Swing Pricing and Flow Dynamics in Light of the Covid-19 Crisis

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Abstract

Swing pricing is a recent liquidity management tool designed to reallocate the liquidity cost from remaining to transacting investors, by adjusting share prices of investment funds. Based on unique text-mining data, we observe that its use is spreading among French funds, is systematically associated with an activation threshold, and is regularly associated with swing factor caps. We find that swing pricing had only a limited impact on the financial stability of funds during the Covid-19 turmoil. By disentangling the impact of the different types of swing pricing and analyzing situations of potential acute dilution, we identify that the observed limited effectiveness of swing pricing is mainly explained by the use of swing factor cap that prevents the stabilizing effect to offset a stigma effect. We thus conclude that while swing pricing has the potential to increase financial stability, funds should refrain from using swing factor caps so as not to mitigate stabilizing effects.

Keywords: Liquidity Management Tools, Swing Pricing, Investment Funds, Runs

JEL classification: G10, G23, G28

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NON-TECHNICAL SUMMARY

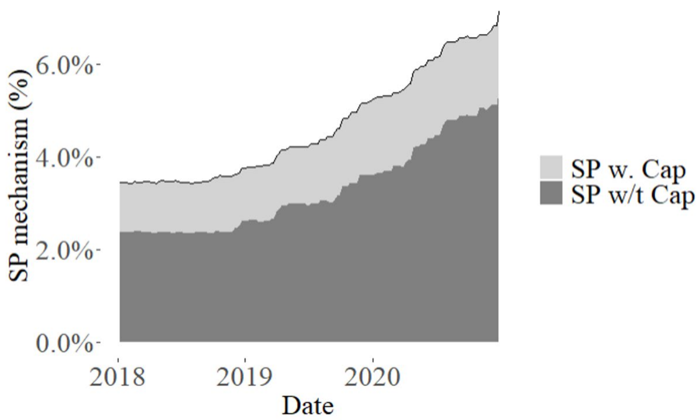
Open-end investment funds engage in a liquidity transformation as they offer shares that are generally more liquid than the assets held. Share redemptions can lead to a decrease in the share price, the net asset value (NAV), due to liquidity costs associated with the sale of assets needed to meet share redemptions. This liquidity cost is usually passed to investors remaining in the funds, inducing an incentive to redeem shares first ("first-mover advantage"). This incentive becomes particularly acute in periods of market stress and can lead to fire sales and runs, jeopardizing financial stability.

Swing pricing is a tool aiming at reallocating the liquidity cost from remaining to transacting investors to mitigate the first-mover advantage. It relies on a NAV adjustment based on the portfolio liquidity and fund flows. If the fund is experiencing outflows, it adjusts the NAV downward to transfer the liquidity cost associated with asset sales to redeeming investors. Similarly, if the fund is experiencing inflows, it adjusts the NAV upward to transfer the cost of asset purchase. The strength of the adjustment decreases with the liquidity of the portfolio and is captured by the swing factor. Swing pricing can be applied for any level of flows (full swing pricing) or only if flows exceed a threshold (partial swing pricing). Second, the swing factor can be capped to assure investors that the NAV will not be too distorted by the mechanism.

This paper focuses on the empirical impact of swing pricing on flow dynamics during market stress. More precisely, we study how, in France, swing pricing has affected flows during the acute market stress situation induced by the Covid-19 crisis. In addition, we study how using a cap on the swing factor influences its efficiency to inform on optimal swing pricing design. To lead this analysis, we rely on the same information that is available to investors: fund prospectuses. Indeed, to use a swing pricing mechanism French funds must disclose it in this document. We extract this information using a text-mining algorithm.

Swing pricing has gained in popularity in France: at the beginning of 2018, 3.4% of investment funds were using swing pricing, they were 7.2% at the end of 2020 (Figure 1). 27% of them use a swing factor cap and all of them use partial swing pricing (minimum adjustment value triggering the activation of the swing pricing). We study the endogenous decision of fund managers to use swing pricing and find that the strength of the liquidity mismatch increases the likelihood to implement swing pricing: the tool is thus used by funds that need it the most.

Figure 1. Investment Funds using a swing pricing tool (%)



Note: The black line indicates the percentage of funds with a swing pricing mechanism every week between January 2018 and December 2020. Funds are split between those with a swing factor cap ("SP w. Cap", represented by the light gray area) and those without a swing factor cap ("SP w/t Cap", represented by the dark gray area).

Then, we turn to the analysis of flow dynamics during the Covid-19 crisis. We find that swing pricing only had a limited impact on the financial stability of funds during this period. Indeed, this tool did not decrease volatility and funds with swing pricing suffered additional outflows. One reason highlighted is the existence of a "stigma" effect: some investors are reluctant to invest in funds using swing pricing, especially during market stress. The other reason lies in the type of swing pricing currently used in France. Indeed, when focusing only on funds without a swing factor cap, we find that swing pricing stabilizes flow dynamics during systemic stress: volatility is reduced as well as outflows.

Our study thus informs on the detrimental effects of having capped swing pricing. It may be explained by the gap created between actual and unconstrained swing factors when the swing factor is capped, preventing accurate internalization of reorganization costs and thus increasing the risk of dilution. Furthermore, the higher the cost of reorganization the larger the gap, mitigating the stabilizing impact when it is the most needed. Complementing the analysis based on systemic stress, we focus on the impact of swing pricing during idiosyncratic stress—situations of large past outflows and liquidity strain. Idiosyncratic stress is particularly relevant to study the swing impact as it is expected to induce large swing factors (and to exceed swing activation threshold for partial swing pricing) and thus large NAV corrections. Contrasting with systemic stress, we find that swing pricing increases flows. In addition, we observe that the stabilizing impact of swing pricing vanishes also during idiosyncratic stress for funds with a swing factor cap. We conclude that the swing pricing is efficient if the price impact is substantial enough to offset the stigma effect highlighted previously.

To conclude, we find that swing pricing has the ability to reduce the exposition of investment funds to risks of fire sales. However, the swing pricing calibration is of paramount importance to achieve the intended objective.

Swing Pricing et dynamique des flux au regard de la crise Covid-19

RÉSUMÉ

Le swing pricing est un outil récent de gestion de la liquidité conçu pour réallouer le coût de la liquidité des investisseurs restants aux investisseurs effectuant des transactions, en ajustant le prix des parts de fonds d'investissement. En se basant sur des données inédites obtenues par analyse automatisée de textes, nous observons que son utilisation se répand parmi les fonds français, est systématiquement associée à un seuil d'activation, et est régulièrement associée à un plafonnement du facteur d'ajustement. Nos résultats indiquent que le swing pricing n'a eu qu'un impact limité sur la stabilité financière des fonds pendant la crise de la Covid-19. En différenciant l'impact des différents types de swing pricing et en analysant les situations de risque de dilution, nous identifions que l'efficacité limitée du swing pricing s'explique principalement par le plafonnement des facteurs de swing qui empêche l'effet stabilisateur de compenser un effet stigma. Nous concluons donc que si le swing pricing a le potentiel d'accroître la stabilité financière, il est important que le facteur d'ajustement soit en mesure de refléter le véritable coût de la liquidité.

Mots-clés : outils de gestion de la liquidité, Swing Pricing, fonds d'investissement, Runs.

Les Documents de travail reflètent les idées personnelles de leurs auteurs et n'expriment pas nécessairement la position de la Banque de France. Ils sont disponibles sur publications.banque-france.fr

1 Introduction

Open-end investment funds engage in a liquidity transformation as they offer shares that are generally more liquid than the assets they hold (Cherkes et al., 2008). Fund managers may be tempted to broaden this liquidity gap to attract more investors by offering better redemption terms or holding more illiquid assets associated with higher returns. However, this also increases the vulnerability of funds to outflows that may be caused by exogenous motives, i.e. a need for liquidity, but also by endogenous motives, i.e. anticipation of outflows by other investors. If fund managers are forced to sell illiquid assets to meet redemptions, it will affect the performance of the fund (Edelen, 1999), causing a dilution of the capital. Therefore, investors who anticipate such sales have an incentive to redeem their shares first which may induce a self-fulfilling phenomenon. This *"first-mover advantage"* is at the root of pro-cyclical fire sales (runs), which materialize in large redemptions in a short amount of time and may induce a liquidity risk jeopardizing the fund's ability to meet redemptions (Coval and Stafford, 2007; Chen et al., 2010; Tirole, 2011).

The recent turmoil in seven French H2O investment funds illustrates the vulnerability caused by a high liquidity gap. Concerns about a high concentration of illiquid assets by these funds resulted in weekly outflows of up to 34% in June 2019. Given the risk, measures of last resort were taken such as the isolation of illiquid assets in side-pocket funds and then, in August 2020, the suspension of subscriptions and redemptions ESMA (2019).

In the last decade, new tools have emerged to help fund managers manage the liquidity of their funds in order to reduce the risks associated with liquidity transformation: liquidity management tools (LMTs). These tools are promoted by the major organizations regulating non-bank financial institutions because they have been identified as essential to strengthen the financial stability of this sector. For example, the Financial Stability Board (FSB, 2017) argues that "authorities should widen the availability of liquidity risk management tools to open-ended funds, and reduce barriers to the use of those tools, to increase the likelihood that redemptions are met even under stressed market conditions". Following this recommendation, the International Organization of Securities Commissions (IOSCO, 2018) considers the implementation of LMTs as one of the four main means of reducing fund liquidity risk. Accordingly, the European Systemic Risk Board (ESRB) in its Recommendation 2017/6 to the European Securities and Markets Authority (ESMA) and the European Commission states that "the availability of a diverse set of LMTs in all Member States could increase the capacity of fund managers to deal with redemption pressures when market liquidity becomes stressed" and recommends the Commission to propose a union legal framework for additional LMTs. Finally, ESMA identifies increasing the availability and use of LMTs as one of the top five priorities for enhancing fund stability in a report dedicated to corporate debt and real estate investment funds (ESMA, 2020).

However, LMTs may induce perverse effects. First, if they are perceived as restricting the liquidity offered, investors may be reluctant to invest in funds with LMTs, introducing a "stigma effect". For price-based LMTs such as swing pricing, the total cost of exiting a fund may increase by passing on the cost of rearranging the portfolio to outgoing investors. Furthermore, during periods of financial stress, they may introduce additional strategic complementarity as investors may have incentives to redeem their shares if they anticipate the activation of LMTs. It could thus decrease financial stability by exacerbating the run phenomenon that is supposed to be mitigated. For example, Li et al. (2021); Dunne and Giuliana (2021) show that the requirement for certain categories of money market funds (MMFs) to consider the application of liquidity management tools if they do not meet a minimum weekly liquidity requirement has led to runs.

Among all LMTs, swing pricing stands out for its relatively widespread use during the Covid-19 crisis and its central role in policy discussions. Swing pricing is estimated to be the most used LMT in Europe during the market stress in February and March 2020 (ESMA, 2020; Claessens and Lewrick, 2021). In addition, it is the most prevalent tool in the recommendations from authorities promoting the use of LMTs (FSB, 2017; IOSCO, 2018; ESMA, 2020) as illustrated by the discussions around its mandatory use by MMFs in the context of the MMFs regulation reform (FSB, 2021; IMF, 2021).

Swing pricing is an anti-dilution tool that aims to protect investors against the negative impact of portfolio adjustments on performance due to subscriptions or redemptions. It allocates this cost to transacting investors by adjusting the net asset value (hereafter NAV). It can reduce the first-mover advantage and mitigate runs by internalizing the negative externalities associated with redemptions. The intensity of the NAV adjustment is set by the swing factor that captures the restructuring cost. In France, there are two possible constraints on the activation and intensity of the mechanism. First, swing pricing can be applied for any level of flows (full swing pricing) or only if flows exceed a threshold (partial swing pricing). Second, the swing factor can be capped to assure investors that the NAV will not be too distorted by the mechanism.

From a theoretical point of view, the three principal studies on swing pricing are divided over the impact of swing pricing on financial stability (for a review see Capponi et al., 2022). While Zeng (2017) and Lewrick and Schanz (2017b) consider an exogenous liquidity shock on sharehoders, Capponi et al. (2020) considers a market shock which not only reduces the value of fund shares, but also exerts downward pressure on the price of assets. More precisely, Zeng (2017) models how active liquidity management can generate runs and discusses the impact of swing pricing along with other LMTs. The model predicts that swing pricing does not mitigate runs as it is not forward-looking. Conversely, Capponi et al. (2020) develop a model of feedback between mutual fund outflows and asset illiquidity, predicting that swing pricing is useful in preventing the first-mover advantage. Finally, Lewrick and Schanz (2017b)'s conclusion is mixed as they find that swing pricing can prevent self-fulfilling runs but that in practice this ability can be weakened due to liquidity constraints on investors. This lack of theoretical consensus and the potential perverse effects underline the need for an in-depth analysis of the consequences of swing pricing. However, we note a discrepancy between the key role dedicated to swing pricing in the policy agenda and the attention dedicated to this tool in empirical studies.

To the best of our knowledge, and even if swing pricing is the most studied LMT, its empirical analysis is limited to three main studies. They conclude on a positive impact of swing pricing during stress periods, while diverging on the intensity of the stress. Jin et al. (2022) study a sample of UK corporate bond mutual funds. They find that swing pricing reduces redemptions during periods of high market stress, with a stabilizing effect particularly visible for institutional investors. No stigma effect was identified outside of stress periods. Lewrick and Schanz (2023) identification strategy relies on the comparison of mutual funds in the United States and Luxembourg at a time when swing pricing was available for Luxembourg funds but not yet for US funds. They find that swing pricing stabilizes flows during normal market conditions, but fails to offset investor first-mover advantages in more stressed markets. Finally, Wu et al. (2022) relies on a sample of funds that report using swing pricing in the database Morningstar Direct mainly in

Luxembourg, Switzerland and United Kingdom. They find that swing pricing can help to mitigate redemption pressures in times of severe market stress, however it may comes with side effects such as higher leverage.[1]

We believe that this lack of studies is due to the relative novelty of swing pricing as well as the difficulty of gathering data on its use. This difficulty is illustrated by how previous studies have collected data. On the one hand, Jin et al. (2022) has the advantage of using a detailed ad-hoc survey however it focuses only on one type of fund (sample of 224 UK bond funds, including 184 with swing pricing—34 implementations during the study period—). On the other hand, Lewrick and Schanz (2023) between-jurisdiction comparison provides a large-scale database, but it increases control group issues and raises questions about the actual use of swing pricing as funds could have not actively implemented this tool. Finally, the Morningstar data used by Wu et al. (2022) are also valuable as they provide information on unswung NAV for funds in different jurisdictions. However, they seem fragmentary as not all funds report their swing pricing use to this private data provider (for example French funds are missing).

This paper analyzes the effect of swing pricing on financial stability through the lens of flow dynamics to assess whether swing pricing has the ability to decrease redemption pressures during severe market stress.

It is the first to analyze the effect of swing pricing based on a quasi-exhaustive sample of funds in a jurisdiction with heterogeneity in usage. Our identification of swing pricing at a fund level based on prospectuses enables us to build a unique database with the use of swing pricing for most French funds: 3013 funds in total, 217 with swing pricing in December 2020, and 126 implementing swing pricing during our study period going from 2018 to 2020[2]. Indeed, we identify the ability to use swing pricing of all French funds as it is mandatory for French fund managers to disclose it in the fund prospectus. We take profit from this regulatory requirement and identify which open-end investment

[1]For other works on LMTs outside of swing pricing, Koenig and Pothier (2020) develop a theory of redemption runs based on the fund managers' acquisition of strategic information that corroborates the predictions of Zeng (2017) regarding the role of gates and redemption fees in reducing risks of runs. Agarwal et al. (2020) assess the impact of in-kind redemptions on U.S.-based equity funds and conclude that it has the ability to mitigate redemptions. Finally, Li et al. (2021) study how the ability of MMF to impose redemption gates and liquidity fees introduced in 2016 by a reform in the United States may exacerbate runs and find an acceleration of outflows during the Covid-19 crisis.

[2]We define the use of swing pricing as the application of a swing pricing formula that could generate a positive swing factor. Implementation of swing pricing refers to the moment a fund starts using swing pricing. Finally, the activation of swing pricing refers to periods when the swing factor is not zero (activation equals use for full swing pricing).

fund mention swing pricing in their prospectus using a novel approach based on a text-mining analysis of fund prospectuses. We thus differ from previous studies as we use the information set available to investors by mandatory legal disclosure to analyse their behavior.

Our study also informs on optimal swing pricing design, a question identified as an area for future research by Capponi et al. (2022). Indeed, our methodology also allows us to identify constraints on swing pricing (cap swing factor or partial swing pricing) as funds also disclose the information via their legal documents. It allows us to identify the differential impact of swing pricing with and without swing factor cap.

Finally, as Wu et al. (2022), our study also benefits from a time frame of three years that includes periods of regular market conditions and periods of intense financial stress: the market turmoil in March 2020. During this turmoil, net outflows from European funds reached up to 5.9% of the net asset value for corporate bond funds—which itself had declined by an average of 17% (-€238 billion)—and the bid-ask spread of corporate bonds increased by almost 20 bps in March 2020 (ESMA, 2020). In total, 215 investment funds (with net assets totalling €73.4 billion) suspended redemptions in March 2020 in Euro Area due to the risk of not being able to meet their redemptions. It is the most stressful financial episode over the last decade and thus since the existence of swing pricing in France. As noted by Falato et al. (2021), no previous work focused on the impact of LMTs during such an important stress event, whereas studying LMTs in abnormal conditions threatening the financial system is of major interest to understand the impact of LMTs on financial stability.

First of all, we note that the use of swing pricing in France is almost always associated with the presence of an activation threshold. In contrast, we find heterogeneity in the use of a swing factor cap: a quarter of the funds with swing pricing have an upper limit on their swing factor. Second, our results suggest that swing pricing had only a limited impact on redemption dynamics during the Covid-19 crisis: we find that swing pricing had no impact on flow volatility, and that it has even deteriorated fund flows. We identify that the observed limited effectiveness of swing pricing is explained by the use of swing factor cap by a significant share of investment funds that prevents the stabilizing effect to offset a stigma effect. Indeed, without cap, swing pricing exhibits stabilizing effects during the crisis: it reduced volatility and prevents outflows. However, adding a cap on the swing factor increased flow volatility and lead to more outflows.

Then, we complement our analysis based on systemic stress by focusing on stress at the fund level: "idiosyncratic stress". This stress—defined as periods where a fund has faced large outflows during liquidity strain—is associated with high exposition to dilution, which should trigger swing pricing activation and high swing factors. We find that swing pricing prevents runs during these periods and that this effect is still driven by funds without swing factor cap. The larger stabilizing impact of swing pricing during idiosyncratic stress compared to systemic stress can be explained by the wide use of activation thresholds. It also suggests that the intensity of swing pricing needs to be strong enough to increase financial stability. Our results therefore consistently point toward a limited stabilizing effect of swing pricing due to the widespread presence of constraints on the swing pricing mechanism in France. Finally, we find that swing pricing is implemented by funds with a prior higher liquidity mismatch and that managers combine this implementation with increased liquidity of their portfolio.

The remainder of this paper is organized as follows: Section 2 presents our data. The hypotheses set and our testing methodology is reported in Section 3. Section 4 presents our results and Section 5 concludes.

2 Data

This section first describes our methodology for collecting information on swing pricing from prospectuses, then provides descriptive statistics on its use, and finally presents our other data and measures.

2.1 Data on swing pricing

2.1.1 Extracting data from prospectuses using text mining

In France, the decision to use swing pricing is the responsibility of asset managers, who have discretionary powers to assess the need for such a measure (prudential authorities do not normally have authority to activate LMT, except for the suspension of redemptions). Fund managers can use swing pricing without prior approval, the only rule being that funds must disclose it in their prospectus (see DOC-2011-20 of the AMF). Thus, our identification methodology consists of two steps: i) collecting all French open-ended fund prospectuses, ii) converting this unstructured information into a structured database.

For the first step, the prospectuses were obtained from two alternative sources. First, we obtained from the French Financial Markets Authority (hereafter "AMF") the latest version of French closed-end and open-end funds at the end of each year from 2017 to 2020, as well as for March 2019, and for June 2020. It represents a total of about 60,000 prospectuses, including 20,500 open-end fund prospectuses.[3] As of the date of the snapshot, this data source is exhaustive because it is mandatory for French investment funds to provide their prospectuses to the AMF. However, with this methodology, we lack information for funds updating their prospectus more than once between two consecutive snapshots to identify the week of implementation. We therefore use Thomson Reuters' "Lipper for Investment Management" (hereafter LIM) service to download all versions of a fund prospectus between 2003 and 2021 for French open-end funds.[4] Using this methodology, we collected 11,545 additional unique prospectuses of French open-end funds.

To collect swing pricing information from prospectuses, we built on the seminal work of Darpeix et al. (2020) to develop a text mining algorithm identifying the availability of swing pricing based on natural language processing.[5] First, we lemmatize the text and remove stopwords, i.e., we reduce inflectional forms of words to their basic form and we remove words that do not add meaning. Second, we identify, based on the vocabulary, whether the document is i) readable (it is not an image), ii) written in French, and iii) whether it is indeed a prospectus.[6] Based on these conditions, we exclude 24% of our sample, which consisted mostly of non-prospectus documents. We then apply a fuzzy matching algorithm, as described in Section A.2 of the Appendix. This analysis of the prospectuses using our algorithm is complemented by manual processing of all funds within an umbrella fund ("SICAV à compartiments" in French): all prospectuses of an

[3]These prospectuses are not unique if they have not been updated between two consecutive snapshots. We have 12% duplicate PDFs in our database.

[4]As this extraction is relatively costly, we only searched for funds for which we knew the flows (see Section 2.3 for more details).

[5]Automated information extraction from investment fund prospectuses for economic research is a growing use of text mining algorithms. For example, Kostovetsky and Warner (2020) studies innovation and product differentiation using a uniqueness measure based on textual analysis of prospectuses. DeHaan et al. (2021) identifies that narrative complexity within fund prospectuses influences total ownership cost as some fund managers try to obfuscate poor performance and keep investors uninformed.

[6]Some documents were actually other legal information for investors such as Key Investor Information Documents (KIIDs), articles of association, notices to shareholders, or audited annual reports.

umbrella fund are concatenated in a single document, preventing an identification relying only on the algorithm.

In addition to identifying the use of swing pricing, our algorithm identifies the precise details of the mechanism, and more precisely the existence of constraints. In France, two types of constraints can be applied to the swing mechanism: i) a triggering threshold (referred to as partial swing pricing), ii) a cap (upper bound) on the adjustment of the NAV, called a swing factor cap. Partial swing pricing activates the NAV adjustment only when the absolute net flows are above a certain threshold. We detect the existence of partial swing pricing as it is publicly disclosed via the prospectus. A swing factor cap limits the maximum adjustment of the NAV.[7] The use of this mechanism is also disclosed in the prospectus along with the level of the cap. It enables us to identify the existence of swing factor caps and their levels.

Our method of identifying swing pricing is thus based on the information available to investors. Indeed, we do not observe the value of the activation threshold and the swing factor over time as this information is not disclosed to investors to avoid gaming effects or influence market timing. Therefore, it allows us to analyze how investors change their investment strategy using their information set.

Finally, to test the performance of our identification, we manually analyzed 400 prospectuses (each prospectus belonging to a different fund) selected using stratified random sampling based on three variables: the presence of swing pricing, year, and type of fund. Then, we divided our sample into two subsets of the same size to train our model and test its performance. We did not identify any error in the results provided by our algorithm on the test sample.

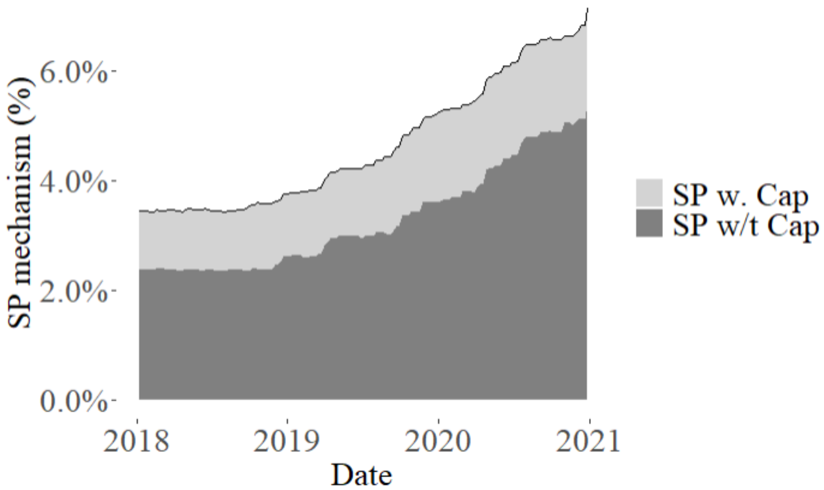
2.2 Descriptive statistics on swing pricing

In this section, we provide descriptive statistics on the availability of swing pricing in France between 2018 and 2020.[8]

[7]We identify the swing pricing mechanism through a variety of sentence structure identifications. For example, the presence of a section in the prospectus whose title is typically "Net asset value (NAV) adjustment method linked to swing pricing with a trigger threshold" indicates the use of a swing pricing mechanism. The typical sentence to disclose the presence of a capped swing pricing is: "the management company will have to make such adjustments, which may not exceed 1.50% of the NAV".

[8]Statistics are presented using the dataset analyzed in our result section. They therefore do not take into account MMFs, shares with a mean total net assets (hereafter *TNA*) lower than €0.1M, funds with too many outliers on flows (95 percentile), and funds younger than six months (see the last paragraph of Section 2.3 for more details).

Figure 1: Percentage of funds with swing pricing



Note: The black line in this figure indicates the percentage of funds with a swing pricing mechanism every week between January 2018 and December 2020. Funds are split between those with a swing factor cap ("SP w. Cap", represented by the light gray area) and those without a swing factor cap ("SP w/t Cap", represented by the dark gray area).

Swing pricing has been introduced in France by the AMF since July 2014 (Darpeix et al., 2020). At the beginning of our study in January 2018, swing pricing was available for about 3.4% of funds (see Figure 1). Swing pricing has gradually spread over the study period to reach 7.2% by the end of 2020. 93 funds used swing pricing at the beginning of our study period, they were 217 at its end. 126 investment funds (375 fund shares) have implemented swing pricing during our study period. While almost all funds that have implemented swing pricing during the study period still use the tool at the end of the period, two funds have withdrawn their swing pricing mechanism.[9] The spread of swing pricing is particularly pronounced between the beginning of 2019 and the end of 2020, with twice as many funds with swing pricing at the end of 2020 compared to the beginning of 2019 (+3.4 p.p.). At the end of 2020, swing pricing was mainly used by bond funds: 22.1% compared to 4.8% for equity funds. No MMF uses swing pricing. Apart from these three fund types, 3.4% of funds use it (e.g. mixed funds or formula funds).

Our algorithm detects that almost all funds that use swing pricing implement partial swing pricing. Indeed, only 2 funds out of the 217 funds with swing pricing are not classified as using an activation threshold. By opening manually their prospectuses, we

[9] For these two funds, removing the swing pricing is associated with other major changes in the fund structure.

conclude that these funds do not provide details on the type of swing pricing used.[10] We thus do not find evidence that, in France, some funds use a full swing pricing mechanism (i.e. swing pricing without activation threshold). This finding contrasts with the situations in the United Kingdom and Luxembourg where respectively 15.7% and 15% of the funds with swing pricing use its full version (ALFI, 2015; Bank of England, 2021). The most commonly applied activation threshold is Luxembourg is between 1-3% and less than 2% in United Kingdom.

Unlike partial swing pricing, we find heterogeneity in the use of a capped swing factor. 27% of investment funds with a swing pricing mechanism limit the value of the swing factor. These cap values range from 0.5% to 2.5%. However, most funds use a 2% cap (83%) or a value close to 2%—the second and third most popular values are 2.5% and 1.75% (more than 5% of the funds each). Thus more than 90% of the funds with a swing factor cap have a cap value close or equal to 2%, we therefore do not analyze the impact of the value of the cap in the remaining of the paper and rather focus on the impact of the type of swing pricing. As in France, fund managers in the United Kingdom can choose whether to apply a swing factor cap and its value. Base on a sample, Bank of England (2021) estimates that 8% of funds use a swing factor cap and its value ranges from 0.25% to 3% . In Luxembourg, on the other hand, fund managers have to apply a swing factor to their swing pricing mechanism but the value is freely chosen. In the United States (SEC 22c-1), a 2% swing factor cap is mandatory for all funds with a swing pricing mechanism. The distribution of cap values in France is comparable to Luxembourg as, according to the Association of the Luxembourg Fund Industry (ALFI, 2015), the most prevalent cap value among Luxembourg funds with capped swing pricing is also 2%.

Although constraints on the swing pricing mechanism could be detrimental to exiting investors as the swing factor would be often inferior to the true portfolio reallocation cost, increasing the risk of dilution, some fund managers may decide to use them as they reduce calibration errors that could penalize investors. Partial swing pricing also reduces the operational cost of having to daily calibrate the swing factor.

[10]In subsequent analyses, we exclude these two funds to have the same sample when assessing the impact of swing pricing and the impact of swing factor cap.

2.3 Open-end investment funds data and measures

We rely on a combination of various sources to assess the funds' situation and to measure systemic financial stress. The definition of all the variables is summarised in Table A-1 of the Appendix while descriptive statistics are in Table A-2 of the Appendix. The first key variable of our analysis is *Flows*, the net flows of funds. We follow the literature and express flows as a percentage of the previous TNA (Agarwal et al., 2020; Capponi et al., 2020). Since flows are central to our study, we keep them at a share level to avoid unnecessary data manipulation when it is possible as we could not observe all shares of a fund and generate misleading variables. Flows and TNA are collected weekly at the share level using EIKON from Thomson Reuters.[11] Average flows are display in Figure 2-a.

We define several fund-individual characteristics that we mainly use as controls. Based on absolute performance and benchmark performance variables, we follow previous studies (e.g. Goldstein et al., 2017) and estimate funds' *Alpha* using a 3-month backward rolling-window regression of weekly excess returns regressed on excess aggregate benchmark returns. *Size* is defined as the natural logarithm of shares' TNA. *Expense ratio* is the fund's total expenses (total costs associated with managing and operating) divided by the TNA. It measures the total costs associated with managing and operating an investment fund. These costs can be covered by management, entry and exit fees.

Alpha, *Size*, and *Expense ratio* are computed weekly using variables collected from LIM. We also derive a fund-level liquidity indicator, *Bid-ask Spread*, defined as the average bid-ask spread weighted by exposure amounts. It is based on information on assets held by each fund (assets held each month by each fund at a security level) provided by "Banque de France" enriched with detailed information on holdings such as ratings, amount outstanding, issuer sector (NACE or ESA) updated monthly from the "Centralised security database" (CSDB) of the ECB as well as the weekly bid-ask prices of all these assets collected from EIKON and Datastream.[12] It is computed weekly based on monthly-updated

[11] Flows are derived by EIKON based on the following formula commonly used in the literature (e.g. Chevalier and Ellison, 1997). $Flows_{i,t} = TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t})$ with r the weekly absolute performance rate.

[12] Some assets do not have bid-ask prices in Eikon or Datastream. In this case, we imputed the bid-ask spread with an iterative methodology based on the average value of all securities of the same issuer over time, then the seniority of the asset, then its synthetic rating (the average of the ratings of S&P, Moody's, Fitch and DBRS). At each step, the imputation is done period by period to take into account the evolution over time. Finally, for assets without this information, we do an imputation based on the weekly average bid-ask of all securities held by studied investment funds.

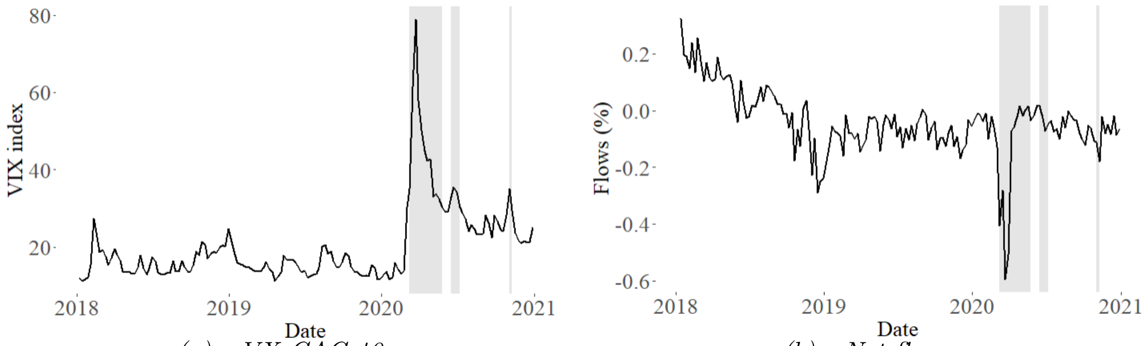
holdings and weekly-updated prices. *Cash ratio* and *Debt ratio* are derived from monthly "Banque de France" data as the total amount of cash and debt held divided by the TNA. Finally, *Institutional* gives the quarterly percentage of institutional investors. It is based on the ECB's Securities Holdings Statistics Sector (SHS-S) database providing the number and outstanding amounts of shares held by investors belonging to the same country and the same institutional sector for securities held by euro area custodians. This information on investors as well as detailed portfolios are also used for matching purposes (see Section 3.2).

We also define some time-invariant characteristics. They include the *Age* of the fund in years at December 2019 and the *NAV frequency* (frequency of the NAV update) in days collected from LIM. In addition, we use data from the AMF to determine the fund investment type within four categories: bond, equity, MMF, and a category "Other" with remaining funds (e.g. mixed funds, formula funds).

Besides fund characteristics, another central challenge is to define the systemic stress periods. We identify these periods based on the VIX CAC40 index following Jin et al. (2022); Kacperczyk et al. (2021). This variable captures the tension in the French financial sector. To set the VIX threshold above which a period is considered under financial stress, we compute the elasticity between stress periods and flows for different thresholds and apply the elbow method (see Section A.4 of the Appendix for details). Based on this methodology, the variable *Stress* is equal to 1 if the VIX CAC40 is above its 90% percentile and 0 otherwise. It corresponds to all periods from 08/03/2020 to 17/05/2020 as well as 3 weeks of June 2020 and one in November 2020. It thus closely matches the Covid-19 crisis. The 90% level is consistent with the fact that during the Covid-19 pandemic, funds experienced intensive but short-lived outflows (see Claessens and Lewrick, 2021 for bond funds). Figure 2 presents the VIX CAC40, the periods of stress and the corresponding flows.

Data treatments include merging databases and removing outliers. To merge data at the fund level, we rely on International Securities Identification Number (hereafter ISIN). However, ISINs are uniquely defined at the share level instead of the fund level. As an answer, we use the ECB's Register of Institutions and Affiliates Database (RIAD) to match shares and funds. For outliers, we follow Jin et al. (2022) by winsorizing at 1% level all continuous variables. The winsorization treatment was applied for each period

Figure 2: VIX CAC40 and net flows during systemic stress



(a) - VX CAC 40 *(b) - Net flows*

Note: Figure (a) presents the weekly value of the VIX CAC40 index between January 2018 and December 2020. Figure (b) gives the average net flows as a percentage of the previous week's TNA after winsorizing at 1% of the extreme values. In the two figures, grey areas correspond to the periods of systemic stress defined as periods with a VIX CAC40 above its 90% threshold value.

separately rather than over the entire sample, in order to limit the impact of obvious outliers without altering the true extreme values of the March 2020 crisis.

After these manipulations, we obtain a complete weekly database including 3169 French open-ended investment funds (6133 fund shares) belonging to 256 financial asset management companies. The total net assets of our sample is equal to €845 billion in September 2019, which represents 93% of the TNA of the investment funds included in Eikon (the seven remaining percents are mainly funds with unreadable prospectus caused by formatting issues) and approximately 81% of the TNA of all open-ended funds available to the public (€1,042 billion, source AMF).[13] We then apply some restrictions to our sample. First, we exclude money market funds (MMF) because no MMF has used swing pricing to date. Next, we impose two standard exclusion criteria to our sample (Massa and Rehman, 2008). Our main dependent variable being flows expressed as a percentage of the TNA, we remove very small fund shares (lower than 100,000€, approximately 2.5% of the sample) as a very small denominator may cause unwanted outliers (see Agarwal et al., 2020 for a similar approach). We remove also observations corresponding to the first six months after the creation of the investment funds as new funds typically start by collecting large inflows before reaching a more stable TNA at maturity. It removes 2.6%

[13] To derive the total TNA of open-ended funds available to the public, we use data by fund types at 30/09/2019 (https://geco.amf-france.org). We first deduct the TNA of investment funds not available to the public from the total TNA of all French funds. Then, we consider a fund to be close-ended if it belongs to a category where all funds are close-ended: for example SCPI (Sociétés Civiles de Placement immobilier - real estate companies), Professional OPCI (Organismes de Placement collect en immobilier - undertakings for collective investment in real estate) or employee saving funds. The derived figure is thus an upper bound of the actual number.

of the observations, mainly at the beginning of our analysis period. The last exclusion to ensure that we deal with representative funds is to remove all funds with more than 5.8% of winsorized values (95 percentile).

3 Hypotheses and methodology

This section presents our hypotheses set and our identification method developed to test them.

3.1 Hypotheses

To give a better understanding of swing pricing, we first provide in Equation 1 a formal definition of how the NAV can be swung. Commonly speaking, it means that the NAV is adjusted upward if subscriptions exceed redemptions and downward otherwise. The strength of the adjustment, i.e. the swing factor, depends on the readjustment cost of the fund's portfolio. Different approaches can be used to compute this cost as detailed in the guidelines on swing pricing to French funds by the *Association Française de la Gestion financière* (hereafter AFG) with the approval of the AMF (AFG, 2016).

$$NAV_{swung} = \begin{cases} NAV_{gross} \times (1 - \frac{C}{(R-S)}) \text{ if } S < R \\ \\ NAV_{gross} \times (1 + \frac{C}{(S-R)}) \text{ if } S > R \end{cases} \tag{1}$$

with the C readjustment cost, R the number of redeemed shares, S the number of subscribed shares. The gross NAV is the NAV calculated without applying the swing factor.

In order to conduct a comprehensive analysis on the impacts of swing pricing, our hypotheses focus on different phases of the swing pricing implementation (the decision of implementation, changes concomitant to the implementation and, the impact of its use on flow dynamics), different measures of financial stability (flow levels and volatility), and different types of stress (systemic and idiosyncratic stress). They also consider the impact of having a cap on the swing factor.

First, we focus on the determinants of the swing pricing implementation. The potential stabilizing impact of swing pricing is higher for funds more prone to the liquidity mismatch as swing pricing is intended to decrease externalities from this mismatch. The efficiency of swing pricing implemented on a voluntary basis would thus be greater if the funds using it are the ones needing it the most. In addition, these funds are supposed to seek tools to help them to manage their relatively high mismatch. We thus assume that:

H 1. *Funds with high liquidity mismatch are more likely to implement swing pricing.*

We then assess how swing pricing affects flow dynamics under stressed market stress conditions (following, for example, Schmidt et al., 2016; Dunne and Giuliana, 2021; Jin et al., 2022). To define stress periods, we exploit the Covid-19 crisis, a perfectly exogenous shock (i.e. systemic stress). We focus on the impact of swing pricing during stress periods on two different measures of flow dynamics: i) flow volatility, and ii) flow level.

Swing pricing mechanisms decrease (respectively increase) the NAV in case of net outflows (respectively inflows), it thus incentivizes investors to adopt contra-cyclical strategies, i.e. to redeem when the fund experiences net inflows, and subscribe when it experiences net outflows. It should thus lead to less volatile flows and thus increase stability as funds with stable flows are less prone to dilution and materialization of first-mover advantage (Cetorelli et al., 2022).

H 2. *Swing pricing reduces flow volatility during systemic stress.*

During stress periods, such as the Covid-19 crisis, excessive redemptions may lead to runs and jeopardize funds' financial stability. Avoiding such redemptions would thus be a valuable characteristic for an LMT. In addition, swing pricing is supposed to disincentive investors from redeeming during stress periods as it internalizes the liquidity cost of potential redemptions (Anadu et al., 2022). We thus study how swing pricing impacts flows during stress periods. Based on the results of Jin et al. (2022), we assume that:

H 3. *Swing pricing increases net flows during systemic stress via a reduction of outflows.*

Next, we focus on another type of stress, idiosyncratic stress: when a fund is facing large outflows with a liquidity strain. We focus on idiosyncratic stress as funds are then particularly prone to dilution and thus to a materialization of the first-mover advantage in the next periods. Because swing pricing is designed to protect investors against dilution, these situations are especially relevant to assess the swing pricing efficiency. As in the previous section, we evaluate how swing pricing affects flows and we thus assume that swing pricing reduces the sensibility of net flows to idiosyncratic stress.

H 4. *Swing pricing reduces outflows during idiosyncratic stress periods*

We are also interested in studying how a capped swing factor influences the swing pricing impact. A cap on the swing factor limits its potential impact. Indeed, it can lead to a mismatch between the swing factor and the effective reallocation cost of the portfolio, therefore increasing the risk of dilution—and the first-mover advantage. We thus assume that the presence of a swing factor cap reduces a potential stabilizing effects of swing pricing.[14]

H 2-Cap. *The stabilizing impact on flow volatility is decreased when the swing factor is capped.*

H 3-Cap. *The stabilizing impact on flows during systemic stress is decreased when the swing factor is capped.*

H 4-Cap. *The stabilizing impact on flows during idiosyncratic stress is decreased when the swing factor is capped.*

Finally, we assess whether the implementation of swing pricing is combined with other changes in the risk management tools (i.e. cash buffer, leverage or asset liquidity). There are two competing hypotheses: either it is associated with the strengthening of the other lines of defense or it is used as a substitute for these lines. The latter hypothesis finds more support in the literature as Jin et al. (2022); Wu et al. (2022); Lewrick and Schanz (2023) provide evidence that swing pricing encourages funds to seek higher returns by lowering their cash buffers or increasing their leverage. We thus assume that:

H 5. *Fund managers substitute other risk management tools with swing pricing.*

3.2 Identification methodology

The decision to implement a swing pricing mechanism depends on the fund manager. It may thus be influenced by the fund's characteristics and financial situation. To correctly estimate the causal effect of swing pricing, we must address a potential confounding effect: the endogeneity of the decision to use swing pricing. To take it into account, we use two strategies: first, we use a panel data model with a within estimator—whenever relevant—,

[14]The following hypotheses assess how a capped swing factor (Cap) affects the different impacts of swing pricing considered above (e.g. H2-Cap is paired with H2).

with time fixed effects to account for the fact that funds implemented swing pricing at different dates. Funds that introduce swing pricing could be structurally different from the others, this strategy aims to correct this bias. Second, we complement full-sample estimates with matched sample estimates (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 1999). We aim to compare two funds with comparable characteristics, except that one of them uses swing pricing and the other does not. We thus match funds on their characteristics at the first date available in our data (mostly beginning of 2018, when only 3.4% of funds used a swing pricing mechanism). The within panel data model excludes by design funds that had already introduced swing pricing prior to our study period, as do the difference-in-differences estimations. We develop two matching samples based either on individual characteristics or portfolio and investor composition.

First, we follow the methodology of Jin et al. (2022) by matching funds on individual characteristics. For each fund with swing pricing, we find the nearest fund without swing pricing using a matching algorithm that minimizes the sum of the absolute percentage differences for our controls (alpha, size, age, expense ratio, bid-ask spread, and percentage of institutional investors).

While this method limits the estimation bias, it relies on information already captured in the specification. To circumvent this shortcoming, previous papers have focused on asset characteristics. Malik and Lindner (2017) compared three funds: one with swing pricing and two without swing pricing that invest in the same assets and are held by the same asset manager. Lewrick and Schanz (2023) used the correlation of the funds' daily returns over the past three months assuming that swing pricing does not affect returns. In our study, we benefit from unique data on the holdings and the composition of investors of each fund. We use this information to go further and match funds on their actual holdings as well as the composition of investors. More precisely, this method relies on six variables describing the nature of the investors and the funds' portfolios: i) the NACE sector of the issuer of the assets, ii) the geographic area of the issuer, iii) the institutional sector of the issuer, iv) the type of financial asset held, v) the rating of the assets[15] and vi) the type of investors (see Section A.5 for details on the categories). Each variable has the same weight. The proximity of two investment funds is defined as the sum of the absolute percentage differences in the values of the six variables presented above (two funds have a distance

[15]Every asset does not have a rating in CSDB. We impute missing values firstly based on the seniority and the rating of the issuer, otherwise we just use the rating of the issuer

of 0 if they have the same portfolio and investor composition). The variables about the composition of the portfolio come from the database *OPC Titres* and the variables about the composition of the investors pool come from *Securities Holdings Statistics by Sectors* from the European System of Central Banks (ESCB). SHS is compiling new security-by-security data on holdings of debt securities and shares by euro area residents on a quarterly basis.

For both matching methods, funds are matched with replacement within a maximum distance of 10%, i.e. funds are matched only if there is another fund that is at least 90% alike based on a k-dimensionality tree nearest neighbor search algorithm. Funds are matched only within types (equity, bond, and other funds). Out of the 217 funds with swing pricing, 213 (98%) and 203 (93%) funds were matched with respectively the matching methodology based on "portfolio and investors" and the one based on the control variables. The two methodologies significantly reduce sample bias between the two groups for the variables used for matching, but also for the flows and their volatility (see Table A-3 and Table A-4).

4 Results

This section presents our empirical results. In Section 4.1, we analyze the factors influencing the implementation of a swing pricing mechanism. Then, we focus on the impacts of its use and we distinguish its effects during calm and financial stress periods. We analyze the impact of swing pricing during systemic stress periods on flow volatility in Section 4.2 and on the capacity of swing pricing to reduce outflows in Section 4.3. Then, in Section 4.4, we perform an analysis similar to the previous section but we focus on idiosyncratic stress situations instead of systemic stress. Finally, we assess whether the implementation of swing pricing is considered a substitute for other changes in the risk management tools in Section 4.5.

4.1 Factors driving the swing pricing implementation

Since 2014 in France, fund managers are free to choose whether to use swing pricing or not. We study the determinants of their decisions. More specifically, we investigate whether a high liquidity mismatch fosters swing pricing implementation. We thus study how ex-ante characteristics affect subsequent implementation.

We test Hypothesis 1, stating that funds with higher liquidity mismatch are more inclined to implement swing pricing, by estimating Equation 2. We regress ex-ante independent variables (observed during the first quarter of our study) on the implementation of swing pricing after March 2018. We only consider investment funds that have not yet implemented swing pricing at the beginning of the study period to avoid reverse causality bias.

$$\begin{aligned} Treated_i \sim\ & \beta_0 + \beta_1\, Flows_i + \beta_2\, Volatility_i + \beta_3\, \textit{Bid-ask spread}_i + \beta_4\, Size_i \\ & + \beta_5\, Age_i + \beta_6\, \textit{NAV frequency}_i + \beta_7\, Institutional_i + \beta_8\, Alpha_i \\ & + \beta_9\, Debt_i + \beta_{10}\, Cash_i + \beta_{11}\, Expense_i + \beta_{12}\, Type_i + \epsilon_i \end{aligned} \tag{2}$$

with $Treated$ a dummy variable constantly equal to one if a fund implements swing pricing between March 2018 and December 2020. $Volatility$ is the variance of the flows, other independent variables are average values between January 2018 and March 2018 and are defined as presented in Table A-1. We estimate this equation with a logistic regression, we have one observation per fund share. Shares with swing pricing before March 2018 are excluded from the estimation sample.

Result 1. *Funds with high liquidity mismatch are more likely to implement swing pricing.*

Support for Result 1: First, we focus on the variables reflecting liquidity on the liability side. The results are presented in Table 1. Columns (1) and (2) present the determinants of the probability to implement swing pricing during our study period. We find that having a high flow volatility has a positive impact on the probability to implement swing pricing (p-value < 0.001 in all models). Moreover, having a low NAV frequency also increases this likelihood (p-value < 0.001 in all models). Thus, funds that are more liquid on the liability side (e.g., funds with high flow volatility and daily NAVs) have a greater propensity to implement swing pricing.

Second, we focus on the variables associated with liquidity of the asset side. The higher the weighted average bid-ask spread of the portfolio (p-value < 0.001 in all models), the more likely a fund is to implement swing pricing. In addition, we find some evidence that low alpha has a similar effect (p-value < 0.001 in model 1). It suggests that funds with lower asset liquidity and under-performing funds (one of the consequences of dilution) are more likely to implement swing pricing.

Finally, total expense ratio also influences the probability to implement swing pricing: funds with a low total expense ratio tend to implement swing pricing more often (p-value < 0.001 in all models). Since having to calibrate the swing factor at each NAV publication represents a significant amount of work that could theoretically lead to increased operating costs for investment funds, funds that already have high operating costs may be disincentives from offering swing pricing in order to remain competitive on fees.

In line with Hypothesis 1, we conclude that swing pricing is implemented by funds with higher liquidity mismatch, having lower asset liquidity and higher liability liquidity.[16] In this regard, this policy seems to be chosen by targeted funds. Furthermore, these results highlight the importance of applying identification methods to estimate the causal effect of swing pricing on the financial stability of funds and to correct this source of endogeneity, as detailed in Section 3.2.

To go further, we adapt Equation 2 to identify the factors explaining the choice of fund managers to either implement swing pricing with or without capped swing factor. The results are presented in Table 1: the dependent variable equal one for swing pricing without cap in model (3) and for swing pricing with cap in model (4). Finally, model (5) is similar to model (4) but estimated only among funds with swing pricing to capture the determinants of implementing cap conditionally on implementing swing pricing.

The variables explaining swing pricing implementation with cap differ slightly from the one driving uncapped implementation: while high volatility has an equal impact on the likelihood of implementing uncapped or capped swing factor (p-value < 0.001 models 3 and 4), funds holding illiquid assets generally prefer to implement uncapped swing pricing. Since swing factor increases with asset illiquidity according to AFG, funds expecting high swing factors may tend not to cap swing factor as they are the ones that most need to have a swing factor that represents the true cost of portfolio reallocation. Alternatively, funds with with expectedly low swing factors may anticipate to be relatively less impacted by this constraint and are thus more willing to implement it to reassure investors.

All else being equal, we find that bond funds are equally likely to implement swing

[16] The impact of the liquidity mismatch is robust to estimating our regressions based on average values between June 2018 (or January 2019) and December 2020, before the implementation of swing pricing, as presented in Table A-5.

pricing than equity funds (p-value > 0.1 model 2). However, bond funds implement more often a cap (p-value < 0.01 in models 4 and 5). This could be explained by the diversity of their assets which increases the difficulty to calibrate swing factor.

4.2 Swing pricing and flow volatility during systemic stress periods

In this section, we take advantage of the high frequency of our observations to assess how swing pricing affects flow volatility. Intuitively, more stable flows should be associated with increased financial stability (Cetorelli et al., 2022). By swinging NAV downwards in case of net redemptions and swinging it upwards otherwise, swing pricing should decrease flow volatility as it gives incentives to investors to adopt contra-cyclical strategies i.e. to redeem when other investors are subscribing and conversely. In addition, it should provide incentives for investors to spread large redemption or large subscriptions over multiple NAV that can be due to several rationales. First, to minimize their portfolio reallocation impact as is it transferred to them. Second, not to overshoot the activation threshold and then have to bear a potentially high swing factor cap. Finally to decrease valuation uncertainty induced by swing pricing.

Formally, we estimate the following equation to test Hypothesis 2:

$$\begin{aligned} Vol_{i,t} \sim \; & \beta_0 + \beta_1\, Stress_t + \beta_2\, SP_{i,t} + \beta_3\, SP_{i,t} \times Stress_t \\ & + \beta_4\, Controls_{i,t-1} + \gamma_i + \phi_t + \epsilon_{i,t} \end{aligned} \tag{3}$$

with SP a dummy variable equal to one if a fund share has a swing pricing mechanism. *Vol* is the standard deviation of the flows (net weekly capital flows divided by the fund share's total net assets of the last week) during the past 3 months of a fund share. $Stress$ is the systemic risk, equal to one if the value of the VIX CAC40 is in the top 10%. γ_i and ϕ_t are fund share and date fixed effects. $Controls$ is a vector of control variables including size, percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio and portfolio's weighted average bid-ask spread. We cluster standard errors by fund shares. We estimate Equation 3 on the full sample and on the sample matched on "portfolio and investors" (models 2 and 3 in Table 2) as well as a model without controls (model 1) and a model without date fixed effects (model 4) to estimate the effect of $Stress$. Table A-6

Table 1: Individuals characteristics and probability to implement swing pricing

	SP implementation		SP without cap	SP with cap	
	(1)	(2)	(3)	(4)	(5)
Flow percent	−0.034	−0.029	−0.037	0.007	0.083
	(0.028)	(0.028)	(0.026)	(0.012)	(0.134)
Volatility	0.078***	0.072***	0.047**	0.025***	0.105
	(0.020)	(0.020)	(0.018)	(0.009)	(0.100)
Bid-ask spread	1.329***	1.441***	1.664***	−0.223***	−1.781***
	(0.133)	(0.143)	(0.130)	(0.061)	(0.652)
Size	−0.002	−0.001	0.021	−0.023***	−0.424***
	(0.019)	(0.019)	(0.017)	(0.008)	(0.108)
Age	0.003	0.002	0.003	−0.001	0.008
	(0.003)	(0.003)	(0.003)	(0.001)	(0.022)
NAV frequency	−0.051***	−0.042***	−0.034**	−0.009	−0.281*
	(0.016)	(0.016)	(0.014)	(0.007)	(0.165)
Institutional	−0.0003	0.00005	−0.0003	0.0004	0.010
	(0.001)	(0.001)	(0.001)	(0.0004)	(0.008)
Alpha	−0.196***	−0.104	−0.085	−0.019	0.385
	(0.066)	(0.070)	(0.064)	(0.030)	(0.480)
Debt	0.002	0.001	0.017	−0.017**	−0.017
	(0.016)	(0.016)	(0.014)	(0.007)	(0.137)
Cash	−0.005	−0.002	−0.003	0.001	0.053
	(0.005)	(0.005)	(0.004)	(0.002)	(0.063)
Expense	−0.117***	−0.110***	−0.155***	0.045***	1.689***
	(0.034)	(0.039)	(0.036)	(0.017)	(0.369)
Type fund: Bond		0.033	−0.152*	0.185***	2.499***
		(0.095)	(0.087)	(0.041)	(0.591)
Type fund: Other		−0.236***	−0.192***	−0.044	0.311
		(0.072)	(0.066)	(0.031)	(0.603)
Sample	All	All	All	All	Swing pricing
Observations	3,936	3,936	3,936	3,936	252
R^2	0.039	0.042	0.051	0.023	0.273

Note: this table presents the logistic regression results for which the dependent variable is a dummy equal to one if a fund implements swing pricing between March 2018 and December 2020 in columns (1) and (2). The dependent variable of column (3) is a dummy equal to one if a fund implements an uncapped swing pricing, and in columns (4) and (5) the dependent variable is a dummy equal to one if a fund implements a capped swing pricing. Independent variables are the average value for each fund between January 2018 and March 2018, there is one observation per fund share. The sample consists of all the funds that have not yet implemented swing pricing in March 2018, and in column (5) the sample is composed of only funds implementing swing pricing between March 2018 and December 2020. *$p<0.1$; **$p<0.05$; ***$p<0.01$.

provides in column (4) an estimate on the sample matched on controls to add robustness.

Result 2. *Swing pricing does not decrease flow volatility during stress periods.*

Support for Result 2: the coefficients associated with $SP \times Stress$ in Table 2 measure the effect of swing pricing on flow volatility during stress periods. In all models, none of these coefficients are statistically significant. We thus conclude against Hypothesis 2. Model (4) that does not include date fixed-effects enables us to measure the impact of financial stress on flow volatility. As expected, we find that financial stress increases flow volatility (p-value < 0.001). It supports that a lower flow variance is associated with greater financial stability. Finally, when focusing on the impact of swing pricing outside of stress periods (coefficients of SP), we find no significant coefficients in models 1 to 3 and a negative effect in model 4 that does not include date fixed effects (p-value $=$ 0.028). We thus do not find converging evidence of an impact of swing pricing during calm periods.

Table 2: Impact of swing pricing on flow volatility

	Volatility			
	(1)	(2)	(3)	(4)
Stress				0.274^{***}
				(0.016)
SP	-0.024	0.004	0.032	-0.112^{**}
	(0.050)	(0.051)	(0.059)	(0.051)
SP x Stress	-0.034	-0.044	-0.095	-0.039
	(0.054)	(0.055)	(0.074)	(0.054)
Controls	No	Yes	Yes	Yes
Matching	No	No	PI	No
Date FE	Yes	Yes	Yes	No
Observations	722,518	662,241	127,077	662,241
R^2	0.360	0.362	0.325	0.349
Note:		*p<0.1; **p<0.05; ***p<0.01		

Note: this table presents the regression results of OLS estimates for which the dependent variable is flow volatility defined as the 3-month standard deviation of the weekly net flows. For all regressions, independent variables include SP, a dummy equal to one if a fund implements swing pricing, Stress, a dummy equal to one if weekly VIX CAC40 is above the 90^{th} percentile of the sample and the interaction of the two variables. In addition, columns (2) to (4) also include control variables as regressors. Control variables are lagged values of size, percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio and portfolio weighted average bid-ask spread. The coefficients of control variables are omitted in this table for sake of clarity, however they can be found in Table A-6. Column (3) uses the sample matched on "portfolio and investors". Columns (1) to (3) have date fixed effects, all columns have fund share fixed effects. Errors are clustered by fund shares. There is one observation by fund share per week. *p<0.1; **p<0.05; ***p<0.01

To investigate further the rationale behind this result, we disentangle the effect of swing pricing without swing factor cap from the effect of swing pricing with cap (Hypothesis 2-Cap). Formally, we estimate the following equation:

$$\begin{aligned} Vol_{i,t} \sim \;& \beta_0 + \beta_1\, Stress_t + \beta_2\, SP_{i,t} + \beta_3\, SP_{i,t} \times Cap_{i,t} \\ & + \beta_4\, SP_{i,t} \times Stress_t + \beta_5\, SP_{i,t} \times Cap_{i,t} \times Stress_t \\ & + \beta_6\, Controls_{i,t-1} + \gamma_i + \phi_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

where all variables are defined as in Equation 3 and Cap is equal to one if a fund share has a capped swing factor. No coefficient is associated with Cap alone as it is impossible for a fund to have a swing factor cap if it does not use a swing pricing mechanism. As in Table 2, we estimate this model on the full sample (columns 1, 2 and 4 in Table 3), on the sample of funds matched with the matching "portfolio and investors" (column 3) and with the matching "controls" in Table A-7. Column (4) is without fixed effects.

Result 2-Cap. *Swing factor cap reduces the stabilizing impact on flow volatility.*

Support for Result 2-Cap: the coefficients associated with $SP \times Cap$ and $SP \times Stress \times Cap$ in Table 3 measure the extent to which the presence of cap on the swing factor affects the impact of swing pricing on flow volatility. In the absence of financial stress, the presence of a swing factor cap does not impact flow volatility (the coefficients associated with $SP \times Cap$ are never significant).

However, during systemic stress, we find that swing pricing reduces flow volatility in all models (coefficient associated with $SP \times Stress$, p-values are between 0.002 in model 2 and 0.007 in model 1). This provides evidence of the ability of swing pricing to decrease flow volatility during stress if uncapped. It thus corresponds to the expected impact as presented in Hypothesis 2. On the contrary, we find that the presence of a cap on the swing factor increases the flow volatility during these periods in all models ($SP \times Stress \times Cap$, p-values between 0.014 in model 2 and 0.033 in model 1). These findings are robust to using the matching based on controls (Table A-7).

This positive coefficient may be explained by a limitation of the efficacy of the mechanism to allocate the portfolio reorganization cost on subscribing or redeeming investors, and a decrease in incentives for investors to adopt countercyclical strategies. In addition, its size (larger than the uncapped swing pricing coefficient) can be explained by the introduction of additional strategic complementarity for investors that would increase volatility. For example, some speculators might be tempted to try to make a profit by entering at a time when they anticipate the swung NAV to be undervalued, and exiting at a time when it is assumed to be overvalued. Alternatively, some investors may be tempted to pre-empt their exit from a fund with swing pricing to avoid its impact, generating excess exits. This phenomenon needs to be overweighted by the direct stabilizing impact of swing pricing in order to have a positive total impact on flow stability, which is not the case when the swing factor is capped.

We thus conclude in favor of Hypothesis 2-Cap: the stabilizing impact on flow volatility is decreased when the swing factor is capped. Swing pricing thus seems to have the ability to stabilize the flow variance, however, adding a cap on the swing factor prevents stabilization.

Table 3: Impact of swing pricing and swing factor cap on flow volatility

	Volatility			
	(1)	(2)	(3)	(4)
Stress				0.275^{***}
				(0.016)
SP	-0.020	0.014	0.039	-0.107^{**}
	(0.052)	(0.054)	(0.061)	(0.053)
SP x Cap	0.042	0.034	0.050	0.073
	(0.108)	(0.119)	(0.121)	(0.120)
SP x Stress	-0.139^{**}	-0.163^{***}	-0.214^{***}	-0.153^{***}
	(0.059)	(0.058)	(0.077)	(0.058)
SP x Stress x Cap	0.313^{***}	0.368^{***}	0.366^{***}	0.354^{***}
	(0.116)	(0.121)	(0.121)	(0.121)
Controls	No	Yes	Yes	Yes
Matching	No	No	PI	No
Date FE	Yes	Yes	Yes	No
Observations	722,518	662,241	127,077	662,241
R^2	0.360	0.362	0.326	0.349

Note: this table presents the regression results of OLS estimates for which the dependent variable is flow volatility defined as the 3-month standard deviation of the weekly net flows. For all regressions, independent variables include SP, a dummy equal to one if a fund implements swing pricing, Cap, the number of constraints on the swing pricing, Stress, a dummy equal to one if weekly VIX CAC40 is above the 90^{th} percentile of the sample and the interaction of these three variables. As funds cannot have cap without swing pricing, the coefficient of Cap (without interaction) is omitted. In addition, columns (2) to (4) also include control variables as regressors. Control variables are lagged values of size, percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio and portfolio weighted average bid-ask spread. The coefficients of control variables are omitted in this table for sake of clarity, however they can be found in Table A-6. Column (3) uses the sample matched on "portfolio and investors". Columns (1) to (3) have date fixed effects, all columns have fund share fixed effects. Errors are clustered by fund shares. There is one observation per fund share and week. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.3 Swing pricing and flow level during systemic stress periods

During stress periods, the liquidity cost associated with portfolio reallocation usually increases. A properly designed swing pricing should thus provide incentives to investors to decrease redemptions during stress periods as they bear the reallocation cost. The Covid-19 crisis of February and March 2020 is a perfectly exogenous shock that affects all mutual funds at the same time and does not depend on the implementation of swing pricing. In this section, we take advantage of this shock to assess the impact of swing pricing on flow levels during periods of systemic stress. As in the previous section, we first study the impact for all types of swing pricing combined and then we differentiate between types. Formally, we start by estimating Equation 5:

$$\begin{aligned} Flows_{i,t} \sim \; & \beta_0 + \beta_1\, Stress_t + \beta_2\, SP_{i,t} + \beta_3\, SP_{i,t} \times Stress_t \\ & + \beta_4\, Controls_{i,t-1} + \gamma_i + \phi_t + \epsilon_{i,t} \end{aligned} \tag{5}$$

As in Equation 3, control variables are size, percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio and portfolio's weighted average bid-ask spread. γ_i and ϕ_t are share and date fixed effects. We cluster standard errors by fund shares. As previously, we estimate four model specifications in Table 4: model (1) without controls, model (2) on the full sample with controls, model (3) on the sample matched on "portfolio and investors" and model (4) without date fixed effects; as well as one specification in Table A-9 with the sample matched on controls as a robustness check.

Result 3. *Swing pricing does not increase net flows during systemic stress.*

Support for Result 3: coefficients associated with $SP \times Stress$ in models (1) to (4) of Table 4 measure the effect of swing pricing on flows during systemic stress periods. We do not find any evidence that swing pricing increases flows during these periods as none of these coefficients are positive. In addition, we find that swing pricing decreases net flows during stress without matching (model 1, 2 and 4: p-values from 0.012 in model 1 to 0.062 in model 4). We thus conclude against Hypothesis 3 which states the opposite. Similarly, coefficients associated with SP models (1) to (4) of Table 4 measure the effect of swing pricing outside of systemic stress periods. We find that SP has no impact on flows in all our models, highlighting the interest to disentangle between stressed and non-stressed periods. Finally, we note that systemic stress has, as expected, a negative effect on flows (coefficient $Stress$, p-value < 0.001 in model 4). Results are robust when using the matching based on controls instead of the portfolio and investors matching (Table A-8, model 4).

We then distinguish the effect of swing pricing on inflows and outflows. Indeed, studying how swing pricing impacts outflows (i.e. when on average investors are redeeming shares) relates directly to the ability of swing pricing to avoid runs. In contrast, focusing on inflows (i.e. when on average investors are subscribing shares) enables us to study if investors are willing to invest in a fund that is a net collector. It thus informs on potential stigma effects, especially if the decrease in inflows dominates the decrease in outflows. Formally, we study consecutively a sample with only net outflows ($Flows < 0$) and with only net inflows ($Flows > 0$).

Models (5) and (6) of Table 4 present these estimations including controls without matching. Estimations without controls and with our matched sample are in models (1), (3), and (4) of Table A-10 for negative flows and Table A-11 for positive flows. We find that swing pricing does not have a statistically significant impact on outflows in either calm or stressed periods (model 6). On the contrary, swing pricing decreases inflows during systemic stress periods (model 5, $SP \times Stress$, p-value < 0.001). These results are robust to removing controls or using matched samples (see Table A-10 and Table A-11). We thus find that the overall effect on net flows is driven by a decrease in inflows. In other words, swing pricing does not seem to be able to decrease outflows during stress periods (i.e. no stabilizing effect), however it reduces inflows.

As swing pricing is a symmetrical tool but its impact appears asymmetrical, the reduction of inflows combined with the absence of impact on the outflows suggests the existence of a stigma effect. This stigma could be explained by the fact that investing in a fund with swing pricing during periods of systemic stress implies that investors would have to bear the cost of reallocation of the fund's portfolio if they decide to redeem their shares, which potentially increases the exit cost and thus decreases subscriptions.

Even when focusing on negative flows (outflows), we do not find a positive effect of swing pricing. We further investigate underlying mechanisms by studying how capped swing pricing affects flows. We thus interact swing pricing and stress periods with the presence of swing factor cap. Formally, we estimate the following equation:

$$\begin{aligned} Flows_{i,t} \sim\ & \beta_0 + \beta_1\, Stress_t + \beta_2\, SP_{i,t} + \beta_3\, SP_{i,t} \times Cap_{i,t} \\ & + \beta_4\, SP_{i,t} \times Stress_t + \beta_5\, SP_{i,t} \times Cap_{i,t} \times Stress_t \\ & + \beta_6\, Controls_{i,t-1} + \gamma_i + \phi_t + \epsilon_{i,t} \end{aligned} \tag{6}$$

where Cap equal one if the fund has a capped swing factor and all other variables are defined as in Equation 5. Consistently with previous estimations, we estimate the same five model specifications varying in the inclusion of controls, date fixed effects, and samples.

Table 4: Impact of swing pricing on flow level

	Flows				Positive flows	Negative flows
	(1)	(2)	(3)	(4)	(5)	(6)
Stress				-0.085^{***}		
				(0.012)		
SP	0.033	0.034	0.023	-0.004	0.062	0.040
	(0.038)	(0.038)	(0.043)	(0.037)	(0.053)	(0.040)
SP x Stress	-0.095^{**}	-0.083^{**}	-0.038	-0.072^{*}	-0.143^{***}	0.008
	(0.038)	(0.039)	(0.053)	(0.039)	(0.043)	(0.053)
Controls	No	Yes	Yes	Yes	Yes	Yes
Matching	No	No	PI	No	No	No
Date FE	Yes	Yes	Yes	No	Yes	Yes
Observations	778,730	712,639	136,656	712,639	300,957	407,136
R^2	0.048	0.049	0.047	0.045	0.135	0.102

Note: this table presents the regression results of OLS estimates for which the dependent variable is either net flows (columns 1 to 4), negative flows (5) or positive flows (6). For all regressions, independent variables include SP, a dummy equal to one if a fund implements swing pricing, Stress, a dummy equal to one if weekly VIX CAC40 is above the 90^{th} percentile of the sample, and the interaction of both variables. In addition, columns (2) to (6) also include controls as regressors. Control variables are lagged values of size, percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio and portfolio weighted average bid-ask spread. The coefficients of control variables are omitted in this table for the sake of clarity, however they can be found in Table A-8. Column (3) uses the sample matched on "portfolio and investors". Columns (5) and (6) use, respectively, samples with only positive and negative flows. All columns have fund share fixed effects and, except column (4), all columns have date fixed effects. Errors are clustered by fund shares. There is one observation per fund share and week. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Result 3-Cap. *A swing factor cap reduces the ability of swing pricing to prevent outflows during systemic stress.*

Support for Result 3-Cap: the coefficients associated with $SP \times Stress \times Cap$ in models (1) to (4) of Table 5 measure the effect of capping the swing factor on flows during systemic stress periods. In all models, these coefficients are negative (p-values between 0.002 in model 1 and 0.006 in model 2, the effect is robust using the "control" matching, see Table A-9). We thus conclude in favor of Hypothesis 3-Cap. By focusing on the coefficients associated with $SP \times Stress$, we observe that the negative impact of swing pricing on net flows during systemic stress periods identified in Table 4 vanishes for swing pricing without cap: Cap and SP are never significant in models (1) to (4). Outside of systemic stress periods, swing pricing with or without cap does not impact net flows: Cap and SP are never significant in models (1) to (4) also here. We thus find that the negative effect of swing pricing on flows during stress periods is due to the use of swing pricing with swing factor cap.

Distinguishing between inflows and outflows enables us to better understand the impact of the cap. In model (6), we find a negative effect of $SP \times Stress \times Cap$ (p = 0.003) and a positive effect of $SP \times Stress$ (p = 0.016) on outflows. It means that swing pricing without cap is effective in decreasing outflows (higher net flows) during stress periods but that adding a cap has the opposite impact. In model (5), we find a negative effect of $SP \times Stress$ (p = 0.001) on inflows but no effect of $SP \times Stress \times Cap$. Results are robust to removing control variables or using the alternative matching methodology presented in Table A-10 and Table A-11. It suggests that, without cap, the swing pricing exhibits a stabilizing effect on flows: swing pricing prevents negative flows at the cost of decreased positive flows. Such a pattern is consistent with our previous findings on volatility as presented in Section 4.2.

This symmetrical impact between inflows and outflows may be related to the inherent functioning of the tool when it is fully operational (without cap). In periods of net inflows, the NAV is swung upward, reducing the financial interest for investors to enter the fund as swing pricing makes it more expensive. The mechanism is perfectly identical for outflows: the same formula is used as adding a cap reduces the swing factor and thus the cost associated with entering/leaving the fund in both cases. However, the upper bound on swing factor impacts negatively outflows without affecting inflows. As outflows might be more sudden and stronger during systemic stress than inflows, the swing factor cap might limits more the strength of the NAV adjustment during outflows than inflows and can thus induce the observed phenomenon.

To conclude on the impact of swing pricing on flow levels, we find that, in aggregate, swing pricing tends to decrease fund flows due to a reduction of positive flows (without impacting significantly outflows). The absence of outflow reduction is driven by the use of swing factor cap: while without cap the swing pricing mitigates outflows, a capped swing factor prevents this stabilizing effect.

4.4 Swing pricing and idiosyncratic stress

We now turn to the analysis of the swing pricing impact in situations of idiosyncratic stress. Idiosyncratic stress is defined at the fund level as situations where a fund is in

Table 5: Impact of swing pricing and swing factor cap on flow level

	Flows				Positive Flows	Negative Flows
	(1)	(2)	(3)	(4)	(5)	(6)
Stress				-0.085^{***}		
				(0.012)		
SP	0.028	0.026	0.014	-0.015	0.071	0.020
	(0.039)	(0.039)	(0.044)	(0.038)	(0.057)	(0.040)
SP x Cap	-0.028	-0.012	-0.008	-0.002	-0.052	0.066
	(0.090)	(0.098)	(0.099)	(0.096)	(0.126)	(0.134)
SP x Stress	-0.004	0.0005	0.046	0.020	-0.152^{***}	0.123^{**}
	(0.038)	(0.038)	(0.052)	(0.038)	(0.046)	(0.051)
SP x Stress x Cap	-0.268^{***}	-0.257^{***}	-0.259^{***}	-0.286^{***}	0.026	-0.391^{***}
	(0.087)	(0.093)	(0.092)	(0.093)	(0.093)	(0.132)
Controls	No	Yes	Yes	Yes	Yes	Yes
Matching	No	No	PI	No	No	No
Date FE	Yes	Yes	Yes	No	Yes	Yes
Observations	778,730	712,639	136,656	712,639	300,957	407,136
R^2	0.048	0.050	0.047	0.045	0.135	0.103

Note: this table presents the regression results of OLS estimates for which the dependent variable is either flows (columns 1 to 4), negative flows (5) or positive flows (6). For all regressions, independent variables include SP, a dummy equal to one if a fund implements swing pricing, Stress, a dummy equal to one if weekly VIX CAC40 is above the 90^{th} *percentile of the sample, Cap, a dummy equal to one if a fund has a capped swing factor. In addition, columns (2) to (6) also include controls as regressors. Control variables are the lagged values of size, percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio and portfolio weighted average bid-ask spread. The coefficients of control variables are omitted in this table for the sake of clarity, however they can be found in Table A-9. Column (3) uses the sample matched on "portfolio and investors". Columns (5) and (6) use, respectively, samples with only positive and negative flows. All columns except (4) have date fixed effects, all columns have fund share fixed effects. Errors are clustered by fund shares. There is one observation per fund share and week.* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

liquidity strain, following periods of large outflows. This type of stress is complementary to systemic stress: while systemic stress has the valuable characteristic of being an exogenous shock that affects macro-financial stability, idiosyncratic stress periods are periods when outflows should be high and exceed the swing pricing activation threshold[17], and when a high level of illiquidity must be reflected in a particularly high swing factor.[18] In addition, these periods of idiosyncratic stress are particularly important from a financial stability point of view: following large redemptions, funds are expected to face further outflows as flows are auto-correlated, especially during runs (Rakowski and Wang, 2009, in our sample the auto-correlation coefficient between consecutive flows in a AR(1) is 0.167, significant at a 1 ‰ level). Furthermore, funds are facing these outflows with a deteriorated liquidity that may involve some dilution and lead to the emergence of a first-mover advantage.

We assess the impact of swing pricing on net flows during idiosyncratic stress by estimating the following equation:

$$\begin{aligned} Flows_{i,t} \sim\ & \beta_1\, SP_{i,t} + \beta_2\, Outflows_{i,t-1} + \beta_3\, Illiquidity_{i,t-1} + \beta_4\, Outflows_{i,t-1} \times SP_{i,t} \\ & + \beta_5\, Illiquidity_{i,t-1} \times SP_{i,t} + \beta_6\, Outflows_{i,t-1} \times Illiquidity_{i,t-1} \\ & + \beta_7\, SP_{i,t} \times Outflows_{i,t-1} \times Illiquidity_{i,t-1} + \beta_8\, Controls_{i,t-1} \\ & + \gamma_i + \phi_t + \epsilon_{i,t} \end{aligned} \tag{7}$$

with *Outflows* a dummy variable equal to one if net flows in period $t-1$ are lower than the first decile, *Illiquidity* a dummy variable equal to one if bid-ask spread in $t-1$ is higher than the top decile. *Controls* is a vector of controls including size, percentage of institutional investors, expense ratio, alpha, debt ratio and cash ratio of funds. γ_i and ϕ_t are fund share and date fixed effects. We estimate Equation 7 on our full sample (model 2 of Table 6 with date fixed effects and model 4 without), on our sample matched on "portfolio and investors" (model 3) and without control variables (model 1). In the Appendix, we present estimations on our sample matched on controls in Table A-12 as well as results with a looser definition of idiosyncratic stress (7^{th} decile threshold for *Illiquidity* and 3^{rd} decile threshold for *Outflows*) in Table A-13 as a robustness test.

As presented in Figure A-2-a, idiosyncratic stress (defined using our stricter definition)

[17] Recall that actual threshold are not disclosed to investors and we base our analysis only on information made public to investors.

[18] This view is consistent with the "code of conduct" of the "Association Française de la Gestion Financière" (AFG, 2016) that proposes to derive the restructuring cost as the multiplication of net flows and average portfolio bid-ask spread.

is highly correlated with the Covid-19 financial stress, however only up to 10% of funds are under idiosyncratic stress at the peak of the crisis and we also observe around 2% of investment funds facing idiosyncratic shock for each of the other periods. When we construct the variable based on the looser definition, observations of idiosyncratic stress are much more evenly distributed throughout the study period (Figure A-2-b).

Result 4. *Swing pricing increases flows during idiosyncratic stress.*

Support for Result 4: the coefficients associated with $SP \times Outflows \times Illiquidity$ in models (1) to (4) of Table 6 measure the effect of swing pricing on net flows under idiosyncratic stress. In all these models, this effect is significantly positive at the 10% confidence level (p-value between 0.056 in model 3 and 0.071 in model 4). This finding is robust to using looser thresholds for outflows and illiquidity, however, it holds with the matching "controls" only when we use the tighter thresholds (see Table A-13 and Table A-12). Our set of evidence is thus almost unanimously converging in favor of Hypothesis 4.

In a situation where outflows of the last period are particularly severe, but with an only mild illiquidity, the swing pricing activation threshold is exceeded but the swing factor could be low as the reallocation cost is moderate. In this situation, we find that swing pricing does not stabilize flows and may even generates more of them: the coefficients associated with $SP \times Outflows$ are negative (p-values between 0.008 in model 2 and 0.07 in model 3).[19] These coefficients suggest that in these situations, some investors tend to preempt their exit out of concern that they will have to bear an even higher swing factor in the following weeks, while the current swing factor does not appear to be high enough to induce them to stay in the fund. However, we note that even with this negative effect, the total impact of swing pricing during idiosyncratic stress ($SP + SP \times Outflows + SP \times Illiquidity + SP \times Outflow \times Illiquidity$) remains positive in all models.

As pointed out earlier, capped swing factor can reduce the stabilizing effect of swing pricing. In situations of idiosyncratic stress, the presence of cap should have a large impact as these are situations where the uncapped swing factor is supposed to be high. To evaluate how swing factor cap impacts flows under idiosyncratic stress, we estimate Equation 7 by successively replacing SP by a dummy variable equal to one if a fund has

[19] The impact is twice as small as $SP \times Outflows \times Illiquidity$ in column (3) with the matching "Portfolio and Investors". The coefficients of SP and $SP \times Illiquidity$ are never significant at the 10% confidence level.

a swing pricing without capped swing factor (model 5 of Table 6) and a dummy variable equal to one if a fund has a swing pricing with capped swing factor (model 6 of Table 6).[20] We estimate these models following the specification of the model (3) of Table 6 and we present the complete results in Table A-12.

Result 4-Cap. *Swing factor cap reduces the stabilizing impact of swing pricing on flows during idiosyncratic stress.*

Support for Result 4-Cap: the coefficient associated with $SP \times Outflows \times Illiquidity$ in model (6) is positive but not statistically significant. It means that with a capped swing factor, swing pricing does not increase net flows during periods of idiosyncratic stress. In contrast, a swing pricing without swing factor cap has a positive effect on net flows ($p = 0.027$). When summing all the coefficients linked to the use of uncapped swing pricing, we find an aggregate impact of swing pricing of about one fifth of the impact of the idiosyncratic shock on net flows.[21] These results are robust when using, respectively, the 70^{th} and 30^{th} percentile threshold for illiquidity and outflows (see Table A-13). We thus conclude in favor of Hypothesis 4-Cap.

Overall, we find that swing pricing reduces the sensitivity of net flows to idiosyncratic stress (situation of large previous outflows and liquidity strain). This stabilizing effect of swing pricing (average impact for all funds, with and without cap) on flows differs from previous results based on systemic stress. A potential explanation is that, during idiosyncratic stress, the magnitude of the NAV adjustments are expected to be high and swing thresholds are expected to be exceeded: the stabilizing impact is thus more likely to offset the stigma effect highlighted previously. Consistently with previous findings, our results also highlight that uncapped swing pricing exhibits a greater ability to increase financial stability compared to its capped version. This result can be explained by the induced deviation between the restructuring cost paid by the fund and the swing factor paid by redeeming investors, generating dilution.

[20] We favor this approach to avoid estimating a model with a quadruple interaction term.

[21] In column (5), the impact of an idiosyncratic shock on net flows is equal to -0.469 -0.043 -0.144 = -0.656. The impact of swing pricing during such a period is 0.056 -0.133 -0.067 +0.266 = +0.122.

Table 6: Impact of swing pricing during idiosyncratic stress

	Net flows					
	(1)	(2)	(3)	(4)	(5)	(6)
Outflows	-0.484^{***}	-0.466^{***}	-0.484^{***}	-0.486^{***}	-0.469^{***}	-0.474^{***}
	(0.015)	(0.015)	(0.042)	(0.016)	(0.015)	(0.015)
Illiquidity	-0.051^{***}	-0.060^{***}	0.026	-0.074^{***}	-0.043^{**}	-0.066^{***}
	(0.018)	(0.019)	(0.040)	(0.017)	(0.018)	(0.018)
SP	0.024	0.020	0.040	-0.033	0.056	-0.062
	(0.036)	(0.037)	(0.041)	(0.036)	(0.037)	(0.093)
SP x Outflows	-0.135^{**}	-0.146^{***}	-0.121^{*}	-0.139^{**}	-0.133^{**}	-0.168
	(0.053)	(0.056)	(0.067)	(0.056)	(0.063)	(0.108)
SP x Illiquidity	0.031	0.050	-0.001	0.043	-0.067	0.140^{**}
	(0.045)	(0.045)	(0.054)	(0.045)	(0.058)	(0.063)
Outflows x Illiquidity	-0.129^{***}	-0.144^{***}	-0.210^{**}	-0.155^{***}	-0.144^{***}	-0.122^{***}
	(0.042)	(0.042)	(0.102)	(0.043)	(0.041)	(0.040)
SP x Outflows x Illiquidty	0.184^{*}	0.193^{*}	0.270^{*}	0.203^{*}	0.266^{**}	0.135
	(0.103)	(0.106)	(0.141)	(0.106)	(0.121)	(0.163)
Type of SP	All	All	All	All	W/O Cap	W/ Cap
Matching	No	No	PI	No	No	No
Controls	No	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	No	Yes	Yes
Observations	778,730	712,639	136,656	712,639	712,639	712,639
R^2	0.054	0.055	0.053	0.051	0.055	0.055
Note:						*p<0.1; **p<0.05; ***p<0.01

Note: this table presents the regression results of OLS estimates for which the dependent variable is net flows. For all regressions, independent variables include SP, Outflows, Illiquidity and their interaction terms. $Outflows$ is a dummy equal to one if flows in period $t-1$ are lower than the first decile, and Illiquidity a dummy variable equal to one if the bid-ask spread in period $t-1$ is higher than the 9th decile. In columns (1) to (4), SP is a dummy variable equal to one if a fund uses any type of swing pricing, in column (5) it is equal to one if a fund uses a swing pricing without capped swing factor, finally in column (6) it is equal to one if a fund uses a swing pricing with capped swing factor. In addition, columns (2) to (6) also include control variables as regressors. Control variables are the lagged values of size, percentage of institutional investors, expense ratio, alpha, debt ratio and cash ratio. The coefficients of control variables are omitted in this table for the sake of clarity, however they can be found in Table A-12. Column (3) uses the sample matched on "portfolio and investors". All columns have fund share and date fixed effects, except column (4) that does not have date fixed effects. Errors are clustered by fund shares. There is one observation per fund share and week. *p<0.1; **p<0.05; ***p<0.01.

4.5 Changes in other risk management tools concomitant with swing pricing implementation

In this section, we assess changes in other risk management tools concomitant with swing pricing implementation to determine whether swing pricing is used in place of these other tools—hypothesis of substitutability—or in combination with their reinforcement—hypothesis of complementarity. Substitutability would indicate that swing pricing is identified by fund managers as an option to provide relatively less costly financial resilience than other tools. Complementarity would be consistent with a swing pricing implementation that is part of a more global willingness of fund managers to increase resilience.

To comprehend the evolution of the other lines of defense, we focus on cash buffer, debt ratio, and liquidity of assets held. We analyze changes in the wake of the swing pricing implementation to increase the likelihood of identifying changes driven by managerial choices concomitant with the implementation of swing pricing instead of indirect consequences of its use. To illustrate this difference, we can consider an increase in cash buffers of a fund with swing pricing: it can be driven by (i) manager's willingness to increase the fund's stability via higher cash buffers, or (ii) a reduction of outflows-induced sales of the most liquid assets (under the "waterfall" approach for asset liquidation for example, Scholes, 2000) that would reduce the pressure on the cash reserves (Chernenko and Sunderam, 2016). In the first case, we would expect it to be already noticeable when swing pricing is implemented or in the weeks that follow, otherwise its impact is expected to be more gradual.

To analyze the short-term impact of swing pricing introduction, we perform a staggered difference-in-differences on the variables studied. The first difference comes from the comparison of funds implementing swing pricing and their matched funds (see Section 3.2). The second difference comes from a before/after implementation comparison. We conduct this comparison ten weeks before and after the swing pricing implementation to identify if some variables evolve simultaneously with the swing pricing implementation. We estimate the following regression on the sample of treated and matched funds centered on the date of implementation:

$$Y_{i,t} \sim \beta_0 + \beta_1 Treated_i + \sum_{t=-10}^{10} (\beta_{2t} RelativeDate_t + \beta_{3t} RelativeDate_t \times Treated_i) + \epsilon_{i,t} \tag{8}$$

with $Y_{i,t}$ the dependent variable (bid-ask spread, debt ratio, cash ratio or net flows), residualized with a date fixed effects in order to be able to compare values for funds implementing swing pricing at different dates. $RelativeDate$ is a dummy for each date relative to the implementation of swing pricing by a treated fund, and $Treated$ a dummy equal one if a fund will implement swing pricing at the relative date zero. All time-varying coefficients are expressed by comparison with the mean of the ten weeks before the swing pricing implementation.[22]

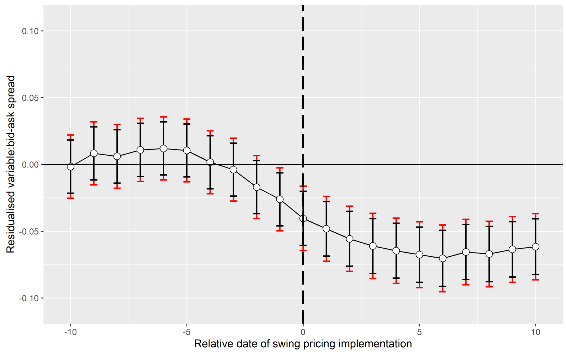
Result 5. *Fund managers do not substitute other lines of defense with swing pricing.*

Support for Result 5: Figure 3 presents how the use of other tools to manage funds' liquidity is revised following the swing pricing implementation. Formally, the coefficients plotted correspond to the interaction terms between being treated and the date relative to the swing pricing implementation (coefficients $\beta_{3,t}$ of Equation 8) estimated using the matching "portfolio and investors". We do not find that funds implementing swing pricing reduce their cash ratio, increase their debt ratio or the average bid-ask spread of their portfolio (no negative coefficients significant at a 10% threshold for *Cash*, no positive ones for *Debt* and *Bid-ask spread*). These results do not support Hypothesis 5 as swing pricing does not appear to be considered in France by fund managers as a substitute for other means of providing financial resilience.

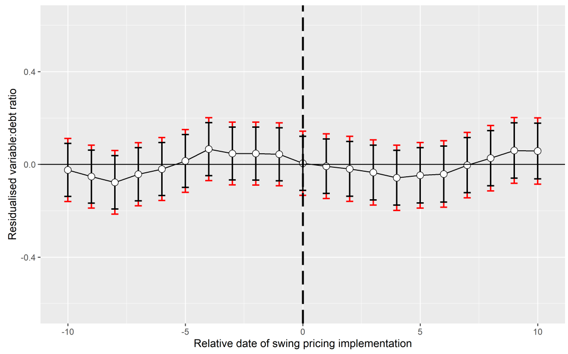
On the contrary, swing pricing is even associated with an increase in asset liquidity: we find a decrease in the average bid-ask spread of fund portfolios starting one week before the swing pricing implementation (p-value < 0.001 for all periods after the swing pricing implementation, model a). These results are robust to using the matching "controls" as presented in Figure A-3. With this matching, we find another effect pointing towards an increase of the other lines of defense: a temporary reduction of the debt ratio during a few weeks immediately after the swing pricing implementation (p-value < 0.001 for weeks

[22] Our sample includes all funds that implemented swing pricing during our study period, funds are included even if we do not observe the entire ten weeks following and preceding the introduction of swing pricing.

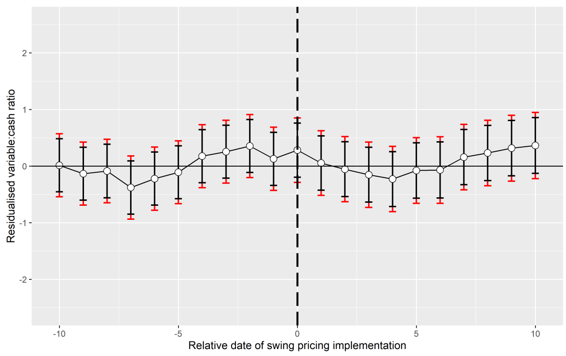
Figure 3: Differences in characteristics between funds with and without swing pricing ("portfolio and investors" matching)



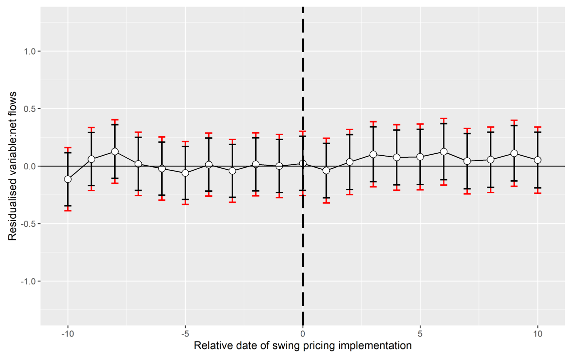
(a) Bid-ask spread



(b) Debt



(c) Cash



(d) Net flows

Note: These figures show the immediate effect of swing pricing implementation on six dependent variables: weighted-average bid-ask spread of the portfolio (a), debt ratio (b), cash ratio (c) and net flows (d). All dependent variables are residualized by controlling for date fixed effects. The dots correspond to the coefficients β_3 estimated based on the Equation 8 equation presenting the staggered difference-in-differences methodology. Treated is equal to one if a fund implements swing pricing at the relative date zero. We plot the interaction coefficients between Treated and all the relative dates (y-axis), between -10 and 10: ten weeks before and ten weeks after the implementation of swing pricing (x-axis). Black solid vertical bars are 95% confidence intervals, red solid vertical bars are 99% confidence intervals, the black dotted vertical bars indicate the implementation date and the black solid horizontal bar indicates the value zero. All variables are four-week rolling moving averages. The sample is constructed with the matching methodology "Portfolio & investors". There is one observation per fund share and week. We cluster standard errors by fund shares.

0 to 3 after the swing pricing implementation, model b). However, this effect vanishes four weeks after swing pricing implementation and it is not robust to using the matching "portfolio and investors".

These results suggest that swing pricing implementation is generally not done in isolation but usually goes with a broader plan to reduce the liquidity mismatch, by also diminishing the average illiquidity of the portfolio (we also find weak evidence of a decreased debt ratio). We thus conclude that swing pricing is not considered in France by fund managers as a substitute for traditional lines of defense, but rather as a complement.

This result is in line with the fact that the funds implementing swing pricing have a higher liquidity mismatch before the implementation of swing pricing as presented in Section 4.1.

Finally, we analyze the immediate impact of swing pricing implementation on net flows to further document the impact of swing pricing on flow dynamics. We do not observe either specific inflows or outflows from funds that implement swing pricing at a 10% confidence level as presented in figure (d) (the p-value is above 50% during most periods). This result is consistent with the absence of any impact of swing pricing on net flows outside of financial stress periods, as presented in Table 4. It is important to note that, unlike other LMTs (e.g. gates), a specificity of swing pricing in France is that its implementation does not trigger a free exit option (see DOC-2011-20 of the AMF, p16) that would provide incentives to redeem shares at implementation.

5 Discussion and conclusion

The March 2020 market turmoil has reignited concerns about the amplification of financial stability risks by open-end funds. Through their activity of liquidity transformation, investment funds can cause financial stability risks. At the height of the Covid-19 crisis, investment funds experienced intensive outflows in a context of severely reduced market liquidity. This episode stimulated discussions about the resilience of investment funds, the size of their liquidity gap, their use of the liquidity management tools available to them, and the impact and adequacy of these tools for financial stability, particularly in times of turmoil.

Using a novel approach based on a text-mining analysis of fund prospectuses, we identify the use of swing pricing by French investment funds from 2018 to 2020, as well as its modalities. We observe that swing pricing has considerably gained in popularity among French investment funds (more than twice as many funds use swing pricing at the end of 2020 compared to the beginning of 2018). We also identify that this tool is associated with constraints on its activation and magnitude: almost all funds use an activation threshold and a quarter use capped swing factors (with an upper limit of around 2%).

As currently used in France, our results suggest that swing pricing has only a limited impact on the financial stability of funds during periods of systemic stress such as the Covid-19 turmoil. We find that this tool does not decrease volatility and that funds with swing pricing suffer additional outflows. However, we find that this result is deeply related to the type of swing pricing currently used in France: almost all funds with swing pricing use an activation threshold and more than a quarter of them use a capped swing factor. When focusing only on funds without a swing factor cap, we find that swing pricing stabilizes flow dynamics during systemic stress: volatility is reduced as well as outflows.

Our study thus informs on the detrimental effects of having a capped swing pricing in line with Capponi et al. (2020). It may be explained by the gap created between actual and unconstrained swing factors when the swing factor is capped, preventing accurate internalization of reorganization costs and thus increasing the risk of dilution. Furthermore, the higher the cost of reorganization the larger the gap, mitigating the stabilizing impact when it is the most needed. Complementing the analysis based on systemic stress, we focus on the impact of swing pricing during idiosyncratic stress—situations of large past outflows and liquidity strain. Contrasting with systemic stress, we find that swing pricing increases flows. Idiosyncratic stress is expected to be associated with large NAV adjustment and exceeded swing threshold (for partial swing pricing). The stabilizing impact is thus more likely to offset a stigma effect as highlighted previously. We observe that the stabilizing impact of swing pricing vanishes also during idiosyncratic stress for funds with a swing factor cap, providing additional evidence of the adverse effects of capping swing factors.

Our finding on the ineffectiveness of swing pricing to limit outflows in times of systemic stress relates to the literature based on the diffusion of caps in studied jurisdictions. Indeed, Lewrick and Schanz (2017a) find that swing pricing has a limited effect during stress episodes in Luxembourg, a jurisdiction where it is mandatory for fund managers to have a cap on the level of swing factor applied (ALFI, 2015). On the contrary, Jin et al. (2022) find a strong stabilizing impact of swing pricing for bond funds in the United Kingdom, where only around 6% of funds with swing pricing use a swing factor cap, ranging from 0.25% to 3% (Bank of England, 2021).

To conclude, we find that swing pricing has the ability to reduce the exposition of investment funds to risks of fire sales. However, the swing pricing calibration is of paramount importance to achieve the intended objective, as the use of swing factor cap appears to have detrimental effects. To maximize its stabilizing impact, we thus recommend using swing pricing without swing factor cap—and authorities to encourage funds not to use caps. This recommendation could lead to important changes as some authorities in the largest jurisdictions provide guidelines or regulations in favor of the use of a capped swing factor.[23]

[23]Comparable to Luxembourg, the amendments to the SEC 22c-1 Rule impose a 2% cap on the swing factor in the United States.

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APPENDIX

A Data and descriptive statistics

A.1 Variable definition

Table A-1: Variable definition

Label	**Definition**	**Units**	**Frequency**
Stress	Dummy variable equal one if VIX index above the 90^{th} percentile		w
SP	Dummy variable equal to one if the fund mentions using a swing pricing mechanism in its prospectus		w
Flows	Fund's net flows divided by previous period TNA	%	w
Volatility	3-month rolling standard deviation of the fund's net flows divided by previous period TNA	%	w
Size	Natural logarithm of the fund total net asset	€	w
Alpha	Intercept from a regression of weekly excess fund returns and weekly excess fund's benchmark return. Risk free rate given by French government bond 10Y. Regression at a fund level using a 3 months rolling-window		w
Bid-ask Spread	Fund's portfolio value-weighted bid-ask spread based on weekly prices and monthly holdings.		w
Institutional	Total value of shares held by institutional investor divided by total value of shares.	%	q
Expense	Total costs associated with managing and operating an investment fund divided by fund's TNA	%	w
Debt	Total loans received divided by total assets/liabilities	%	m
Cash	Total deposit claims divided by total assets/liabilities	%	m
Type fund	Fund's investment strategy in four categories: 'Equity', 'Bond', 'Money-market funds' and 'Other'.		
Age	Age of the fund as of December 2017	Year	
NAV frequency	Number of days between two consecutive NAV publications (a NAV frequency of one indicates a daily NAV)	Day	

Note: The notation for the frequency column is "w" for weekly, "m" for monthly, "q" for quarterly and empty for time-invariant variables.

A.2 Identification of swing pricing

In order to identify which investment funds use a swing pricing mechanism, our study is based on a data mining approach that uses investment fund prospectuses as an input. This prospectuses are in PDF format. There is one prospectus per fund per update date, or every six months maximum if no update has been detected.

Regarding the content of the PDFs, we first standardize words by removing non-alphabetic characters, make them lower case, and stem words (process of finding the root word) by applying the French stemmer dictionary developed by Bird (2006). We create a bag-of-words for each sentence, keeping the information of the start and end of each sentence.

Then, we identify the presence of swing pricing if the words "swing" and "pricing" are present in the document, in the same sentence, within 10 words of each other. If the words "partial" or "threshold" are also present in the same sentence within a radius of 10 words around "swing", then a partial swing pricing is identified. The presence of the words "adjustment", "liquidative" and "value" next to each other also trigger a detection of the swing pricing mechanism if "partial" and/or "threshold" are also close to this expression. Because words have been stemmed, any variation of these words are also considered by our algorithm, for example singular/plural variations. The wording for indicating in a prospectus the use of swing pricing is fairly standardised and most funds use the wording proposed as an example by the AMF. However, this methodology cannot be applied for umbrella funds as they publish a single prospectus containing information on all sub-funds and some sub-funds can use single pricing while other do not. Our algorithm cannot distinguish in this case which sub-funds use swing pricing. To circumvent this shortcoming, if the PDF is longer than 60 pages, there are more than 10 ISINs present indicated in the prospectus and there is a textual reference to an "umbrella fund", the PDF is identified as a prospectus of an umbrella funds. These prospectuses are analyzed manually. Some examples of sentences that trigger the identification of swing pricing use by our algorithm are:

- "As of October 10, 2016, the management company has implemented a net asset value (NAV) adjustment method (swing pricing) with a triggering threshold" (ISIN FR0000003196)
- "Adjustment method of the net asset value linked to swing pricing with trigger threshold: In order not to penalize holders remaining in the fund, an adjustment factor will be applied to those who subscribe or redeem significant amounts of the fund's assets, which is likely to generate costs for holders entering or leaving the fund, which would otherwise be charged to holders present in the fund" (ISIN FR0013365129).
- "A swing pricing mechanism has been implemented by the management company as part of its valuation" (ISIN FR0000011074)
- "Swing pricing: if net subscription and redemption orders valued at the last available net asset value on a valuation day exceed a certain threshold on that valuation day, as determined and revised periodically by the management company, the net asset value may be adjusted upwards or downwards to reflect trading costs and other costs that may be incurred when buying or selling assets to cover the daily net transactions" (ISIN FR0000289027)

Finally, we detect the presence of a swing factor cap. Once the swing pricing is identified, we look 100 words past where the mechanism was identified. If the word "exceeded" is present, we check if the word "risk" is present more than five times. If it is, that means we have moved on to another section of the prospectus dealing with the composition of the portfolio and the associated level of risk. If not, we assume that we are in the section of the document that is of interest to us and we look for the symbol or the word "percentage". We then identify the number directly before if it is lower than 10. If there is more than one, then the case is treated manually. An example of a sentence with this information can be: "It is also not possible to predict exactly how often the management company will have to make such adjustments, **which may not exceed 1.50% of the NAV**" (ISIN FR0013365129).

Our algorithm detects the use of swing pricing. It does not detect the activation of the swing pricing mechanism (as the swing pricing activation threshold is kept secret) nor the intensity of the swing factor (as the values and the formula are kept secret). Thus, we use the same level of information that investors have when making investment decisions.

A.3 Summary Statistics

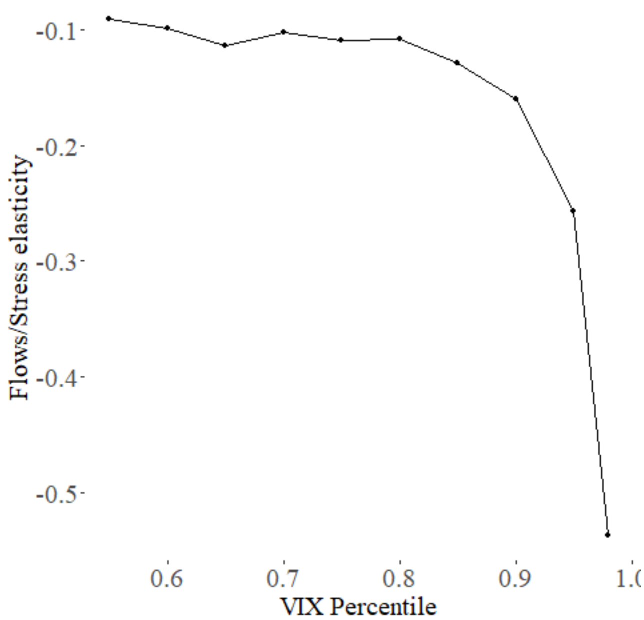
Table A-2: Summary Statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Main variables						
Flows	−0.04	1.86	−26.92	−0.14	0.01	11.26
Volatility	1.06	1.36	0.00	0.12	1.53	12.69
Swing-related variables						
Swing pricing	0.09	0.28	0	0	0	1
Cap	0.03	0.17	0	0	0	1
Other share time-varying variables						
TNA (in M€)	97.21	354.33	0.01	5.99	77.59	19,445
Institutional	72.54	28.44	0.00	56.40	98.30	100
Alpha	−0.03	0.39	−1.35	−0.18	0.10	1.57
Debt	0.85	2.43	0.00	0.00	0.32	14.63
Cash	3.92	6.62	0.00	0.27	4.96	55.58
Bid-ask spread	0.39	0.28	0.03	0.18	0.50	1.50
Other share-level variables						
Type of fund						
Equity	40.58	49.11	0	0	100	100
Bond	21.26	40.91	0	0	0	100
Other	38.15	48.58	0	0	100	100
Age	14.01	9.50	0.70	6.30	19.80	56.10
Expense	1.61	0.83	0.00	1.02	2.13	7.49
Redemption charges	0.42	1.28	0.00	0.00	0.00	12.50
NAV frequency	1.69	1.91	1	1	1	7
Macroeconomic variable						
VIX crisis	0.10	0.30	0	0	0	1

A.4 VIX CAC40 and stress

Following Jin et al. (2022); Kacperczyk et al. (2021), we construct a dummy variable of stress based on a continuous index of market stress. To determine the appropriate threshold, we use the elbow method. We iteratively define different stress variables equal to one if the VIX CAC40 is above a certain percentile. Then, we regress each stress variable on investment fund flows using OLS regressions. Finally, we select the 90% percentile for being at the elbow of the curve in Figure A-1.

Figure A-1: Impact of stress of flows for different stress levels



Note: The flows/systemic stress elasticities are estimated using OLS regressions. For each point, the variable Stress is equal to one for all periods when a VIX CAC40 is above the percentile indicated on the x-axis.

A.5 Matching methodologies

This section presents the variables used in our matching on portfolio and investors, as well as descriptive statistics on the quality of our matching method.

A.5.1 Categories of the "portfolio and investors" matching method

- **NACE sector of the issuer**: manufacturing, construction, wholesale activities, information and communication, financial activities, Scientific and technical activities, Public administration and defence and other (all other modalities that represent less than 5% of the total).

- **Geographic area of the issuer**: France, Germany, Luxembourg, United Kingdom, East Europe, North Europe, South Europe, Asia, North America and Other (all other modalities that represents less than 5% of the total)

- **Institutional sector of the issuer** (based on the ESA 2010 classification): NFC Public, NFC Private Monetary financial institutions, Non-MMF investment funds, financial intermediaries, Captive financial institutions, Government and Other (all other modalities that represent less than 5% of the total).

- **Type of instrument held** (based on the ESA 2010 classification): Debt securities - Short-term, Debt securities - Long-term, Equity and Investment fund shares.
- **Rating of the instruments**: from AAA to D (22 levels of rating).
- **Type of investors**: Insurance, Banks, Investment funds, NFC, Government and Households.

A.5.2 Descriptive statistics on matching methods

Table A-3: Quality of the matching methodology "Controls"

	No matching	With matching
Flows	0.248	0.103
Volatility	0.469	0.171
TNA	0.115	0.054
Institutional	0.425	0.032
Alpha	0.167	0.019
Bidask	0.129	0.052
Age	1.122	0.403
Expense	0.376	0.001

Note: This table reports the difference of means between funds that will use swing pricing and the others, with and without the matching "controls", for each variable that is used to construct this matching (lower part of the table) and other benchmark variables (upper part). The sample period is Q1 2018.

Table A-4: Quality of the matching methodology "Portfolio and investors"

	No matching	With matching
Flows	0.248	0.178
Volatility	0.469	0.317
NACE sector of the issuer	11.569	1.948
Geographic area of the issuer	13.353	5.563
Institutional sector of the issuer	21.999	5.847
Type of instrument held	37.484	10.473
Rating of the instruments	2.889	0.889
Type of investors	15.691	3.184

Note: This table compares funds that will use swing pricing and the others, with and without the matching "controls", for each variable that is used to construct this matching (lower part of the table) and other benchmark variables (upper part). The difference of each categorical variable is compute as the sum of the absolute differences of the mean percentages of allocation in each category. It thus ranges from 0 to 200 and the percentage difference is given by the index divided by 2. For continuous variables, it reports the difference of means. Ratings of instruments are expressed on a numerical scale and are thus considered as continuous. The sample period is Q1 2018.

B Factors driving the swing pricing implementation

Table A-5 is a robustness check of Table 1 as it replicates the regressions with *Treated* a dummy variable equal to one if a fund implements swing pricing between June 2018 and December 2020 in columns (1) to (4) and between January 2019 to December 2020 in columns (5) to (8). Shares with swing pricing before respectively June 2018 and January 2019 are excluded from the estimation sample.

Table A-5: Individuals characteristics and probability to implement swing pricing

	Swing pricing implementation		SP without cap	SP with cap	Swing pricing implementation		SP without cap	SP with cap
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flow percent	−0.057	−0.045	−0.043	−0.003	−0.049	−0.049	0.003	−0.052***
	(0.035)	(0.035)	(0.032)	(0.015)	(0.042)	(0.042)	(0.039)	(0.017)
Volatility	0.103***	0.093***	0.068***	0.025**	0.050**	0.047**	0.025	0.022**
	(0.023)	(0.023)	(0.021)	(0.010)	(0.021)	(0.021)	(0.019)	(0.009)
Bid-ask spread	1.336***	1.461***	1.690***	−0.229***	0.698***	0.687***	0.801***	−0.114***
	(0.134)	(0.143)	(0.130)	(0.063)	(0.096)	(0.104)	(0.095)	(0.042)
Size	−0.013	−0.011	0.014	−0.026***	0.001	0.002	0.016	−0.014**
	(0.019)	(0.019)	(0.017)	(0.008)	(0.015)	(0.015)	(0.014)	(0.006)
Age	0.004	0.003	0.004	−0.002	−0.001	−0.002	−0.0001	−0.002
	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
NAV frequency	−0.052***	−0.041***	−0.031**	−0.010	−0.028**	−0.025**	−0.021*	−0.005
	(0.015)	(0.016)	(0.014)	(0.007)	(0.012)	(0.012)	(0.011)	(0.005)
Institutional ratio	0.0001	0.001	−0.00001	0.001	0.0001	0.0003	0.0001	0.0002
	(0.001)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.0003)
Alpha	−0.115	−0.032	−0.015	−0.017	−0.213	−0.193	−0.404***	0.211***
	(0.081)	(0.085)	(0.077)	(0.037)	(0.164)	(0.164)	(0.150)	(0.067)
Debt ratio	0.009	0.008	0.026*	−0.018***	0.022*	0.022*	0.033***	−0.011**
	(0.016)	(0.016)	(0.014)	(0.007)	(0.013)	(0.013)	(0.012)	(0.005)
Cash ratio	−0.004	−0.001	−0.002	0.001	−0.005	−0.004	−0.005	0.001
	(0.005)	(0.005)	(0.004)	(0.002)	(0.004)	(0.004)	(0.004)	(0.002)
Total expense ratio	−0.136***	−0.124***	−0.164***	0.040**	−0.029	−0.014	−0.070**	0.056***
	(0.034)	(0.039)	(0.035)	(0.017)	(0.027)	(0.031)	(0.028)	(0.013)
Type fund: Other		−0.249***	−0.209***	−0.040		−0.033	0.025	−0.058***
		(0.069)	(0.063)	(0.030)		(0.053)	(0.048)	(0.021)
Type fund: Bond		0.040	−0.151*	0.191***		0.064	0.026	0.039
		(0.096)	(0.087)	(0.042)		(0.074)	(0.067)	(0.030)
Sample	All	All	All	All	All	All	All	All
Beginning sample	Q3 2018	Q3 2018	Q3 2018	Q3 2018	Q1 2019	Q1 2019	Q1 2019	Q1 2019
Observations	4,025	4,025	4,025	4,025	4,470	4,470	4,470	4,470
R^2	0.038	0.042	0.051	0.021	0.016	0.017	0.025	0.019

Note: *p<0.1; **p<0.05; ***p<0.01

C Swing pricing and flow volatility

Table A-6 and Table A-7 respectively replicate the three last columns of Table 2 and Table 3 while giving the coefficients of the controls in columns (1) to (3). In addition, column (4) replicates column (2) using the matched sample based on controls.

Table A-6: Impact of swing pricing on flow volatility

	Volatility			
	(1)	(2)	(3)	(4)
Stress			0.274^{***}	
			(0.016)	
SP	0.004	0.032	-0.112^{**}	0.054
	(0.051)	(0.059)	(0.051)	(0.061)
SP x Stress	-0.044	-0.095	-0.039	-0.080
	(0.055)	(0.074)	(0.054)	(0.078)
Size	-0.0005	0.001	-0.001	0.0001
	(0.001)	(0.002)	(0.001)	(0.002)
Institutional	-0.001	0.007^{**}	-0.001	0.006^{**}
	(0.001)	(0.003)	(0.001)	(0.003)
Total expense	-0.033	-0.314^{**}	-0.007	-0.241^{**}
	(0.036)	(0.124)	(0.036)	(0.123)
Alpha	-0.042^{***}	-0.088^{**}	-0.152^{***}	-0.110^{***}
	(0.014)	(0.039)	(0.014)	(0.040)
Debt	-0.006^{*}	-0.016^{**}	-0.005	0.002
	(0.004)	(0.007)	(0.004)	(0.007)
Cash	0.009^{***}	0.003	0.010^{***}	0.005
	(0.002)	(0.004)	(0.002)	(0.004)
Bid-ask spread	-0.112^{**}	-0.114	-0.021	-0.084
	(0.046)	(0.073)	(0.041)	(0.087)
Matching	No	PI	No	Controls
Date FE	Yes	Yes	No	Yes
Observations	662,241	127,077	662,241	127,321
R^2	0.362	0.325	0.349	0.322

Note: this table presents the regression results of OLS estimates for which the dependent variable is flow volatility defined as the 3-month standard deviation of the weekly net flows. For all regressions, independent variables include SP, a dummy equal to one if a fund uses swing pricing, Stress, a dummy equal to one if weekly VIX CAC40 is above the 90^{th} percentile of the sample and the interaction of the two variables. All columns include control variables as regressors: lagged values of size, percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio and portfolio weighted average bid-ask spread. Column (2) uses the sample matched on "portfolio and investors" and column (4) the sample matched on "controls". All columns except column (3) have date fixed effects, all columns have fund share fixed effect. Errors are clustered by fund shares. There is one observation by fund share per week. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A-7: Impact of swing pricing and swing factor cap on flow volatility

	Volatility			
	(1)	(2)	(3)	(4)
Stress			0.275^{***}	
			(0.016)	
SP	0.014	0.039	-0.107^{**}	0.064
	(0.054)	(0.061)	(0.053)	(0.064)
SP x Cap	0.034	0.050	0.073	0.033
	(0.119)	(0.121)	(0.120)	(0.121)
SP x Stress	-0.163^{***}	-0.214^{***}	-0.153^{***}	-0.202^{**}
	(0.058)	(0.077)	(0.058)	(0.081)
SP x Cap x Stress	0.368^{***}	0.366^{***}	0.354^{***}	0.365^{***}
	(0.121)	(0.121)	(0.121)	(0.124)
Size	−0.0004	0.001	−0.001	0.0002
	(0.001)	(0.002)	(0.001)	(0.002)
Institutional	−0.001	0.007^{**}	−0.001	0.006^{**}
	(0.001)	(0.003)	(0.001)	(0.003)
Total expense	−0.034	-0.327^{***}	−0.008	-0.250^{**}
	(0.036)	(0.123)	(0.036)	(0.123)
Alpha	-0.041^{***}	-0.086^{**}	-0.152^{***}	-0.107^{***}
	(0.014)	(0.039)	(0.014)	(0.040)
Debt	-0.006^{*}	-0.016^{**}	−0.005	0.002
	(0.004)	(0.007)	(0.004)	(0.007)
Cash	0.009^{***}	0.003	0.010^{***}	0.005
	(0.002)	(0.004)	(0.002)	(0.004)
Bid-ask spread	-0.121^{***}	-0.135^{*}	−0.028	−0.110
	(0.046)	(0.073)	(0.041)	(0.088)
Matching	No	PI	No	Controls
Date FE	Yes	Yes	No	Yes
Observations	662,241	127,077	662,241	127,321
R^2	0.362	0.326	0.349	0.323

Note: this table presents the regression results of OLS estimates for which the dependent variable is flow volatility defined as the 3-month standard deviation of the weekly net flows. For all regressions, independent variables include SP, a dummy equal to one if a fund uses swing pricing, Cap, the number of constraints on the swing pricing, Stress, a dummy equal to one if weekly VIX CAC40 is above the 90^{th} *percentile of the sample and the interaction of these three variables. As funds cannot have Cap without swing pricing, no coefficients are associated with Cap alone. All columns include control variables as regressors: lagged values of size, percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio and portfolio weighted average bid-ask spread. Column (2) uses the sample matched on "portfolio and investors" and column (4) the sample matched on "controls". All columns except column (3) have date fixed effects, all columns have fund share fixed effect. Errors are clustered by fund shares. There is one observation by fund share per week.* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

D Impact of swing pricing on the level of flows

Table A-8 and Table A-9 respectively replicate columns (2) to (4) of Table 4 and Table 5 while giving the coefficients of the controls. In addition, column (4) replicates column (2) using the matched sample based on controls. Table A-10 and Table A-11 respectively replicate columns (5) and (6) of Table 4 in column (2). In addition, they provide robustness by estimating the specifications without controls (column 1), on the sample matched on "portfolio and investors" (column 3) and matched on "controls" (column 4). Similarly, they respectively replicate, in column (6), column (5) and column (6) of Table 5.

Table A-8: Impact of swing pricing on flow level

	Flows			
	(1)	(2)	(3)	(4)
Stress			-0.085^{***}	
			(0.012)	
SP	0.034	0.023	-0.004	0.046
	(0.038)	(0.043)	(0.037)	(0.042)
SP x Stress	-0.083^{**}	-0.038	-0.072^{*}	-0.058
	(0.039)	(0.053)	(0.039)	(0.055)
Size	-0.005^{***}	-0.003	-0.005^{***}	-0.006^{*}
	(0.002)	(0.003)	(0.002)	(0.003)
Institutional	0.0004	0.002	-0.0002	-0.001
	(0.001)	(0.002)	(0.001)	(0.002)
Total expense	0.087^{***}	0.108	0.123^{***}	0.086
	(0.029)	(0.098)	(0.028)	(0.078)
Alpha	0.037^{***}	-0.003	0.019^{*}	0.039
	(0.011)	(0.034)	(0.011)	(0.033)
Debt	-0.025^{***}	-0.006	-0.027^{***}	0.005
	(0.004)	(0.009)	(0.004)	(0.008)
Cash	0.020^{***}	0.020^{***}	0.020^{***}	0.020^{***}
	(0.002)	(0.005)	(0.002)	(0.005)
Bid-ask spread	-0.246^{***}	-0.191^{***}	-0.158^{***}	-0.165^{**}
	(0.037)	(0.065)	(0.033)	(0.071)
Matching	No	PI	No	Controls
Date FE	Yes	Yes	No	Yes
Observations	712,639	136,656	712,639	136,960
R^2	0.049	0.047	0.045	0.049

Note: this table presents the regression results of OLS estimates for which the dependent variable is net flows. For all regressions, independent variables include SP, a dummy equal to one if a fund uses swing pricing, Stress, a dummy equal to one if weekly VIX CAC40 is above the 90^{th} percentile of the sample and the interaction of the two variables. All columns include control variables as regressors: lagged values of size, percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio and portfolio weighted average bid-ask spread. Column (2) uses the sample matched on "portfolio and investors" and column (4) the sample matched on "controls". All columns except column (3) have date fixed effects, all columns have fund share fixed effect. Errors are clustered by fund shares. There is one observation by fund share per week. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A-9: Impact of swing pricing and swing factor cap on flow level

	Flows			
	(1)	(2)	(3)	(4)
Stress			-0.085^{***}	
			(0.012)	
SP	0.026	0.014	-0.015	0.040
	(0.039)	(0.044)	(0.038)	(0.042)
SP x Cap	-0.012	-0.008	-0.002	-0.029
	(0.098)	(0.099)	(0.096)	(0.099)
SP x Stress	0.0005	0.046	0.020	0.028
	(0.038)	(0.052)	(0.038)	(0.054)
SP x Cap x Stress	-0.257^{***}	-0.259^{***}	-0.286^{***}	-0.258^{***}
	(0.093)	(0.092)	(0.093)	(0.094)
Size	-0.005^{***}	-0.003	-0.005^{***}	-0.006^{*}
	(0.002)	(0.003)	(0.002)	(0.003)
Institutional	0.0004	0.002	-0.0002	-0.001
	(0.001)	(0.002)	(0.001)	(0.002)
Total expense	0.087^{***}	0.116	0.123^{***}	0.092
	(0.029)	(0.098)	(0.028)	(0.078)
Alpha	0.037^{***}	-0.004	0.019^{*}	0.038
	(0.011)	(0.034)	(0.011)	(0.033)
Debt	-0.025^{***}	-0.006	-0.027^{***}	0.005
	(0.004)	(0.009)	(0.004)	(0.008)
Cash	0.020^{***}	0.020^{***}	0.019^{***}	0.019^{***}
	(0.002)	(0.005)	(0.002)	(0.005)
Bid-ask spread	-0.240^{***}	-0.177^{***}	-0.152^{***}	-0.147^{**}
	(0.037)	(0.065)	(0.033)	(0.071)
Matching	No	PI	No	Controls
Date FE	Yes	Yes	No	Yes
Observations	712,639	136,656	712,639	136,960
R^2	0.050	0.047	0.045	0.050

Note: this table presents the regression results of OLS estimates for which the dependent variable is net flows. For all regressions, independent variables include SP, a dummy equal to one if a fund uses swing pricing, Cap, the number of constraints on the swing pricing, $Stress$, a dummy equal to one if weekly VIX CAC40 is above the 90^{th} percentile of the sample and the interaction of these three variables. As funds cannot have cap without swing pricing, the coefficient of Cap (without interaction) is omitted. All columns include control variables as regressors: lagged values of size, percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio and portfolio weighted average bid-ask spread. Column (2) uses the sample matched on "portfolio and investors" and column (4) the sample matched on "controls". All columns except column (3) have date fixed effects, all columns have fund share fixed effect. Errors are clustered by fund shares. There is one observation by fund share per week. *p<0.1; **p<0.05; ***p<0.01.

Table A-10: Impact of swing pricing and swing factor cap on negative flows

	Negative flows							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SP	0.049	0.040	0.021	0.029	0.033	0.020	0.008	0.003
	(0.038)	(0.040)	(0.045)	(0.047)	(0.040)	(0.040)	(0.048)	(0.046)
SP x Cap					0.043	0.066	0.062	0.055
					(0.111)	(0.134)	(0.136)	(0.135)
SP x Stress	-0.021	0.008	0.040	0.036	0.092^{*}	0.123^{**}	0.153^{**}	0.154^{**}
	(0.052)	(0.053)	(0.070)	(0.073)	(0.053)	(0.051)	(0.071)	(0.068)
SP x Cap x Stress					-0.366^{***}	-0.391^{***}	-0.383^{***}	-0.382^{***}
					(0.124)	(0.132)	(0.133)	(0.131)
Size		-0.003	-0.00001	-0.004		-0.003	-0.004	0.00001
		(0.002)	(0.004)	(0.004)		(0.002)	(0.004)	(0.004)
Institutional		0.001	-0.003	-0.004^{**}		0.001	-0.004^{**}	-0.003
		(0.001)	(0.002)	(0.002)		(0.001)	(0.002)	(0.002)
Total expense		0.042^{*}	0.259^{***}	0.209^{**}		0.042^{*}	0.216^{**}	0.267^{***}
		(0.024)	(0.089)	(0.089)		(0.024)	(0.089)	(0.088)
Alpha		0.048^{***}	0.059^{*}	0.072^{**}		0.048^{***}	0.070^{**}	0.058
		(0.010)	(0.035)	(0.036)		(0.010)	(0.035)	(0.035)
Debt		-0.014^{***}	0.003	0.003		-0.014^{***}	0.002	0.002
		(0.004)	(0.007)	(0.007)		(0.004)	(0.007)	(0.007)
Cash		0.003	0.007^{*}	0.007^{*}		0.002	0.007^{*}	0.007^{*}
		(0.002)	(0.004)	(0.004)		(0.002)	(0.004)	(0.004)
Bid-ask spread		-0.049	-0.032	0.038		-0.042	0.059	-0.015
		(0.035)	(0.058)	(0.065)		(0.035)	(0.065)	(0.057)
Matching	No	No	PI	Controls	No	No	PI	Controls
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	447,651	407,136	78,961	78,776	447,651	407,136	78,776	78,961
R^2	0.103	0.102	0.091	0.091	0.103	0.103	0.091	0.091

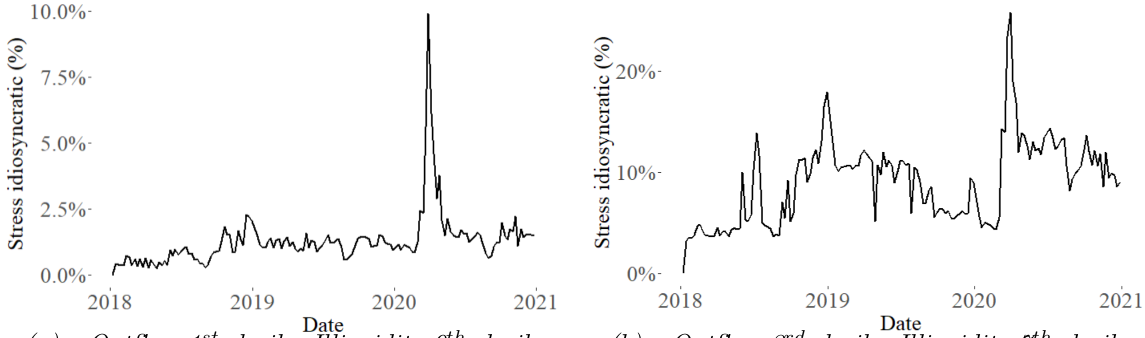
Note: this table presents the regression results of OLS estimates for which the dependent variable is negative flows. For regressions in columns (1) to (4), regressors include SP, a dummy equal to one if a fund uses swing pricing, and $Stress$, a dummy equal to one if weekly VIX CAC40 is above the 90^{th} percentile of the sample and the interaction of these variables. For regression columns (5) to (8), regressors also include Cap, equal to one for capped swing factors, and its interaction with SP and $Stress$. Columns (3), and (7) use the sample matched on "portfolio and investors" while Columns (4), and (8) use the sample matched on "Controls". All columns have date fixed effects and fund share fixed effect. All columns include control variables as regressors: lagged values of size, percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio and portfolio weighted average bid-ask spread. Control variables are one-week lagged values. Errors are clustered by fund shares. There is one observation by fund share per week. *p<0.1; **p<0.05; ***p<0.01.

Table A-11: Impact of swing pricing and capped swing factor on positive flows

	Positive flows							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SP	0.065	0.062	0.059	0.104^{*}	0.061	0.071	0.117^{*}	0.068
	(0.052)	(0.053)	(0.059)	(0.060)	(0.056)	(0.057)	(0.064)	(0.063)
SP x Cap					0.015	−0.052	−0.076	−0.054
					(0.116)	(0.126)	(0.127)	(0.127)
SP x Stress	-0.135^{***}	-0.143^{***}	-0.107^{*}	-0.121^{**}	-0.122^{***}	-0.152^{***}	-0.130^{**}	-0.115^{*}
	(0.042)	(0.043)	(0.062)	(0.062)	(0.045)	(0.046)	(0.065)	(0.064)
SP x Cap x Stress					−0.033	0.026	0.021	0.021
					(0.088)	(0.093)	(0.096)	(0.093)
Size		-0.006^{**}	-0.010^{**}	-0.009^{*}		-0.006^{**}	-0.009^{*}	-0.010^{**}
		(0.002)	(0.004)	(0.005)		(0.002)	(0.005)	(0.004)
Institutional		−0.001	0.002	0.0003		−0.001	0.0003	0.002
		(0.001)	(0.003)	(0.003)		(0.001)	(0.003)	(0.003)
Total expense		0.059	−0.065	−0.042		0.059	−0.041	−0.064
		(0.038)	(0.156)	(0.117)		(0.038)	(0.117)	(0.156)
Alpha		−0.006	-0.071^{*}	−0.051		−0.006	−0.051	-0.070^{*}
		(0.015)	(0.038)	(0.041)		(0.015)	(0.041)	(0.038)
Debt		-0.020^{***}	−0.011	0.004		-0.020^{***}	0.004	−0.011
		(0.004)	(0.010)	(0.009)		(0.004)	(0.009)	(0.010)
Cash		0.028^{***}	0.028^{***}	0.027^{***}		0.028^{***}	0.027^{***}	0.028^{***}
		(0.003)	(0.005)	(0.005)		(0.003)	(0.005)	(0.005)
Bid-ask spread		-0.243^{***}	-0.176^{**}	-0.201^{**}		-0.244^{***}	-0.204^{**}	-0.177^{**}
		(0.046)	(0.075)	(0.087)		(0.046)	(0.087)	(0.075)
Matching	No	No	PI	Controls	No	No	PI	Controls
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	325,978	300,957	57,368	57,732	325,978	300,957	57,732	57,368
R^2	0.135	0.135	0.114	0.114	0.135	0.135	0.114	0.114

Note: this table presents the regression results of OLS estimates for which the dependent variable is positive flows. For regressions in columns (1) to (4), regressors include SP, a dummy equal to one if a fund uses swing pricing, and $Stress$, a dummy equal to one if weekly VIX CAC40 is above the 90^{th} percentile of the sample and the interaction of these variables. For regression columns (5) to (8), regressors also include Cap, equal to one for capped swing factors, and its interaction with SP and $Stress$. Columns (3), and (7) use the sample matched on "portfolio and investors" while Columns (4), and (8) use the sample matched on "Controls". All columns have date fixed effects and fund share fixed effect. All columns include control variables as regressors: lagged values of size, percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio and portfolio weighted average bid-ask spread. Control variables are one-week lagged values. Errors are clustered by fund shares. There is one observation by fund share per week. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Figure A-2: Funds under idiosyncratic stress per period



(a) - Outflow 1^{st} decile, Illiquidity 9^{th} decile *(b) - Outflow 3^{rd} decile, Illiquidity 7^{th} decile*

Note: Figures (a) and (b) indicate the percentage of funds under idiosyncratic stress per period. In Figure (a), idiosyncratic stress corresponds to outflows in the first decile and liquidity in the last. In Figure (b), it corresponds to outflows in the third decile and liquidity in the seventh.

E Swing pricing and idiosyncratic stress

Table A-12 replicates Table 6, except columns (1) and (4), while giving the coefficients of all the control variables. For robustness check, Table A-12 add new specifications: column (2), (5) and (8) present the results with the matching on control variables. Columns (5) and (6) in Table 6 corresponds to columns (6) and (9) in Table A-12. Table A-13 corresponds to Table A-12 but outflows and illiquidity dummies are dummies variables equal to one if outflows and bid-ask spread in period $t-1$ is higher than the $7th$ decile instead of $9th$ decile, for robustness check.

F Interaction with other components of liquidity mismatch

Table A-12: Impact of swing pricing during idiosyncratic stress (percentile 90 for illiquidity and percentile 10 for outflows)

	Net flows								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Outflows	−0.466***	−0.513***	−0.484***	−0.469***	−0.531***	−0.505***	−0.474***	−0.540***	−0.524***
	(0.015)	(0.043)	(0.042)	(0.015)	(0.040)	(0.039)	(0.015)	(0.036)	(0.035)
Illiquidity	−0.060***	0.100***	0.026	−0.043**	0.090***	0.051	−0.066***	0.031	−0.009
	(0.019)	(0.037)	(0.040)	(0.018)	(0.034)	(0.035)	(0.018)	(0.035)	(0.036)
SP	0.020	0.075*	0.040	0.056	0.115***	0.071*	−0.062	−0.033	−0.043
	(0.037)	(0.041)	(0.041)	(0.037)	(0.041)	(0.040)	(0.093)	(0.094)	(0.093)
SP x Outflows	−0.146***	−0.087	−0.121*	−0.133**	−0.058	−0.092	−0.168	−0.093	−0.107
	(0.056)	(0.069)	(0.067)	(0.063)	(0.075)	(0.072)	(0.108)	(0.113)	(0.112)
SP x Illiquidity	0.050	−0.097*	−0.001	−0.067	−0.195***	−0.106*	0.140**	0.047	0.099
	(0.045)	(0.052)	(0.054)	(0.058)	(0.062)	(0.062)	(0.063)	(0.070)	(0.069)
Outflows x Illiquidity	−0.144***	−0.107	−0.210**	−0.144***	−0.082	−0.162*	−0.122***	−0.023	−0.095
	(0.042)	(0.087)	(0.102)	(0.041)	(0.077)	(0.085)	(0.040)	(0.071)	(0.078)
SP x Outflows x Illiquidty	0.193*	0.187	0.270*	0.266**	0.258*	0.293**	0.135	0.056	0.115
	(0.106)	(0.134)	(0.141)	(0.121)	(0.143)	(0.142)	(0.163)	(0.175)	(0.177)
Size	−0.005***	−0.006*	−0.003	−0.005***	−0.005*	−0.003	−0.005***	−0.006*	−0.003
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Institutional	0.063	−0.030	0.211	0.060	−0.027	0.206	0.065	−0.010	0.230
	(0.080)	(0.172)	(0.220)	(0.080)	(0.172)	(0.220)	(0.080)	(0.170)	(0.218)
Expense	0.082***	0.091	0.126	0.082***	0.085	0.124	0.081***	0.088	0.117
	(0.028)	(0.076)	(0.094)	(0.028)	(0.075)	(0.093)	(0.028)	(0.076)	(0.093)
Alpha	0.029***	0.022	−0.020	0.029***	0.025	−0.017	0.029***	0.022	−0.018
	(0.011)	(0.032)	(0.032)	(0.011)	(0.032)	(0.033)	(0.011)	(0.032)	(0.032)
Debt	−2.381***	0.625	−0.421	−2.388***	0.615	−0.451	−2.388***	0.624	−0.436
	(0.348)	(0.787)	(0.835)	(0.348)	(0.791)	(0.837)	(0.349)	(0.794)	(0.842)
Cash	1.970***	1.886***	2.014***	1.969***	1.894***	2.016***	1.972***	1.905***	2.023***
	(0.208)	(0.440)	(0.486)	(0.208)	(0.441)	(0.487)	(0.208)	(0.442)	(0.486)
Type of SP	All	All	All	W/O Cap	W/O Cap	W/O Cap	W/ Cap	W/ Cap	W/ Cap
Matching	No	Controls	PI	No	Controls	PI	No	Controls	PI
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	712,639	136,960	136,656	712,639	136,960	136,656	712,639	136,960	136,656
R^2	0.055	0.056	0.053	0.055	0.056	0.053	0.055	0.056	0.053
Note:									*p<0.1; **p<0.05; ***p<0.01

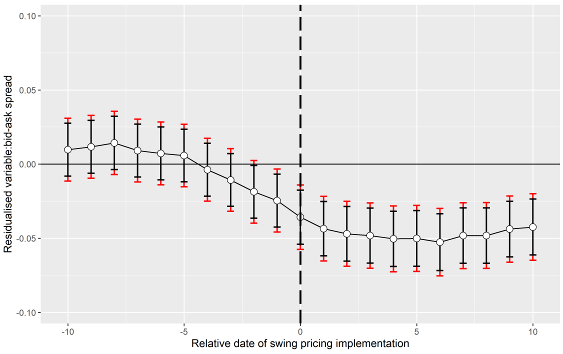
*Note: this table presents the regression results of OLS estimates for which the dependent variable is net flows. For all regressions, independent variables include SP, $Outflows$, $Illiquidity$ and their interaction terms. $Outflows$ is a dummy equal to one if flows in period $t-1$ are lower than the first decile, and $Illiquidity$ a dummy variable equal to one if the bid-ask spread in period $t-1$ is higher than the 9th decile. In columns (1), (2) and (3), SP is a dummy variable equal to one if a fund uses any type of swing pricing, in columns (4) to (6) it is equal to one if a fund uses a swing pricing without capped swing factor, finally in column (7) to (9) it is equal to one if a fund uses a swing pricing with capped swing factor. Columns (3), (6) and (9) use the sample matched on "portfolio and investors", while columns (2), (5) and (8) use the sample matched on control variables. All columns have date fixed effects and fund share fixed effect. All columns include control variables as regressors: lagged values of size, percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio and portfolio weighted average bid-ask spread. Control variables are one-week lagged values. Errors are clustered by fund shares. There is one observation per fund share and week. *p<0.1; **p<0.05; ***p<0.01.*

Table A-13: Impact of swing pricing during idiosyncratic stress (percentile 70 for Illiquidity and percentile 30 for Outflows)

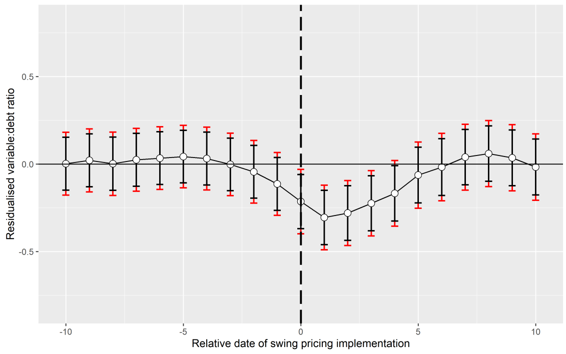
	Net flows								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Outflows	−0.321***	−0.405***	−0.391***	−0.322***	−0.407***	−0.395***	−0.329***	−0.429***	−0.416***
	(0.010)	(0.034)	(0.033)	(0.010)	(0.033)	(0.033)	(0.010)	(0.027)	(0.027)
Illiquidity	−0.010	−0.057	−0.015	−0.007	−0.039	−0.007	−0.019	−0.094***	−0.060*
	(0.012)	(0.039)	(0.041)	(0.012)	(0.038)	(0.039)	(0.012)	(0.034)	(0.034)
SP	0.095**	0.074	0.068	0.122***	0.109**	0.094**	−0.038	−0.091	−0.068
	(0.040)	(0.047)	(0.046)	(0.041)	(0.047)	(0.046)	(0.112)	(0.114)	(0.113)
SP x Outflows	−0.135***	−0.066	−0.068	−0.134***	−0.064	−0.065	−0.137	−0.044	−0.054
	(0.040)	(0.051)	(0.050)	(0.042)	(0.052)	(0.050)	(0.139)	(0.140)	(0.140)
SP x Illiquidity	−0.097**	−0.041	−0.071	−0.159***	−0.127**	−0.137**	0.048	0.140	0.101
	(0.046)	(0.055)	(0.056)	(0.047)	(0.055)	(0.055)	(0.115)	(0.114)	(0.114)
Outflows x Illiquidity	−0.049***	−0.041	−0.089	−0.055***	−0.045	−0.082	−0.037**	0.030	−0.008
	(0.017)	(0.052)	(0.057)	(0.017)	(0.048)	(0.051)	(0.017)	(0.041)	(0.044)
SP x Outflows x Illiquidty	0.112*	0.125*	0.157**	0.199***	0.219***	0.227***	0.021	−0.029	0.005
	(0.059)	(0.076)	(0.078)	(0.059)	(0.075)	(0.074)	(0.160)	(0.163)	(0.164)
Size	−0.005***	−0.005	−0.003	−0.005***	−0.005	−0.003	−0.005***	−0.005	−0.003
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Institutional	0.055	−0.067	0.174	0.054	−0.070	0.170	0.058	−0.059	0.184
	(0.080)	(0.173)	(0.222)	(0.080)	(0.173)	(0.221)	(0.080)	(0.172)	(0.219)
Expense	0.082***	0.075	0.109	0.082***	0.074	0.111	0.082***	0.073	0.105
	(0.028)	(0.075)	(0.093)	(0.028)	(0.075)	(0.092)	(0.028)	(0.075)	(0.093)
Alpha	0.029***	0.024	−0.015	0.029***	0.026	−0.013	0.029***	0.025	−0.015
	(0.011)	(0.032)	(0.033)	(0.011)	(0.032)	(0.032)	(0.011)	(0.032)	(0.032)
Debt	−2.377***	0.556	−0.441	−2.373***	0.558	−0.441	−2.362***	0.616	−0.393
	(0.348)	(0.804)	(0.841)	(0.350)	(0.805)	(0.845)	(0.349)	(0.808)	(0.844)
Cash	1.941***	1.908***	2.018***	1.938***	1.906***	2.012***	1.934***	1.889***	1.993***
	(0.207)	(0.440)	(0.485)	(0.208)	(0.441)	(0.486)	(0.207)	(0.443)	(0.485)
Type of SP	All	All	All	W/O Cap	W/O Cap	W/O Cap	W/ Cap	W/ Cap	W/ Cap
Matching	No	Controls	PI	No	Controls	PI	No	Controls	PI
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	712,639	136,960	136,656	712,639	136,960	136,656	712,639	136,960	136,656
R^2	0.054	0.056	0.053	0.054	0.056	0.054	0.054	0.056	0.053

*Note: this table presents the regression results of OLS estimates for which the dependent variable is net flows. For all regressions, independent variables include SP, Outflows, Illiquidity and their interaction terms. $Outflows$ is a dummy equal to one if flows in period $t-1$ are lower than the third decile, and Illiquidity a dummy variable equal to one if the bid-ask spread in period $t-1$ is higher than the 7th decile. In columns (1), (2) and (3), SP is a dummy variable equal to one if a fund uses any type of swing pricing, in columns (4) to (6) it is equal to one if a fund uses a swing pricing without capped swing factor, finally in column (7) to (9) it is equal to one if a fund uses a swing pricing with capped swing factor. Columns (3), (6) and (9) use the sample matched on "portfolio and investors", while columns (2), (5) and (8) use the sample matched on control variables. All columns have date fixed effects and fund share fixed effect. All columns include control variables as regressors: lagged values of size, percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio and portfolio weighted average bid-ask spread. Control variables are one-week lagged values. Errors are clustered by fund shares. There is one observation per fund share and week. *p<0.1; **p<0.05; ***p<0.01.*

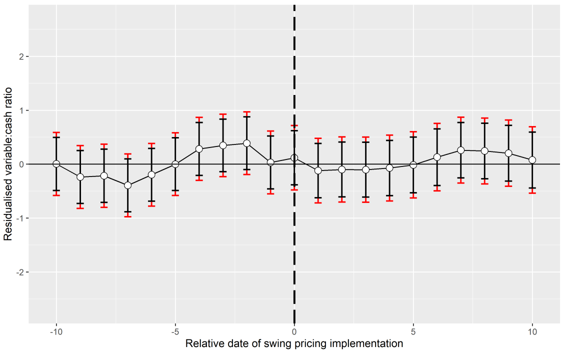
Figure A-3: Difference in characteristics between funds with and without swing pricing ("controls" matching)



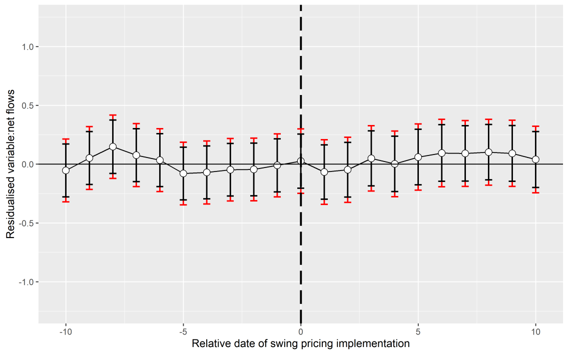
(a) Bid-ask spread



(b) Debt



(c) Cash



(d) Net flows

Note: These figures show the immediate effect of swing pricing implementation on six dependent variables: weighted-average bid-ask spread of the portfolio (a), debt (b), cash (c) and net flows (d). All dependent variables are residualized by controlling for date fixed effects. The dots corresponds to the coefficients β_3 estimated based on the Equation 8 equation presenting the staggered difference-in-differences methodology. Treated is equal to one if a fund implements swing pricing at the relative date zero. We plot the interaction coefficients between Treated and all the relative dates (y-axis), between -10 and 10: ten weeks before and ten weeks after the implementation of swing pricing (x-axis). Black solid vertical bars are 95% confidence intervals, red solid vertical bars are 99% confidence intervals, the black dotted vertical bars indicates the implementation date and the black solid horizontal bar indicates the value zero. All variables are four-week rolling moving averaged. The sample is constructed with the matching methodology "Portfolio & investors". There is one observation per fund share and week. We cluster standard errors by fund shares.