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. We study its impact on French investment funds' financial stability in light of the Covid-19 crisis. We find that swing pricing had only a limited impact on fund stability during the financial turmoil. Our study highlights two new underlying mechanisms that explain this result. First, constraints on the activation and intensity of swing pricing decrease its stabilizing effect. Second, it suffers from a stigma effect: we observe a deterioration of inflows during systemic stress as well as a flight of investors immediately after the implementation. However, we highlight a strong stabilizing effect in the absence of constraints or when the portfolio restructuring cost is high. We thus conclude that while swing pricing has the potential to increase financial stability, its calibration is crucial to ensure that the stabilizing effect offsets the stigma effect.

Keywords: liquidity management tools, swing pricing, investment funds, runs.
JEL codes: G10, G23, G28.

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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

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motives, i.e. a need for liquidity, but also by endogenous motives, i.e. the 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 that can 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). Concerns about a high concentration of illiquid assets by these funds resulted in weekly outflows of up to 30% during the COVID-19 crisis (Schwabe and Ed-Diaz, 2020). The turmoil that occurred in seven French H2O investment funds in August 2020 illustrates the vulnerability caused by a high liquidity gap. Given the risk, measures of last resort were taken such as the suspension of subscriptions and redemptions as well as the isolation of illiquid assets in side-pocket funds.

In the last decade, new tools have emerged to help fund managers manage the liquidity of their funds in order to reduce the risk of dilution and the "first-mover advantage": the 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 limit this liquidity mismatch and 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". By passing on the cost of rearranging the portfolio to outgoing investors, the total cost of exiting a fund may increase. 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 implementation by money market funds 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 due to subscriptions or redemptions. It allocates this cost on subscribing or redeeming investors by adjusting the net asset value (hereafter NAV). Intuitively, it aims to mitigate runs by internalizing the negative externalities associated with redemptions, and thus reducing the first-mover advantage. 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) but also only if the 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. First, 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) conclusion is mixed as they find that swing pricing can prevent self-fulfilling runs on the fund, 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 two 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 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 (2017a) identification strategy relies on the comparison of mutual funds in the U.S. and Luxembourg at a time when swing pricing was available for Luxembourg funds but not yet for U.S. funds. They find that swing pricing stabilizes flows during normal market conditions, but fails to offset investor first-mover advantages in more stressed markets.[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 availability. 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 (34 U.K. bond funds implementing swing pricing out of 224). On the other hand, Lewrick and Schanz (2017a) base their identification of swing pricing on a comparison

[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.

between the U.S. (no swing pricing available) and Luxembourg (swing pricing available for all funds). This 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.

In France, it is mandatory to disclose in the fund prospectus the implementation of a swing pricing mechanism, i.e. the ability to use the tool. We take profit of this regulatory requirement to identify the implementation of swing pricing for each French open-end investment fund using a novel approach based on a text-mining analysis of fund prospectuses. If the swing pricing is full, then the mechanism is constantly activated, and its implementation is equivalent to its activation. If partial swing pricing is implemented, then it is activated only when net flows are above the activation threshold. Focusing on the implementation instead of only studying the activation allows us to identify potential stigma effects related to the implementation, as well as to study the impact of the activation conditions of the mechanism on its efficiency.

Our identification of swing pricing at a fund level based on prospectuses enables us to build a unique database with the implementation of swing pricing for most French funds: 3074 funds, 249 with swing pricing at the end of our study period, and 155 implementing swing pricing during this period. It allows us to be the first study to analyze the effect of the swing pricing implementation on all types of funds in a jurisdiction with implementation heterogeneity. In addition, our study spans from 2018 to 2020. It thus benefits from a time frame that includes periods with 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 a 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). It is the most stressful financial episode over the last decade and thus since the existence of swing pricing in France (Falato et al., 2021). As noted by Falato et al. (2021) no previous work focuses 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.

Our results suggest that swing pricing had only a limited impact on redemption pressures during the Covid-19 crisis in France: we find that swing pricing has amplified fund outflows while there is only weak evidence in favor of net flows stabilization. We identify two new underlying mechanisms that explain this surprising result. First, swing pricing suffers from a stigma effect: we observe a flight of investors immediately after the introduction of swing pricing and, in the long run, swing pricing reduces inflows during periods of systemic stress. A second reason is the widespread use of partial swing pricing and capped swing factor in France. Our results suggest that restrictions on the swing pricing activation and intensity decrease flow stability and amplify redemptions during financial turmoil. However, when the swing factor is theoretically high (and thus when even the partial swing pricing is activated), we find that swing pricing is able to absorb large redemption shocks. We thus conclude that the tool has the potential to increase fund stability but that the underlying calibration is crucial to ensure that its stabilizing effect offsets the associated stigma effect.

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 implementation, and finally presents our other data and measures.

2.1 Data on swing pricing

2.1.1 Extracting data from prospectus using text mining

Funds must publicly disclose the implementation of swing pricing via their prospectus (see DOC-2011-20 of the AMF). Our identification methodology consists of two steps: i) the collection of all French open-ended fund prospectuses, ii) the conversion of this unstructured information into a structured database.

For the first step, the prospectuses were obtained from two alternative sources. First, we received 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. This represents a total of about

60,000 prospectuses, including 20,500 open-end fund prospectuses.[2] 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.[3] Using this methodology, we collected an additional 11,545 unique prospectuses for 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. 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.[4] Based on these conditions, we exclude 24% of our sample, which consisted mostly of non-prospectus documents. We then apply a fuzzy matching algorithm to each paragraph combined with the detection of a list of block-words i.e. we detect the existence of a fuzzy match if the corresponding blockwords are absent.[5] This analysis of the prospectuses using our algorithm is complemented by a manual processing of all funds within an umbrella funds ("SICAV à compartiments" in French): all prospectuses of an umbrella fund are concatenated in a single document preventing an identification based only on the algorithm.

In addition to identifying the implementation 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 on the adjustment of the Net

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

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

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

[5] Blockwords are important to avoid false-positive as the absence of swing pricing is sometimes mentioned in a prospectus, e.g. "Implementation of swing pricing: None".

Asset Value (hereinafter NAV), called a swing factor cap. Unlike full swing pricing, 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 as it is publicly disclosed via the prospectus. However, the value of the swing threshold is not disclosed to investors to avoid gaming effects or influence market timing. A swing factor cap limits the maximum adjustment of the NAV.[6] 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 level.

Finally, to test the performance of our identification, we manually analyzed 400 prospectuses (each prospectus belongs to a different fund) selected using stratified random sampling based on three variables: presence of swing pricing, year and type of fund. Then, we divided our sample into two subsets of 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

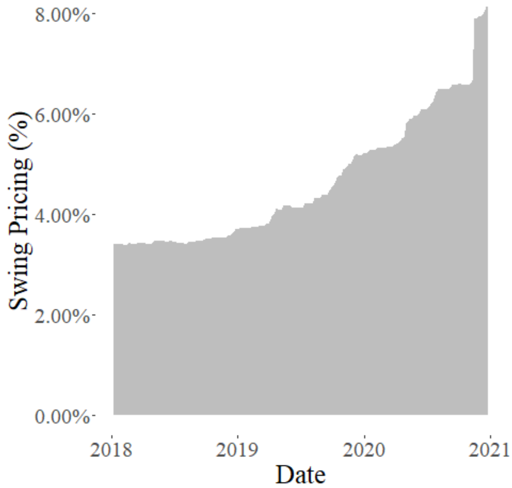
In this section, we provide descriptive statistics on the availability of swing pricing in France between 2018 and 2020.[7]

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 implementation has gradually increased by 1-2 percentage points per year over the study period to reach 8.1% by the end of 2020. 94 funds implemented swing pricing at the beginning of our study period, they were 249 at the end of the period. It means that we have a sample of 155 investment funds (426 fund shares) that implemented swing pricing during our study. The spread of swing pricing is particularly pronounced between September 2019 and the end of 2020,

[6] We identify the swing pricing mechanism through a variety of sentence structure identification. 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 implementation of a swing pricing mechanism. An absence of reference to a swing threshold is considered as the implementation of the reference mechanism, i.e. the full swing pricing. The typical sentence to disclosed 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".

[7] 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, and funds younger than six months (see the last paragraph of Section 2.3 for more details).

Figure 1: Percentage of fund shares with swing pricing from 2018 to 2020



Note: the x-axis gives the week while the y-axis gives the corresponding percentage of fund shares with a swing pricing mechanism.

with twice as many funds with swing pricing (+5 p.p.).[8] At the end of 2020, swing pricing was mainly used by bond funds: 21.3% compared to 6.3% for equity funds. No MMF uses swing pricing. Apart from these three fund types, 4.2% of funds have implemented it (e.g. mixed funds or formula funds). All the switching events have been almost exclusively in one direction: while 157 funds introduce swing pricing during the analysis period, only two funds have withdrawn their swing pricing mechanism.

Table 1 provides descriptive statistics on the type of swing pricing. At the end of our study period, most funds use a partial rather than a full swing pricing (185 funds with partiel swing pricing out of 249 with swing pricing at the end of December 2020). In addition, in October 2020, the full swing pricing was used by less than 1% of the funds (27 funds, compared to 5 funds during January 2018) compared to 5.7% for partial swing pricing (175 funds, compared to 89 funds during January 2018). This finding is consistent 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). 33% 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 (80%) or a value close to 2%—the second and third most popular values are 2.5% (for 7.5% of the funds) and 1.75% (for 5.4% of the funds). Again, France

[8]The sharp increase of full swing pricing in November 2020 is due to the umbrella SICAV of Lyxor Asset Management (45 investment funds in total) which implements full swing pricing for 38 funds on 8/11/2021.

Table 1: Implementation of constraints among swing pricing mechanisms

		Partial swing pricing	
		No	Yes
Swing factor cap	No	12.7% (0)	59.0% (1)
	Yes	1.6% (1)	26.8% (2)

Note: the numbers in parenthesis correspond to the number of constraints. The percentages correspond to the statistics at the end of 2020.

is comparable to Luxembourg as, according to the Association of the Luxembourg fund industry (ALFI, 2015), the most prevalent cap value among Luxembourgian funds with capped swing pricing is 2%. To analyze the effect of the constraints, we construct a continuous variable corresponding to the total number of constraints on swing pricing in a fund (the possible values are between 0 and 2 as presented in Table 1). We use this methodology to reduce the dimension for econometric analysis and to avoid analyzing categories with few observations that could suffer from a small sample bias (e.g. inflated false discovery rate).

2.3 Open-end investment funds data and measures

We rely on a combination of various sources to assess 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 in our study, we keep them at a share level to avoid unnecessary data manipulation when it is possible. Flows and TNA are collected weekly at the share level using EIKON from Thomson Reuters.[9] Average flows are display in Figure 2-a.

We define several fund-individual characteristics that we mainly use as controls. Based on funds' absolute performance and funds' benchmark performance, 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 bench-

[9]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.

mark returns. *Size* is defined as the natural logarithm of shares' TNA. *Expense ratio* is the fund total expenses (total costs associated with managing and operating) divided by its TNA. It measures the total costs associated with managing and operating an investment fund. These costs can be covered by management fees, entry and exit fees.

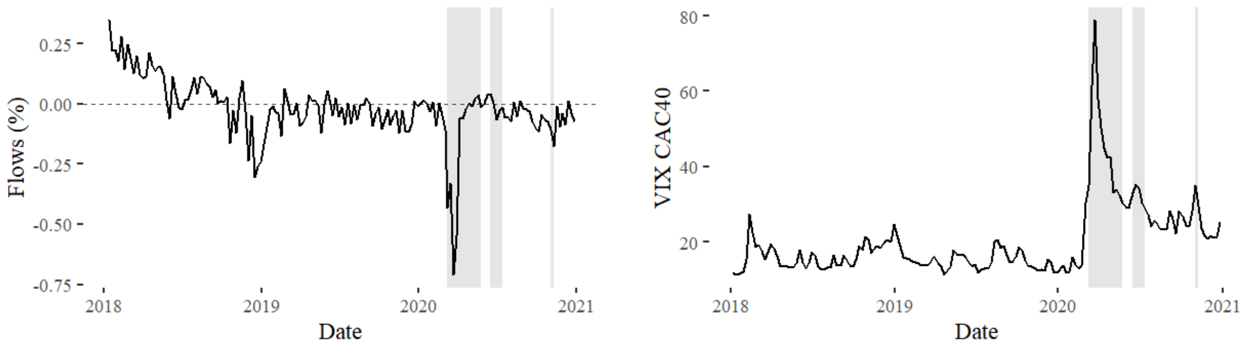
Alpha, *Size*, and *Expense ratio* are computed weekly using variables collected from LIM. We also derive a fund-level liquidity indicator, *Bid-ask Spread*, defined as the average bid-ask spread weighted by exposure amounts. It is based on information of assets held by each fund (the amount of asset 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.[10] It is computed weekly based on monthly-updated 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 fund's 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. These 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 funds 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

[10] 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.

Figure 2: VIX CAC40 and net flows during systemic stress



(a) - Flows *(b) - VIX CAC40*

Note: Figure (a) gives the average net flows as a percentage of previous week TNA. Grey areas correspond to periods of systemic stress defined as periods with a VIX CAC40 above its 90% threshold value, while Figure (b) presents the weekly value of the VIX CAC40 index between 2018 and 2021.

stress, we compute the elasticity between stress periods and flows for different thresholds and apply the elbow method (see Section A.3 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 match 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 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 3074 French open-ended investment funds (5608 fund shares) belonging to 256 financial asset management companies. The total net assets of our sample is equal to €844 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 80% of the TNA of all open-ended funds available to the public (€1,042 billion, source AMF).[11] We then apply some restrictions to our sample. First, we exclude money market funds (MMF) because no MMF has implemented 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 shares with the smallest TNA (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). Finally, we exclude funds with less than 6 months of activity as new funds typically start by collecting large inflows before reaching a more stable TNA at maturity. It removes 2.6% of the observations, mainly at the beginning of our analysis period.

3 Hypotheses and methodology

This section presents our set of hypotheses and our identification method.

3.1 Hypotheses

The impact of swing pricing can be divided into different steps and analyzed by different metrics. In order to conduct a comprehensive analysis, our hypotheses focus on different phases of swing pricing implementation (the choice of implementation, the effect of introduction, and the overall impact), different measures of financial stability (flow levels and volatility), and different types of stress (systemic and idiosyncratic stress). They also consider the impact of constraints on swing pricing.

First, we focus on the determinants of the introduction of swing pricing. Swing pricing is intended to decrease externalities from the liquidity mismatch, thus we assume that funds with higher liquidity mismatch are more likely to implement swing pricing.

H 1. *Funds with a high liquidity mismatch are inclined to implement swing pricing.*

[11] 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 bond of the actual number.

Second, we study the immediate effect of implementing swing pricing, i.e. the consequences of swing pricing immediately after its introduction. Some investors might prefer to redeem their shares not to invest in a fund with swing pricing because of, for example, a stigma effect. We thus assume that:

H 2. *Swing pricing implementation causes immediate outflows.*

Then, we focus on the impact of swing pricing in the long run. Our first approach is to assess this impact on the flow volatility. Swing pricing mechanisms decrease (respectively increase) the NAV after outflows (resp. inflows), it thus incentivizes investors to spread large transactions over time to reduce transaction costs. It should thus enable funds to experience less volatile flows. We assume that funds with stable flows are less prone to dilution and materialization of first-mover advantage (Cetorelli et al., 2022).

H 3. *Swing pricing increases stability by reducing flow volatility.*

Following the literature (Schmidt et al., 2016; Dunne and Giuliana, 2021; Jin et al., 2022), our second approach is to assess how swing pricing address redemption pressures under stressed market stress conditions. To define stress periods, we exploit the Covid-19 crisis, a perfectly exogenous shock (i.e. systemic stress) that have caused lead to redemptions. Based on Jin et al. (2022), we assume that:

H 4. *Swing pricing increases net flows during systemic stress via a reduction of outflows.*

Next, we focus on another type of stress, the idiosyncratic stress, when funds are facing large outflows during periods of 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 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 5. *Swing pricing reduces outflows during idiosyncratic stress periods*

A gap between the swing factor and the effective reallocation cost of the portfolio might reduce the swing pricing impacts on flows. The presence of constraints (partial swing pricing and capped swing factor) could increase this gap by deactivating the mechanism or limiting the maximum swing factor. We suppose that these constraints reduce the stabilizing effects of swing pricing.[12]

H 3-CO. *The stabilizing impact on flow volatility is decreased when swing pricing is constrained.*

H 4-CO. *The stabilizing impact on flows during systemic stress is decreased when swing pricing is constrained.*

More specifically, during idiosyncratic stress, partial swing pricing should be activated as funds experienced previous large outflows. In addition, the high restructuring cost should imply large swing factors. However, in this situation, a capped swing factor could still prevents the swing factor from exceeding a certain value and thus induces a large deviation from the unconstrained swing factor level, thus increasing the risk of dilution—and the first-mover advantage. We thus assume that:

H 5-CO. *The implementation of a swing factor cap does not allow funds to increase flows during idiosyncratic stress periods as much as without this constraint.*

3.2 Identification methodology

The decision to implement a swing pricing mechanism depends solely 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 implement swing pricing. To take it into account, we use two strategies: first, we use a panel data model with a within estimator—whenever relevant—, 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 implements swing pricing and the other does not. We thus match funds on their characteristics at the beginning of the study period

[12]The following hypotheses assess how constraints (CO) affect the different impacts of swing pricing considered above (e.g. H3-CO is paired with H-3).

(01/01/2018) 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 investors 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) at the beginning of 2018, before the implementation of swing pricing.

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 (2017a) 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[13] and vi) the type of investors (see Section A.4 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, measured at the beginning of 2018 (two funds have a distance of 0 if they have the same portfolio and investor composition).

For both matching methods, funds are matched with replacement with a threshold 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 249 funds with swing pricing at the end

[13] 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 2020, 215 (86%) and 240 (96%) funds were matched with respectively the matching methodology based on "portfolio and investors" and the one based on the control variables. The ability of the applied matching methodologies to reduce sample bias between the two groups is documented in Table A-3 and Table A-4. The two methodologies significantly reduce the difference in the variables used for matching, but also in the flows and their volatility. This result is also visually supported by Figure 3, where the flows between funds that will implement swing pricing and their matches are non statistically different at the 5% confidence interval before the mechanism implementation.

4 Results

This section presents our empirical results. In Section 4.1, we analyze the factors influencing the implementation of a swing pricing mechanism. In Section 4.2, we conduct an event study to estimate the immediate impact of implementation. Then, we focus on longer-term impact and we distinguish effects during calm and stress periods. We analyze the impacts of systemic stress on the flow volatility in Section 4.3 and on the capacity of swing pricing to reduce outflows in Section 4.4. Finally, in Section 4.5, we perform an analysis similar to the previous section but focused on idiosyncratic stress situations instead of systemic stress.

4.1 Factors driving the swing pricing implementation

Since 2014, investment funds are free to choose whether to implement swing pricing or not. We study the determinants of this endogenous decision. Specifically, we investigate whether funds with the highest liquidity mismatch, and thus those with the greatest need for swing pricing, are indeed implementing this tool. We therefore study how ex-ante characteristics affect subsequent implementation.

As detailed in Equation 1, we regress ex-ante independent variables (from date t_1 to t_2) on the following implementation of swing pricing (from date t_2 to December 2020). We vary the studied period to evaluate the impact at different points in time. We only consider investment funds that have not yet implemented swing pricing at the beginning of the studied period to avoid a reverse causality bias.

$$Treat_{i,t>t_2} \sim \beta_0 + \beta_1\, \overline{Flows}_{i,t\in[t_1;\,t_2]} + \beta_2\, Volatility_{i,t\in[t_1;\,t_2]} + \beta_3\, \overline{Controls}_{i,t\in[t_1;\,t_2]} + \epsilon_{i,t} \tag{1}$$

with $Treat$ a dummy variable constantly equal to 1 if the fund introduces swing pricing after t_2. $\overline{Flows}$ is the average level of flows between t_1 and t_2. $Volatility$ is the variance of the flows from t_1 to t_2. $\overline{Controls}$ is a vector of controls including age, type, NAV frequency, size, percentage of institutional investors, total expense ratio, alpha, leverage ratio, cash ratio, debt ratio, and weighted average portfolio bid-ask spread. Controls are averaged between t_1 and t_2. To provide evidence of the robustness of our results, we test several model specifications depending on the time period (t_1 and t_2) from which we analyze the variables explaining the implementation of swing pricing. In model (1), we analyze whether funds implement swing pricing after June 2018, based on data from the first half of 2018 (t_1 = 01/01/2018 and t_2 = 06/30/2018). In models (2) and (3), we replicate this approach for different dates, January 2019 and January 2020, respectively, based on earlier data (t_1 = 01/01/2018; t_2 equal to 12/31/2018 and 12/31/2019, respectively). Finally, in model (4), we replicate model (3) but based only on 2019 observations (t_1 = 12/31/2018 and t_2 = 12/31/2019). Models are logistic regressions. For each specification, funds implementing swing pricing before t_2 are excluded from the estimation sample. We have one observation per fund share.

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

Support for Result 1: First, we focus on the variables reflecting the liquidity on the liability side. The results are presented in Table 2. We find that the NAV frequency (p-value < 0.001 in all models) and the total expense ratio (p-value < 0.001 in all models), decrease the probability of implementing swing pricing. We also find that the flow volatility has a positive impact on this probability (p-value < 0.001 in all models). Thus, funds with a high liquidity on the liability side have a higher propensity to implement swing pricing.

Second, we focus on the variables associated with the liquidity of the fund's portfolio. The higher the weighted average bid-ask spread of the portfolio (p-value < 0.001 in all models) and the lower the cash ratio (p-values < 0.001 in models 3 and 4), the more likely a fund is to implement swing pricing. It suggests that funds with lower asset liquidity are more likely to implement swing pricing. Finally, the age of the fund also influences the likelihood of implementation: newer funds tend to implement swing pricing more often (p-value < 0.001 in models 2 to 4). This could be explained by a status quo bias from older funds, i.e. they are more reluctant to use new tools.

We conclude that swing pricing is implemented by funds with higher liquidity mismatch, having low asset liquidity and high liability liquidity. 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 for this source of endogeneity.

4.2 Immediate impact of swing pricing introduction

In this section, we assess the short-term impact of swing pricing introduction using an event study difference-in-differences. We first focus on the impact on flows to assess how investors respond to the introduction. Next, we focus on other fund characteristics to investigate whether funds tend to substitute swing pricing for other ways of managing their day-to-day flows, such as having cash buffers and holding liquid assets.

The introduction of a swing pricing mechanism may trigger immediate outflows due to anticipation of the impact of swing pricing as well as updated beliefs about the funds' situation at the time of introduction. First, investors may anticipate that swing pricing should provide greater financial stability and thus triggers inflows from investors seeking safer investments. On the other hand, they may anticipate that this tool could represent a potential additional cost when redeeming shares. They may thus reallocate their portfolio towards funds without swing pricing. If this latter effect dominates the former, anticipations could lead to net redemptions. Second, the introduction may be perceived by investors as a signal of vulnerability as they may suspect that funds implementing swing pricing are the most vulnerable to liquidity risk consistently with our findings in Section 4.1. The asymmetry of information between the fund manager and investors could be reduced by the announcement, inducing a negative update of investors' beliefs about the fund's ability to perform and thus lead to redemptions.

To analyze the short-term impact of swing pricing introduction, we use a two-step approach: first, we follow Jin et al. (2022) by computing residualized flows to be able

Table 2: Individuals characteristics and probability to implement swing pricing

	Implementation of swing pricing			
	(1)	(2)	(3)	(4)
Net flows	−0.001	−0.003**	−0.002	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Volatility	0.003***	0.002***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Bid-ask spread	0.041***	0.039***	0.034***	0.020***
	(0.005)	(0.004)	(0.004)	(0.003)
Size	0.00001	0.0003	0.001***	0.001**
	(0.0005)	(0.0005)	(0.0004)	(0.0004)
Age	−0.0001	−0.0003***	−0.0003***	−0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
NAV frequency	−0.002***	−0.003***	−0.002***	−0.002***
	(0.001)	(0.001)	(0.0005)	(0.0005)
Institutional ratio	−0.003	−0.005	−0.007**	−0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
Alpha	−0.001	−0.005	−0.005	−0.018***
	(0.003)	(0.003)	(0.005)	(0.006)
Debt ratio	−0.065	−0.006	0.081*	0.079*
	(0.050)	(0.051)	(0.044)	(0.044)
Cash ratio	−0.017	−0.021	−0.035***	−0.034***
	(0.015)	(0.015)	(0.013)	(0.013)
Expense ratio	−0.006***	−0.009***	−0.007***	−0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Type fund : Other	−0.005**	−0.007***	−0.003	−0.0003
	(0.002)	(0.002)	(0.002)	(0.002)
Type fund : Bond	0.001	−0.003	−0.008***	−0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Duration	6M	12M	24M	12M
Start swing pricing	Q3 2018	Q1 2019	Q1 2020	Q1 2020
Observations	3,816	4,182	4,282	4,280
R^2	0.044	0.051	0.052	0.041

Reading note: this table presents the regression results of a logistic estimation for which the dependent variable is a dummy equal to one if a fund implements swing pricing after the "start swing pricing" date. Independent variables are measured over the "duration" period to the "start swing pricing" date". The sample consists of all the funds that have not yet implemented swing pricing at the date indicated by the "start swing pricing" line. There is one observation per fund share. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

to compare flows from different funds at different dates, then we perform a difference-in-differences on these residualized flows. Since the decision to implement swing pricing is endogenous, we would ideally like to observe the counterfactual behavior of the funds in the absence of the treatment. Such a counterfactual cannot be directly observed in the data, so we use our two matching methodologies presented in Section 3.2 to find a close counterfactual fund for each investment fund implementing swing pricing. Contrary to the rest of the paper, the analyses in this section is at the fund level rather than the fund share level since we only match our funds to fund-level variables and we want to match one entity to exactly one other entity. It is based on the 155 funds that implemented swing pricing during our study period (see Table A-5 of the Appendix for new implementations by quarter). The time span is six months before and six months after implementation, in order to capture the announcement effect of the swing pricing implementation while having enough periods to ensure the parallel trend and to observe potential short-term effects.

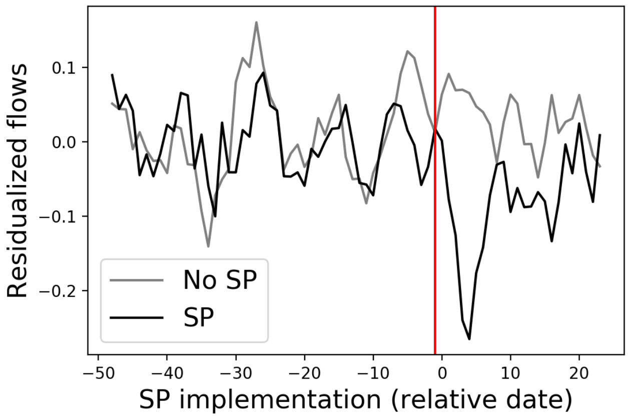
Residualized flows are obtained after applying date fixed effects and controlling for a set of fund-specific time-varying characteristics during the precedent period. Formally:

$$Flows_{i,t} \sim \beta_0 + \beta_1 \, Controls_{i,t-1} + \beta_2 \, \phi_t + \epsilon_{i,t} \tag{2}$$

with ϕ the date fixed effects. Controls are the same as in the other sections: size (TNA), percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio, and the weighted average portfolio's bid-ask spread. Residualized flows are defined as the residuals of this equation, ϵ. Equation 2 is our model specification (i), in addition we define a more parsimonious model specification (model ii) in which we do not include control variables. We use our sample matched on "portfolio and investors" and, as for the rest of the paper, we provide evidence of robustness using the sample matched on controls in the appendix. Our sample includes 430 funds, of which 215 have swing pricing, and with a maximum of 52 observations per fund. Each observation corresponds to a fund during a week. To increase the robustness of the event study, the residualized flows are smoothed monthly because of the high flow volatility. The results of the residualized flows estimation with the two model specifications are presented in the Table A-6 of the Appendix.

First, we graphically assess whether there is a parallel trend between the flows of

Figure 3: Residualized flows for funds with and without swing pricing



Note: this figure plots residualized flows (y-axis) against relative implementation date (x-axis) for the funds that will implement swing pricing at the relative date zero (the treated group, represented by the black line) and the control group composed of their matched twins that will not implement swing pricing (the grey line). The red vertical line indicates the last period before the relative implementation date of swing pricing (x = -1 by design). Residualized flows are calculated following the model specification (i) and smoothed monthly, the sample is obtained with the matching methodology "portfolio and investors".

the funds that will implement swing pricing and their counterparty. Figure 3 presents the residualized flows obtained with the specification (i), with controls, for the sample of funds in the matching method "portfolio and investors". In this graph, we observe that the residualized flows before the implementation of swing pricing by the treated funds are highly similar to flows of their matched twins. However, in the wake of the implementation of swing pricing by the treated funds, they experience large outflows, while the net flows of the control group remain stable. After one month, the difference in flows between both groups decreases. In the sample "portfolio and investors", the standard deviation of the residualized flows for each group is 0.25 for both residualized flows specifications. Thus, a residualized flows difference of 0.4 pp between the Treated and the Control group correspond to a difference of 1.6 standard deviation. The presence of a parallel trend followed by immediate outflows after the swing pricing introduction are also observed using residualized flows without control variables (specification ii) and our other matching methodology (see Figure A-2).

To perform a formal test, we compute the difference in flows between the treated and the control group with a staggered difference-in-differences event-study six months before and six months after the implementation of swing pricing by the treated group. We estimate the following regression on the sample of treated and matched funds centered on the date of swing pricing implementation:

$$\tilde{\epsilon}_{i,t} \sim \quad \beta_0 + \beta_1 Treated_i + \sum_{t=-26}^{26} (\beta_{2t} RelativeDate_t + \beta_{3t} RelativeDate_t \times Treated_i) + \epsilon_{i,t} \tag{3}$$

with $\tilde{\epsilon}$ the residualized flows of Equation 2, *RelativeDate* a dummy for each date relative to the implementation of swing pricing by the treated fund, and *Treated* a dummy equals to one if the fund will implement swing pricing at the relative date zero. All time-varying coefficients are expressed by comparison with the relative date -1, the week prior to the implementation of swing pricing for the treated group.[14]

Result 2. *Swing pricing implementation causes immediate outflows*

Support for Result 2: Figure 4 presents the results of the interaction terms between being treated and the date relative to the swing pricing implementation. Formally, it corresponds to the coefficients $\beta_{3,t}$ of Equation 3. First, for all periods before implementation, there is no statistical difference at a 5% level between both groups. We thus conclude that there is a parallel trend before the treatment. In addition, we can compare the ex-ante similarity between treated and control funds to evaluate the quality of both matching methods. Similar to "portfolio and investors", we find that the parallel trend hypothesis is verified at the 5% threshold for the matching method on controls (Figure A-3). However, with this latter matching method flows are less similar between the treated and the control groups (Figure A-2). We therefore favor the matching "portfolio and investors" in order to better identify similar funds. We thus present the following analyses based on the "control" matching in Section A.4 of the Appendix.

Three and four weeks after implementation, the interaction coefficient between *Treated* and *Relative date* is significantly negative at the 5% confidence interval. Coefficient values are around -0.3pp meaning that just after the introduction of swing pricing, the aggregated residualized flows of treated funds were -0.3pp lower during two weeks. Therefore, we find that a swing pricing implementation triggers outflows during the following weeks. As presented in Figure A-3, results are robust to our other specification of residualized flows (controlling only for the date) and even stronger with the "controls" matching method,

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

with a significantly negative effect at the 5% confidence level from the second week to the sixth weeks following the implementation.

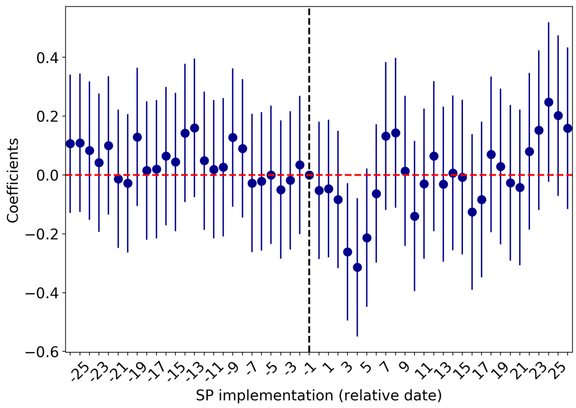
To complement our previous analysis, we also perform a staggered difference-in-differences estimation that assess the impact on the short-term (up to 2 months after implementation) and the mid-term (from 2 to 6 months) instead of analyzing the impact on each period individually (see Table A-7 in Appendix). Consistently with previous findings, we observe a sudden exit of investors in the two months following the implementation. After these periods, we find no evidence of further outflows. In addition, we use this approach to assess the potential interaction effect between constraints on swing pricing and the induced stigma effect. Intuitively, investors might react more strongly to the implementation of an unconstrained mechanism because it increases the additional exit cost. We find weak evidence of such an interaction effect. Based on our matching method "Portfolio and Investors", we find that implementing a constrained swing pricing mitigates the outflows (Table A-7, model (5), coefficient of $Post : \textit{short-term} \times Treated \times Constraints$: 0.208, p-value=0.072). However this effect is not statistically significant with the matching method "Controls" (Table A-7, model (6), coefficient of $Post : \textit{short-term} \times Treated \times Constraints$: 0.148, p-value=0.262).

It is important to note that unlike other LMTs (e.g. gates), the implementation of swing pricing in France does not trigger a free exit option.[15] Our findings cannot thus be explained by a short-term incentive to redeem investments and indeed reflect a stigma effect associated with swing pricing. However, besides a change in outflows, the implementation of swing pricing could be associated with other structural changes in the fund for several reasons. The implementation could be the decision of a new manager and thus combined with other modifications. It could also affect the investor pools by attracting more risk-averse investors. In addition, funds could implement swing pricing but decrease other more traditional lines of defense to manage redemption. Intuitively, funds could substitute away from other liquidity management strategies if swing pricing is a less costly option, either in terms of its direct implementation cost or through its effect on performance.

These confounding factors could prevent a correct assessment of the swing pricing effect. We therefore study whether other variables are affected by the introduction. For-

[15] See DOC-2011-20 (p16) of the AMF.

Figure 4: Difference of residualized flows between funds with and without swing pricing



Note: the dependent variable is the residualized flows computed following Equation 2, with the model (i): dates FE and controls, with the matching methodology "portfolio and investors". Residualized flows are smoothed monthly and are explained by Treated and the relative date, which is the date relative to the implementation of swing pricing by the treated funds (see Equation 3). Treated is equal to one if the fund will implement a swing pricing mechanism at the relative date zero. We plot the interaction coefficients between Treated and all the relative dates (y-axis), between -26 and 26, except -1 the reference date: it corresponds to six months before and six months after the implementation of swing pricing (x-axis). Blue solid vertical bars are 95% confidence intervals and the dark dotted vertical bar indicates the week before the swing pricing introduction (the coefficient of the relative date -1 is equal to zero by design). The sample is constructed with the matching methodology "portfolio and investors". The unit of observation is fund by week. We cluster standard errors by funds.

mally, we compare the relative trends, across treatment and control groups, for various fund characteristics around the implementation of swing pricing. These characteristics are the percentage of institutional investors, total expense ratio, cash ratio, debt ratio, weighted average portfolio bid-ask spread, and three-month average alpha. We estimate the event study difference-in-differences presented in Equation 3, except that the dependent variable is successively one of these six variables after being residualized based on the model specification (ii) of Equation 2. Figure 5 presents the results of these regressions, the values of the interaction coefficients are presented with a 95% confidence interval.

We find that for all time periods and all variables, there are no significant differences between treated and untreated funds prior to implementation at the 5% level.[16] First, this provides additional evidence on the quality of the matching and its relevance for identifying causal effects. Indeed, the untreated funds are appropriate counterfactuals for assessing how the treated funds could have behaved without swing pricing. Second, there

[16] We observe tendency breaks between relative dates 6 and 7 for the variables "total expense ratio" and "bid-ask spread". They are due to the fact that a SICAV of Lyxor Asset Management introduced swing pricing at the same time for 45 investment funds in November 2020. The study period finishes exactly seven weeks after these 45 funds implemented swing pricing, these funds are thus not present after relative date 6.

is also no significant difference after the implementation. Specifically, we find no evidence of substitution of swing pricing for traditional means of managing large redemption, either by holding cash or by holding more liquid assets (measured by *Cash ratio* and *Bid-ask spread*).

There are no significant change for institutional investors either: the outflows immediately following the implementation of swing pricing do not come from a particular group of investors. Our results thus suggest that swing pricing is not associated with other immediate structural changes and thus do not identify confounding effects that could prevent a proper assessment of the causal impact of the implementation of swing pricing.

4.3 Swing pricing and flow volatility

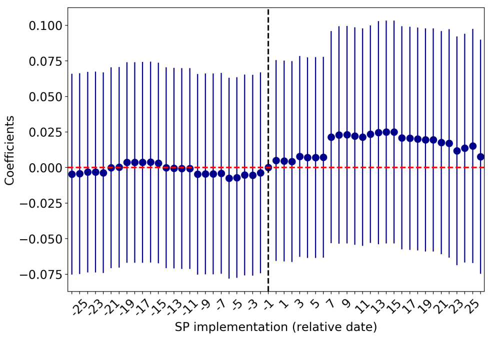
In this section, we take advantage of the high frequency of our observations to evaluate how swing pricing affects the flow volatility. Intuitively, more stable flows should be associated with increased financial stability (Cetorelli et al., 2022). By aiming to transfer the cost of portfolio reallocation to redeeming investors, swing pricing should decrease flow volatility as it gives incentives to investors to spread large redemption or large subscriptions over multiple NAV.

Formally, we estimate the following equation to test Hypothesis 3:

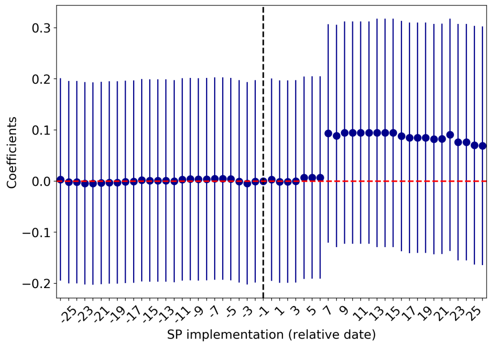
$$\begin{aligned} Vol_{i,t} \sim \quad & \beta_0 + \beta_1\, Stress_t + \beta_2\, SP_{i,t} + \beta_3\, SP_{i,t} \times Stress_t \\ & + \beta_4\, Controls_{i,t-1} + \beta_5\, \gamma_i + \beta_6\, \phi_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

with SP a dummy variable equal to one if a fund has a swing pricing mechanism. *Vol* is the standard deviation of the net weekly capital flows during the past 3 months of a fund share divided by the fund share's total net assets of the last week. $Stress$ is the systemic risk, equals to one if the value of the VIX CAC40 is in the top 10%. γ and ϕ are fund share and date fixed effects. $Controls$ is a vector of controls including the size of the fund, the percentage of institutional investors, the expense ratio, the alpha values, the debt ratio, the cash ratio, the portfolio's weighted average bid-ask spread. We cluster standard errors by fund shares. To assess robustness, we estimate Equation 4 on the full sample and on the sample matched on "portfolio and investors" (models 2 and 3 in Table 3) 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-8 provides in columns (4) an

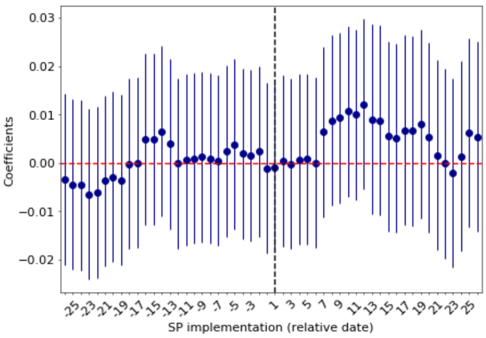
Figure 5: Difference in characteristics between funds with and without swing pricing



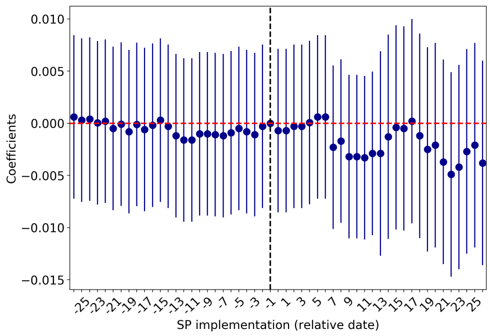
(a) % of institutional investors



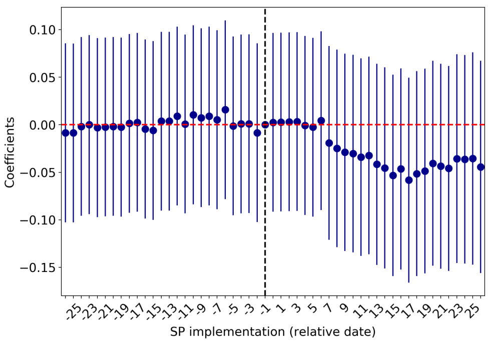
(b) Total expense ratio



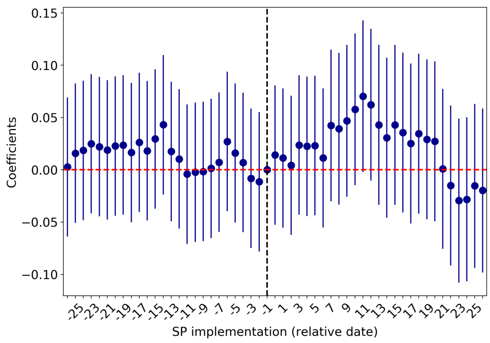
(c) Cash ratio



(d) Debt ratio



(e) Bid-ask spread



(f) Alpha

Note: Dependent variables are the percentage of institutional investors (a), the expense ratio (b), the cash ratio (c), the debt ratio (d), the portfolio weighted-average bid-ask spread (e) and the alpha (f). All dependent variables are residualized by estimating the model (i) of the Equation 2. All variables are four-week rolling moving averaged. Treated is equal to one if the fund will implement a swing pricing mechanism at the relative date zero. We plot the interaction coefficients between Treated and all the relative dates (y-axis), between -26 and 26: six months before and six months after the implementation of swing pricing (x-axis). Blue solid vertical bars are 95% confidence intervals and dark dotted vertical bars indicate the implementation date. The sample is constructed with the matching methodology "portfolio and investors". The unit of observation is fund by week. We cluster standard errors by fund.

estimation on the sample matched on controls.

Result 3. *There is weak evidence that implementing swing pricing decreases flow volatility.*

Support for Result 3: the coefficients associated with SP and $SP \times Stress$ in Table 3 measure the effect of swing pricing on the flow volatility. In models (1) and (2), none of these coefficients are statistically significant. In model (3), the coefficient associated with $SP \times Stress$ is negative (p = 0.063) and model (4) suggests an effect of SP on volatility (p = 0.011). We thus find weak evidence in favor of Hypothesis 3. In addition, we note that $Stress$ has a very statistically significant positive impact on the volatility (p < 0.001 in model 4). It supports that a lower flow variance is associated with higher financial stability.

Table 3: Flow volatility and swing pricing

	Volatility			
	(1)	(2)	(3)	(4)
Stress	-	-	-	0.309^{***}
				(0.017)
SP	-0.019	-0.017	-0.013	-0.153^{**}
	(0.059)	(0.061)	(0.070)	(0.061)
SP × Stress	0.026	-0.005	-0.151^{*}	0.004
	(0.055)	(0.057)	(0.081)	(0.057)
Controls	No	Yes	Yes	Yes
Matching	No	No	PI	No
Date FE	Yes	Yes	Yes	No
Observations	763,605	649,635	132,440	649,635
R^2	0.424	0.431	0.416	0.417

Note: this table presents regression results from OLS estimations for which the dependant variable is flow volatility defined as the 3-months standard deviation of the net weekly capital flows. For all regression, regressors include SP, a dummy equals to one if a fund implements swing pricing, Stress, a dummy equals 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 (4) 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. Controls coefficients are omitted in this table for sake of clarity, however they can be found in Table A-8. Column (4) uses the sample matched on "portfolio and investors". Columns (1) to (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

We interacted the effect of swing pricing with the effect of stress to evaluate Hypothesis 3. To assess Hypothesis 3-CO, we interact these two variables with the number of constraints (as a continuous variable) on the swing pricing. Formally, we estimate the following equation:

$$\begin{aligned} Vol_{i,t} \sim \quad & \beta_0 + \beta_1\, Stress_t + \beta_2\, SP_{i,t} + \beta_3\, SP_{i,t} \times Constraints_{i,t} \\ & + \beta_4\, SP_{i,t} \times Stress_t + \beta_5\, SP_{i,t} \times Constraints_{i,t} \times Stress_t \\ & + \beta_6\, Controls_{i,t-1} + \beta_7\, \gamma_i + \beta_8\, \phi_t + \epsilon_{i,t} \end{aligned} \tag{5}$$

where all variables are defined as in Equation 4 and *Constraints* is the number of constraints on the swing pricing mechanism.[17] As in Table 3, we estimate this model on the full sample (columns 1, 2 and 4 in Table 4), on the sample of funds matched with the matching "portfolio and investors" (column 3) and with the matching "controls" in Table A-9. Column (4) is without fixed effects.

Result 3-CO. *Constraints on swing pricing reduce the stabilizing impact on flow volatility.*

Support for Result 3-CO: the coefficients associated with *Constraints* and $SP \times Stress \times Constraints$ in Table 4 measure how the presence of constraints on the swing pricing mechanism affects the impact of swing pricing on flow volatility. In the absence of stress, unconstrained and constrained swing pricing does not impact the flow volatility (coefficient associated with SP and $SP \times Constraints$ are never significant). However, during systemic stress, we find that unconstrained swing pricing reduces the flow volatility in all models (coefficient associated with $SP \times Stress$, p-values are between 0.001 in model 3 and 0.058 in model 1). This provides evidence on the ability of swing pricing to decrease flow volatility during stress if unconstrained (absence of swing factor cap and swing threshold). On the contrary, we find that the presence of constraints on swing pricing increase the flows volatility during these periods in all models ($SP \times Stress \times Constraints$, 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-9). This tool thus seems to have overall some stabilizing effect on the flow variance, however the absence of a stronger effect is explained by the fact that constraints decrease its impact. We thus conclude in favor of Hypothesis 3-CO: the stabilizing impact on flow volatility is decreased when swing pricing is constrained.

[17] *Constraints* is not present outside of its interaction with *SP* as a fund cannot have constraints on the swing pricing without having implemented this tool.

Table 4: Flow volatility, swing pricing and constraints

	Volatility			
	(1)	(2)	(3)	(4)
Stress	-	-	-	0.310***
				(0.017)
SP	0.117	0.175	0.118	0.019
	(0.120)	(0.135)	(0.145)	(0.134)
SP × Constraints	−0.141	−0.205	−0.137	−0.183
	(0.109)	(0.125)	(0.126)	(0.125)
SP × Stress	−0.219*	−0.299**	−0.456***	−0.263**
	(0.116)	(0.121)	(0.136)	(0.121)
SP × Stress × Constraints	0.200**	0.241**	0.252**	0.220**
	(0.094)	(0.098)	(0.104)	(0.098)
Controls	No	Yes	Yes	Yes
Matching	No	No	PI	No
Date FE	Yes	Yes	Yes	No
Observations	763,605	649,635	132,440	649,635
R^2	0.424	0.431	0.416	0.417

*Note: this table presents regression results from OLS estimations for which the dependant variable is flow volatility defined as the 3-months standard deviation of the net weekly capital flows. For all regression, regressors include SP, a dummy equals to one if a fund implements swing pricing, Stress, a dummy equals to one if weekly VIX CAC40 is above the 90^{th} percentile of the sample, Constraints the number of constraints on the swing pricing and the interaction of these variables. In addition, columns (2) to (4) also include controls as regressors. Control variables include the lagged values of Size, percentage of institutional investors, expense ratio, alpha, debt ratio, cash ratio and portfolio weighted average bid-ask spread. Controls coefficients are omitted in this table for seek of clarity, however they can be found in Table A-9. Column (4) uses the sample matched on "portfolio and investors". Columns (1) to (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.*

4.4 Swing pricing during stress periods and flow level

Excessive capital outflows may lead to dilution and thus to the emergence of a first mover advantage. Empirically, these outflows are more likely to occur during periods of systemic stress, when uncertainty and information asymmetry are high. Moreover, these periods are associated with reduced portfolio liquidity and high uncertainty fund fragility. 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. It allows us to estimate the impact of implementing swing pricing on the elasticity of flows in situation of high uncertainty and market downturn. In this section, we therefore assess the impact of swing pricing on flow levels during periods of systemic stress. As in previous section, we first study the impact for all types of swing pricing combined then we differentiate between types. Formally, we start by estimating Equation 6:

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

As in Equation 4, controls are the size of the fund, the percentage of institutional investors, the expense ratio, the alpha values, the debt ratio, the cash ratio, the portfolio's weighted average bid-ask spread. γ and ϕ are share and date fixed effects. We cluster standard errors by fund shares. As previously, we estimate four model specifications in Table 5: model (1) without controls, model (2) on the full sample, 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-11: sample matched on controls.

In addition, we aim to disentangle the effect of swing pricing in situations of inflows and outflows. Indeed, the effect of swing pricing on both types of flows is associated with different issues. Identifying outflows enable us to study how swing pricing impacts outflows when, on average, investors are redeeming shares. It thus relates to the ability of swing pricing to avoid runs. By opposition, positive flows enable 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 this decrease of inflows dominates the decrease in outflows. Formally, we substitute $Flows_{i,t}$ in Equation 6 by, consecutively, outflows ($Flows \times \mathbb{1}_{Flows<0}$), and inflows ($Flows \times \mathbb{1}_{Flows>0}$) (as defined in Jin et al., 2022). We estimate these new equations on our sample matched on "portfolio and investors" (model 5 and 6 of Table 5) as well as without controls and with our sample matched on controls (models 1 and 3 of Table A-12 and Table A-13).

Result 4. *Swing pricing does not increase net flows or outflows during systemic stress*

Support for Result 4: coefficients associated with $SP \times Stress$ in models (1) to (4) of Table 5 measure the effect of swing pricing on flows during systemic stress periods. In all models, we find that swing pricing decreases net flows during these periods (p-values from 0.001 in model 1 to 0.038 in model 3). We thus conclude against Hypothesis 4. Similarly, coefficients associated with SP models (1) to (4) of Table 5 measure the effect of swing pricing outside of systemic stress periods. In all models, SP has no impact on flows except in model (2) (p = 0.077). Therefore, there is not enough evidence to conclude that the negative impact of swing pricing during stress periods is offset by a positive impact in other periods. Finally, we note that $Stress$ has, as expected, a negative effect on flows (model 4, $p < 0.001$). Using the matching based on controls (Table A-10, model 4), SP and $SP \times Stress$ have no impact on net flows, supporting Result 4.

To better understand the mechanisms behind this surprising negative impact of swing pricing, we now focus on inflows and outflows. We find that swing pricing does not have a statistically significant impact on flows in either calm or stressed periods (model 5). On the contrary, swing pricing decreases inflows during systemic stress periods (model 6, $SP \times Stress$, $p < 0.001$). These results are robust to removing controls or using the sample matched on controls (see Table A-12 and Table A-13). We thus find that the overall effect on net flows is driven by a decrease of 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. This result suggests that investors are reluctant from investing in funds with swing pricing when there are tensions in the economy but no specific tensions on the fund. The fact that outflows are not affected but inflows are reduced highlights a stigma effect. This can be explained by the fact that investing in a fund with swing pricing during periods of systemic stress implies that the investors will 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.

Even when focusing on negative flows (outflows), we do not find a positive effect of swing pricing. We continue our investigation of underlying mechanisms by studying how constraints on swing pricing affect flows. We thus interact swing pricing and stress periods with the number of constraints on the swing pricing.

Formally, we estimate the following equation:

$$\begin{aligned} Flows_{i,t} \sim\ & \beta_0 + \beta_1\, Stress_t + \beta_2\, SP_{i,t} + \beta_3\, SP_{i,t} \times Constraints_{i,t} \\ & + \beta_4\, SP_{i,t} \times Stress_t + \beta_5\, SP_{i,t} \times Constraints_t \times Stress_t \\ & + \beta_6\, Controls_{i,t-1} + \beta_7\, \gamma_i + \beta_8\, \phi_t + \epsilon_{i,t} \end{aligned} \tag{7}$$

where all variables are defined as in Equation 6 and $Constraints$ is the number of constraints on the swing pricing mechanism. Consistently with previous estimations, we

Table 5: Impact of swing pricing on the level of flows

	Flows				Negative flows	Positive flows
	(1)	(2)	(3)	(4)	(5)	(6)
Stress	-	-	-	-0.148^{***}	-	-
				(0.014)		
SP	0.090	0.114^{*}	0.085	0.052	0.018	0.067
	(0.059)	(0.064)	(0.059)	(0.063)	(0.033)	(0.050)
SP × Stress	-0.142^{***}	-0.125^{***}	-0.126^{**}	-0.105^{**}	0.011	-0.137^{***}
	(0.042)	(0.044)	(0.061)	(0.044)	(0.048)	(0.036)
Controls	No	Yes	Yes	Yes	Yes	Yes
Matching	No	No	PI	No	PI	PI
Date FE	Yes	Yes	Yes	No	Yes	Yes
Observations	843,843	715,493	146,322	715,493	146,322	146,322
R^2	0.054	0.059	0.050	0.054	0.066	0.095

*Note: this table presents regression results from OLS estimations for which the dependent variable is either flows (columns 1 to 4), negative flows (5) or positive flows (6). For all regression, regressors include SP, a dummy equals to one if a fund implements swing pricing, Stress, a dummy equals 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. Controls coefficients are omitted in this table for the seek of clarity, however they can be found in Table A-10. Columns (3), (5), and (6) use the sample matched on "portfolio and investors". Except column (4) all columns 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.*

estimate five model specifications varying regarding the inclusion of controls, date fixed effects, and samples and we cluster errors by fund shares.

Result 4-CO. *Constraints on swing pricing reduce its ability to prevent outflows during systemic stress.*

Support for Result 4-CO: the coefficients associated with $SP \times Stress \times Constraints$ in models (1) to (4) of Table 6 measure the effect of constraints on flows during systemic stress periods. In all models, these coefficients are negative (p-values between 0.007 in model 1 and 0.038 in model 2, effects robust with "control" matching method, see Table A-11). We thus conclude in favor of Hypothesis 4-CO. 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 5 vanishes for unconstrained swing pricing. Outside of systemic stress periods, unconstrained and constrained swing pricing do not impact net flows, outflows or inflows: in models (1) to (4) *Constraints* is never significant while SP is significantly positive at a 10% level only in the model (2) (p = 0.065). Distinguishing between inflows and outflows highlights the asymmetrical effects of swing pricing. In model (5), we find a negative effect of $SP \times Stress \times Constraints$ (p = 0.020) and a positive effect of $SP \times Stress$ (p = 0.018) on outflows. This finding is robust to removing controls or using our other matching method (see Table A-12). It means that swing pricing without constraints is effective in decreasing outflows (higher net flows) during stress periods but that constraints mitigate this impact. In model (6), we find a negative effect of $SP \times Stress$ (p = 0.099) on inflows but no effect of $SP \times Stress \times Constraints$. It implies that constraints on the swing pricing mechanism do not impact the stigma effect during systemic stress periods highlighted previously. Results are robust to removing controls or using the alternative matching methodology as presented in Table A-13.

Table 6: Impact of swing pricing and constraints on flow levels

	Flows				Negative flows	Positive flows
	(1)	(2)	(3)	(4)	(5)	(6)
Stress	-	-	-	-0.149^{***}	-	-
				(0.014)		
SP	0.213	0.312^{*}	0.121	0.224	-0.042	0.163
	(0.143)	(0.169)	(0.140)	(0.168)	(0.069)	(0.127)
SP × Constraints	-0.154	-0.244	-0.061	-0.216	0.058	-0.120
	(0.126)	(0.151)	(0.127)	(0.149)	(0.068)	(0.108)
SP × Stress	0.108	0.086	0.100	0.145	0.207^{**}	-0.106^{*}
	(0.096)	(0.101)	(0.108)	(0.102)	(0.087)	(0.064)
SP × Stress × Constraints	-0.203^{***}	-0.173^{**}	-0.186^{**}	-0.205^{**}	-0.161^{**}	-0.025
	(0.076)	(0.084)	(0.085)	(0.084)	(0.069)	(0.048)
Controls	No	Yes	Yes	Yes	Yes	Yes
Matching	No	No	PI	No	PI	PI
Date FE	Yes	Yes	Yes	No	Yes	Yes
Observations	823,235	698,810	142,446	698,810	142,446	142,446
R^2	0.055	0.060	0.051	0.055	0.066	0.096

Note: this table presents regression results from OLS estimations for which the dependent variable is either flows (columns 1 to 4), negative flows (5) or positive flows (6). For all regression, regressors include SP, a dummy equals to one if a fund implements swing pricing, Stress, a dummy equals to one if weekly VIX CAC40 is above the 90^{th} *percentile of the sample, Constraints the number of constraints on the swing pricing and the interaction of these variables. 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. Controls coefficients are omitted in this table for seek of clarity, however they can be found in Table A-11. Columns (3), (5) and (6) use the sample matched on "portfolio and investors". All columns except (4) 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.* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

To conclude on the impact of swing pricing on flow levels, we find that overall swing pricing decreases fund flows due to a reduction of positive flows. This effect is driven by the use of constraints that prevent swing pricing from mitigating outflows.

4.5 Swing pricing and idiosyncratic stress

As it is implemented currently in France, swing pricing does not seem to be effective in limiting outflows during periods of systemic stress. In addition to a stigma-effect, this lack of stabilizing effect seems to be driven by the swing pricing calibration: the presence of constraints strongly limit its efficiency. To go a step further, we isolate the impact of swing pricing in situations where it should be activated even if there is a swing threshold, and should have a high restructuring cost: after large outflows in situation of liquidity strain. Indeed, large outflows should trigger the activation of partial swing pricing and the combination of large outflows and low liquidity implies a large portfolio restructuring cost.[18] 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 (the auto-correlation coefficient between consecutive flows in a AR(1) is 0.167, significant at the 0.001% level). Furthermore, funds are facing these outflows with a deteriorated liquidity that may involve some dilution and thus the emergence of a first-mover advantage. The swing pricing could therefore increase funds financial stability if it is able to reduce the sensibility of flows to idiosyncratic stress.

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

$$\begin{aligned} Flows_{i,t} \sim \; & \beta_1\, LMT_{i,t} + \beta_2\, \mathit{Outflows}_{i,t-1} + \beta_3\, \mathit{Illiquidity}_{i,t-1} + \beta_4\, \mathit{Outflows}_{i,t-1} \times LMT_{i,t} \\ & + \beta_5\, \mathit{Illiquidity}_{i,t-1} \times LMT_{i,t} + \beta_6\, \mathit{Outflows}_{i,t-1} \times \mathit{Illiquidity}_{i,t-1} \\ & + \beta_7\, LMT_{i,t-1} \times \mathit{Outflows}_{i,t-1} \times \mathit{Illiquidity}_{i,t-1} + \beta_8\, Controls_{i,t-1} \\ & + \beta_9\, \gamma_i + \beta_{10}\, \phi_t + \epsilon_{i,t} \end{aligned} \tag{8}$$

with *Outflows* a dummy variable equals to 1 if the net flows in period $t-1$ are lower than the first decile, *Illiquidity* a dummy variable equals to 1 if the bid-ask spread in

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

$t-1$ is higher than the last decile. $Controls$ is a vector of controls including the size, the percentage of institutional investors, the expense ratio, the alpha values, the debt ratio and the cash ratio of funds. γ and ϕ are fund share and date fixed effects. This equation is our baseline equation, to test for robustness we also estimate it without controls (model 1 of Table 7). In addition, we estimate Equation 8 on our full sample (model 2) and on our sample matched on "portfolio and investors" (model 3). In appendices, we present the results with a $8th$ decile threshold in Table A-15 and with continuous variables in Table A-16.

Result 5. *Swing pricing increases flows during idiosyncratic stress.*

Support for Result 5: the coefficients associated with $SP \times$*Outflows*$\times$*Illiquidity* in models (1) to (3) of Table 7 measure the effect of swing pricing on net flows under idiosyncratic stress. In each model, except model (3), this effect is strongly positive (p-values between less than 0.01 in model 1 and 0.02 in model 3).

This finding is robust to using $8th$ decile threshold or continuous variables (models 1 and 2 of, respectively, Table A-15 and Table A-16). We thus conclude in favor of Hypothesis 5. In addition, we observe that the coefficients associated with *SP* $\times$ *Outflows* and *SP* $\times$ *Illiquidity* are negative (p-values < 0.001) in these models. In a situation where the outflows in the last period are particularly severe, but with a rather standard liquidity, or the opposite, the fund is in a situation of relative stress but the restructuring cost that the swing pricing is supposed to transfer is low. These coefficients highlight the fact that in these situations, the stigma effect of swing pricing could be greater than its stabilizing effect. It also implies that the total effect of swing pricing ($SP + SP \times Outflows + SP \times Illiquidity + SP \times Outflow \times Illiquidity$) is rather small in all models. All these results are robust to using the 8^{th} decile threshold or continuous variables (see Table A-15 and Table A-16).

As pointed out earlier, the presence of constraints can reduce the stabilizing effect of swing pricing. In situations of idiosyncratic stress, only one of the potential constraints on the swing factor is restrictive: the capped swing factor. To evaluate the effect of swing factor caps on the impact of swing pricing under idiosyncratic stress, we estimate Equation 8 by successively replacing SP by a dummy variable equals to 1 if funds have a swing pricing without capped swing factor (model 4 of Table 7) and a dummy variable equals to 1 if funds have a swing pricing with capped swing factor (model 5 of Table 7).[19] We estimate these models following the specification of model (3) of Table 7 and we present the results in Table A-15 and Table A-16. To be consistent with our previous results, we should identify that the existence of a swing factor cap reduce the ability of the swing pricing mechanism to increase net flows during idiosyncratic stress.

Result 5-CO. *Implementing a swing factor cap does not enable funds to increase flows during idiosyncratic stress.*

Support for Result 5-CO: the coefficient associated with $SP \times Outflows \times Illiquidity$ in model (5) is negative and not statistically significant (p = 0.57). 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 a swing factor cap has a strong positive effect on net flows (p = 0.029). When we sum all the coefficients linked to the swing pricing implementation, we find an aggregate impact of about one-third of the impact of the idiosyncratic shock on net flows.

These results are even more salient when using the 80^{th} percentile threshold (see Table A-15). We thus conclude in favor of Hypothesis 5-CO.[20]

Overall, we find that swing pricing reduces the sensitivity of net flows to idiosyncratic stress (situation of large previous outflows and liquidity strain). It shows that, when facing high restructuring cost and thus potential dilution, swing pricing is effective in improving the fund position. However capped swing factor reduces this effect by inducing a deviation between the restructuring cost paid by the fund and the swing factor paid by redeeming investors, generating dilution. Our results highlight the crucial importance of the general formula driving the swing pricing mechanism.

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,

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

[20] According to the AMF, some fund managers have requested permission to increase their swing factor higher than the swing factor cap disclosed in their prospectus during the COVID-19 crisis. We may thus underestimate the impact of swing pricing in the absence of a swing factor cap. The fact that the identified effect is so clear despite these discussions add robustness to our result.

Table 7: Impact of swing pricing for large levels of swing factor, during idiosyncratic stress

	Flows				
	(1)	(2)	(3)	(4)	(5)
Outflows	−0.544***	−0.543***	−0.591***	−0.593***	−0.649***
	(0.050)	(0.019)	(0.050)	(0.046)	(0.043)
Illiquidity	−0.095***	−0.103***	0.011	0.036	−0.013
	(0.024)	(0.022)	(0.041)	(0.034)	(0.036)
SP	0.065	0.073	0.079	0.114*	−0.089
	(0.062)	(0.067)	(0.061)	(0.064)	(0.108)
SP x Outflows	−0.219***	−0.202***	−0.121	−0.152*	0.043
	(0.067)	(0.065)	(0.080)	(0.087)	(0.124)
SP x Illiquidity	−0.129**	−0.138***	−0.077	−0.080	0.039
	(0.060)	(0.048)	(0.118)	(0.095)	(0.090)
Outflows x Illiquidity	0.094*	0.125***	0.009	−0.081	0.080
	(0.051)	(0.048)	(0.057)	(0.074)	(0.066)
SP x Outflows x Illiquidity	0.294***	0.265**	0.204	0.348**	−0.104
	(0.111)	(0.114)	(0.159)	(0.159)	(0.186)
Type of SP	All	All	All	W/O cap	W/ cap
Matching	No	No	PI	PI	PI
Controls	No	Yes	Yes	Yes	Yes
Observations	823,235	734,047	142,648	142,648	142,648
R^2	0.061	0.066	0.057	0.057	0.057
Note:					*p<0.1; **p<0.05; ***p<0.01

*Note: this table presents regression results from OLS estimations for which the dependent variable is flows. For all regression, regressors include SP, Outflows, Illiquidity and their interaction terms. Outflows is a dummy equals to 1 if flows in period $t-1$ are lower than the first decile, and Illiquidity a dummy variable equals to 1 if the bid-ask spread in period $t-1$ is higher than the 9th decile. In columns (1) to (3), SP is a dummy variable equal to 1 if a fund uses any type of swing pricing, in column (4) it is equal to 1 only if a fund use a swing pricing without capped swing factor, finally in column (5) it is equal to 1 only if a fund use a swing pricing with capped swing factor. In addition, columns (2) to (5) also include controls as regressors. Control variables are the lagged values of size, percentage of institutional investors, expense ratio, alpha, debt ratio and cash ratio. Controls coefficients are omitted in this table for seek of clarity, however they can be found in Table A-14. Columns (3) to (5) use the sample matched on "portfolio and investors". All columns have fund share and date 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.*

investment funds experienced intensive outflows in a context of severely reduced market liquidity. This episode stimulated discussions about the resilience of investment funds, 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 implementation of swing pricing—ability to use swing pricing independently of activation—by French investment funds from 2018 to 2020, as well as the modalities of its use. Our results suggest that swing pricing has only a limited impact on the financial stability of funds as it is implemented today in France. During idiosyncratic stress—situations of large past outflows and liquidity strain—swing pricing increases flows. However, we find only weak evidence that swing pricing reduces flow volatility. Moreover, during periods of systemic stress such as the Covid-19 turmoil, funds that implemented swing pricing had more negative flows than others. These results contrast with Jin et al. (2022), which argues that swing pricing significantly reduces outflows during market stress on a sample of UK bond funds.

Our study highlights two new mechanisms that explain this limited stabilizing effect. First, part of the explanation lies in the existence of a stigma effect. This stigma is identified by an immediate flight of investors after the introduction of swing pricing, as well as a deterioration of inflows during periods of systemic stress. It suggests that some investors are reluctant to invest in funds with swing pricing.

The other part comes from the fact that the stabilizing effect of swing pricing is diminished by the widespread use of constrained swing pricing in France. Indeed, we find that adding constraints to swing pricing increases the flow volatility and amplifies outflows in times of systemic stress. On the contrary, we find that swing pricing has the intended effects when it is implemented without constraints: the liquidity management tool appears to be effective to decrease flow volatility and mitigate outflows during systemic stress. This effect is central since, in France, more than 85% of swing pricing mechanisms are constrained by the existence of a swing threshold, and 28% of funds have swing factor caps. In addition, we find converging evidence on the central role of constraints by focusing on idiosyncratic stress. During these periods, partial swing pricing thresholds should be exceeded and the restructuring cost is high. We find that swing pricing is a effective tool to reduce outflows during idiosyncratic stress. However, in presence of a swing factor cap, the stabilizing effect vanishes consistent with the fact that this constraint strongly reduces the swing factor in such situations.

Therefore, we find that swing pricing has the potential to reduce the liquidity mismatch between assets and liabilities faced by investment funds. However, it is crucial that the calibration enables the stabilizing effect to offset the stigma effect. To maximize its stabilizing impact, we recommend implementing swing pricing with no swing cap or threshold. To decrease the stigma effect, one possibility could be to make swing pricing implementation mandatory for all funds. This could remove incentives for investors to switch to non-swing priced funds in the same jurisdiction. Another solution could be to implement swing pricing at a macroprudential level as proposed by the ESRB, in order to take into account systemic vulnerabilities and spillovers in the calibration of the swing pricing parameters.

References

AFG (2016). Code of conduct for asset managers using swing pricing and variable anti dilution levies. Technical report.

Agarwal, V., Ren, H., Shen, K., and Zhao, H. (2020). Redemption in kind and mutual fund liquidity management. *Available at SSRN 3527846*.

ALFI (2015). Swing pricing, association of the luxembourg fund industry. Technical report.

Bank of England (2021). Liquidity management in uk open-ended funds. *Bank of England*.

Capponi, A., Glasserman, P., and Weber, M. (2020). Swing pricing for mutual funds: Breaking the feedback loop between fire sales and fund redemptions. *Management Science*.

Cetorelli, N., La Spada, G., and Santos, J. A. (2022). Monetary policy and the run risk of loan funds. *FRB of New York Staff Report*, (1008).

Chen, Q., Goldstein, I., and Jiang, W. (2010). Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics*, 97(2):239–262.

Cherkes, M., Sagi, J., and Stanton, R. (2008). A liquidity-based theory of closed-end funds. *The Review of Financial Studies*, 22(1):257–297.

Chevalier, J. and Ellison, G. (1997). Risk taking by mutual funds as a response to incentives. *Journal of political economy*, 105(6):1167–1200.

Claessens, S. and Lewrick, U. (2021). Open-ended bond funds: systemic risks and policy implications. *BIS Quarterly Review*, page 37.

Coval, J. and Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, 86(2):479–512.

Darpeix, P.-E., Le Moign, C., Même, N., and Novakovic, M. (2020). Overview and inventory of french funds' liquidity management tools. *Banque de France Working paper*.

Dehejia, R. H. and Wahba, S. (1999). Causal effects in nonexperimental studies: Reevaluating the evaluation of training programs. *Journal of the American statistical Association*, 94(448):1053–1062.

Dunne, P. G. and Giuliana, R. (2021). Do liquidity limits amplify money market fund redemptions during the covid crisis?

Edelen, R. M. (1999). Investor flows and the assessed performance of open-end mutual funds. *Journal of Financial Economics*, 53(3):439–466.

ESMA (2020). Recommendation of the european systemic risk board (esrb) on liquidity risk in investment funds. Technical report.

Falato, A., Goldstein, I., and Hortaçsu, A. (2021). Financial fragility in the covid-19 crisis: The case of investment funds in corporate bond markets. *Journal of Monetary Economics*, 123:35–52.

FSB (2017). Policy recommendations to address structural vulnerabilities from asset management activities. Technical report.

FSB (2021). Policy proposals to enhance money market fund resilience. Technical report.

Goldstein, I., Jiang, H., and Ng, D. T. (2017). Investor flows and fragility in corporate bond funds. *Journal of Financial Economics*, 126(3):592–613.

IMF (2021). Investment funds and financial stability: Policy considerations. Technical report.

IOSCO (2018). Recommendations for liquidity risk management for collective investment schemes. Technical report.

Jin, D., Kacperczyk, M., Kahraman, B., and Suntheim, F. (2022). Swing pricing and fragility in open-end mutual funds. *The Review of Financial Studies*, 35(1):1–50.

Kacperczyk, M., Perignon, C., and Vuillemey, G. (2021). The private production of safe assets. *The Journal of Finance*, 76(2):495–535.

Koenig, P. J. and Pothier, D. (2020). Safe but fragile: Information acquisition, liquidity support and redemption runs. *Journal of Financial Intermediation*, page 100898.

Lewrick, U. and Schanz, J. F. (2017a). Is the price right? swing pricing and investor redemptions. *BIS Working Papers*, 664.

Lewrick, U. and Schanz, J. F. (2017b). Liquidity risk in markets with trading frictions: What can swing pricing achieve?

Li, L., Li, Y., Macchiavelli, M., and Zhou, X. A. (2021). Liquidity restrictions, runs, and central bank interventions: Evidence from money market funds. *Runs, and Central Bank Interventions: Evidence from Money Market Funds (May 13, 2021)*.

Malik, S. and Lindner, P. (2017). *On swing pricing and systemic risk mitigation*. International Monetary Fund.

Massa, M. and Rehman, Z. (2008). Information flows within financial conglomerates: Evidence from the banks–mutual funds relation. *Journal of Financial Economics*, 89(2):288–306.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Schmidt, L., Timmermann, A., and Wermers, R. (2016). Runs on money market mutual funds. *American Economic Review*, 106(9):2625–57.

Schwabe, H. and Ed-Diaz, M. (2020). Developments in relation to risk management for european investment funds. *Journal of Risk Management in Financial Institutions*, 13(4):357–373.

Zeng, Y. (2017). A dynamic theory of mutual fund runs and liquidity management. *Available at SSRN 2907718*.

APPENDICES

A Data and descriptive statistics

A.1 Variable definition

Table A-1: Variable definition

Label	Definition	Units	Frequency
Stress	Dummy variable equals one if VIX index above the 90^{th} percentile		w
SP	Dummy variable equals 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.	%	m
Expense ratio	Total costs associated with managing and operating an investment fund divided by fund's TNA	%	w
Debt ratio	Total loans received divided by total assets/liabilities	%	m
Cash ratio	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 and empty for time-invariant variables.

A.2 Summary Statistics

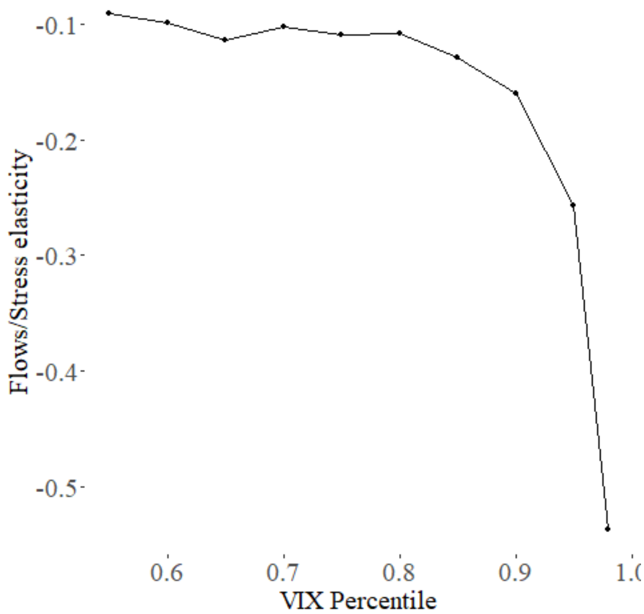
Table A-2: Summary Statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Flows	−0.022	2.050	−26.917	−0.152	0.015	11.257
Volatility	1.16	1.47	0	0.14	1.71	12.69
Swing pricing	0.089	0.284	0	0	0	1
Swing constraints	0.110	0.392	0	0	0	2
TNA (in M)	102.411	366.257	0.010	7.685	83.141	19,445.070
Institutional	0.734	0.293	0.000	0.590	0.987	1.000
Alpha	−0.034	0.388	−1.353	−0.179	0.103	1.591
Debt	0.008	0.025	0.000	0.000	0.001	0.149
Cash	0.040	0.072	0.000	0.002	0.051	0.591
Bid-Ask Spread	0.390	0.290	0.033	0.157	0.504	1.538
Type of fund						
Equity	0.401	0.490	0	0	1	1
Bond	0.217	0.412	0	0	0	1
Other	0.382	0.486	0	0	1	1
Age	13.911	9.422	1	6.3	19.7	56
Expense	1.587	0.838	0.000	1.000	2.100	7.490
Redemption charge	0.454	1.333	0.000	0.000	0.000	12.500
NAV frequency	1.675	1.896	1	1	1	7
VIX crisis	0.093	0.291	0	0	0	1

A.3 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 the 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, stress is equal to 1 for all periods with a VIX CAC40 above the percentile indicated on the x-axis.

A.4 Matching methodologies

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

A.4.1 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.4.2 Descriptive statistics on matching methods

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

	No matching	With matching
Flows	0.033	0.009
Volatility	0.417	0.081
TNA	11.809	1.503
Institutional	0.018	0.004
Alpha	0.154	0.001
Bidask	0.114	0.031
Age	1.300	0.314
Expense	0.367	0.008

Note: This table reports the difference of means between funds that will implement swing pricing (named Treated group in Section 4.2) and the others, for each variable that is used in the "Controls" methodology (lower part of the table) and benchmark variables (upper part). The sample period is December 2017.

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

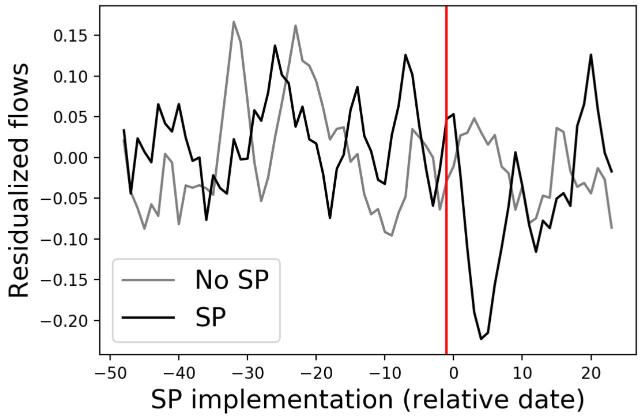
	No matching	With matching
Flows	0.033	0.029
Volatility	0.417	0.129
NACE sector of the issuer	36.191	5.966
Geographic area of the issuer	77.931	7.842
Institutional sector of the issuer	71.537	4.223
Type of instrument held	40.051	8.278
Rating of the instruments	8.833	1.955
Type of investors	22.256	8.326

Note: this table compares funds that will implement swing pricing (named Treated group in Section 4.2) and the other funds. Variables in the lower part of the table are used in the "Portfolio and investors" matching methodology, while variables on the upper part are benchmark variables. This table reports, for each categorical variable, 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 December 2017.

B Immediate impact of swing pricing introduction

Table A-5 shows the distribution of the introduction of swing pricing by investment funds over time. We observe a sharp increase in the popularity of the swing pricing mechanism since 2018: 18 investment funds implemented swing pricing in 2018, compared to 89 funds in 2020. Figure A-2 replicates Figure 3 with the matching on "controls". Figure A-3 replicates Figure 4 while varying the specification to estimate residualized flows and the matching methodology.

Figure A-2: Residualized flows for funds with and without swing pricing - matching "controls"



Note: this figure plots residualized flows (y-axis) against relative implementation date (x-axis) for the funds that will implement swing pricing at the relative date zero (the treated group, represented by the black line) and the control group composed of their matched twins that will not implement swing pricing (the grey line). The red vertical line indicates the last period before the relative implementation date of swing pricing (x = -1). Residualized flows are calculated following the model specification (i) and with the matching methodology "controls" and smoothed monthly.

Table A-5: Implementation of swing pricing by quarter (switching funds)

Year	Quarter	Shares of fund (nbr)	Funds (nbr)
2018	1	15	2
2018	2	21	4
2018	3	19	4
2018	4	11	8
2019	1	15	4
2019	2	29	10
2019	3	36	13
2019	4	70	21
2020	1	20	5
2020	2	60	22
2020	3	45	15
2020	4	85	47
Total		426	155

Note: Additional number of funds and shares with a swing pricing mechanism by quarter. Lecture: in 2019 Q4, 21 investment funds implemented swing pricing in our sample.

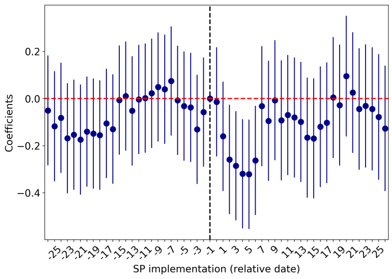
The results presented in Table A-7 are the estimation of Equation 3 by considering the relative date as a categorical variable. This new variable contains three modalities: (i) "Post: before" before the implementation of the swing pricing by the Treated group (relative date < 0), "Post: short-term" during the two months following the swing pricing implementation and (iii) "Post: medium-term" from the third to the sixth month. The reference date are all the weeks before the implementation date ("Post: before"). The value of the coefficient "Treated $\times$ Post: short-term" is between -0.165 and -0.202, and

Table A-6: Estimation of the residualized flows

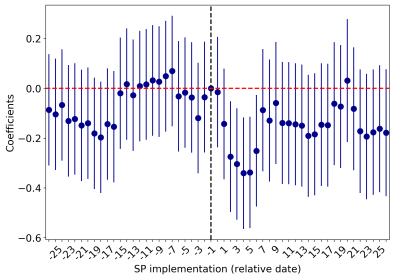
	Flow			
	(1)	(2)	(3)	(4)
Type fund : Other	0.024	0.045	0.046	0.048
	(0.043)	(0.047)	(0.049)	(0.058)
Type fund : Bond	0.025	0.046	0.020	0.037
	(0.035)	(0.044)	(0.041)	(0.052)
Size	-	-0.000	-	-0.000^{**}
		(0.000)		(0.000)
Bid-ask spread	-	-0.072	-	-0.034
		(0.048)		(0.052)
Alpha	-	0.080^{*}	-	0.012
		(0.046)		(0.058)
Cash ratio	-	-0.133	-	0.176
		(0.380)		(0.332)
Debt ratio	-	-0.663	-	-1.206^{***}
		(0.453)		(0.396)
Institutional	-	0.087	-	0.104
		(0.057)		(0.065)
Expense ratio	-	0.005	-	0.039
		(0.024)		(0.034)
Matching	PI	PI	Controls	Controls
Observations	66,836	66,836	75,460	75,460
R^2	0.011	0.011	0.007	0.008

Note: the dependent variable is the net flows The model specifications are presented in Equation 2. Columns (1) and (3) corresponds to the model specification (ii) based on the "portfolio and investors" and "control" matchings. Similarly, columns (2) and (4) corresponds to the model specification (i). All specifications have date fixed effects. The unit of observation is fund by week. We cluster standard errors by funds. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

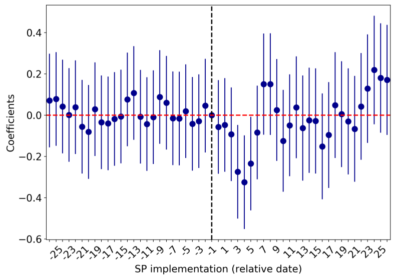
Figure A-3: Difference of residualized flows between funds with and without swing pricing - robustness



(a) Matching Controls, model (i)



(b) Matching Controls, model (ii)



(c) Matching PI, model (ii)

Note: the dependent variable is the residualized flows computed following Equation 2 obtained with model (i) for (a) (with dates FE and controls), and (ii) for (b) and (c) (with dates and no controls). (a) and (b) are based on the "control" matching method while (c) is based on the "portfolio and investors" matching method. Residualized flows are smoothed monthly and are explained by Treated and the relative date, which is the date relative to the implementation of swing pricing by the Treated found (see Equation 3). Treated is equal to one if the fund will implement a swing pricing mechanism at the relative date zero. We plot the interaction coefficients between Treated and all the relative dates (y-axis), between -26 and 26, except -1 the reference date: it corresponds to six months before and six months after the implementation of swing pricing (x-axis). Blue solid vertical bars are 95% confidence intervals and the dark dotted vertical bar indicates the week before the swing pricing implementation (the coefficient of the relative date -1 is equal to zero by design). The sample is constructed with the matching methodology "portfolio and investors". The unit of observation is fund by week. We cluster standard errors by fund.

statistically significant at the 1% or 5% confidence level. It provides robustness to the results obtained in Figure A-3.

Table A-7: Effect of the implementation of swing pricing on residualized flows

	Residualized flows					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.008	0.037	−0.018	0.004	0.019	−0.00002
	(0.010)	(0.034)	(0.040)	(0.040)	(0.040)	(0.047)
Post: short-term	0.021	0.013	0.050	0.038	0.004	0.062
	(0.044)	(0.048)	(0.048)	(0.048)	(0.050)	(0.057)
Post: middle-term	−0.007	−0.017	0.080	0.060	−0.025	0.069
	(0.031)	(0.041)	(0.052)	(0.052)	(0.039)	(0.063)
Treated × Constraints					0.032	0.009
					(0.043)	(0.047)
Post: short-term × Treated	-0.183^{**}	-0.203^{***}	-0.167^{**}	-0.167^{**}	-0.393^{***}	-0.348^{**}
	(0.074)	(0.076)	(0.078)	(0.078)	(0.143)	(0.175)
Post: medium-term × Treated	0.010	−0.046	0.020	0.010	0.093	0.113
	(0.044)	(0.058)	(0.072)	(0.072)	(0.114)	(0.167)
Post: short-term × Treated × Constraints					0.208^{*}	0.148
					(0.115)	(0.132)
Post: medium-term × Treated × Constraints					−0.140	−0.112
					(0.092)	(0.121)
Matching	PI	PI	Controls	Controls	PI	Controls
Observations	66,836	66,836	75,460	75,460	66,836	75,460
R^2	0.0003	0.0004	0.001	0.0004	0.001	0.001

Note: the dependent variable is the residualized flows computed following Equation 2 obtained with model (ii) for columns (1) and (3) (with dates FE but no controls), and (i) for columns (2) and (4) to (6) (with dates FE and controls). (1), (2) and (5) are based on the "portfolio and investors" matching while (3), (4) and (6) are based on the "control" matching. Residualized flows are explained by Treated and Post. Treated is equal to one if the fund will implement a swing pricing mechanism at the relative date zero. The reference category of the variable Post is before the implementation of swing pricing by the Treated group. The two other categories of the variable Post are "short-term" during the two months after the swing pricing implementation and "medium-term" otherwise. The unit of observation is fund by week. Constraints correspond to the number of constraints of the swing pricing mechanism. All columns have date and fund type fixed effects. We cluster standard errors by funds. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

C Swing pricing and flow volatility

Table A-8 and Table A-9 respectively the three last columns of Table 3 and Table 4 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-8: Flow volatility and swing pricing

	Volatility			
	(1)	(2)	(3)	(4)
Stress	-	-	0.309***	-
			(0.017)	
SP	−0.017	−0.013	−0.153**	0.002
	(0.061)	(0.070)	(0.061)	(0.070)
SP × Stress	−0.005	−0.151*	0.004	−0.115
	(0.057)	(0.081)	(0.057)	(0.077)
Size	−0.073***	−0.067	−0.067***	−0.049
	(0.019)	(0.046)	(0.019)	(0.041)
Institutional	0.020	0.531**	−0.044	0.695***
	(0.126)	(0.268)	(0.124)	(0.269)
Expense ratio	−0.055	−0.171	−0.023	−0.053
	(0.042)	(0.142)	(0.042)	(0.139)
Alpha	−0.036**	−0.006	−0.163***	0.004
	(0.016)	(0.041)	(0.016)	(0.043)
Debt ratio	−0.479	−1.349*	−0.420	−0.844
	(0.369)	(0.758)	(0.367)	(0.725)
Cash ratio	0.948***	0.566	1.030***	0.476
	(0.189)	(0.427)	(0.189)	(0.417)
Bid-ask spread	−0.110**	−0.070	−0.033	−0.131
	(0.047)	(0.081)	(0.043)	(0.081)
Matching	No	PI	No	Controls
Date FE	Yes	Yes	No	Yes
Observations	649,635	132,440	649,635	142,114
R^2	0.431	0.416	0.417	0.391

Note: this table presents regression results from OLS estimations for which the dependant variable is flow volatility defined as the 3-months standard deviation of the net weekly capital flows. For all regression, regressors include SP, a dummy equals to one if a fund implements swing pricing and Stress, a dummy equals to one if weekly VIX CAC40 is above the 90^{th} percentile of the sample and the interaction of both variables. 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. The observation level is fund share per week. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A-9: Flow volatility, swing pricing and constraints

	Volatility			
	(1)	(2)	(3)	(4)
Stress	-	-	0.310***	-
			(0.017)	
SP	0.175	0.118	0.019	0.200
	(0.135)	(0.145)	(0.134)	(0.141)
Constraints	−0.205	−0.137	−0.183	−0.208
	(0.125)	(0.126)	(0.125)	(0.129)
SP × Stress	−0.299**	−0.456***	−0.263**	−0.432***
	(0.121)	(0.136)	(0.121)	(0.131)
SP × Stress × Constraints	0.241**	0.252**	0.220**	0.247**
	(0.098)	(0.104)	(0.098)	(0.098)
Size	−0.074***	−0.068	−0.067***	−0.043
	(0.019)	(0.046)	(0.019)	(0.041)
Institutional	0.010	0.503*	−0.053	0.663**
	(0.126)	(0.268)	(0.124)	(0.270)
Expense ratio	−0.055	−0.187	−0.023	−0.065
	(0.042)	(0.143)	(0.041)	(0.137)
Alpha	−0.035**	−0.002	−0.163***	0.006
	(0.016)	(0.041)	(0.016)	(0.043)
Debt ratio	−0.478	−1.338*	−0.420	−0.951
	(0.369)	(0.757)	(0.367)	(0.725)
Cash ratio	0.957***	0.589	1.038***	0.692
	(0.189)	(0.425)	(0.189)	(0.420)
Bid-ask spread	−0.117**	−0.093	−0.039	−0.149*
	(0.046)	(0.080)	(0.042)	(0.080)
Matching	No	PI	No	Controls
Date FE	Yes	Yes	No	Yes
Observations	649,635	132,440	649,635	142,114
R^2	0.431	0.416	0.417	0.391

Note: this table presents regression results from OLS estimations for which the dependant variable is flow volatility defined as the 3-months standard deviation of the net weekly capital flows. For all regression, regressors include SP, a dummy equals to one if a fund implements swing pricing, Stress, a dummy equals to one if weekly VIX CAC40 is above the 90^{th} *percentile of the sample, Constraints the number of constraints on the swing pricing and the interaction of these variables. 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. The observation level is fund share per week.* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

D Swing pricing during stress periods and flow level

Table A-10 and Table 6 respectively replicate columns (2) to (4) of Table 5 and Table 6 while giving the coefficients of the controls. In addition, column (4) replicates column (2) using the matched sample based on controls. Table A-12 and Table A-13 respectively replicate, in column (2), column (5) and column (6) of Table 5. In addition, they provide robustness by estimating the specifications on the full sample (column 1) and on the sample matched on "controls" (column 3). Similarly, they respectively replicate, in column (5), column (5) and column (6) of Table 6 and provide robustness.

Table A-10: Flow level and swing pricing

	Flows			
	(1)	(2)	(3)	(4)
Stress	-	-	-0.148^{***}	-
			(0.014)	
SP	0.114^{*}	0.085	0.052	0.107
	(0.064)	(0.059)	(0.063)	(0.065)
SP × Stress	-0.125^{***}	-0.126^{**}	-0.105^{**}	-0.075
	(0.044)	(0.061)	(0.044)	(0.061)
Size	-0.246^{***}	-0.207^{***}	-0.236^{***}	-0.210^{***}
	(0.018)	(0.034)	(0.018)	(0.032)
Institutional	0.273^{**}	0.586^{**}	0.209^{*}	1.117^{***}
	(0.123)	(0.235)	(0.122)	(0.388)
Expense ratio	0.072^{**}	0.001	0.126^{***}	-0.189
	(0.036)	(0.166)	(0.035)	(0.146)
Alpha	0.045^{***}	0.055	0.017	-0.012
	(0.013)	(0.035)	(0.013)	(0.043)
Debt ratio	-2.324^{***}	0.670	-2.474^{***}	-0.280
	(0.403)	(0.773)	(0.409)	(0.823)
Cash ratio	1.964^{***}	0.725	1.830^{***}	1.568^{***}
	(0.233)	(0.466)	(0.233)	(0.512)
Bid-ask spread	-0.239^{***}	-0.060	-0.180^{***}	-0.037
	(0.038)	(0.060)	(0.035)	(0.064)
Matching	No	PI	No	Controls
Date FE	Yes	Yes	Yes	No
Observations	698,810	142,446	698,810	152,632
R^2	0.060	0.050	0.055	0.057

Note: this table presents regression results from OLS estimations with flows level as dependent variable. For all regression, regressors include SP, a dummy equals to one if a fund implements swing pricing, Stress, a dummy equals to one if weekly VIX CAC40 is above the 90^{th} percentile of the sample and the interaction of both variables. All columns include controls as regressors. Columns (2) uses the sample matched on "portfolio and investors" and column (4) the matching on "controls". Except column (3) all columns have date fixed effects, all columns have fund share fixed effect. Control variables are one-week lagged values. Errors are clustered by fund shares. The observation level is fund share per week. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A-11: Impact of swing pricing and constraints on flows levels

	Flows			
	(1)	(2)	(3)	(4)
Stress	-	-	-0.149^{***}	-
			(0.014)	
SP	0.312^{*}	0.121	0.224	0.250
	(0.169)	(0.140)	(0.168)	(0.159)
SP × Constraints	-0.244	-0.061	-0.216	-0.183
	(0.151)	(0.127)	(0.149)	(0.142)
SP × Stress	0.086	0.100	0.145	0.155
	(0.101)	(0.108)	(0.102)	(0.108)
SP × Stress × Constraints	-0.173^{**}	-0.186^{**}	-0.205^{**}	-0.188^{**}
	(0.084)	(0.085)	(0.084)	(0.082)
Size	-0.247^{***}	-0.208^{***}	-0.236^{***}	-0.211^{***}
	(0.018)	(0.033)	(0.018)	(0.031)
Institutional	0.266^{**}	0.594^{**}	0.203^{*}	1.097^{***}
	(0.121)	(0.236)	(0.119)	(0.375)
Expense ratio	0.073^{**}	0.004	0.127^{***}	-0.177
	(0.036)	(0.166)	(0.035)	(0.141)
Alpha	0.047^{***}	0.055	0.018	-0.008
	(0.013)	(0.035)	(0.013)	(0.042)
Debt ratio	-2.328^{***}	0.651	-2.478^{***}	-0.291
	(0.402)	(0.768)	(0.407)	(0.819)
Cash ratio	1.964^{***}	0.727	1.829^{***}	1.563^{***}
	(0.233)	(0.466)	(0.233)	(0.511)
Bid-ask spread	-0.235^{***}	-0.047	-0.176^{***}	-0.029
	(0.038)	(0.061)	(0.035)	(0.065)
Matching	No	PI	No	Controls
Date FE	Yes	Yes	Yes	No
Observations	698,810	142,446	698,810	152,632
R^2	0.060	0.051	0.055	0.058

Note: this table presents regression results from OLS estimations with flows level as dependent variable. For all regression, regressors include SP, a dummy equals to one if a fund implements swing pricing, Stress, a dummy equals to one if weekly VIX CAC40 is above the 90^{th} percentile of the sample and the interaction of both variables. Constraints is the number of constraints on the swing pricing and the interaction of these variables. All columns include controls as regressors. Columns (2) uses the sample matched on "portfolio and investors" and column (4) the matching on "controls". Except column (3) all columns have date fixed effects, all columns have fund share fixed effect. Control variables are one-week lagged values. Errors are clustered by fund shares. The observation level is fund share per week. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A-12: Negative flows and swing pricing

	Negative flows					
	(1)	(2)	(3)	(4)	(5)	(6)
SP	0.034	0.018	0.021	−0.020	−0.042	−0.056
	(0.029)	(0.033)	(0.032)	(0.064)	(0.069)	(0.066)
SP × Constraints	-	-	-	0.051	0.058	0.076
				(0.061)	(0.068)	(0.062)
SP × Stress	−0.041	0.011	0.039	0.140*	0.207**	0.227***
	(0.034)	(0.048)	(0.047)	(0.079)	(0.087)	(0.084)
SP × Stress × Constraints	-	-	-	−0.149**	−0.161**	−0.153**
				(0.066)	(0.069)	(0.065)
Size	−0.095***	−0.107***	−0.103***	−0.095***	−0.106***	−0.102***
	(0.010)	(0.020)	(0.018)	(0.010)	(0.020)	(0.017)
Institutional	0.101*	0.131	0.235*	0.103*	0.145	0.253*
	(0.055)	(0.140)	(0.139)	(0.055)	(0.141)	(0.140)
Expense ratio	0.050***	0.065	−0.018	0.051***	0.074	−0.012
	(0.018)	(0.090)	(0.058)	(0.018)	(0.090)	(0.058)
Alpha	0.045***	0.038	0.018	0.045***	0.036	0.015
	(0.008)	(0.023)	(0.023)	(0.008)	(0.023)	(0.023)
Debt ratio	−0.985***	0.877	0.330	−0.986***	0.867	0.331
	(0.259)	(0.535)	(0.529)	(0.258)	(0.530)	(0.525)
Cash ratio	0.297**	−0.123	0.119	0.292**	−0.134	0.100
	(0.129)	(0.328)	(0.336)	(0.129)	(0.327)	(0.335)
Bid-ask spread	−0.056**	0.004	0.044	−0.052**	0.017	0.055
	(0.023)	(0.039)	(0.038)	(0.023)	(0.040)	(0.038)
Matching	No	PI	Controls	No	PI	Controls
Observations	698,810	142,446	152,632	698,810	142,446	152,632
R^2	0.069	0.066	0.065	0.069	0.066	0.065

Note: this table presents regression results from OLS estimations with negative flows as dependent variable. For regressions in columns (1) to (3), regressors include SP, a dummy equals to one if a fund implements swing pricing, and Stress, a dummy equals to one if weekly VIX CAC40 is above the 90^{th} percentile of the sample and the interaction of these variables. For regression columns (4) to (6), regressors also include Constraints, the number of constraints on the swing pricing, and its interaction with SP and Stress. Columns (2), and (5) use the sample matched on "portfolio and investors" while Columns (3), and (6) use the sample matched on "Controls". All columns have date fixed effects and fund share fixed effect. Control variables are one-week lagged values. Errors are clustered by fund shares. The observation level is fund share per week. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A-13: Positive flows and swing pricing

	Positive flows					
	(1)	(2)	(3)	(4)	(5)	(6)
SP	0.080	0.067	0.087	0.332**	0.163	0.306**
	(0.055)	(0.050)	(0.056)	(0.153)	(0.127)	(0.145)
SP × Constraints	-	-	-	−0.295**	−0.120	−0.259**
				(0.136)	(0.108)	(0.129)
SP × Stress	−0.084***	−0.137***	−0.115***	−0.054	−0.106*	−0.072
	(0.025)	(0.036)	(0.036)	(0.061)	(0.064)	(0.065)
SP × Stress × Constraints	-	-	-	−0.024	−0.025	−0.035
				(0.048)	(0.048)	(0.048)
Size	−0.151***	−0.101***	−0.107***	−0.152***	−0.102***	−0.109***
	(0.015)	(0.028)	(0.028)	(0.014)	(0.028)	(0.027)
Institutional	0.173*	0.455***	0.882***	0.163*	0.449***	0.843***
	(0.097)	(0.159)	(0.315)	(0.094)	(0.159)	(0.301)
Expense ratio	0.021	−0.064	−0.171	0.022	−0.070	−0.165
	(0.029)	(0.107)	(0.124)	(0.029)	(0.107)	(0.119)
Alpha	0.001	0.018	−0.030	0.002	0.019	−0.023
	(0.010)	(0.022)	(0.032)	(0.010)	(0.022)	(0.031)
Debt ratio	−1.339***	−0.206	−0.610	−1.341***	−0.216	−0.622
	(0.245)	(0.425)	(0.460)	(0.244)	(0.426)	(0.460)
Cash ratio	1.667***	0.848***	1.449***	1.672***	0.861***	1.463***
	(0.153)	(0.245)	(0.270)	(0.154)	(0.245)	(0.271)
Bid-ask spread	−0.183***	−0.064	−0.081*	−0.183***	−0.065	−0.083*
	(0.027)	(0.041)	(0.045)	(0.027)	(0.041)	(0.045)
Matching	No	PI	Controls	No	PI	Controls
Observations	698,810	142,446	152,632	698,810	142,446	152,632
R^2	0.105	0.096	0.101	0.105	0.096	0.102
Note:						*p<0.1; **p<0.05; ***p<0.01

*Note: this table presents regression results from OLS estimations with positive flows as dependent variable. For regressions in columns (1) to (3), regressors include SP, a dummy equals to one if a fund implements swing pricing, and $Stress$, a dummy equals to one if weekly VIX CAC40 is above the 90^{th} percentile of the sample and the interaction of these variables. For regression columns (4) to (6), regressors also include $Constraints$, the number of constraints on the swing pricing, and its interaction with SP and $Stress$. Columns (2), and (5) use the sample matched on "portfolio and investors" while Columns (3), and (6) use the sample matched on "Controls". All columns have date fixed effects and fund share fixed effect. Control variables are one-week lagged values. Errors are clustered by fund shares. The observation level is fund share per week. *p<0.1; **p<0.05; ***p<0.01.*

E Swing pricing and idiosyncratic stress

Table A-14 replicates columns (2) to (4) of Table 2 while giving the coefficients of the controls. In addition, columns (5) to (7) replicates columns (2) to (4) with the sample matched on "controls" instead of "portfolio and investors".

Table A-14: Impact of swing pricing for large levels of swing factor, during idiosyncratic stress (percentile 90)

	Flows						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outflows	−0.543***	−0.591***	−0.593***	−0.649***	−0.585***	−0.594***	−0.652***
	(0.019)	(0.050)	(0.046)	(0.043)	(0.051)	(0.046)	(0.043)
Illiquidity	−0.103***	0.011	0.036	−0.013	0.040	0.081**	0.009
	(0.022)	(0.041)	(0.034)	(0.036)	(0.048)	(0.037)	(0.040)
SP	0.073	0.079	0.114*	−0.089	0.111	0.172**	−0.153
	(0.067)	(0.061)	(0.064)	(0.108)	(0.068)	(0.075)	(0.127)
SP × Outflows	−0.202***	−0.121	−0.152*	0.043	−0.148*	−0.169*	0.003
	(0.065)	(0.080)	(0.087)	(0.124)	(0.080)	(0.087)	(0.119)
SP × Illiquidity	−0.138***	−0.077	−0.080	0.039	−0.173*	−0.154*	−0.033
	(0.048)	(0.118)	(0.095)	(0.090)	(0.100)	(0.084)	(0.081)
Outflows × Illiquidity	0.125***	0.009	−0.081	0.080	0.029	−0.110	0.128*
	(0.048)	(0.057)	(0.074)	(0.066)	(0.063)	(0.077)	(0.069)
SP × Outflows × Illiquidity	0.265**	0.204	0.348**	−0.104	0.297**	0.427***	−0.026
	(0.114)	(0.159)	(0.159)	(0.186)	(0.145)	(0.155)	(0.178)
Size	−0.246***	−0.206***	−0.206***	−0.206***	−0.211***	−0.211***	−0.211***
	(0.017)	(0.033)	(0.033)	(0.033)	(0.031)	(0.031)	(0.031)
Institutional	0.329***	0.635***	0.634***	0.663***	1.153***	1.143***	1.184***
	(0.117)	(0.228)	(0.228)	(0.224)	(0.378)	(0.375)	(0.385)
Expense ratio	0.081**	0.015	0.016	0.007	−0.115	−0.109	−0.120
	(0.033)	(0.153)	(0.153)	(0.151)	(0.141)	(0.140)	(0.141)
Alpha	0.042***	0.046	0.048	0.047	−0.014	−0.011	−0.013
	(0.012)	(0.033)	(0.033)	(0.033)	(0.041)	(0.041)	(0.041)
Debt ratio	−2.159***	0.626	0.616	0.642	−0.265	−0.279	−0.271
	(0.382)	(0.749)	(0.751)	(0.757)	(0.800)	(0.804)	(0.807)
Cash ratio	1.914***	0.712	0.707	0.714	1.711***	1.704***	1.717***
	(0.220)	(0.446)	(0.448)	(0.449)	(0.518)	(0.520)	(0.521)
Type of SP	All	All	W/O cap	W/ cap	All	W/O cap	W/ cap
Matching	No	PI	PI	PI	controls	Controls	Controls
Observations	734,047	142,648	142,648	142,648	153,917	153,917	153,917
R^2	0.066	0.057	0.057	0.057	0.065	0.065	0.065

Note: this table presents regression results from OLS estimations for which the dependent variable is flows. For all regression, regressors include SP, Outflows, Illiquidity and their interaction terms. Outflows is a dummy equals to 1 if flows in period $t-1$ are lower than the first decile, and Illiquidity a dummy variable equals to 1 if the bid-ask spread in period $t-1$ is higher than the 9th decile. In columns (1), (2) and (4), SP is a dummy variable equal to 1 if a fund uses any type of swing pricing, in columns (3) and (6) it is equal to 1 only if a fund use a swing pricing without capped swing factor, finally in column (4) and (7) it is equal to 1 only if a fund use a swing pricing with capped swing factor. Columns (2) to (4) use the sample matched on "portfolio and investors", while columns (5) to (7) use the sample matched on. All columns have fund share and date fixed effects. Errors are clustered by fund shares. The observation level is fund share per week. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A-15: Impact of swing pricing for large levels of swing factor, during idiosyncratic stress (percentile 80)

	Flows						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outflows	−0.392***	−0.435***	−0.433***	−0.485***	−0.434***	−0.436***	−0.490***
	(0.013)	(0.039)	(0.038)	(0.034)	(0.039)	(0.038)	(0.034)
Illiquidity	−0.016	0.045	0.062	−0.007	0.060	0.087**	0.005
	(0.016)	(0.046)	(0.040)	(0.036)	(0.049)	(0.042)	(0.038)
SP	0.111	0.105	0.150**	−0.121	0.133*	0.207**	−0.196
	(0.072)	(0.067)	(0.071)	(0.118)	(0.076)	(0.082)	(0.133)
SP × Outflows	−0.174***	−0.109*	−0.130*	0.052	−0.133**	−0.149**	−0.002
	(0.054)	(0.065)	(0.068)	(0.137)	(0.065)	(0.069)	(0.126)
SP × Illiquidity	−0.134***	−0.138**	−0.136**	−0.030	−0.217***	−0.191***	−0.081
	(0.027)	(0.068)	(0.059)	(0.054)	(0.071)	(0.060)	(0.057)
Outflows × Illiquidity	0.006	−0.052	−0.143**	0.118	−0.046	−0.170**	0.152*
	(0.052)	(0.064)	(0.070)	(0.084)	(0.067)	(0.073)	(0.086)
SP × Outflows × Illiquidity	0.196**	0.200**	0.305***	−0.094	0.293***	0.380***	0.0004
	(0.077)	(0.098)	(0.098)	(0.162)	(0.100)	(0.099)	(0.152)
Size	−0.245***	−0.203***	−0.203***	−0.204***	−0.209***	−0.209***	−0.209***
	(0.017)	(0.033)	(0.033)	(0.033)	(0.031)	(0.031)	(0.031)
Institutional	0.330***	0.638***	0.630***	0.662***	1.152***	1.134***	1.176***
	(0.116)	(0.227)	(0.227)	(0.223)	(0.376)	(0.373)	(0.385)
Expense ratio	0.082**	0.011	0.013	−0.001	−0.121	−0.118	−0.124
	(0.032)	(0.152)	(0.151)	(0.151)	(0.141)	(0.139)	(0.140)
Alpha	0.040***	0.048	0.051	0.048	−0.011	−0.007	−0.010
	(0.012)	(0.033)	(0.033)	(0.033)	(0.041)	(0.041)	(0.041)
Debt ratio	−2.149***	0.631	0.608	0.691	−0.270	−0.298	−0.231
	(0.385)	(0.759)	(0.763)	(0.766)	(0.812)	(0.814)	(0.819)
Cash ratio	1.889***	0.687	0.686	0.683	1.688***	1.690***	1.682***
	(0.221)	(0.449)	(0.451)	(0.453)	(0.522)	(0.523)	(0.526)
Type of SP	All	All	W/O cap	W/ cap	All	W/O cap	W/ cap
Matching	No	PI	PI	PI	controls	Controls	Controls
Observations	734,047	142,648	142,648	142,648	153,917	153,917	153,917
R^2	0.065	0.057	0.057	0.057	0.065	0.065	0.065

Note: this table presents regression results from OLS estimations for which the dependent variable is flows. For all regression, regressors include SP, Outflows, Illiquidity and their interaction terms. Outflows is a dummy equals to 1 if flows in period $t-1$ are lower than the first decile, and Illiquidity a dummy variable equals to 1 if the bid-ask spread in period $t-1$ is higher than the 8th decile. In columns (1), (2) and (4), SP is a dummy variable equal to 1 if a fund uses any type of swing pricing, in columns (3) and (6) it is equal to 1 only if a fund use a swing pricing without capped swing factor, finally in column (4) and (7) it is equal to 1 only if a fund use a swing pricing with capped swing factor. In addition, regressors include control variables. Columns (2) to (4) use the sample matched on "portfolio and investors", while columns (5) to (7) use the sample matched on. All columns have fund share and date fixed effects. Errors are clustered by fund shares. The observation level is fund share per week. *p<0.1; **p<0.05; ***p<0.01.

Table A-16: Impact of swing pricing for large levels of swing factor, during idiosyncratic stress (continous)

	Flows			
	(1)	(2)	(3)	(4)
SP	0.015	0.003	0.073	0.039
	(0.060)	(0.064)	(0.060)	(0.065)
Flows_{t-1}	0.146^{***}	0.142^{***}	0.144^{***}	0.153^{***}
	(0.016)	(0.008)	(0.018)	(0.017)
Bid-ask spread	-0.177^{***}	-0.225^{***}	-0.038	-0.069
	(0.038)	(0.033)	(0.054)	(0.059)
SP × Flows_{t-1}	0.056^{**}	0.065^{***}	0.056^{*}	0.051^{*}
	(0.022)	(0.024)	(0.029)	(0.028)
SP × Bid-ask spread	0.116^{*}	0.160^{***}	-0.001	0.105
	(0.064)	(0.060)	(0.067)	(0.070)
Flows_{t-1} × Bid-ask spread	0.034	0.038^{***}	0.024	0.029
	(0.024)	(0.015)	(0.033)	(0.030)
SP × Flows_{t-1} × Bid-ask spread	-0.091^{***}	-0.093^{***}	-0.084^{*}	-0.083^{**}
	(0.029)	(0.034)	(0.046)	(0.042)
Size	-	-0.260^{***}	-0.228^{***}	-0.228^{***}
		(0.016)	(0.030)	(0.028)
Institutional	-	0.236^{**}	0.494^{**}	0.949^{***}
		(0.107)	(0.207)	(0.332)
Expense ratio	-	0.064^{**}	0.022	-0.159
		(0.031)	(0.147)	(0.123)
Alpha	-	0.038^{***}	0.051^{*}	-0.012
		(0.011)	(0.030)	(0.037)
Debt ratio	-	-2.030^{***}	0.536	-0.236
		(0.349)	(0.661)	(0.698)
Cash ratio	-	1.736^{***}	0.636	1.372^{***}
		(0.203)	(0.400)	(0.433)
Matching	No	No	PI	Controls
Observations	734,613	694,500	141,550	151,722
R^2	0.079	0.084	0.075	0.085

Note: this table presents regression results from OLS estimations for which the dependent variable is flows. For all regression, regressors include SP, lagged net flows, portfolio value-weighted bid-ask spread in period $t-1$ and their interaction terms. SP is a dummy variable equal to 1 if a fund uses any type of swing pricing. In addition, regressors include control variables. Columns (3) use the sample matched on "portfolio and investors", while columns (4) use the sample matched on. All columns have fund share and date fixed effects. Errors are clustered by fund shares. The observation level is fund share per week. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.