggesting investment funds could hoard cash in times of outflows. Instead of using a cash buffer to meet the outflows, Morris et al. (2017) find that funds generally sell more assets than required to prevent forced sales of illiquid assets in the future. Such "voluntary" sales amplify the decline in asset prices and trigger further runs based on the theoretical model by Zeng (2018).

3. *Data and Methodology*

We discuss the data sample and empirical methodology in this section. Section 3.1 describes the data used and highlights key observations from raw data. Section 3.2 introduces the various models used to answer questions set out in Section 1. All our OEF-level data are retrieved from Morningstar Direct.[9] Our data sample covers the period from January 2012 to December 2020.

3.1. Data sample

We first draw a sample of "swing' OEFs from Morningstar Direct. We identify an OEF as a "swing" OEF if it (i) is eligible to use swing pricing; and (ii) uses swing pricing at least once during the sample period. We classify an OEF as eligible to use swing pricing if it is domiciled in a jurisdiction that allows swing pricing (Annex C). The use of swing pricing by an OEF is based on its "unswung" fund price retrieved from Morningstar Direct. Denoted by $NAV_{i,t}^{T}$, the "unswung" price of OEF *i* on day *t* refers to its theoretical net asset value excluding the swing pricing applied (if any). Together with OEF's "actual" price (i.e. the net asset value including swing pricing applied (if any), denoted by $NAV_{i,t}^{A}$), we can calculate the swing factor of OEF *i* on day *t* as the percentage difference between $NAV_{i,t}^{A}$ and $NAV_{i,t}^{T}$. Then, a non-zero swing factor would indicate the OEF applies swing pricing on a given day. It should be noted that not all OEFs eligible to use swing pricing report their "unswung price" to Morningstar Direct. In such cases, we denote such OEFs as "swing-eligible but not disclosed" OEFs.

A total of 993 "swing" OEFs are identified based on the above, all of which are domiciled in European jurisdictions, including Luxembourg, Ireland, the United Kingdom and Switzerland. As shown in Figure 3, they account for just 2.5% of all European OEFs that are allowed to use swing pricing (in terms of assets), or 4.2% if OEFs that are known to have not used swing pricing (based on "unswung" price information) are also accounted for. The dominant share of

[9] Morningstar Direct's data providers do not guarantee the accuracy, completeness or timeliness of any information provided by them and shall have no liability for their use.

“swing-eligible but not disclosed” OEFs (i.e. rest of the OEFs) include OEFs that adopt swing pricing but had not disclosed its usage, [10] as well as those that are eligible to use but choose not to adopt swing pricing.

To identify the effect of swing pricing, our OEFs sample also includes matched samples of “swing-eligible but not disclosed” OEFs and “swing-ineligible” OEFs. As mentioned in the previous paragraph, “swing-eligible but not disclosed” OEFs refer to OEFs domiciled in jurisdictions where swing pricing is allowed, but not disclosing the usage of swing pricing. “Swing-ineligible” OEFs refer to OEFs domiciled in jurisdictions where swing pricing is not allowed. Based on these definitions, however, there are much more “swing-eligible but not disclosed” OEFs and “swing-ineligible” OEFs than the number of “swing” OEFs identified (993). To better identify the effects of swing pricing, we follow the matching algorithm employed by Jin et al. (2021) to match an equal number of “swing-eligible but not disclosed” OEFs and “swing-ineligible” OEFs in our empirical analysis.

In applying the matching algorithm, we randomly draw a “swing” OEF from a pool of “swing” OEFs and match it with an OEF drawn from a pool of “swing-ineligible” OEFs that have the same investment area, same major asset class (equity or fixed income, based on portfolio share), and smallest absolute percentage difference in terms of OEF size (denoted by $Size$), age (denoted by Age), and return (denoted by Ret).[11] We repeat the same matching algorithm for all other “swing” OEFs. The advantage of this sampling method is that the final sample of “swing” OEFs and “swing-ineligible” OEFs are highly comparable in major OEF characteristics that may affect OEFs flows. Out of the 993 “swing” OEFs, 632 OEFs can be successfully matched with their “swing-ineligible” peers, resulting in 632 “swing” OEFs and 632 “swing-ineligible” OEFs. Next, with 632 “swing-ineligible” OEFs, we identify the same number of “swing-eligible but not disclosed” OEFs by the same matching algorithm.[12] As a result, our final sample contains 1,896 OEFs (or 632 OEFs for each group of “swing”, “swing-ineligible” and “swing-eligible but not disclosed” OEFs).

Table 1.5 shows that our matching algorithm has successfully minimised the differences in other characteristics among the three OEFs groups. In particular, the differences in the mean share of assets in equities (denoted by $Equity$) and fixed income (denoted by FI), mean OEF return (denoted by *Ret*), size (denoted by *Size*) and age (denoted by *Age*) between any two of the three OEF groups are all statistically insignificant.[13] Their similarities in these major OEF characteristics is further demonstrated by Figure 4, which depicts the mean “distance” among OEF groups with (blue bars) and without sample matching (red bars) over the sample period. It shows that the mean distances of “swing” OEFs with both “swing-eligible but not disclosed” OEFs (left part) and “swing-ineligible” OEFs (right part) are significantly reduced by the sample matching. The former is even close to zero. This ensures any impacts of swing pricing we found are not confounded with the heterogeneities in major OEF characteristics.

[10] We implicitly assume that Morningstar Direct is the major public channel for OEFs to disclose historical daily usage of swing pricing. OEFs, on the other hand could provide a summary on usage of swing pricing (during a certain period) and certain operational details of swing pricing in public documents, such as prospectus, fact sheet or annual reports. It is also possible that OEFs disclose the relevant details to individual investors on request.

[11] The matched “swing” OEF and “swing-ineligible” OEF will then be removed from the pool (i.e. we match without replacement).

[12] Instead of matching with “swing” OEFs. This allows “swing-ineligible” OEFs to be the reference group when we test the effect of non-disclosure in Section 3.2.4.

[13] See Tables 1.2 – 1.4 for summary statistics.

Our OEF sample highlights three key observations. First, the left part of the box plots in Figure 5 shows that despite OEFs in general suffered larger outflows in March-2020 (compared to normal or even other stressful periods), the outflows were less severe for both “swing” and “swing-eligible but not disclosed” OEFs than “swing-ineligible” OEFs, especially at the low-end (see the 10th percentile). This tentatively confirms that swing pricing would help to reduce the redemption pressures of OEFs in times of market stress. The second observation points to the elevated swing factors adopted by the “swing” OEFs in March-2020 (Figure 6). This can be expected as both larger redemption pressures and liquidity stress during the episode triggered a sharp rise in the liquidation costs, and therefore a larger swing factor was charged on redeeming investors. Lastly, we observe that the average return variance ($\text{Var}_{i,t}^{Return}$) and flow variance (denoted by $\text{Var}_{i,t}^{Return}$ and $\text{Var}_{i,t}^{Flow}$ respectively), as well as the leverage (denoted by *Lev*), are larger for “swing” OEFs and “swing-eligible but not disclosed” OEFs compared to “swing-ineligible” OEFs, though the Wald test suggests that such differences are not statistically significant (Table 1.5). We will test empirically whether the use of swing pricing by an OEF could also be associated with higher volatility of fund returns and flows, as well as higher leverage in Section 3 and 4.

3.2. Empirical models

3.2.1. Does swing pricing mitigate OEFs' redemption pressures by reducing investors' FMA?

We address this question in two steps. In the first step, we test whether “swing” OEFs experienced lower redemption pressures than “swing-ineligible” OEFs in stressful periods, especially the March-2020 episode. Specifically, the following fixed effects model is considered:

$$Flow_{i,t} = \beta_1 Stress_t + \beta_2 March20_t + \beta_3\, SW_i \times Stress_t + \beta_4\, SW_i \times March20_t$$
$$+\gamma_1\, Ret_{i,t-1} + \gamma_2\, SW_i \times Ret_{i,t-1} + \delta_1 Control_{i,t-1} + \delta_2 VIX_t + \mu_i + \varepsilon_{i,t}. \qquad (1)$$

In this model, $Flow_{i,t}$ refers to the monthly OEF flows, calculated as the monthly percentage change in total net assets, net of OEF returns in month t. $Stress_t$ is a time dummy variable equal to one when the Chicago Board Options Exchange's CBOE Volatility Index (or VIX index hereafter) in month t exceeds the 50th percentile of the sample (but excludes March-2020), and zero otherwise. $March20_t$ is another time dummy variable equal to one for March-2020 observations, and zero otherwise. SW_i is an OEF-level dummy variable that equals one for “swing” OEFs, and zero for “swing-ineligible” OEFs.

We are primarily interested in the regression coefficient of the interaction term $SW_i \times March20_t$, i.e. β_4 in Equation (1). It represents the difference in the OEF flows in March-2020 between “swing” OEFs and “swing-ineligible” OEFs. If swing pricing could help OEFs to mitigate redemption pressures, we expect β_4 to be positively significant. β_3 is also of interest besides β_4, as it reflects the mitigating effect of swing pricing in other stressful periods.

As swing pricing protects mainly long-term investors from the transaction costs incurred by investors trading in and out of the OEFs, it is more likely for long-term investors to invest in “swing” than “swing-ineligible” OEFs, other things being equal. Such differences in investor compositions, however, could cause differential OEF flows, such that β_4 may capture the heterogeneities in investor composition (albeit driven by swing pricing), rather than the impact of swing pricing rule per se.

It is therefore necessary to control for the heterogeneities in investor composition in Equation (1). However, as information on OEFs' investor composition is not available, we attempt to control for this factor by allowing the flow-return relationship of "swing" OEFs to be different from "swing-ineligible" OEFs.[14] We do so by including OEF's returns in previous month (i.e., $Ret_{i,t-1}$) and its interaction with SW_i (i.e., $SW_i \times Ret_{i,t-1}$) in Equation (1).

Besides controlling for the differences in flow-return relationships between two OEF groups, Equation (1) also include $Control_{i,t-1}$ to control for other determinants of OEF flow, including OEFs size (*Size*), age (*Age*), equity (*Equity*), fixed-income (*FI*) and cash holdings (*Cash*). Finally, the model includes the VIX index (*VIX*) to control for aggregate market condition, while OEF-fixed effect (denoted by μ_i) is added to control for time-invariant OEF characteristics.

In the second step, we verify whether the mitigating effect of swing pricing, if any, increases with reduced FMA. Focusing on the sample of "swing" OEFs, we consider the following specification;

$$Flow_{i,t} = \beta_1 Stress_t + \beta_2 March20_t + \theta_3 FMA^{-}_{i,t} + \theta_4\, FMA^{-}_{i,t} \times Stress_t + \theta_5\, FMA^{-}_{i,t} \times March20_t + \gamma_1\, Ret_{i,t-1} + \delta_1 Control_{i,t-1} + \delta_2 VIX_t + \mu_i + \varepsilon_{i,t} \quad (2)$$

where $FMA^{-}_{i,t}$ refers to the reduction in FMA by swing pricing while the other variables follow the same as Equation 1. The extent of reduction in FMA (denoted by $FMA^{-}_{i,t}$) can be measured by the dilution cost charged on redeeming investors. However, as the dilution cost is not known before the actual redemption takes place, we proxy it by the dilution cost in the previous month[15] and is given by the following:

$$FMA^{-}_{i,t} = SF_{i,t-1} /\, Flow_{i,t-1} \quad (3)$$

In short, the dilution cost is calculated as the swing factor (in previous month, denoted by $SF_{i,t-1}$) divided by OEF flow (also in the previous month, denoted by $flow_{i,t-1}$). $SF_{i,t-1}$ equals the percentage difference between the OEFs actual and theoretical net asset value ($NAV^{A}_{i,t-1}$ and $NAV^{T}_{i,t-1}$ respectively) as mentioned in the previous section. Thus, a positive (negative) difference means that the OEF actual NAV is swung up (down) from the theoretical net asset value. We divide the swing factor by the OEF flows for two reasons. First, as the dilution cost increases with both the illiquidity of underlying assets and magnitude of OEF flows, $FMA^{-}_{i,t}$

[14] Brandao-Marques et al. (2015), Humphrey et al. (2013) and Benson et al. (2010) show that OEFs with different end-investors exhibit different flow-return relationships.
[15] The choice of $SF_{i,t-1}$ is justified by its high correlation with $SF_{i,t}$ at 0.56, while the average historical swing factor over a longer span (3, 6 and 12 months) all show smaller correlation.

calculated in this way allows us to capture only the former.[16] Secondly, we can also make sure the $FMA^{-}_{i,t}$ will be positive, and a larger value will always indicate a higher dilution cost.[17,18]

The primary interest in Equation (2) is θ_5, which represents the incremental mitigating effect of swing pricing in March-2020. If the mitigating effect of swing pricing increases with the reduction of FMA, we should observe a positive θ_5. Similarly, θ_4 tests the incremental mitigating effect of swing pricing during other stressful periods.

3.2.2. Does swing pricing-led return volatility lead to a larger volatility of OEF's flows?

To answer this question, we compare the flow volatility of "swing" OEFs and "swing-ineligible" OEFs. We first decompose that part of the OEF return caused by swing pricing. Recall that swing factor is the percentage difference between an OEF's actual and theoretical net asset value;

$$NAV^{A}_{i,t} = NAV^{T}_{i,t} \times (1 + SF_{i,t}) \tag{4}$$

By taking log-difference on both sides of Equation (4), we obtain the following;

$$r_{i,t} = ur_{i,t} + \Delta sf_{i,t} \tag{5}$$

where $r_{i,t} = ln(NAV^{A}_{i,t}) - ln(NAV^{A}_{i,t-1})$ is the daily OEF return; $ur_{i,t} = ln(NAV^{T}_{i,t}) - ln(NAV^{T}_{i,t-1})$ is daily log-change in OEF's theoretical net asset value; and $\Delta sf_{i,t} = ln(SF_{i,t}) - ln(SF_{i,t-1})$ is the log-change in swing factor. By taking variance on both sides, Equation (5) becomes

$$\text{Var}(r_{i,t}) = \text{Var}(ur_{i,t}) + \text{Var}(\Delta sf_{i,t}) + 2\text{Cov}(ur_{i,t}, \Delta sf_{i,t}) \tag{6}$$

where Var ($ur_{i,t}$) can be considered as the fundamental component of OEF return variance (which is the part due to OEFs' theoretical net asset value, denoted by Var^{NAV}) and Var ($\Delta sf_{i,t}$) + 2Cov($ur_{i,t}$, $\Delta sf_{i,t}$) as the swing component (which is the additional return variance due to swing pricing, denoted by Var^{SF}) respectively. Through this decomposition we can assess to what extent swing pricing increases the variance of OEFs returns.[19]

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[16] This is a simplified assumption as in reality the relationship between outflows and dilution costs could be convex (i.e. the cost increases at a faster rate as outflows increase).

[17] $SF_{i,t-1}$ could be either positive or negative value depending on the direction of $Flow_{i,t-1}$, with both larger positive and negative values indicating the dilution on OEF values caused by OEF trading of assets.

[18] In estimation, we standardise $FMA^{-}_{i,t}$ into unity variance for ease of interpretation.

[19] While it is more common to use the standard deviation of OEF returns as the measure of volatility, we use variance instead due to its additive nature.

With the flow variance and the two components of return variance for "swing" OEFs obtained above, we test whether the swing component contributes to the flow volatility of "swing" OEFs based on a panel data regression model in Equation (7):

$$\mathrm{Var}_{i,t}^{Flow} = \theta_1 Stress_t + \theta_2 March20_t + \theta_3 \mathrm{Var}_{i,t-1}^{NAV} + \theta_4 \mathrm{Var}_{i,t-1}^{SF} + \gamma_1\, Ret_{i,t-1} + \delta_1 Control_{i,t-1} + \delta_2 VIX_t + \mu_i + \varepsilon_{i,t} \qquad (7)$$

where $\mathrm{Var}_{i,t}^{NAV}$ and $\mathrm{Var}_{i,t}^{SF}$ denote fundamental and swing components of OEF return variance calculated by Equation (7); and $\mathrm{Var}_{i,t}^{Flow}$ is the variance of daily flows of OEF *i* in month *t*. In this set-up, the primary interest in this model is θ_4, which tests whether the swing component of OEF return variance has a significant impact on the flow volatility of "swing" OEFs.

3.2.3. Does swing pricing encourage higher leverage by OEFs?

We address the question by comparing leverages of "swing" OEFs and "swing-ineligible" OEFs. We employ the following panel data regression model to assess whether swing pricing boosts higher leverage by OEFs;

$$Lev_{i,t} = \beta_1 + \beta_2 SW_i + \beta_3 Lev_{i,t-1} + \gamma_1\, Ret_{i,t-1} + \delta_1 Control_{i,t-1} + \delta_2 VIX_t + \varepsilon_{i,t} \qquad (8)$$

where $Lev_{i,t}$ denotes the level of leverage employed by OEF *i* in month *t*, which is defined as the ratio of total long position to total net assets of an OEF (Avalos et al, 2015); and SW_i is a dummy variable that equals to one if for "swing" OEF, and zero for "swing-ineligible' OEFs.

We are interested in the coefficient of β_2 which measures the average difference in the level of leverage between these two groups of OEFs. In particular, a significantly positive β_2 denotes a higher leverage on average for "swing" OEFs, holding other things constant.

3.2.4. Does the non-disclosure practice of OEFs reduce the effectiveness of swing pricing?

To answer this question, we compare the differences in flows of "swing" OEFs and "swing-eligible but not disclosed" OEFs. In practice, we consider a similar panel data regression model in Equation (1) that also includes the "swing-eligible but not disclosed" OEFs;

$$Flow_{i,t} = \beta_1 Stress_t + \beta_2 March20_t + \beta_3\, SW_i \times Stress_t + \beta_4\, SW_i \times March20_t + \beta_5 ND_i \times Stress_t + \beta_6 ND_i \times March20_t + \gamma_1\, Ret_{i,t-1} + \gamma_2\, SW_i \times Ret_{i,t-1} + \gamma_3\, ND_i \times Ret_{i,t-1} + \delta_1 Control_{i,t-1} + \delta_2 VIX_t + \mu_i + \varepsilon_{i,t} \qquad (9)$$

Where SW_i is a dummy variable equal to one for either "swing" OEFs or "swing-eligible but not disclosed" OEFs, and zero for "swing-ineligible" OEFs; and ND_i is another dummy variable equal to one for "swing-eligible but not disclosed" OEFs, and zero for "swing" or "swing-ineligible" OEFs. Like Equation (1), the model includes $Ret_{i,t-1}$, $SW_i \times Ret_{i,t-1}$ and $ND_i \times Ret_{i,t-1}$to control for the differences in the flow-return relationships between the three OEFs groups. Other model variables follow the same as Equation (1).

The coefficients of interest in Equation (9) are β_4 and β_6. β_4 represents the differences in fund flows between "swing" OEFs and "swing-ineligible" OEFs during the March-2020 episode. Similarly, the sum of β_4 and β_6 captures the differences in fund flows between "swing-eligible but not disclosed" OEFs and "swing-ineligible" OEFs during the same period. Then, the difference between β_4+β_6 and β_4, which is simply β_6, will reflect the effect of non-disclosure. Figure 7 visualises the way to identify the effect of non-disclosure as described above.[20]

While both β_4+β_6 and β_4 are expected to be positive (i.e. OEFs suffered less outflows in March-2020 due to their eligibility to use swing pricing), the former should be less positive due to a negative β_6. This is because the disclosure of historical swing factors informs redeeming investors of the potential cost of redemption such that these investors could be more cautious in making their redemption decisions, while non-disclosure creates uncertainty and potentially leads to underestimations in the cost for doing so, and therefore reduce the effect of swing pricing.

4. *Empirical findings*

4.1 Does swing pricing mitigate OEFs' redemption pressures by reducing investors' FMA?

The empirical results of Equation (1) show that swing pricing will reduce OEFs' redemption pressures in times of market stress. Specifically, the estimation results of Equation (1) show that the estimated β_4 is statistically significant at 1.72 (i.e. Column 1 of Table 2.1). This implies that, on average[21], "swing" OEFs will suffer less outflows than "swing-ineligible" OEFs by 1.72 percentage points (ppts) in March-2020, other things being equal. Considering the average outflows of 2.58 ppts for our sample OEFs in March-2020, the estimated effect is also economically significant as it implies a 67% (i.e., 1.72 / 2.58) reduction in outflows.[22] For other stressful periods, the estimated β_3 is also significant at 0.19, albeit significantly smaller than the estimated β_4 (see row "$\beta_4 - \beta_3$" in Column 1). Together, these results highlight the effect of swing pricing in containing OEFs liquidity risks in stressful periods.[23,24]

Column 1 also reveals that the flow-return relationship for "swing" OEFs is less positive compared to "swing-ineligible" OEFs, as reflected by the negative and statistically significant γ_2. This is consistent with the conjecture that by attracting more long-term investors, the flows of "swing" OEFs tend to be less pro-cyclical to past performance. This justifies our decision to

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[20] In a similar vein, β_5 represents the effect of non-disclosure in other stressful periods.

[21] Assuming zero fund return in previous month for simplicity. Taking into account the actual average OEF return in February-2020 (-4.06%), the effect becomes 1.72(β_4)-0.03(γ_2)*(-4.06= 2 ppts, or a 77% (2/2.58) reduction in outflows.

[22] This contrasts with the findings by Lewrick and Schanz (2017b, see Section 2), which may be explained by the fact that OEFs used a much larger swing factor in March-2020 than during the Taper Tantrum (See Annex D), thus being better at discouraging redemptions by investors.

[23] In Annex E we also show that swing pricing has reduced OEFs chances of closure after the March-2020 market episode, providing additional evidence that swing pricing has helped to contain OEFs' liquidity risk.

[24] Annex F, which reports the results of Placebo test, confirms that the effect of swing pricing in March-2020 turmoil we identified does not appear by random.

account for differences in flow-return relationship between "swing" and "swing-ineligible' OEFs in Equation (1).[25]

Given the above finding, we attempt to further isolate the impact of investor composition from the estimated β_4, by dividing our sample into retail and institutional OEFs and matching them separately.[26] Column 2 and 3, which report the model estimates using the retail and institutional OEFs samples respectively, show that the estimated β_4 remain positive and statistically significant in both cases.[27] These results provide further support that the effect of swing pricing we found is not driven by differences in investor types.

We further find that swing pricing mitigates OEF's outflows in market stress by reducing investors' FMA. Specifically, Column 1 of Table 2.2 shows that the estimated θ_5 is 0.11, meaning that a one-SD reduction in FMA (represented by a rise in $FMA_{i,t}^{-}$) would, on average, reduce OEFs' outflows (a rise in OEF flows) by 0.11 ppts in March-2020. For other stressful periods, however, the estimation is not statistically significant. The positive relationship between reductions in investors' FMA and OEFs' outflows supports the notion that investors would have weaker incentives to take the FMA if they had to take up larger dilution costs in times of market stress. Similar to Table 2.1, Column 2 and 3 of Table 2.2 show that the estimated θ_5 remains statistically significant when we separate the sample into retail and institutional OEFs.

4.2 Does swing pricing-led return volatility lead to larger volatility of OEF's flows?

By decomposing the OEFs' total return variance into the fundamental and swing components using Equation (6), we find that swing pricing would significantly increase the total return variance during periods of market stress. In March-2020, the average swing component of OEFs' total return variance was 2.97 units during the month (see the red portion in the left part of Figure 8). Considering the fundamental component of OEFs' total return variance (green portion) at 6.02 units, swing pricing increased the total return variance by almost 50% (2.97/6.02) during the month. For other stressful periods, the increment in total return variance due to swing pricing remained considerable, driving the total return variance up by 36% (0.17/0.47) on average (middle part of Figure 8).[28] Taken together, this decomposition analysis shows that intensive use of swing pricing could significantly increase the volatility of OEF returns in times of market stress.

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[25] It should be noted that Equation (1) assumes that the flow-return relationship of each OEF group does not change over time. Annex G relaxes this assumption and shows that statistical significance of β_4 remain robust when we allow the flow-return relationships to vary between stressful and normal times.

[26] We first label each OEF as retail or institutional (based on minimum subscription size or fund fee, see Witmer (2012)). We then include this label as extra matching criteria in the matching algorithm such that a "swing" retail (institutional) OEF can only be matched with a "swing-ineligible" retail (institutional) OEF. Separate matched samples of retail and institutional OEFs are then created.

[27] The estimated β_4 for institutional OEFs is much larger than that of retail OEFs, which may be explained by the fact the swing pricing tends to benefit long-term investors more. Institutional investors are also likely to have better understanding or knowledge on the impact of swing pricing on their investment decisions. All these could contribute to a larger impact of swing pricing on "institutional" OEFs.

[28] The percentage increase in total return variance due to swing pricing also increases with the illiquidity of OEFs' underlying assets. In March 2020, swing pricing pushed up the return variance of fixed-income OEFs by 75.7%, compared to 47.7% for other OEFs. See Annex Figure H.1 for illustration.

The estimation results of Equation (7) also show that the swing pricing-induced OEF return variance could result in a larger variance of OEF flows. In particular, Table 3.1 shows that a one-unit increase in the swing component of OEFs' total return variance in the current month is associated with a significant 0.08 unit increase in the OEF flow variance in the subsequent month.[29] Considering the average 2.97 units of the swing component of OEFs' total return variance in March-2020, the variance of the "swing" OEFs flows in the subsequent month (i.e. April-2020) would increase by 0.24 units (2.97×0.08), other things being equal.[30] Such impact is also significant economically as it represents around a 13% increase in the average variance of "swing" OEFs flows (i.e., 1.77 units, see Column 2 of Table 1.2).[31]

4.3 Does swing pricing encourage higher leverage by OEFs?

We find that swing pricing would stimulate higher leverage by OEFs.[32] Our empirical results for Equation (8) show that, during the sample period prior to the March-2020 episode (i.e. January-2012 to February-2020), the average leverage ratio of "swing" OEFs was larger than that of "swing-ineligible" OEFs by 9.75 ppts, other things being equal (Table 4.1). This implies swing pricing could result in higher leverage in "swing" OEFs, which we have further shown is attributable to the "lost attractiveness" argument in *Introduction*.[33]

4.4 Does the non-disclosure practice of OEFs reduce the effectiveness of swing pricing?

Our estimation results of Equation (9) suggest that OEFs' practice of non-disclosure would reduce the effectiveness of swing pricing in times of extreme stress. Specifically, Column 1 of Table 5.1 shows that, in the March-2020 episode, the reduction in outflows for "swing-eligible but not disclosed" OEFs (i.e., the sum of estimated β_4 and β_6) is 1.61 ppts while that of "swing" OEFs was much larger at 3.29 ppts (i.e. estimated β_4).[34] In other words, the non-disclosure practice has reduced the mitigating effect of swing pricing by as much as 1.68 ppts (i.e. estimated β_6), or a maximum 51% reduction in mitigating effect (i.e., -1.68/3.29).[35] In other

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[29] The estimation result is robust if we first filter the effect of the fundamental component on OEF flow variance and then estimate the impact of the swing component on OEF flow variance, amid concern over the series correlation between both components. See Annex I for detailed estimation results.

[30] This prediction is in line with the observations in April 2020, where a larger flow variance for "swing" OEFs is observed (Annex Figure J.1).

[31] Our unreported results further show that the effect of the swing component of OEF return variance is more pronounced on fixed-income OEF flow variance. The average 0.92 unit of swing component of fixed-income OEF return variance in March 2020 could significantly lead to an increase of 0.36 units in fixed-income OEF flow variance in April 2020, representing 25.3% of the mean flow variance.

[32] We are also able to replicate the negative relationship between swing pricing and OEFs' liquidity buffer as documented in Lewrick and Schanz (2017b), using our OEFs sample. See Annex K for detailed estimation results.

[33] Specifically, Annex L shows that the use of leverage by "swing" OEFs could lessen the reduction in inflows during normal periods, compared to "swing" OEF's that do not.

[34] For robustness, we match the three OEF groups with the "swing" OEFs as the alternative reference group, providing another way to capture the effect of non-disclosure by comparing the flows between comparable groups of "swing" OEFs and "swing-eligible but not disclosed" OEFs. Annex M shows the results remain robust to this alternative matched sample.

[35] The estimate is viewed as the maximum impact of non-disclosure as we cannot tell whether each of the "swing-eligible but not disclosed" OEFs actually adopt swing pricing or not. The actual β_6 would be less negative than our estimation if some "swing-eligible but not disclosed" OEFs do not adopt swing pricing in reality.

stressful periods, however, the effect did not differ, as the estimated β_5 is statistically insignificant at -0.12 ppts.[36]

Taken together, our results show that the lack of disclosure on swing pricing usage could limit the effectiveness of the tool in times of market stress, such as the March-2020 episode, even though it may not cause a substantial difference during less stressful periods.

5 Conclusion and implications

The March-2020 episode raised questions on whether OEFs' liquidity management tools, which were increasingly adopted by regulators after the GFC, have succeeded in mitigating OEFs' liquidity pressures in this stress episode. As one of the fast-rising liquidity management tools in the post-GFC reform, swing pricing appeared to be able to reduce OEFs redemption pressure during market stress. With information on the usage of swing pricing by individual OEFs, we show that the mitigating effect of swing pricing will lower the OEFs redemption pressure by reducing investors' FMA.

Despite the positive findings above, our analysis raises three issues that could limit the effectiveness of swing pricing during market stress. First, the swing pricing-led volatility of OEF returns due to elevated transaction costs will lead to a larger volatility of OEFs' flows. This could, at least, partially offset the mitigating effect of swing pricing on fund flows in the near term and destabilise the OEFs' liquidity management. Secondly, swing pricing will encourage OEFs to raise leverage during normal periods, which may lead to substantial losses and amplify the redemption pressures in times of market stress. Finally, some OEFs may not disclose the use of swing pricing, but such non-disclosure practice will weaken the mitigating effect of swing pricing as observed in March 2020.

Taken together, our findings have two policy implications. First, while our findings suggest that swing pricing would be one effective tool for liquidity management of OEFs, it may come with "side effects", including larger flow volatility and higher leverage. A proper design and combination with other risk management tools, as highlighted in Lewrick and Schanz (2017b), may be necessary for swing pricing to work in a more effective way. For example, in the context of higher leverage, the co-usage of swing pricing and leverage limit may be considered. Secondly, policies to promote a higher level of relevant disclosures may also enhance the effectiveness of swing pricing.[37]

There are two caveats in this study. Our inferences are drawn from a small sample of OEFs that publicly disclose their daily usage of swing pricing, creating uncertainty on the generalisability of our results. Again, this also points to the importance of disclosures by more OEFs as this will greatly improve our understanding of the tool. Secondly, we rely on Morningstar Direct as our source of information. While we believe that this already captures most of the OEFs providing the information on swing pricing usage, we may miss out those disclosing the information elsewhere. A systematic way of disseminating OEFs disclosures by OEFs could facilitate policy makers or researchers on further analysis.

[36] This may be explained by the lower uncertainty in the transaction cost of assets (and thereby the potential swings factor to be applied) in less stressful periods, so that the non-disclosure would not have a material impact on investors' decisions.

[37] The need for more transparency is also highlighted by both regulators (e.g. the UK Financial Conduct Authority) and market participants (e.g. BlackRock).

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Table 1. Summary Statistics

The matched sample includes 1896 European-domiciled OEFs from 2012 to 2020 with 70,612 fund-month observations. They come from three OEF groups – “swing”, “swing-eligible but not disclosed” and “swing-ineligible” OEFs – matched as described in Section 4. Table 1.1 summarises notations, definitions and data sources of key variables. Table 1.2 through 1.4 report summary statistics of the key variables for each OEF group. In Table 1.5, Column 1 shows mean differences in the key variables between “swing” and “swing-eligible but not disclosed” OEFs. Column 2 shows the mean differences between “swing” and “swing-ineligible” OEFs. Column 3 shows the mean differences between “swing-eligible but not disclosed” and “swing-ineligible” OEFs. All of the mean differences are tested by the Wald test and found statistically insignificant at the 10% level.

Table 1.1: Definitions and sources of variables

Notation	Definition	Data source
$Flow$	Monthly fund flow, calculated as the percentage change in a fund’s total net assets, net of the fund’s return (%)	Morningstar Direct
FMA	Monthly average of daily swing factor divided by daily fund flow (%)	
Ret	Monthly fund return (%)	
$Size$	Month-end total net assets of a fund (in logarithm)	
Age	Fund age (in year)	
$Equity$	Equities held by a fund as percentage of its total net assets (%)	
FI	Fixed-income securities held by a fund as percentage of its total net assets (%)	
$Cash$	Cash or equivalent held by a fund as percentage of its total net assets (%)	
Lev	Total long position of a fund as percentage of its total net assets (%)	
$\mathrm{Var}_{i,t}^{Return}$	Variance of daily fund returns of the month	
$\mathrm{Var}_{i,t}^{Flow}$	Variance of daily fund flows of the month	

Table 1.2: Summary statistics of “swing” OEFs

	No of OEFs	Obs	Mean	SD	Skewness	25p	Median	75p
$Flow$	632	29,680	0.70	5.35	1.21	-2.18	-0.12	2.11
SF	632	29,680	0.02	0.03	1.86	0.00	0.005	0.02
Ret	632	29,680	0.33	2.35	-0.41	-0.58	0.40	1.56

$Size$	632	29,680	17.30	1.54	0.23	16.2	17.2	18.4
Age	632	29,680	6.15	5.56	1.40	2.20	4.24	8.18
$Equity$	632	29,680	44.29	39.9	0.25	0.00	40.2	95.7
FI	632	29,680	46.4	38.1	0.08	0.26	45.0	89.3
$Cash$	632	29,680	4.79	4.49	1.22	1.34	3.35	6.76
Lev	632	29,680	159.64	52.47	0.61	105.47	155.18	192.85
$\text{Var}_{i,t}^{Return}$	632	29,680	0.36	0.54	2.06	0.04	0.12	0.42
$\text{Var}_{i,t}^{Flow}$	632	29,680	1.77	4.21	3.08	0.11	0.26	0.80

Table 1.3: Summary statistics of "swing-eligible but not disclosed" OEFs

	No of OEFs	Obs	Mean	SD	Skewness	25p	Median	75p
$Flow$	632	20,174	0.74	4.90	1.07	-1.86	-0.0002	2.32
SF	632	20,174	--	--	--	--	--	--
Ret	632	20,174	0.48	2.30	-0.12	-0.53	0.42	1.65
$Size$	632	20,174	17.80	1.58	0.20	16.49	17.63	19.00
Age	632	20,174	6.67	5.34	1.12	2.66	4.96	9.40
$Equity$	632	20,174	44.81	41.52	0.23	0.00	33.17	96.29
FI	632	20,174	43.25	38.78	0.18	0.01	39.82	85.69
$Cash$	632	20,174	6.05	7.21	1.51	1.02	3.53	8.74
Lev	632	20,174	139.60	56.89	1.74	101.33	110.24	156.66
$\text{Var}_{i,t}^{Return}$	632	20,174	0.36	0.53	1.97	0.03	0.11	0.45
$\text{Var}_{i,t}^{Flow}$	632	20,174	1.34	3.08	3.07	0.11	0.24	0.66

Table 1.4: Summary statistics of "swing-ineligible" OEFs

	No of OEFs	Obs	Mean	SD	Skewness	25p	Median	75p
$Flow$	632	20,758	0.44	4.36	0.99	-2.16	-0.18	2.13
SF	632	20,758	--	--	--	--	--	--
Ret	632	20,758	0.38	1.95	-0.25	-0.50	0.36	1.44
$Size$	632	20,758	18.05	1.64	-0.20	16.91	18.14	19.29
Age	632	20,758	7.43	6.54	1.08	2.38	5.03	11.02
$Equity$	632	20,758	40.50	39.25	0.37	0.00	31.21	84.98
FI	632	20,758	45.32	36.64	0.10	4.30	43.43	82.33
$Cash$	632	20,758	9.35	11.86	1.37	1.31	4.51	14.01
Lev	632	20,758	114.07	23.34	1.62	100.13	103.57	121.40
$\text{Var}_{i,t}^{Return}$	632	20,758	0.30	0.44	1.94	0.02	0.10	0.38
$\text{Var}_{i,t}^{Flow}$	632	20,758	0.93	1.86	3.10	0.16	0.27	0.63

Table 1.5: Mean differences in key fund characteristics across OEF types

	(1)	(2)	(3)
	"Swing" - "swing-eligible but not disclosed"	"Swing" - "swing-ineligible"	"Swing-eligible but not disclosed" - "swing-ineligible"
$Flow$	-0.04	0.26	0.30
FMA	--	--	--
Ret	-0.15	-0.05	0.1

$Size$	-0.50	-0.75	-0.25
Age	-0.52	-1.28	-0.76
$Equity$	-0.52	3.79	4.31
FI	3.15	1.08	-2.07
$Cash$	-1.26	-4.56	-3.3
Lev	20.04	45.57	25.53
$\mathrm{Var}_{i,t}^{Return}$	0.00	0.06	0.06
$\mathrm{Var}_{i,t}^{Flow}$	0.43	0.84	0.41

Note: Statistical significance is tested by the Wald test for each figure, with *, ** and *** denoting statistical significance at 1, 5 and 10% levels, respectively.

Table 2: Impacts of swing pricing on fund flows

Table 2.1 presents estimation results of Equation (1) using the matched sample of "swing" and "swing-ineligible" OEFs. Table 2.2 presents estimation results of Equation (2) using the sample of "swing" OEFs only. The matched samples are matched as described in Section 4. The dependent variable $Flow_{i,t}$ is a OEF *i*'s flows in month *t*. Independent variables are as defined earlier. "×" denotes interaction terms between corresponding variables. Column (1) shows the baseline result. Columns (2) and (3) show results using the matched sample of retail funds and institutional funds, respectively. Differences between the estimated β_4 and β_3 (denoted by $\beta_4 - \beta_3$) indicates the additional effect of swing pricing on fund flows in March 2020 over other stressful periods and is tested by the Wald test. Standard errors are clustered at the OEF level and t-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 2.1: Estimation results for Equation (1)

	Dependent variable:		
	$Flow_{i,t}$ (1)	$Flow_{i,t}$ (2)	$Flow_{i,t}$ (3)
$Stress_t$ (β_1)	-0.44***	-0.64***	-0.53
$March20_t$ (β_2)	-3.87***	-4.70***	-4.29***
$SW_i \times Stress_t$ (β_3)	0.19*	0.32*	0.11
$SW_i \times March20_t$ (β_4)	1.72***	1.15*	3.94***
$Ret_{i,t-1}$ (γ_1)	0.03***	0.10***	0.005
$SW_i \times Ret_{i,t-1}$ (γ_2)	-0.03*	-0.06**	-0.02
$\beta_4 - \beta_3$	1.53***	0.83*	3.83***
Model	Fixed effect	Fixed effect	Fixed effect
Control	Yes	Yes	Yes
VIX_t	Yes	Yes	Yes
OEF FE	Yes	Yes	Yes
Sample	"Swing" and "swing-ineligible" OEFs		
of which:	All	Retail	Institutional
Number of OEFs	1,264	702	458
Number of observations	50,438	34,121	15,573

Table 2.2: Estimation results for Equation (2)

	Dependent variable:		
	$Flow_{i,t}$ (1)	$Flow_{i,t}$ (2)	$Flow_{i,t}$ (3)
$Stress_t$ (β_1)	-0.09	-0.07	-0.49
$March20_t$ (β_2)	-1.66*	-2.34***	-1.15**
$Ret_{i,t-1}$ (γ_1)	-0.01	0.02	-0.02
$FMA^-_{i,t}$ (θ_3)	-0.02	-0.01	0.03
$FMA^-_{i,t} \times Stress_t$ (θ_4)	0.10	0.09	0.05
$FMA^-_{i,t} \times March20_t$ (θ_5)	0.11*	0.22**	0.08***
Model	Fixed effect	Fixed effect	Fixed effect
Control	Yes	Yes	Yes
VIX_t	Yes	Yes	Yes
OEF FE	Yes	Yes	Yes
Sample	"Swing" and "swing-ineligible" OEFs		
of which:	All	Retail	Institutional
Number of OEFs	632	351	229
Number of observations	29,680	19,739	3,980

Table 3: Impacts of swing pricing on volatility of fund flows

Table 3.1 presents estimation results of Equation (7) using the matched sample of "swing" OEFs only. The dependent variable $FlowVol_{i,t}$ is a fund i's flow variance in month t. Independent variables are as defined earlier. Standard errors are clustered at the fund level and t-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 3.1: Estimation results for Equation (7)

	Dependent variable:
	$FlowVol_{i,t}$
	(1)
$\text{Var}_{i,t-1}^{NAV}$	0.03*
$\text{Var}_{i,t-1}^{SF}$	0.08***
Model	Fixed effect
$Ret_{i,t-1}$	Yes
Control	Yes
VIX_t	Yes
OEF FE	Yes
Sample	"Swing" OEFs
Number of OEFs	632
Number of observations	29,680

Table 4: Impacts of swing pricing on leverage

Table 4.1 presents estimation results of Equation (8) using the matched sample of "swing" and "swing-ineligible" OEFs, which are matched as described in Section 4, for January 2012 to February 2020. The dependent variable $Lev_{i,t}$ is a fund i's total long position as a percentage of its net assets in month t. Independent variables are as defined earlier. Standard errors are clustered at the fund level and t-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 4.1: Estimation results for Equation (8)

	Dependent variable:
	$Lev_{i,t}$
	(1)
SW_i	9.75***
Model	OLS
$Lev_{i,t-1}$	Yes
$Ret_{i,t-1}$	Yes
Control	Yes
VIX_t	Yes
Sample	"Swing" and "swing-ineligible" OEFs[2]
Number of OEFs	1,264
Number of observations	50,438

Table 5: Impacts of non-disclosure on the effectiveness of swing pricing

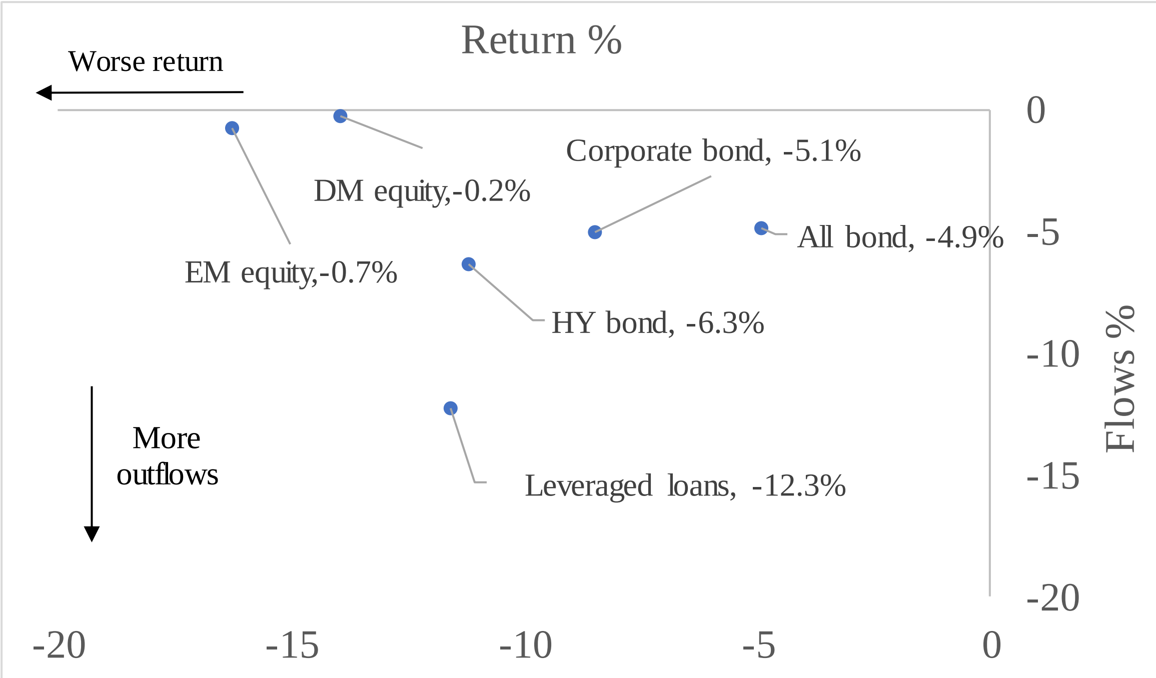
Table 5.1 presents estimation results of Equation (9) using the matched sample of “swing”, “swing-eligible but not disclosed” and “swing-ineligible” OEFs, which are matched as described in Section 4. The dependent variable $Flow_{i,t}$ is a fund i's flow variance in month t. Independent variables are as defined earlier. “×” denotes interaction terms between corresponding variables. Column (1) shows the baseline result. Columns (2) and (3) show results using the matched sample of retail funds and institutional funds, respectively. The sum $\beta_4 + \beta_6$ indicates the overall effect of swing pricing on “swing-eligible but not disclosed” OEFs, and is tested by the Wald test. Standard errors are clustered at the fund level and t-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 5.1: Estimation results for Equation (9)

	Dependent variable:		
	$Flow_{i,t}$ (1)	$Flow_{i,t}$ (2)	$Flow_{i,t}$ (3)
$Stress_t$ (β_1)	-0.82	-0.39	-4.61**
$March20_t$ (β_2)	-4.79***	-3.92***	-9.61***
$SW_i \times Stress_t$ (β_3)	0.61	0.68	3.88*
$SW_i \times March20_t$ (β_4)	3.29***	1.07*	13.28***
$ND_i \times Stress_t$ (β_5)	-0.12	-0.80	1.71
$ND_i \times March20_t$ (β_6)	-1.68**	-0.83*	-13.02***
$Ret_{i,t-1}$ (γ_1)	0.06	0.25	-0.05
$SW_i \times Ret_{i,t-1}$ (γ_2)	-0.04	-0.11	0.11
$ND_i \times Ret_{i,t-1}$ (γ_3)	0.11	-0.02	0.84
$\beta_4 + \beta_6$	1.61*	0.24*	0.26*
Model	Fixed effect	Fixed effect	Fixed effect
Control	Yes	Yes	Yes
VIX_t	Yes	Yes	Yes
OEF FE	Yes	Yes	Yes
Sample	“Swing”, “swing-eligible but not disclosed” and “swing-ineligible” OEFs		
of which:	All	Retail	Institutional
Number of OEFs	1,896	1,053	687
Number of observations	70,612	43,891	23,360

Figure 1: Outflows from OEFs during the March-2020 market episode

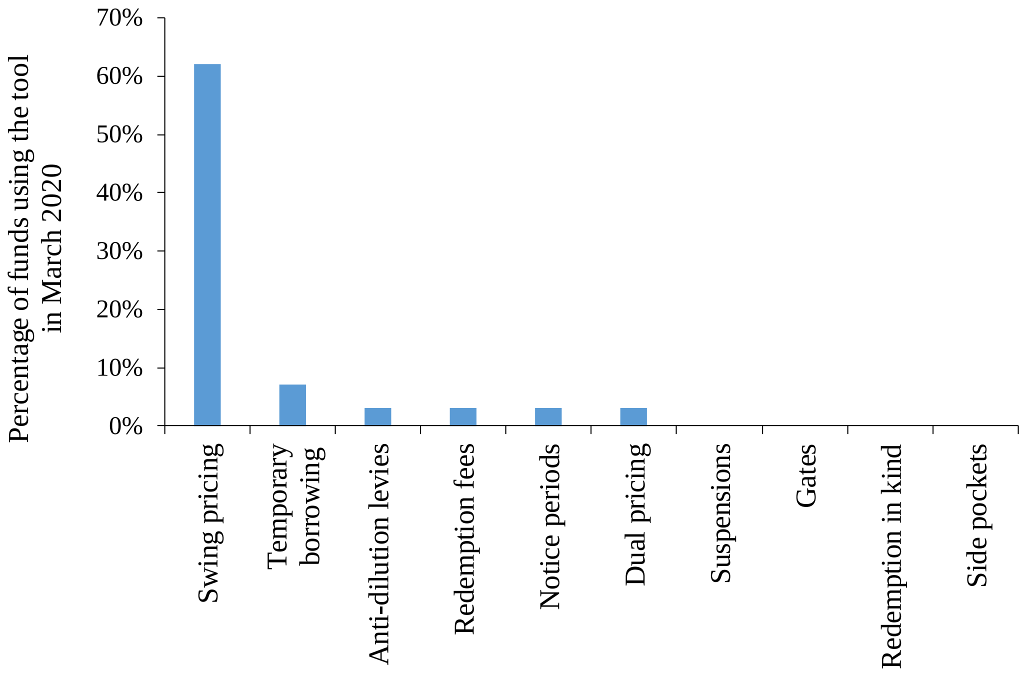
This figure depicts the outflows from various types of OEFs in March 2020. The x-axis denotes the fund returns of each OEF type, and y-axis denotes fund flows in percentage (of total net assets). The figure next to the OEF type denotes its outflows in the same month.



Source: EPFR

Figure 2: Usage of liquidity management tools by European OEFs in March 2020

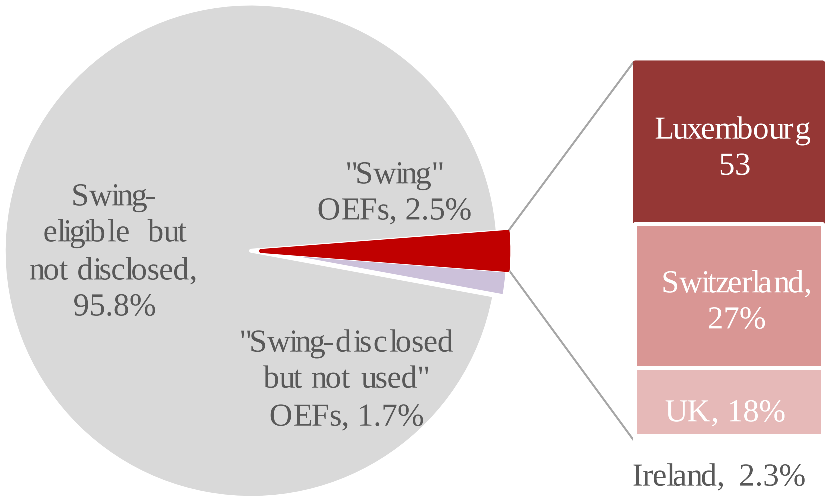
This figure plots the percentage of European OEFs using liquidity management tools in March 2020, based on 29 fund complexes' responses to Investment Company Institute Global Survey.



Source: Investment Company Institute Global Survey Data

Figure 3: Geographic distribution of the "swing" OEFs

This figure depicts geographic distribution of "swing" OEFs at the end of 2019. All "swing" OEFs identified are domiciled in Europe, with half of them from Luxembourg, followed by Switzerland and UK. "Swing" OEFs together account for 2.5% of all European OEFs that are allowed to use swing pricing. The rest include OEFs that disclosed the usage but had not used swing pricing during the sample period (1.7%, "swing-disclosed but not used" OEFs) and those that have not disclosed the usage (i.e., "swing-eligible but not disclosed", 96% of the total).



Source: Morningstar Direct

Figure 4: Mean distance among OEF groups over the sample period

The figure shows mean distances, or average absolute percentage differences in key variables including fund returns (%), fund size (in log), and fund age (in years) among OEF groups. The LHS bars denote the mean distance between "swing" OEFs and "swing-eligible but not disclosed" OEFs before (in red) and after (in blue) matching as described in Section 4. The RHS bars denote the mean distance between "swing" OEFs and "swing-ineligible" OEFs.

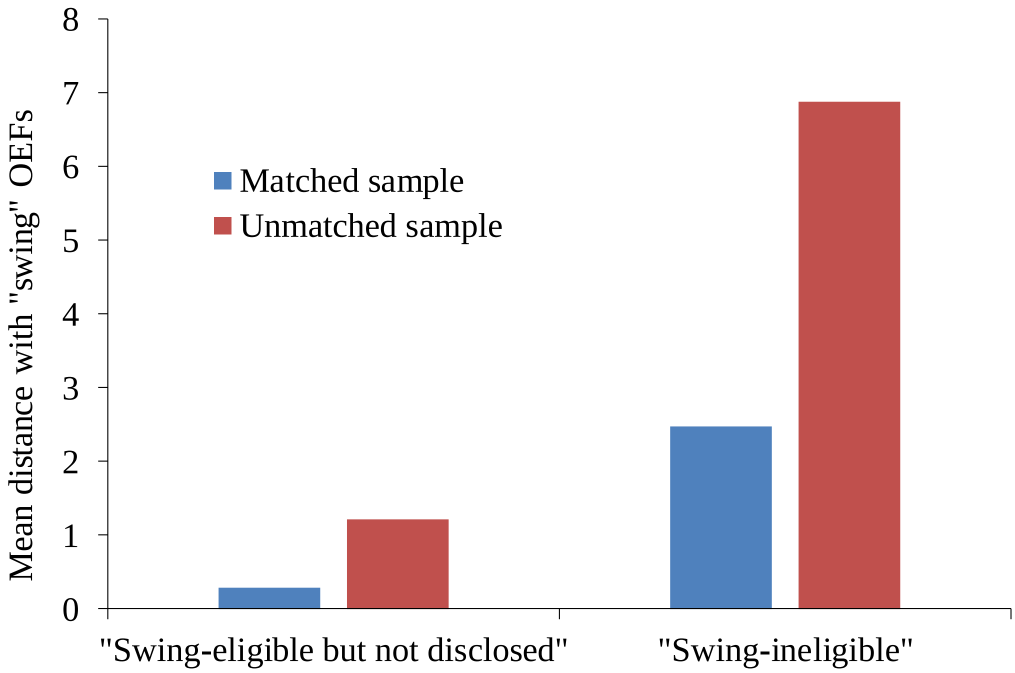
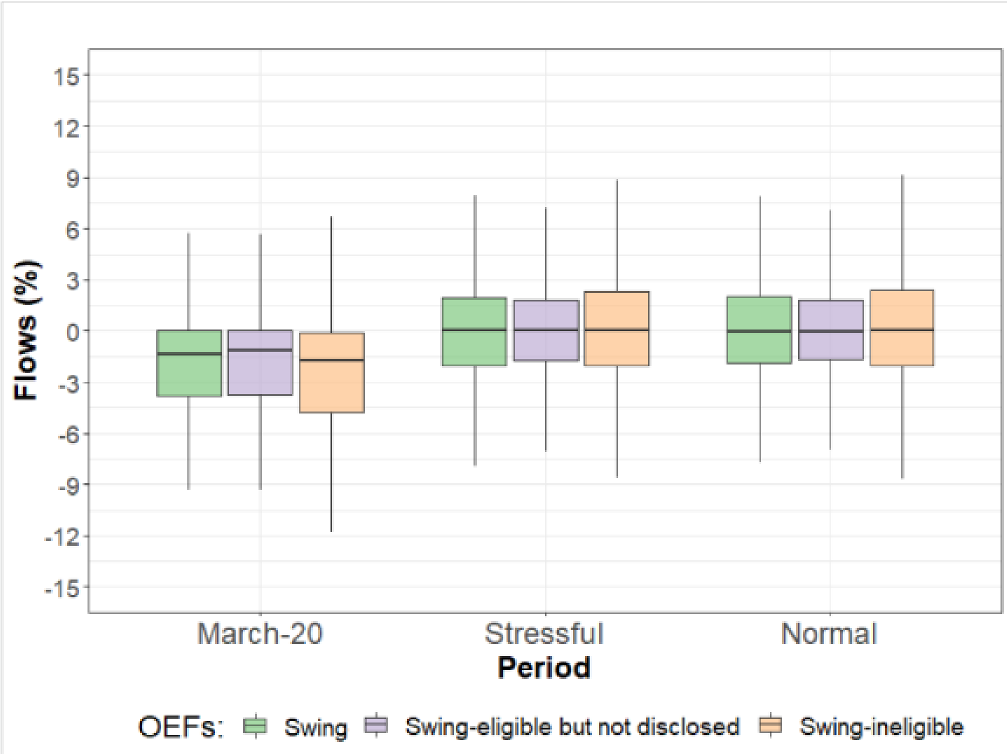


Figure 5: Fund flows by OEF type and period

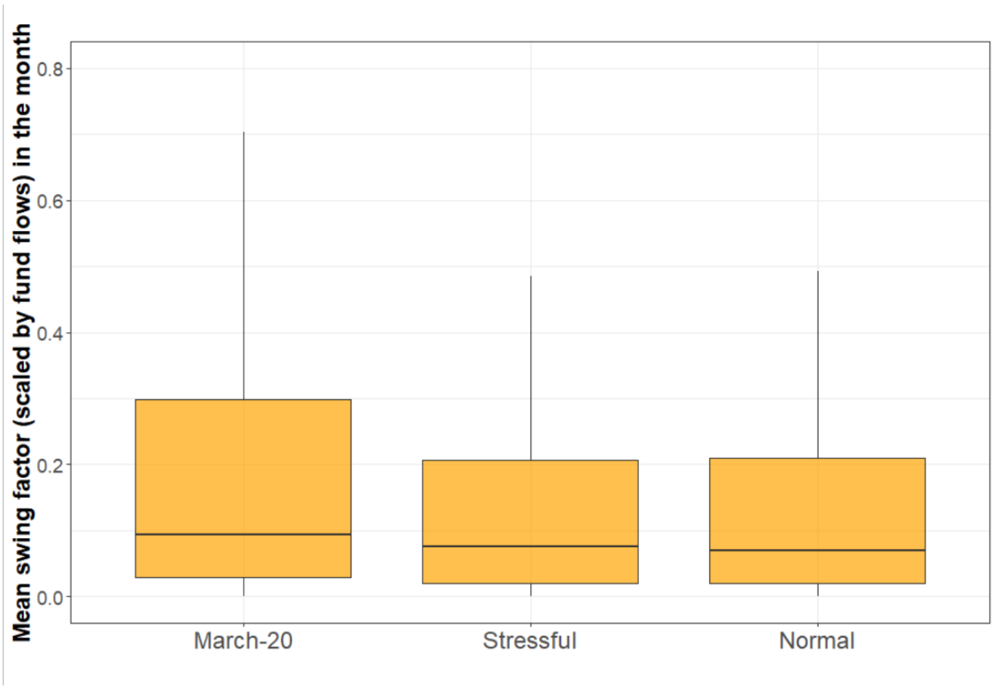
This figure depicts the boxplots of fund flows by OEF type and period. The x-axis denotes the sample period, and the y-axis denotes the fund flows. OEF types are represented by colour, where green boxplots denote "swing" OEFs, purple boxplots denote "swing-eligible but not disclosed" OEFs, and orange boxplots denote "swing-ineligible" OEFs.



Source: Morningstar Direct

Figure 6: Distribution of OEFs' swing factor by period

This figure depicts the boxplots of daily average swing factors (scaled by fund flows) implemented by "swing" OEFs in March 2020 (LHS), other stressful periods (MID) and normal periods (RHS).



Source: Morningstar Direct

Figure 7: Identification of the non-disclosure effect during March-2020 episode with Equation (10)

This figure visualizes how we identify the effect of non-disclosure on the mitigating effect of swing pricing in March 2020. The orange area illustrates that the effect of "swing pricing without disclosure" can be identified by the difference in fund flows between "swing-eligible but not disclosed" and "swing-ineligible" OEFs ($\beta_4 + \beta_6$). In the meantime, the green area illustrates that the effect of "swing pricing with disclosure" can be identified by the difference in fund flows between "swing-ineligible" and "swing" OEFs (β_4). Finally, the blue area illustrates that the effect of "non-disclosure" is equivalent to the difference between both aforementioned effects, or (β_6).

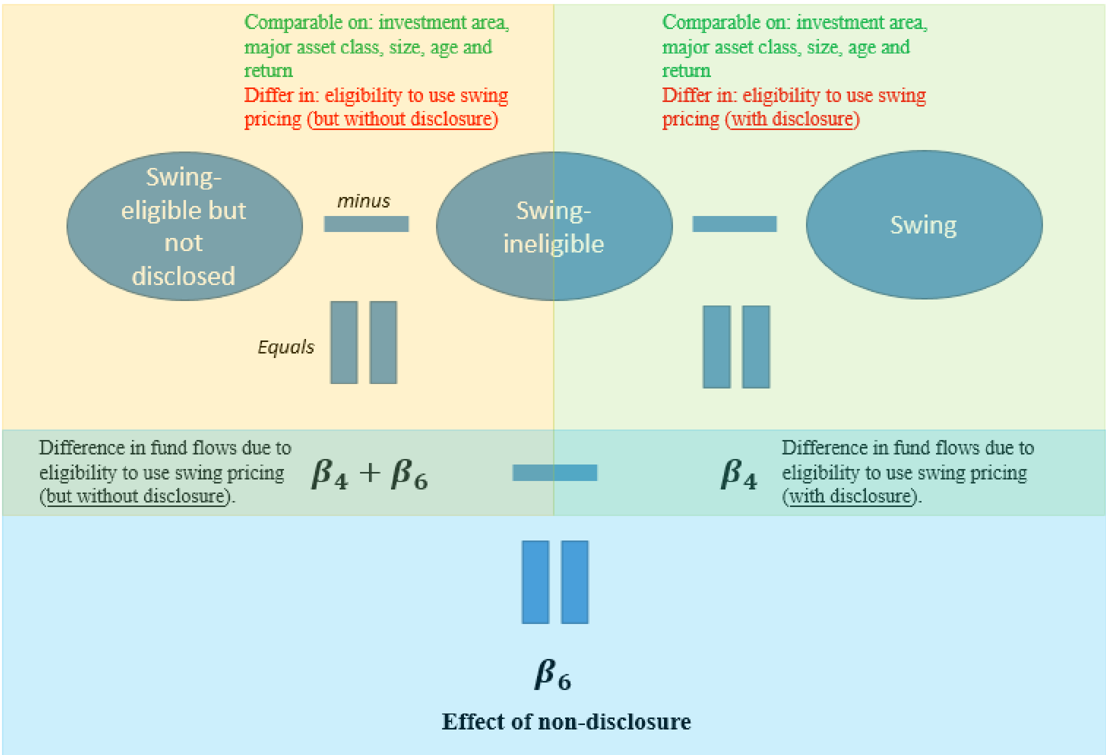
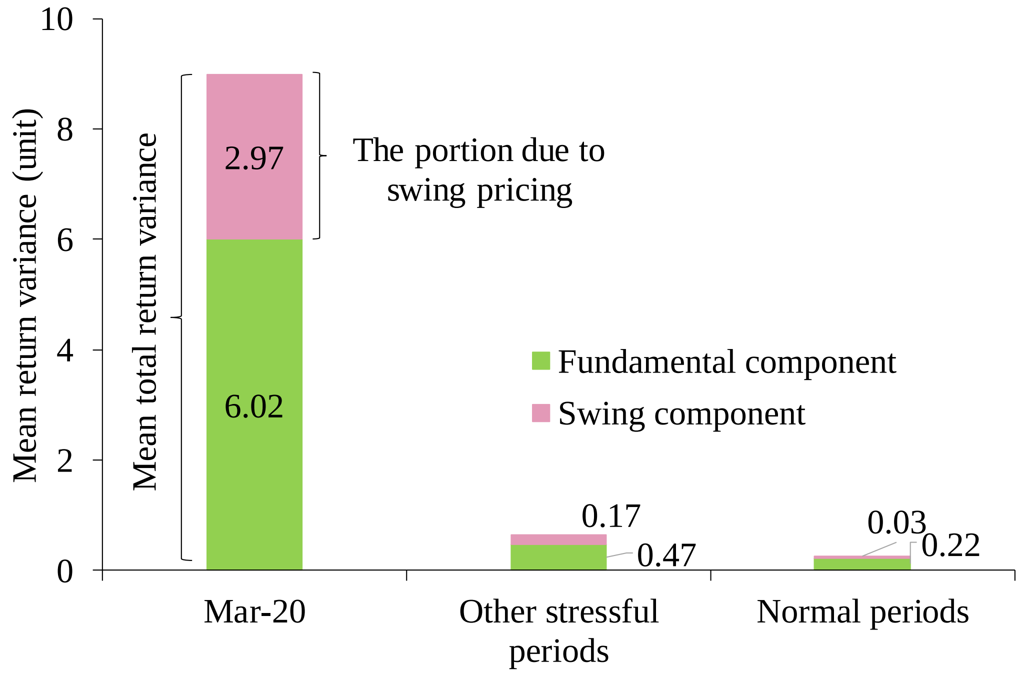


Figure 8: Swing pricing's contribution to average return variance of "swing" OEFs by period

This figure depicts the average return variance of "swing" OEFs by period, and the proportion contributed by swing pricing. In the figure, three bars denote the average return variance of "swing" OEFs in March 2020 (LHS), other stressful periods (MID) and normal periods (RHS). Fundamental component refers to the portion of OEFs' return variance attributable to OEFs' theoretical NAV, while swing component captures the residuals induced by swing pricing (Equation 7). The pink portions represent swing component, while the green portions denote the fundamental component. The figure next to each component indicates the level of that component.



Annex A: How can swing pricing mitigate FMA and OEFs redemption pressures?

As mentioned in *Introduction*, FMA in OEF redemptions exist as a dilution in OEF values will fall on remaining investors rather than the redeeming investors. More specifically, for a net redemption on an OEF at day t, redeeming investors are entitled to receive an OEF price equal to its net asset value (NAV) at the end of day *t*.[38] Assuming that the OEF has to sell its assets afterwards, at say day *t+1*, to raise cash to meet the redemption orders, these asset sales will incur explicit costs, such as brokerage fees and taxes, as well as implicit costs like selling at a lower bid-price and possible market valuation changes caused by the transactions. These transaction costs increase with the magnitude of redemptions and are higher in times of stress as the markets may become illiquid or OEFs may have to accept a lower price for selling their assets.

Under traditional pricing rules, these costs would only be priced in OEF's NAV after the transactions have taken place, i.e. day *t+1*, and OEF's NAV would be "diluted" as a result. More importantly, as these costs are reflected in OEF's NAV at day *t+1*, but not day *t*, meaning investors redeeming at day t do not have to bear these costs. Instead, these costs dilute the OEFs' values of remaining investors and hurt their interests (e.g. when they redeem at *t+1* they have to accept a "diluted" OEF NAV), with the dilution being more pronounced in times of stress due to heightened transaction costs.

Conversely, swing pricing transfers the potential dilutions back to the redeeming investors. More specifically, OEFs would "swing" their NAV (and thereby their price) "up" or "down" to reflect the expected transaction costs associated with net investors' orders **on the same day**. When large net redemptions occur, the OEF price will be swung "down" such that redeeming investors would now bear the dilutions on OEFs' values (i.e., the transaction costs of asset sales) by selling at an OEF price lower than what its portfolio is worth. Annex B provides a numerical example for this case.

While the intention of swing pricing is to protect remaining investors from diluting the value of OEFs, it also helps to reduce OEFs' redemption pressures in times of financial stress. It does so by affecting the behaviour of the following three groups of investors. First, for investors who redeem to take advantage of by-passing the dilution costs to redeeming investors, they will find it is not beneficial to do so anymore as they have to bear the liquation costs under swing pricing. Secondly, for those who redeem simply to avoid dilutions by other investors, they may now remain with the OEFs as the swing pricing protects their interests from being diluted. Their incentive to remain with the OEF would be stronger if they expect a larger dilution cost being transferred to redeeming investors, whereas the actual dilution cost is only determined after investors flows are realised. Thirdly, for those who have a genuine need to redeem (e.g. to raise cash), they may also become more cautious in timing their redemption under swing pricing as they could face a sizeable dilution cost for redeeming a larger amount. In particular, these investors could split their redemptions over a period (instead of concentrating on a single day) or even reduce the amount of redemption. All these help to stabilise redemptions from OEFs.

[38] Here we assume daily dealing for simplicity.

Annex B: A numerical example of swing pricing

In this annex, we will illustrate how "partial" and "full" swing pricings are invoked with numerical example. Table B.1 shows the case of a hypothetical OEF which NAV USD 100 at day t with total AUM of USD 100 million) at day *t-1*, with the swing threshold set at 5% such that swing pricing would be invoked if the net capital activity (either net subscription or redemption) on that day exceeds 5% (or USD 5 million based on total AUM at t-1) for the case of "partial" swing pricing. For "full" swing pricing, the NAV would be adjusted to whenever the net capital activity is non-zero.

Table B.1: Case set-up

NAV per share (day t)	USD 100.00
Total fund AUM (day t-1)	USD 100,000,000
Swing threshold (applicable to "partial" swing pricing only)	5.00% of total AUM (or USD 5,000,000)

Suppose there are three investors making different subscription or redemption decisions on day *t*. Table B.2 present four scenarios for illustration. "Full" swing pricing is invoked in all scenarios except Scenario 3 where net subscription/redemption is zero. By contrast, "partial" swing pricing is invoked only when the net redemption (Scenario 1) or subscription (Scenario 4) exceeds the swing threshold (USD 5 mn). As also highlighted in Section 3, the swing factor is determined based on the estimated transaction costs associated with the net subscription/redemption amount and is therefore different across scenarios. Take Scenario 1 as an example. Assuming the swing factor is determined at -0.6% (a negative factor since as there are net redemptions), the fund price at transaction would then become USD 99.4 (= USD 100 x (1 – 0.6%)). Every investor subscribes or redeems at this price. In this case, Investors 1 and 2 receive 0.6% less proceeds for redemption (as compared to the NAV), while Investor 3 enjoys 0.6% discount for subscription.

Table B.2: Application of swing pricing

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Investor 1*	(USD 3 mn)	USD 2 mn	USD 3 mn	(USD 2 mn)
Investor 2*	(USD 5 mn)	USD 1 mn	(USD 2 mn)	USD 3 mn
Investor 3*	USD 2 mn	(USD 4 mn)	(USD 1 mn)	USD 5 mn
Net subscription (redemption)	(USD 6 mn)	(USD 1 mn)	zero	USD 6 mn
Swing factor applied	-0.6%	-0.1%	/	+0.5%
Transacted fund price				
- "Partial" swing pricing	99.4 (100*(1-0.6%))	100 (No adjustment)	100 (No adjustment)	100.5 (100*(1+0.5%))
- "Full" swing pricing	99.4 (100*(1-0.6%))	99.9 (100*(1-0.1%))	100 (No adjustment)	100.5 (100*(1+0.5%))

Note: *The amount of subscription (redemption) by each investor is denoted without (with) parenthesis.

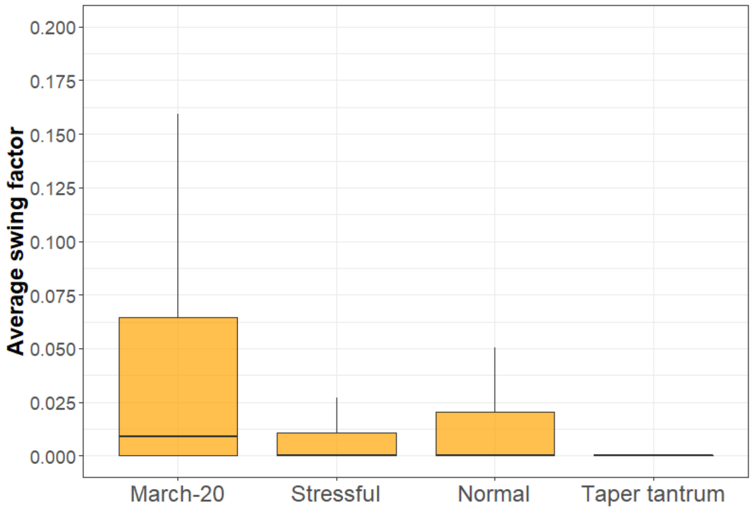
Annex C: List of European markets in our OEF sample that allow the use of swing pricing

Swing pricing is allowed	Swing pricing is not allowed
• France • Ireland • Luxembourg • Switzerland • United Kingdom	• Czech Republic • Denmark • Greece • Italy • Latvia • Lithuania • Malta • Slovenia • Sweden

Source: BlackRock (2020)

Annex D: Swing factors applied by sample "swing" OEFs during different periods

Figure D.1: Distribution of swing factors applied by sample "swing" OEFs' during different periods



Notes:
(i) The figure depicts the distribution of the absolute value of swing factors used by sample "swing" OEFs' in each specified period.

Annex E: Additional analysis on the effectiveness of swing pricing during the March-2020 market episode

This annex covers the technical details of the additional empirical analyses on the effectiveness of swing pricing not discussed in *Empirical findings*. The panel regression model and estimates for each case are reported below:

E1. Disaggregation of the mitigating effects of swing pricing by OEF type

In this section, we describe the panel regression model used to assess whether the effects of swing pricing differ from the illiquidity of OEFs' underlying assets. Specifically, we compare the effect between mixed/equity OEFs and fixed-income OEFs (where the underlying assets are less liquid in general). The empirical models are expanded from Equation (1) and (2) and are given by:

$$\begin{aligned} Flow_{i,t} = {} & \beta_1 Stress_t + \beta_2 March20_t + \beta_3\, SW_i \times Stress_t + \beta_4\, SW_i \times March20_t \\ & + \beta_5 SW_i \times Stress_i \times Bond_i + \beta_6 SW_i \times March20_t \times Bond_i \\ & + \beta_7 Bond_i \times Stress_i + \beta_8 Bond_i \times March20_t + \gamma_1\, Ret_{i,t-1} \\ & + \gamma_2\, SW_i \times Ret_{i,t-1} + \delta_1 Control_{i,t-1} + \delta_2 VIX_t + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{10}$$

$$Flow_{i,t} = \beta_1 Stress_t + \beta_2 March20_t + \theta_3 FMA^{-}_{i,t} + \theta_4\, FMA^{-}_{i,t-1} \times Stress_t$$
$$+\theta_5\, FMA^{-}_{i,t-1} \times March20_t + \theta_6 FMA^{-}_{i,t} \times Bond_i$$
$$+\theta_7 FMA^{-}_{i,t} \times Stress_t \times Bond_i + \theta_8 FMA^{-}_{i,t} \times March20_t \times Bond_i$$
$$+\gamma_1\, Ret_{i,t-1} + \delta_1 Control_{i,t-1} + \delta_2 VIX_t + \mu_i + \varepsilon_{i,t} \quad (11)$$

where $Bond_i$ is a dummy variable equal to 1 if OEF i is a fixed-income OEF, and zero otherwise. For Equation (10), the coefficients of interest are β_5 and β_6, which measure the additional effect of swing pricing on fixed-income OEF flows in stressful periods and March-20, respectively. For Equation (11), they are θ_7 and θ_8.

The estimation results of both equations suggest that the mitigating effect of swing pricing is more pronounced for fixed-income OEFs. Column 1 of Table E.1 shows that, the swing pricing-led OEF flows is greater for fixed-income "swing" OEFs by 1.18 ppts than other "swing" OEFs in March-20, or 0.34 ppts in other stressful periods. This is in line with regression results for Equation (11), where Column 2 shows that one-SD reduction in FMA led to an additional increase in fixed-income "swing" OEF flows by 0.20 ppts and 0.43 ppts in stressful periods and March-20, respectively, compared to that in other "swing" OEF flows. The above results suggest the FMA-prone OEFs like fixed-income OEFs could benefit more from swing pricing in managing their own liquidity risk.

Table E.1: Estimation results for Equation (10) & (11)[1]

	Dependent variable:	
	$Flow_{i,t}$	$Flow_{i,t}$
	(1)	(2)
$Stress_t$ (β_1)	-0.29***	-0.15
$March20_t$ (β_2)	-3.32***	-2.28***
$SW_i \times Stress_t$ (β_3)	0.01	--
$SW_i \times March20_t$ (β_4)	1.39***	--
$SW_i \times Stress_t \times Bond_i$ (β_5)	0.34**	--
$SW_i \times March20_t \times Bond_i$ (β_6)	1.18**	--
$Bond_i \times Stress_t$ (β_7)	0.19	--
$Bond_i \times March20_t$ (β_8)	2.08***	--
$Ret_{i,t-1}$ (γ_1)	0.02**	0.01
$SW_i \times Ret_{i,t-1}$ (γ_2)	-0.02**	--
$FMA^{-}_{i,t}$ (θ_3)	--	-0.002
$FMA^{-}_{i,t} \times Stress_t$ (θ_4)	--	-0.01
$FMA^{-}_{i,t} \times March20_t$ (θ_5)	--	0.11**
$FMA^{-}_{i,t} \times Bond_i$ (θ_6)	--	-0.05
$FMA^{-}_{i,t} \times Stress_t \times Bond_i$ (θ_7)	--	0.20**
$FMA^{-}_{i,t} \times March20_t \times Bond_i$ (θ_8)	--	0.43***
Model	Fixed effect	Fixed effect
Control	Yes	Yes
VIX_t	Yes	Yes
Share class FE	Yes	Yes
Sample	"Swing" and "swing-ineligible" OEFs [3]	"Swing" OEFs
Number of OEFs	1,264	632
Number of observations	50,438	29,680

Note: (1). p<0.1; **p<0.05; ***p<0.01; (2) The matched samples of "swing" and "swing-ineligible" OEFs are the same as in Table 2.

E2. The impact of swing pricing on the probability of OEF closure after March 2020

In addition to fund flows, we assess the impact of swing pricing on the probability of OEF closure after March 2020 to further confirm the usefulness of swing pricing. The estimate of the impact by a cross-sectional logistic regression model is given by:

$$Close_i = \theta_0 + \theta_1 SW_i + \gamma_1\ Ret_i + \gamma_2\ SW_i \times Ret_i + Control_i^* + \varepsilon_{i,t} \tag{12}$$

$$Close_i = \theta_0 + \theta_1 SW_i + \theta_2 ND_i + \gamma_1\ Ret_i + \gamma_2\ SW_i \times Ret_i + \gamma_3\ ND_i \times Ret_i + Control_i^* + \varepsilon_{i,t} \tag{13}$$

where $Close_i$ is a dummy variable equal to one if an OEF i is closed between April-2020 and December-20 (i.e. the nine months after the turmoil). $Control_i^*$ is the same set of control variables as in Equation (1), but at February-2020 position (except OEF returns which are in March-2020 to capture the shock experienced in that month). Under this set-up, θ_1 measures the effect of swing pricing on OEFs closure, and a negative value would mean swing pricing reduced OEFs' chances of closure after the March-2020 market episode. θ_2 measures the effect of non-disclosure of swing pricing, with a positive value meaning non-disclosure on swing pricing usage would undermine the reduction in chances of closure by swing pricing after the March-2020 market episode (if any).

Table E.2 shows that swing pricing lowers the probability of OEF closure (in the nine months after the March-2020 market episode) by 68.3%, which is transformed from the estimate of -1.15 in Column 2.[39] However, this effect is reduced when OEFs do not disclose the usage, with the reduction in probability of OEF closure at 64.7% only.[40]

Table E.2: Estimation results for Equation (12) and (13)[1]

	Dependent variable:	
	$Close_i$ (1)	$Close_i$ (2)
SW_i (θ_1)	-1.45**	-1.15***
ND_i (θ_2)	--	0.11*
Ret_i (γ_1)	0.12	0.12
$SW_i \times Ret_i$ (γ_2)	0.15	0.11
$ND_i \times Ret_i$ (γ_3)	--	-0.27
Model	Logit	Logit
Control	Yes	Yes

[39] The probability is obtained from one minus the natural exponential function of the estimated coefficient.

[40] This is consistent with our sample where only 1.37% of "swing" OEFs were closed after March-20, compared to 4.07% of "swing-eligible but not disclosed" OEFs and 5.79% of "swing-ineligible" OEFs.

Sample	"Swing" and "swing-ineligible" OEFs[2]	"Swing", "swing-eligible but not disclosed" and "swing-ineligible" OEFs [2]
Number of OEFs	1,264	1,896
Number of observations	1,264	1,896

Note: (1). p<0.1; **p<0.05; ***p<0.01. (2). The OEF sample is the same as the one used in Equation (1) except the time dimension covers February 2020 only (i.e. it is a cross-sectional sample).

Annex F: Placebo tests on the mitigating effects of swing pricing

This annex verifies the effects of swing pricing in March 2020, identified using Equation (1), do not appear by random. We do so by conducting the Placebo test which validates the results using pseudo-events. In particular, if swing pricing did mitigate "swing" OEFs liquidity risk in March 2020, we should not see β_4 to be significant when we replace $March20_t$ with another dummy variable that represents some "normal" months. More specifically, we consider the following model;

$$Flow_{i,t} = \beta_1 Stress_t + \beta_2 Pseudo_t + \beta_3\, SW_i \times Stress_t + \beta_4\, SW_i \times Pseudo_t + \gamma_1\, Ret_{i,t-1} + \gamma_2\, SW_i \times Ret_{i,t-1} + \delta_1 Control_{i,t-1} + \delta_2 VIX_t + \mu_i + \varepsilon_{i,t}. \quad (14)$$

The above equation is basically the same as Equation (1), except that we replace the dummy variable $March20_t$ with $Pseudo_t$, another dummy variable that equals one for specified month and zero vice versa. Column 1 to 4 of Table F.1 report the results of Equation (14) when $Pseudo_t$ represents March 2017, March 2019, December 2019 and January 2020 respectively. They are randomly picked from the full sample period where the VIX index is lower than sample median (i.e. the "normal" months). The estimated β_4 is not significant in all four cases, providing support that the mitigating effect of swing pricing in March 2020 do not appear by random.

Table F.1: Estimation results for Equation (14)[1]

	Dependent variable:			
	$Flow_{i,t}$ (1)	$Flow_{i,t}$ (2)	$Flow_{i,t}$ (3)	$Flow_{i,t}$ (4)
$Stress_t$ (β_1)	-0.17*	-0.23***	-0.08	-0.88***
$Pseudo_t$ (β_2)	1.14***	-1.08***	2.24***	-1.48*
$SW_i \times Stress_t$ (β_3)	0.22**	0.25**	0.20*	1.01***
$SW_i \times Pseudo_t$ (β_4)	-0.64	0.60	-0.57	1.34
$Ret_{i,t-1}$ (γ_1)	0.04***	0.04***	0.04***	0.08**
$SW_i \times Ret_{i,t-1}$ (γ_2)	-0.04***	-0.04***	-0.04***	-0.04
$\beta_4 - \beta_3$	-0.86	0.35	-0.77**	0.33
$Pseudo_t$	March 2017	March 2019	December 2019	January 2020
Model	Fixed effect	Fixed effect	Fixed effect	Fixed effect
Control	Yes	Yes	Yes	Yes
VIX_t	Yes	Yes	Yes	Yes
OEF FE	Yes	Yes	Yes	Yes
Sample	"Swing" and "swing-ineligible" OEFs[2]			
Number of OEFs	1,264	1,264	1,264	1,264

Number of observations	50,438	50,438	50,438	50,438

Note: (1). p<0.1; **p<0.05; ***p<0.01; (2). The matched sample of "swing" and "swing-ineligible" OEFs are matched as described in Section 4.

Annex G: Robustness check of the mitigating effect of swing pricing in Equation (1)

The annex checks whether the statistical significance of β_4 (i.e. the mitigating effect of swing pricing in March2020) still holds when we relax the assumption on the time-invariant flow-return relationship of each OEF group. In particular, we allow the relationship to vary between normal and stressful times by considering the following model:

$$Flow_{i,t} = \beta_1 Stress_t + \beta_2 March20_t + \beta_3\, SW_i \times Stress_t + \beta_4\, SW_i \times March20_t + \gamma_1\, Ret_{i,t-1} + \gamma_2\, SW_i \times Ret_{i,t-1} + \gamma_3\, Stress_t \times Ret_{i,t-1} + \gamma_4\, March20_t \times Ret_{i,t-1} + \gamma_5\, SW_i \times Stress_t \times Ret_{i,t-1} + \gamma_6\, SW_i \times March20_t \times Ret_{i,t-1} + \delta_1 Control_{i,t-1} + \delta_2 VIX_t + \mu_i + \varepsilon_{i,t}. \quad (15)$$

Equation (15) allows the flow-return relationship of both "swing' and "swing-ineligible" OEFs to vary between normal, stressful times and March-2020 by including interaction terms $Stress_t \times Ret_{i,t-1}$, $March20_t \times Ret_{i,t-1}$, $SW_i \times Stress_t \times Ret_{i,t-1}$ and $SW_i \times March20_t \times Ret_{i,t-1}$. Column 1 of Table G.1 shows that the estimated β_4 remain positive and statistically significant under the relaxed assumption, providing further support on the effectiveness of swing pricing we identified. Column 1 also reveals that the weaker pro-cyclicality of swing" OEFs flows observed in Table 2 is mainly attributable to the weaker flow-return relationship during stressful times, especially March-2020, as reflected the negative γ_5 and γ_6. The findings largely hold for separate samples of retail and institutional OEFs (Column 2 and 3).

Table G.1: Estimation results for Equation (15)[1]

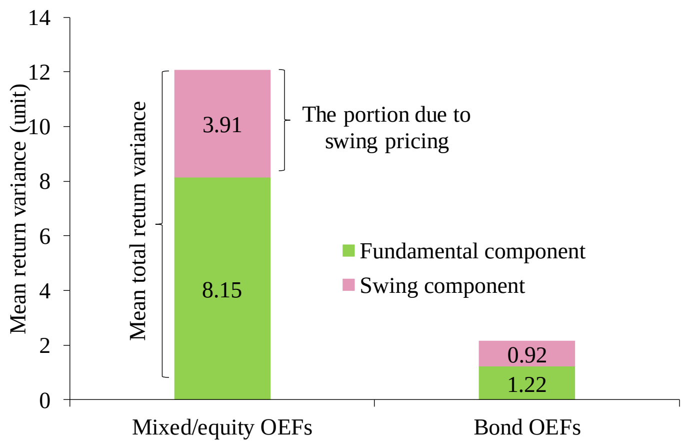
	Dependent variable:		
	$Flow_{i,t}$ (1)	$Flow_{i,t}$ (2)	$Flow_{i,t}$ (3)
$Stress_t$ (β_1)	-0.33***	-0.29*	-0.01
$March20_t$ (β_2)	-1.77***	-4.13***	-2.76***
$SW_i \times Stress_t$ (β_3)	0.28***	0.08	-0.19
$SW_i \times March20_t$ (β_4)	0.87**	1.55*	0.83*
$Ret_{i,t-1}$ (γ_1)	0.10***	-0.06	0.02
$Ret_{i,t-1} \times SW_i$ (γ_2)	0.08***	0.13**	0.02
$Ret_{i,t-1} \times Stress_t$ (γ_3)	0.14***	0.45***	0.34*
$Ret_{i,t-1} \times March20_t$ (γ_4)	0.36***	0.16***	-0.06
$Ret_{i,t-1} \times Stress_t \times SW_i$ (γ_5)	-0.13***	-0.16***	-0.00
$Ret_{i,t-1} \times March20_t \times SW_i$ (γ_6)	-0.50***	-0.23***	-0.65**
$\beta_4 - \beta_3$	0.59**	1.47*	1.02*
Model	Fixed effect	Fixed effect	Fixed effect
Control	Yes	Yes	Yes
VIX_t	Yes	Yes	Yes
OEF FE	Yes	Yes	Yes

Sample	"Swing" and "swing-ineligible" OEFs[2]		
of which:	All	Retail	Institutional
Number of OEFs	1,264	702	458
Number of observations	50,438	34,121	15,573

Note: (1). p<0.1; **p<0.05; ***p<0.01; (2). The matched sample of "swing" and "swing-ineligible" OEFs are matched as described in Section 4.

Annex H: Effect of swing pricing on the variance of OEF return

Figure H.1: Swing pricing's contribution to return variance of "swing" OEFs in March-2020



Notes:
(i) Fundamental component refers to the portion of total OEF's return variance attributable to OEF's theoretical NAV, while swing component captures the residuals (Equation 7).

Annex I: Robustness test of the effect of swing pricing-led return variance on flow variance

Despite weakly positive correlation between $\text{Var}_{i,t-1}^{NAV}$ and $\text{Var}_{i,t-1}^{SF}$ at 0.1 over the sample period, there may still be a concern over serial correlation when both variables are considered together in Equation (8). Therefore, in this section we test the robustness of our results in Table 4 by first filtering the effect of $\text{Var}_{i,t-1}^{NAV}$ out of $FlowVol_{i,t}$ using Equation (16), before regressing the residuals on $\text{Var}_{i,t-1}^{SF}$ using Equation (17).

$$Var_{i,t}^{Flow} = \beta_0 + \beta_1 \text{Var}_{i,t-1}^{NAV} + \delta_{i,t} \tag{16}$$

$$\widehat{\delta_{i,t}} = \theta_1 Stress_t + \theta_2 March20_t + \theta_3 \text{Var}_{i,t-1}^{SF} + \gamma_1\ Ret_{i,t-1} + \delta_1 Control_{i,t-1}$$
$$+\delta_2 VIX_t + \mu_i + \varepsilon_{i,t} \tag{17}$$

where $\widehat{\delta_{i,t}}$ is the residual from Equation (16), which serves as the flow variance free from the effect of the fundamental component of return variance. Our coefficient of interest is θ_3 for Equation (17) which measures the effect of the swing component on flow variance.

As shown in Table I.1, after filtering the effect of fundamental component from flow variance (Column 1), we still see that one unit of swing component leads to 0.06 unit of flow variance at 1% level of significance (Column 2). This estimate is virtually no different to that estimated using Equation (7), confirming the issue of serial correlation between $\text{Var}_{i,t-1}^{NAV}$ and $\text{Var}_{i,t-1}^{SF}$ is not material to our results.

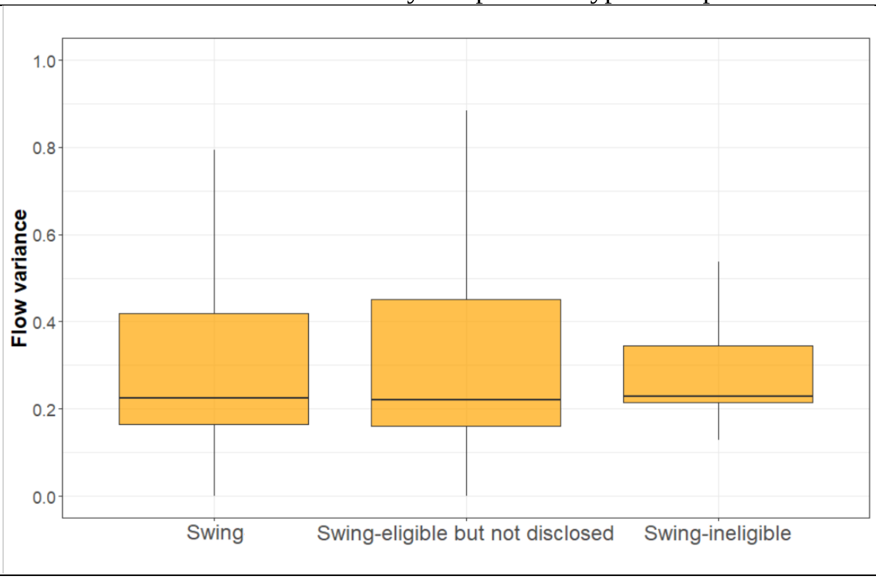
Table I.1: Estimation results for Equation (16) and (17)[1]

	Dependent variable:	
	$Var_{i,t}^{Flow}$	$\widehat{\delta_{i,t}}$
	(1)	(2)
$\text{Var}_{i,t-1}^{NAV}$ (β_1)	0.07***	--
$\text{Var}_{i,t-1}^{SF}$ (θ_3)	--	0.07***
Model	OLS	Fixed effect
$Ret_{i,t-1}$	No	Yes
Control	No	Yes
VIX_t	--	Yes
OEF FE	--	Yes
Sample	"Swing" OEFs	"Swing" OEFs
Number of OEFs	632	632
Number of observations	29,680	29,680

Note: (1). p<0.1; **p<0.05; ***p<0.01.

Annex J: Distribution of flow variances by sample OEF types in April-2020

Figure J.1: Distribution of flow variances by sample OEF types in April-2020



Annex K: The effect of swing pricing on OEFs' liquid buffer

In this annex, we investigate whether the negative impact of swing pricing on a liquid buffer documented in Lewrick and Schanz (2017b) also applies to our OEFs sample. To do so, we consider the same model as Equation (8), but replace leverage (Lev) with liquidity buffer (proxied by cash or equivalents held by an OEF, denoted as $Cash$), specifically as follows:

$$Cash_{i,t} = \beta_1 + \beta_2 Cash_{i,t-1} + \beta_3 SW_i + \gamma_1\, Ret_{i,t-1} + \delta_1 Control_{i,t-1} + \delta_2 VIX_t + \varepsilon_{i,t} \quad (18)$$

$$Cash_{i,t} = \beta_1 + \beta_2 Cash_{i,t-1} + \beta_3 SW_i + \beta_4 Bond_i + \beta_5 SW_i \times Bond_i + \gamma_1\, Ret_{i,t-1} + \\ +\delta_1 Control_{i,t-1} + \delta_2 VIX_t + \varepsilon_{i,t} \quad (19)$$

where β_2 measures the effect of swing pricing on a cash buffer. As shown in Column 1 of Table K.1 below, we consistently find a negative impact of swing pricing on the cash buffer (-3.48), similar to what is documented in Lewrick and Schanz (2017b). Our results are robust for restricting to cash only, but not cash or equivalents.

As Lewrick and Schanz (2017b) focus on fixed-income OEFs only, it is possible that our result above could be driven by the fixed-income OEFs in our sample. To verify this, we added an interaction term ($SW_i \times Bond_i$) in Equation (19) to disentangle the impact on mixed/equity and fixed-income OEFs. Column 2 of Table L.1 shows that the negative impact applies to both groups of OEFs, even though the effect is more pronounced for fixed-income OEFs (i.e. -5.23 = (-2.84) + (-2.39), compared to -2.84 for mixed/equity OEFs). These results suggest that the negative impact of swing pricing on the liquid buffer is not limited to fixed-income OEFs (as in Lewrick and Schanz, 2017), but also to mixed/equity OEFs as well, albeit to a lesser extent.

Table K.1: Estimation results for Equation (18) and (19)[1]

	Dependent variable:	
	$Cash_{i,t}$ (1)	$Cash_{i,t}$ (2)
SW_i (β_3)	-3.48***	-2.84***
$Bond_i$ (β_4)	--	-5.30***
$SW_i \times Bond_i$ (β_5)	--	-2.39***
Model	OLS	OLS
$Cash_{i,t-1}$	Yes	Yes
$Ret_{i,t-1}$	Yes	Yes
Control	Yes	Yes
VIX_t	Yes	Yes
Sample	"Swing" and "swing-ineligible" OEFs[2]	"Swing" and "swing-ineligible" OEFs[2]
Number of OEFs	1,264	1,264
Number of observations	50,438	50,438

Note: (1). p<0.1; **p<0.05; ***p<0.01. (2). The matched sample of "swing" and "swing-ineligible" OEFs are matched as described in Section 4. The sample period covers January 2012 to February 2020.

Annex L: Evidence on lost attractiveness of "swing" OEFs and compensation by leverage

In this annex, we assess whether a "swing" OEF is less attractive than a "swing-ineligible" OEF before March-2020, and whether leverage could compensate for the lost attractiveness, using the following regression model:

$$Flow_{i,t} = \theta_1 + \theta_2 SW_i + \theta_3 SW_i \times L_{i,t} + \theta_4 L_{i,t} + \gamma_1 \, Ret_{i,t-1} + \gamma_2 \, SW_i \times Ret_{i,t-1}$$
$$+\delta_1 Control_{i,t-1} + \delta_2 VIX_t + \varepsilon_{i,t} \quad (20)$$

where $L_{i,t}$ is a dummy variable equal to 1 if OEF i takes leverage in month t-1 (or $Lev_{i,t-1} > 100$), and zero otherwise. We restrict the sample period to either before March-2020 or in normal periods (i.e. both stress dummies equal to 0). The coefficients of our interest are θ_2 and θ_3, which measure the lost attractiveness due to swing pricing and compensation by leverage, respectively.

As shown in Column 1 of Table L.1, a "swing" OEF received less flows than a "swing-ineligible" OEF by 0.62 ppts before March-20, suggesting swing pricing makes OEFs less attractive among investors. Taking leverage, a "swing" OEF would receive similar fund flows as a "swing-ineligible" OEF did, as reflected in the insignificant flow difference at -0.14 ppts (see row "$\theta_2 + \theta_3$"). A similar conclusion holds when we just focus on normal periods (Column 2). This confirms our conjecture that the use of leverage by "swing" OEFs could lessen the reduction in inflows during normal periods and validates the "lost attractiveness" argument discussed in *Introduction*.

Table L.1: Estimation results for Equation (20)[1]

	Dependent variable:	
	$Flow_{i,t}$ (1)	$Flow_{i,t}$ (2)
SW_i (θ_2)	-0.62***	-0.65***
$SW_i \times L_{i,t}$ (θ_3)	0.48**	0.27**
$L_{i,t}$ (θ_4)	-0.84***	-0.76***
$Ret_{i,t-1}$ (γ_1)	0.11**	0.13***
$SW_i \times Ret_{i,t-1}$ (γ_2)	-0.06	-0.05
$\theta_2 + \theta_3$	-0.14	-0.38
Model	OLS	OLS
Control	Yes	Yes
VIX_t	Yes	Yes
Sample	"Swing" and "swing-ineligible" OEFs[2]	"Swing" and "swing-ineligible" OEFs[2]
Sample period	Jan 2012 – Feb 2020	VIX < sample median
Number of OEFs	1,264	1,264
Number of observations	43,235	23,513

Note: (1). p<0.1; **p<0.05; ***p<0.01. (2). The matched sample of "swing" and "swing-ineligible" OEFs are matched as described in Section 4.

Annex M: Robustness test of the effect of non-disclosure practice for "swing-eligible but not disclosed" OEFs

In this annex we show that the effect of non-disclosure reported in Table 5 remains robust when we use the "swing' OEFs as the reference group (in matching the sample of "swing-eligible but not disclosed" OEFs) and re-estimate Equation (9). Specifically, Table M.1 shows that the reduction in outflows for "swing-eligible but not disclosed" OEFs (i.e. the sum of β_4 and β_6) is 1.76 ppts compared to 3.12 ppts for "swing" OEFs (β_4) in the March-2020 episode. This result suggests the non-disclosure practice reduces the effect of swing pricing by 44% (i.e., -1.36/3.12) and is close to estimate using the baseline matched sample. This suggests that the impact of non-disclosure practice found are robust to alternative matched samples based on "swing" OEFs.

Table M.1: Estimation results for Equation (9) using an alternative matched sample ("swing" OEFs as the reference group)[1]

	Dependent variable:
	$Flow_{i,t}$
	(1)
$Stress_t$ (β_1)	-0.76
$March20_t$ (β_2)	-3.65***
$SW_i \times Stress_t$ (β_3)	0.51
$SW_i \times March20_t$ (β_4)	3.12**
$ND_i \times Stress_t$ (β_5)	0.02
$ND_i \times March20_t$ (β_6)	-1.36**
$Ret_{i,t-1}$ (γ_1)	0.02
$SW_i \times Ret_{i,t-1}$ (γ_2)	-0.03
$ND_i \times Ret_{i,t-1}$ (γ_3)	0.02
Model	Fixed effect
Control	Yes
VIX_t	Yes
OEF FE	Yes
Sample	"Swing", "swing-eligible but not disclosed" and "swing-ineligible" OEFs[2]
Number of OEFs	1,896
Number of observations	70,612

Note: (1). *p<0.1; **p<0.05; ***p<0.01; and (2). The matched sample of "swing", "swing-eligible but not disclosed" and "swing-ineligible" OEFs are matched with the former as the reference group.