The impact of return shocks on mutual funds' flows: an example based on French bond mutual funds[1]

Work in progress

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Abstract

We study the shape of the relationship between French bond mutual funds' returns and their flows by using Datastream data for the period 2005-2017. Beyond considering the effect of relative performance, we also study the effects of absolute short-term returns on funds' flows. We find empirical evidence of a mechanism demonstrating that mutual funds can generate financial instability. Indeed, it is possible that negative shocks that affect short-term returns and generate outflows can result in a loop between funds' flows and their returns. Our model allows for nonlinear effects in the shape of the relationship between flows and performance. The results demonstrate that mutual funds presenting very negative short-term returns experience greater outflows than funds presenting less negative short-term returns (this effect appears at the bottom negative return quintile). Conversely, this nonlinear effect is not present in the positive short-term returns segment. Irrespective of mutual funds' returns, investors seem to redeem more during periods of financial stress. Additional results show that for institutional investors (which are here defined as the owners of the largest shares and thus whose decisions are the most influential for the market), the nonlinear effect first appears in the fourth negative return quintile. We hence confirm the presence of a potential source of fragility and risk coming from negative shocks to bond mutual funds' short-term returns.

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1. Introduction

The recent growth of shadow banking and, most important, of mutual funds has raised concerns for regulatory institutions. Since the year 2000, mutual funds have attracted many investors seduced by the diversification and liquidity of the proposed investments. According to the IMF (2015), the largest 500 mutual funds had assets under management (AuM) valued at 35 trillion in 2000, compared to 79 trillion in 2013. Despite a decline during the financial crisis of 2007-2008, the asset management sector has remained particularly dynamic. In France, bond funds posted growth in AuM of almost 40% between 2011 and 2016, passing from 184 billion euros to 257 billion euros according to the AMF (Autorité des Marchés Financiers) (2017). This growth in bond funds' AuM is explained by a more accommodative monetary policy stance effected by both a decline in key interest rates and a bond purchasing program intended to lower the medium-to-long-term interest rates. The decline in interest rates has had a positive effect on bond prices and contributed to making bond mutual funds more attractive than their equity counterparts.

Given the importance of the assets managed by this industry (with bond funds being a privileged support for pension savings around the world) and its sway in financial markets, understanding the investment choices made by these agents is fundamental for both academics and regulatory institutions. Various studies by regulatory institutions (OFR (2013), FSB (2017), IMF (2015)) have emphasized that mutual funds' activities are subject to multiple risks, including a particularly pronounced liquidity risk[2]. In the event of a negative shock to the funds' returns, investors may be tempted to redeem their shares, which is synonymous with outflows. Mutual funds may be forced to rapidly sell bonds to honor these demands. Hence, the flow-performance relationship can become a vicious circle if bond sales induce transaction costs or exert negative pressure on asset prices (a case that is particularly plausible in the less liquid part of the bond funds' portfolios, as shown by Coudert and Salakhova (2019) for French bond funds).

Consequently, for open-ended mutual funds, a liquidity mismatch between assets and liabilities may contribute to the emergence of a negative loop between flows and performance. This loop can be self-perpetuating and may impair global financial stability.

[2] In response to an FSB proposition to identify mutual funds as systemic institutions, several authors have examined the contribution of mutual funds to systemic risk, for example, Jin and De Simone (2015) and Roncalli and Weisang (2015)

From a theoretical perspective, the link between flows and performance is rooted in the principal-agent relationship between mutual funds' managers and final investors. Because investors are unable to directly observe the skills of fund managers, they will attempt to infer these skills by examining funds' past returns (Berk and Green (2004)). Investors will thus use past returns to make their investment decisions.

The flow-performance relationship is the subject of numerous articles examining open-ended equity funds. The literature (see Sirri and Tufano (1998) and Chevalier and Ellison (1997) for American open-ended mutual funds and Bellando and Tran-Dieu (2011) for French open-ended mutual funds) demonstrates the existence of a convex relationship between flows and performance: investors do not redeem more of their shares in a fund that has exhibited poor performance, but well performing funds seem to attract inflows. This convex form may encourage mutual fund managers to engage in risk-taking behavior; however, it does not suggest that equity funds are fragile, as they would not face massive outflows in response to poor performance.

In contrast, in the case of bond mutual funds, more recent studies (Chen and Qin (2017), Goldstein et al. (2017), IMF (2015)) suggest a positive relationship for all return segments: investors will redeem their shares if the past returns have been negative. In addition, Goldstein et al. (2017) demonstrate that a fund that possesses more illiquid assets will exhibit an even sharper positive flow-performance relationship because investors remaining in the fund will have to bear higher costs. Therefore, the remaining investors will have an incentive to redeem before others do. Finally, these funds may be particularly sensitive to monetary policy shocks (Banegas et al. (2016)), which may constitute the starting point of a vicious circle between flows and returns.

It is thus important to study the fragilities exhibited by bond mutual funds. To do so, the present article will empirically study bond mutual funds using a database including bond mutual funds domiciled in France between January 2005 and December 2017. Specifically, we are interested in what may trigger the mechanism described above: do negative short-term returns prompt massive outflows?

The majority of articles studying the shape of the flow-performance relationship consider long-term relative returns: the funds are ranked according to their one-year or longer performance, and the ranking of funds thus obtained is used to explain flows (according to the traditional model of Sirri and Tufano (1998)). This performance measure does not seem to be adequate to correctly display the funds' fragilities in response to a shock. Hence, we propose to include the short-term absolute return in the model. Our principal hypothesis is that investors are sensitive to short-term signals (and particularly to very negative signals).

Our results show that investors consider not only the ranking of funds (constructed according to the model of Sirri and Tufano (1998)) but also the funds' short-term performance (at a one-month horizon). In addition, they are also sensitive to the general market's performance, expressed by the median of past short-term returns. We also show that, other things being equal, investors redeem more of their shares in the funds with the most negative one-month returns. This effect is additive with respect to the other responses of flows to relative and absolute returns. In this respect, it constitutes the first indication of the fragility posed by bond funds in terms of a negative loop between flows and performance.

We are also interested in studying the effect of uncertainty or a financial crisis on our results. Indeed, crisis periods are susceptible to increased caution and even investor mistrust of mutual funds (see Goldstein et al. (2017), among others). The results confirm a negative effect of periods of financial stress on funds' flows. This effect is again in addition to those previously mentioned, and it seems to confirm that the bond mutual fund market exhibits global fragility. This shows that our initial result is not induced by periods of crisis or uncertainty: an isolated fund presenting a very negative short-term return will still suffer more outflows, regardless of whether these poor returns occur a "stress" period.

Finally, we analyze the possibility of behavioral differences among different types of investors. The literature has demonstrated an interest in this kind of question (see Ferreira et al. (2012) and James and Karceski (2006) for equity mutual funds). Institutional investors should be less sensitive to short-term raw returns because they are supposed to be more professional than retail investors. By using an indirect measure of investor type, we show that both types of investors are sensitive to very negative short-term returns. The results show that institutional funds' reaction to poor returns is observed for a larger range of negative returns: their outflows are larger and set in at less negative levels of short-term returns and thus may occur more often. As institutional investors are characterized by more substantial shareholding, the above-described effect on flows may be strengthened.

In sum, our results show that negative signals have a significant effect on flows and that these outcomes are additive. Our study supplements existing research and seems to confirm the previously reported fragilities presented by bond funds and the risks that they pose to financial stability.

Our article is organized as follows: the second part details the hypotheses, the third part presents the data used and descriptive statistics, and the fourth part reports and comments on the results. The last part concludes the article.

2. Hypothesis development

The hypotheses that we propose to test are based on the assumption that short-term returns are an investment criterion for investors.

Most studies conducted thus far (based on equity or bond mutual funds) demonstrate that the long-term relative return (the ranking of funds at a one-year horizon) influences agents' investment choices. We suggest that it is also important to include past short-term returns in the model.

Our first reason for pursuing this approach is that a change in a fund's position in the ranking does not capture the intensity of the short-term returns that a fund exhibited. A fund that has accumulated a good relative return over the past 11 months can still be well ranked (on the basis of the one-year return), even if its short-term return has suffered a shock. By including only the ranking of long-term performance, we may ignore the effect of a substantial decline or improvement in the short-term performance of a fund. Moreover, if two funds are simultaneously subject to a shock, their ranking may not be affected, whereas out- or inflows can still occur. Thus, irrespective of the change in its ranking, a mutual fund that presents a strong short-term return may be subject to important flows.

Given the results of the studies that have included measures of short-term performance in their models (see, for example, Del Guercio and Reuter (2014) for equity mutual funds and IMF (2015) for equity and bond mutual funds), we expect that investors are also sensitive to short-term returns.

Furthermore, if the bond market in general is affected by a shock (positive or negative), this may generate flows irrespective of the individual short-term performance of a fund. As long as the majority of funds is subject to a decline in returns (which affects the median of short-term fund returns), it is possible that investors will withdraw their shares from a fund even if it presents a strong past return. The reason for this is that investors may be aware of a possible contagion effect from the market to the individual funds.

Indeed, investors could believe that the individual return of a fund is composed of two elements: one term reflecting the more general market return (which we measure here by the median of short-term returns) and an idiosyncratic term specific to each fund (which reflects the risk level taken by a fund, among other factors). For these reasons, we believe it is important to include the median of short-term fund returns in the model to account for the effect of global market performance.

The first hypothesis can be expressed as follows:

H1-a: The funds' flows are sensitive to short-term fund returns.

H1-b: In addition to short-term fund returns, the funds' flows are also affected by global market performance.

The following hypothesis is intended to allow for nonlinear effects of the absolute returns considered in the first hypothesis: it is indeed possible that investors do not react in the same way to positive or negative individual or median performance or that their reaction may not be similar for more or less negative returns.

First, it is plausible to assume that agents are more sensitive to individual negative performance. Symmetrically, we can assume that the effect of market returns on flows is more pronounced when the median of returns is negative. The second hypothesis is thus defined as follows:

H2: Investors react differently to individual and median returns depending on whether they are positive or negative.

As we intend to study the fragilities that bond mutual funds might exhibit, we are particularly interested in studying situations with the potential to generate massive outflows. Indeed, the recent literature examines possible liquidity problems that mutual funds can be subject to in the event of substantial outflows.

To capture this effect, we assume that the various signals represented by different levels of short-term returns could have asymmetric impacts. Thus, we want to be able to capture nonlinear effects for "extreme" values of short-term returns, particularly on the negative segment. By doing so, we evaluate the plausibility of situations in which certain mutual funds face initial difficulties (materialized by very low returns) that are exacerbated by meaningful outflows. This could indeed expose mutual funds to liquidity problems: Coudert and Salakhova (2019) show that massive outflows have an important negative impact on corporate bond yields. Galanti and Le Quéré (2016) confirm that flows affect the yields of both corporate and sovereign bonds. In sum, we enrich the model detailed in the second hypothesis by allowing for an asymmetric effect to capture the specific effect of very negative short-term returns. The third hypothesis can thus be expressed as follows:

H3: The relation between flows and short-term returns is not linear, and very negative returns lead to larger outflows.

To complete the study, we examine whether flows are sensitive to financial conditions. As Goldstein et al. (2017) and the IMF (2015) have demonstrated, investors' behavior changes with financial conditions.

Furthermore, according to the previous hypothesis, we can imagine substantial negative outflows for those funds with extreme values of short-term returns. In other words, by using this empirical model, we can capture a simple effect of financial crisis periods, especially because these periods are present in our sample. Therefore, we examine whether the effect of a crisis coincides with extreme returns or whether it is additive to extreme returns. Specifically, we attempt to analyze whether larger flows are observed during periods of financial stress irrespective of the performance of each fund. Therefore, the fourth hypothesis can be phrased as follows:

H4-a: Irrespective of the level of individual return, investors redeem more of their shares during periods of financial stress than in normal periods.

H4-b: This effect supplements the fact that investors remain sensitive to very low short-term returns.

The last hypothesis that we examine is intended to clarify the origin of the potentially different reaction to short-term returns across distinct types of investors. The distinction between retail investors and institutional investors is widely considered in the literature. We use the minimum initial investment requirement in each part to separate the two types of clients. As institutional investors hold larger shares, their redemption decisions have the potential to more severely affect mutual funds.

Institutional clients are considered to be more sophisticated and less subject to inertia or a strong reaction to a signal. The literature demonstrates (see Ferreira et al. (2012) and James and Karceski (2006) for equity funds) different responses to long-term relative performance: institutional investors are less sensitive to strong long-term relative returns than are their retail counterparts. Furthermore, according to the IMF (2015), institutional investors seem to react less to recent returns than do retail investors. This behavior can be explained by the fact that, for example, the contractual commitments of institutional investors to their principal constrains their managerial decisions[3]. In contrast, two types of arguments can explain a greater reactivity of institutional investors to recent performance. First, keeping their shares in a poorly performing fund can lead to reputational loss and harm future activity. Hence, following a similar choice as that presented in a window-dressing context, institutional investors would redeem their most poorly performing shares to avoid the appearance that they made a poor investment decision. Second, the sensitivity of clients to short-term performance can be justified if such returns exhibit sufficient persistence.

We present the final hypothesis in the following terms:

H5: The different types of investors do not show the same reaction to distinct types of performance.

3. Data and sample

3.1 Database cleaning

We use data from Datastream on shares of OPCVM (open-ended mutual) funds domiciled in France from January 2005 to December 2017. We concentrate on shares because the different available shares have different characteristics: the amount of the initial investment, purchasing fees, redemption fees, and management fees can differ. Because these fees impact the returns (because they are net of fees in the database), which represent a central variable in this article, it is important to study returns at the share level and not at the fund level.

Specifically, we consider shares with a "bond" classification in Datastream. Unfortunately, some shares classified as "bonds" by Datastream are classified as "diversified"

[3] For example, institutional clients can classify the shares in their portfolios by using agencies' grades and can fix the share of each grade at a certain percentage (see Cantor et al. (2007)). This can lead to maintaining a share in a mutual fund despite its recent poor return.

or have a different classification according to the AMF[4]. We choose to retain shares for every month in which they are also classified as “bonds” by the AMF and thus drop the months in which shares are labeled “diversified” or other by the AMF. We drop observations for which a fund’s total net assets (TNA) are below 300,000 euros because, according to AMF rules, the fund must be liquidated when net assets fall below this threshold. We also drop observations of funds with an age of less than one year to ensure a sufficient time length. Finally, share prices (net asset value (NAV) per share) have been adjusted for splits.

As we study flows of shares, we do not retain closed-ended funds (which have a fixed number of shares), ETF funds (the shares of which are traded on an exchange and the prices of which can differ from their intrinsic values), or feeder funds (the returns of which follow those of the master fund in which they are invested). Furthermore, we have excluded shares for which coupons are distributed (because their returns do not include the distributed coupons, on which data are not available), and shares not labeled in euros (as the returns could capture movements in the foreign exchange market).

The final sample includes 883 different shares from 576 unique funds. For each share and each month, we have the NAV per share and the TNA under management. Thus, in total, there are 53,433 month-share observations.

3.2 Variable definitions

Measurement of flows

In accordance with the majority of studies, our variable of interest is the percentage of net fund flows ($Flow_{i,t}$), which corresponds to inflows minus outflows, between t and t-1, as a percentage of TNA in period t-1 ($TNA_{i,t-1}$).

As inflows and outflows are missing from our database, we reconstruct them following the traditional method, which consists of using the monthly TNA and the growth in a share’s NAV between t and t-1:

$$R_{i,t} = \frac{NAV_{i,t}}{NAV_{i,t-1}} - 1$$

[4] The AMF is the financial market regulatory authority, which is responsible for supervising mutual funds domiciled in France.

As we can see below, the change in a share's TNA can be separated into two terms: a first effect that is synonymous with a "valuation" effect and a second term that is synonymous with a "volume" effect linked to inflows:

$$TNA_{i,t} = TNA_{i,t-1}(1 + R_{i,t}) + Flow_{i,t} * TNA_{i,t-1}$$

Hence, flows between t and t-1 are defined using the following formula:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}}$$

Definitions of explanatory variables

The principal explanatory variables used in this study are performance measures.

Long-term relative performance

The model used by Sirri and Tufano (1998) is usually applied to define relative performance. This model captures the effect on flows of the ranking of shares constructed by using their long-term returns. This measure is based on the long-term raw return (at a one-year horizon), defined as follows:

$$R_{i,t-12,t} = \frac{NAV_{i,t}}{NAV_{i,t-12}} - 1$$

For each AMF category-month, shares are ranked according to their long-term performance. For each share-month, a variable $Rank_{i,t}$ taking values between 0 and 1 is constructed. It represents the share's performance rank standardized to 1[5].

The originality of the model described in Sirri and Tufano (1998) is that it allows for the presence of a nonlinear relationship between flows and performance rank[6].

Hence, by using their model, we allow the slope of the relationship to differ across 3 groups of relative performance: the first group, LowPerf, includes only funds in the first performance quintile; the second group, MidPerf, represents funds ranked between 0.2 and 0.8; and the variable HighPerf corresponds to the highest performance quintile:

[5] For example, if during month t, 10% of shares have a lower performance than the one presented by the share X, then the $Rank_{i,t}$ for the share X will be 0,1.

[6] The principal result obtained by Sirri and Tufano (1998) and confirmed by other studies on equity mutual funds is the presence of a convex shape of the flow-relative performance relationship

$LowPerf_{i,t}$ = Min (0.2; $Rank_{i,t-1}$)

$MidPerf_{i,t}$ = Min (0.6; $Rank_{i,t-1}$ - $LowPerf_{i,t}$)

$HighPerf_{i,t}$= $Rank_{i,t-1}$ - $LowPerf_{i,t}$ - $MidPerf_{i,t}$

Short-term raw returns[7]

The return of the share "i" between month t-1 and month t is defined by the following formula:

$$R_{i,t} = \frac{NAV_{i,t}}{NAV_{i,t-1}} - 1$$

The control variables

The following variables are widely used in the existing literature (for example, Goldstein et al. (2017) and Chen and Qin (2017) for bond mutual funds and Ferreira et al. (2012) for equity mutual funds).

The age of each share

It is important to control for the age of shares, as a share can benefit from more marketing following its creation. This can attract new investors irrespective of the share's performance. The definition of this variable varies across articles, and we adopt the measure used by Goldstein et al. (2017). Consequently, the natural logarithm of the share's age measured in years since its inception is used as a control variable.

The size of each share

According to the literature, the size of each share is calculated as the natural logarithm of past-month AuM. Previous studies demonstrate that if net flows are not proportional to the share's size, percentage net flows should be smaller as shares grow in size. As our dependent variable is percentage net flows, we expect the results to show a negative relationship between the dependent variable and share size.

[7] Definitions of short-term returns other than raw monthly returns may be used. Indeed, short-term performance may be calculated differently depending on, for example, the period's risk-free rates. We are also interested in testing the robustness of our results to alternative measures of absolute short-term returns: in excess of the one-month Euribor rate or in excess of the sovereign bond rates, for example.

The standard deviation of monthly returns:

As is common practice in the literature, this variable is calculated as the standard deviation of the past 12-month return. We include this as a standard control variable because net flows could be influenced by investors' sensitivity to the risk level selected by the manager in his portfolio decisions.

3.3. Descriptive statistics

The AuM and the number of shares exhibit an increasing trend during the 2005-2017 period (cf. Figure 1).

Figure 1

Assets under management (monthly, 2007-2017, in millions of euros)

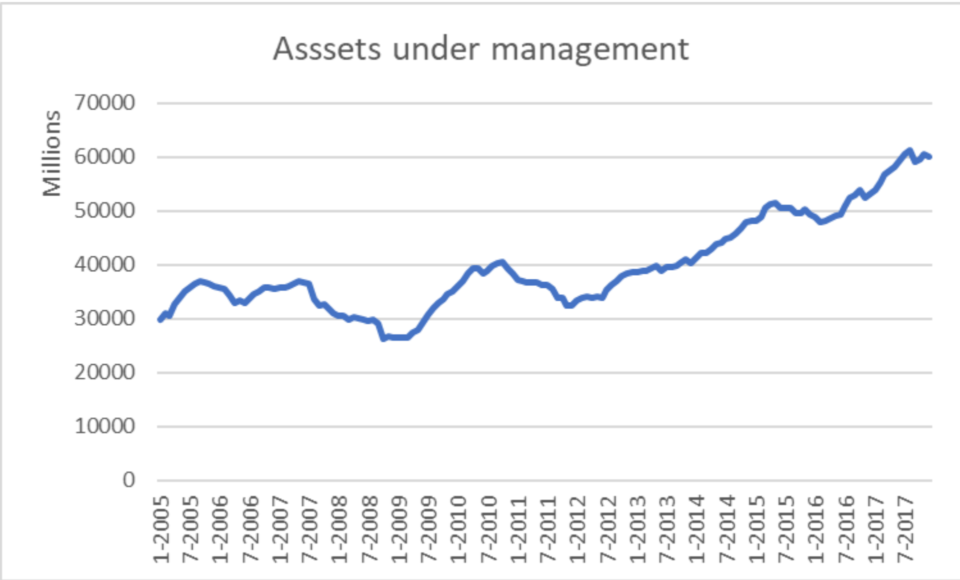
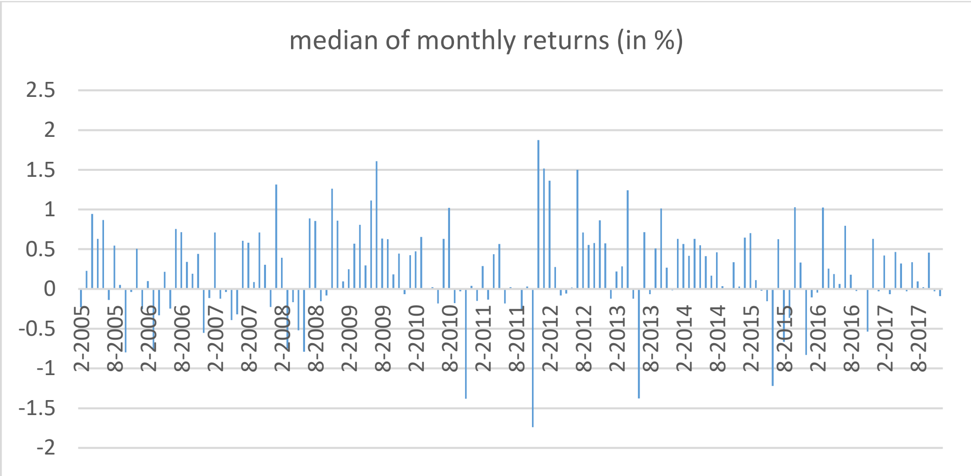


Figure 1 shows that between January 2005 and December 2017, AuM increased by approximately 100%. The effects of two major crises are apparent: the global financial crisis (AuM decreased by 26% between June 2007 and April 2009) and the European sovereign debt crisis (AuM decreased by 20% between October 2010 and December 2011).

These crises also affect our sample, but to a lesser extent, as shown in Figure 2, which represents the evolution of the median of the monthly shares' returns in the sample.

Figure 2

Evolution of the median of share returns (monthly, 2005-2017)



Finally, in Table 1, we present the mean, standard deviation, and the 5th, 25th, 50th, 75th and 95th percentiles of the distributions of the variables used in our models, in addition to the number of observations.

Table 1: Descriptive statistics

	Mean	Standard deviation	P5	P25	P50	P75	P95	N
Flow	-0.002	0.079	-0.115	-0.019	-0.001	0.007	0.113	53,433
Lagged monthly return	0.003	0.014	-0.016	-0.002	0.002	0.008	0.022	53,433
Ln(lagged TNA)	17.27	1.59	14.468	16.286	17.376	18.396	19.62	53,433
Ln(age)	2.04	0.894	0.47	1.364	2.104	2.777	3.333	53,433
Standard deviation of the past 12-month returns	0.01	0.01	0.001	0.004	0.008	0.013	0.024	53,433
Median of lagged monthly returns	0.002	0,006	-0.008	-0.001	0.002	0.006	0.012	154

Note that more than half of the observations correspond to outflows (negative net flows). The monthly returns are positive on average (0.3%) and amount to an annual return of approximately 3.7%. However, for 5% of observations, the monthly return is at most –1.6%, which corresponds to approximately –18% per year. Finally, the median of AuM is approximately 35 million euros, while the average age of a share is approximately 7.5 years.

4. Model and results

4.1. The model

In this subsection, we present our modeling choices.

Concerning the dependent variable, we drop observations above the 99th percentile and below the 1st percentile of the distribution of flows to limit the influence of outliers[8].

In every model, we add share fixed effects because we want to control for characteristics that are constant over time and could be correlated with other variables in the model, notably management fees, which could be unchanged over the life of the share but correlated with the share's return (the higher the management fees, the lowest the share's return[9]). We also cluster errors at the fund level to allow for the autocorrelation of residuals within a given fund[10].

4.2 Results concerning the first hypothesis: short-term returns' impact on flows

We first investigate whether short-term returns influence investors' decisions. In the following regression, testing H1-a is synonymous with testing whether β_4 is significantly different from zero.

$$Flow_{i,t} = \beta_0 + \beta_1 LowPerf_{i,t} + \beta_2 MidPerf_{i,t} + \beta_3 HighPerf_{i,t} + \beta_4 R_{i,t-1} + \beta_5 Controls_{i,t} + \gamma_i + \varepsilon_{i,t} \quad (1)$$

The results are given in the first column of Table 2. We first comment on the control variables and the variables concerning the relative long-term returns. As the results regarding these variables are identical when testing H1-b to H4, we will only comment on them here.

[8] Because we study situations that are likely to provoke substantial outflows, dropping the 1st and 99th percentiles of flows could affect the results. However, we have tested other truncations (0.5%, 2.5%, and 5%), and the results are qualitatively similar.

[9] As a robustness check, we also included the total expense ratio (TER) as an explanatory variable. The results show that the coefficient of this variable is never significantly different from zero, whatever the model tested, so we do not retain the variable in the main analysis presented in this article.

[10] The results are similar if we cluster errors at the share level.

Table 2: Hypotheses 1-a and 1-b: reaction to short-term absolute returns at the individual and market levels

	(1)	(2)
LowPerf	0.053***	0.054***
	(0.000)	(0.000)
MidPerf	0.013***	0.014***
	(0.000)	(0.000)
HighPerf	0.063***	0.065***
	(0.000)	(0.000)
Lagged raw return	0.380***	0.309***
	(0.000)	(0.000)
Median		0.369***
		(0.000)
Log(TNA)	-0.006***	-0.006***
	(0.000)	(0.000)
Std Dev	-0.129	-0.144
	(0.151)	(0.110)
Log(age)	-0.007***	-0.007***
	(0.000)	(0.000)
Intercept	0.093***	0.092***
	(0.000)	(0.000)
Observations	53,433	53,433
R-squared	0.016	0.017

The dependent variable is the net flows in % (truncation of observations above the 99th percentile and below the 1st percentile of the distribution). *LowPerf, MidPerf, and HighPerf* are indicators of relative long-term performance (12 months), constructed as in Sirri and Tuffano (1998). *Lagged raw return* is the past month's raw share return. *Median* is the median of past-month share returns on all funds. Control variables include the natural logarithm of net assets under management for the past month (*log(TNA)*), the natural log of the number of years since the inception of the share (*log(age)*) and past standard deviation of monthly returns (over the past 12 months: *Std dev*). We use fixed effects at the share level and clustered errors by fund. Stars indicate p-values (*** p<0.01, ** p<0.05, * p<0.1).

Concerning long-term relative returns, Wald tests indicate that LowPerf and HighPerf are significantly different from MidPerf (at the 99% level), whereas the LowPerf and HighPerf coefficients are not different from one another. We interpret this as indicating a concave relation between low returns and moderate returns and as a convex relation between moderate returns and high returns.

In other words, whatever the initial ranking of a fund, an increase in the ranking is rewarded with inflows, and a lowering of the ranking is punished with outflows. However, if the initial position of the share's ranking is in the middle segment, the impact of rank on flows is weaker (the coefficient of MidPerf is lower). This flow-performance relationship confirms that found by Chen and Qin (2017) for US bond funds. The convex form on the right-hand side of the relationship (for high relative returns) can entail risk-taking incentives or tournament phenomena, as Chevalier and Ellison (1997), Ferreira et al. (2012) and Kim (2017) have shown for equity funds. In the moderate- and low-performance segments, the concave shape indicates a sanction for poor performance. This effect indicates precautionary behavior by investors and aligns with the results of Chen and Qin (2017) and the IMF (2015) for US bond funds. However, it also indicates that investors react strongly to poor relative performance, and this effect could complement that on absolute short-term returns[11].

The results in Table 2 indicate that the raw short-term return is an important determinant of flows and confirm the value of including this variable in addition to the Sirri-Tuffano effects. A fund with a 1-percentage-point increase in the past month's raw return will have, all else being equal, a surplus inflow of 0.38%. This positive and significant relation between flows and lagged short-term returns confirms findings in the literature (Del Guercio and Reuter (2014), IMF (2015)). Investors are sensitive to fund rankings but also to raw short-term returns. Our hypothesis H1-a is thus validated.

Hypothesis H1-b tests whether, beyond individual funds' performance, the global return of the fund market could influence flows. We thus add the "*Median*" variable, the median of past-month share returns. It is intended to capture positive (negative) shocks affecting numerous funds, which could increase (decrease) the monthly median of performance. For example, an investor observing a generalized decrease in returns may choose to redeem his shares from bond funds. To a certain extent, the *Median* variable is a way to introduce time fixed effects[12].

We thus proceed to this second regression, the results of which are reported in the second column of Table 2.

$$Flow_{i,t} = \beta_0 + \beta_1 LowPerf_{i,t} + \beta_2 MidPerf_{i,t} + \beta_3 HighPerf_{i,t} + \beta_4 R_{i,t-1} + \beta_5\, Median_t + \beta_6 Controls_{i,t} + \gamma_i + \varepsilon_{i,t} \quad (2)$$

Compared with the first regression, the results are globally similar. The *"Median"* variable has a positive and statistically significant coefficient. Investors thus also react to the

[11] For example, a fund suddenly facing a lower ranking could experience outflows, which could in turn trigger a negative flow-performance feedback loop.

[12] We tested hypothesis 1 when including time fixed effects, and the results were unchanged (see appendix 1). As the median of past-month returns is constant across all shares in a given month, it is not possible to introduce the median and time fixed effects in the same model.

global performance of bond funds[13]. This indicates the fragility of a fund when confronted with a global decrease in the bond fund market. Hypothesis 1-b seems to be validated.

4.3 Results on hypothesis 2: the impact of positive vs negative individual and median returns

We now attempt to capture the nonlinear effects of short-term returns. First, we hypothesize that investors may not react in the same way in response to negative and positive returns. To test H2, we use the following regression, in which we add interaction terms with dummy variables that indicate the sign of past individual, or median, returns.

$$Flow_{i,t} = \beta_0 + \beta_1 LowPerf_{i,t} + \beta_2 MidPerf_{i,t} + \beta_3 HighPerf_{i,t} + \beta_4 R_{i,t-1} + \beta_5 R_{i,t-1} * I(Ret_{neg}) + \beta_6 Median_t + \beta_7 Median_t * I(Med_{neg}) + \beta_8 I(Ret_{neg}) + \beta_9 I(Med_{neg}) + \beta_{10} Controls_{i,t} + \gamma_i + \varepsilon_{i,t} \quad (2')$$

Variables defined above are the same. $I(ret_{neg})$ and $I(med_{neg})$ are equal to 1 when the past individual or median return was negative, respectively. If the reaction is stronger when the signal is negative, we expect the coefficients β_5 and β_7 to be significantly positive. In addition, β_8 and β_9 could capture an additional negative effect on net flows. Table 3 presents the results.

Investors seem to react identically to an increase and a decrease in past individual positive and negative returns. The coefficient for past returns is still significantly positive, but the interaction term is not significant. However, we observe a shift in the flow-performance relationship: the dummy variable $\mathrm{I}(\mathrm{ret}_{\mathrm{neg}})$ is significant and negative. This shows that, whatever the initial sign of past returns (positive or negative), flows react in the same way to a decrease in returns. However, when a decrease occurs for already negative returns, there is a supplementary outflow of 0.9%, compared with the decrease that occurs for initially positive returns. In other words, in the flow-performance relationship, the slope is the same for negative and positive returns, but the intercept is lower for shares with negative returns.

Furthermore, we observe that the coefficient for the median loses significance and that there is no additional effect (β_8 is not significant). It seems that the importance accorded to the

[13] We could add another element of the short-term return of a share: the gap between a share's return and the global median return of funds. In appendix 2, we replace individual return with its return in excess of the median return, and the results do not qualitatively change. Investors react to both the individual and the global component of the short-term return.

median is no longer sizable when the initial sign of past-month share return is taken into account.

Table 3: Hypothesis 2: difference in the sensitivity to raw short-term and median returns depending on their sign

LowPerf	0.053***
	(0.000)
MidPerf	0.012***
	(0.000)
HighPerf	0.064***
	(0.000)
Lagged raw return	0.235***
	(0.000)
Lagged raw return*I(Ret_neg)	-0.078
	(0.439)
Median	0.076
	(0.556)
Median*I(Med_neg)	0.273
	(0.193)
Log(TNA)	-0.006***
	(0.000)
Std Dev	-0.127
	(0.171)
Log(age)	-0.007***
	(0.000)
I(Ret_neg)	-0.009***
	(0.000)
I(Med_neg)	0.001
	(0.417)
Intercept	0.096***
	(0.000)
Observations	53,433
R-squared	0.019

The dependent variable is the net flows in % (truncation of observations above the 99^{th} percentile and below the 1^{st} percentile of the distribution). *LowPerf, MidPerf, and HighPerf* are indicators of relative long-term performance (12 months), constructed as in Sirri and Tuffano (1998). *Lagged raw return* is the past-month raw share return. *Median* is the median of past-month share returns of all funds. $I(ret_{neg})$ = 1 if the lagged monthly return is negative and 0 otherwise. $I(med_{neg})$ = 1 if the median of lagged monthly returns is negative and 0 otherwise. Interaction terms between $I(ret_{neg})$ and *Lagged raw return and* between $I(med_{neg})$ and *Median* have been introduced to allow for the presence of different slopes in the relations between the positive/negative segments of lagged returns and median returns. Control variables include the natural logarithm of net assets under management in the past month (*log(TNA)*), the natural log of the number of years since the inception of the share (*log(age)*) and the past standard deviation of monthly returns (over the past 12 months: *Std dev*). We use fixed effects at the share level and clustered errors by fund. Stars indicate p-values (*** p<0.01, ** p<0.05, * p<0.1).

4.4 Results concerning hypothesis 3: the effect of the worst negative returns

The previous regression shows no difference in slopes, but there is a difference in the intercepts of the model depending on whether the raw short-term return is negative or positive. As a preamble to testing hypothesis 3, we report in appendix 3 the results of a regression that allows the intercepts to differ according to the quintiles of negative returns and quintiles of positive returns. The bounds of the quintiles are defined over the whole sample. We define IN-0-20 as a variable equal to 1 if the individual raw return in the previous month is in the bottom 20% of the worst negative returns and zero otherwise. IN-20-40 takes value 1 if the individual raw return in the previous month is between the 20th and 40th percentiles of negative returns, and so forth. Similarly, we construct dummy variables on the positive side: for example, IP-0-20 takes value 1 if the raw return of the previous month is below the 20th percentile of positive returns. We choose the highest quintile of positive returns as the reference, i.e., IP-80-100. The results are reported in appendix 3.

We observe that the coefficients of all negative quintiles are significantly negative. We test the differences among these coefficients and show that the coefficient of the worst negative returns, IN-0-20, is significantly lower than the other coefficients. The other four quintile coefficients are not significantly different from one another; hence, they can be grouped into a single dummy variable, IN-20-100.

On the positive side of past individual returns, the coefficients of the dummies are not significantly different from 0, considered either individually or globally (according to the Fisher test of all coefficients being equal to zero).

This leads to our main model, which will henceforth be our benchmark model and includes dummies for the most negative (IN-0-20) and the other negative (IN-20-100) returns[14]:

$$Flow_{i,t} = \beta_0 + \beta_1 LowPerf_{i,t} + \beta_2 MidPerf_{i,t} + \beta_3 HighPerf_{i,t} + \beta_4 R_{i,t-1} + \beta_5 Mediane_{\ t} + \beta_6 \text{ IN-0-20-} + \beta_7 \text{ IN-20-100} + \beta_8 Controls_{i,t} + \gamma_i + \varepsilon_{i,t} \quad (3)$$

The results are reported in Table 4.

[14] Introducing year fixed effects does not significantly change the results.

Table 4: Hypothesis 3: investors' reactions depending on the level of negative short-term raw share return

LowPerf	0.053***
	(0.000)
MidPerf	0.012***
	(0.000)
HighPerf	0.064***
	(0.000)
Lagged raw return	0.148***
	(0.000)
Median	0.128
	(0.137)
Log(TNA)	-0.006***
	(0.000)
Std Dev	-0.080
	(0.365)
Log(age)	-0.007***
	(0.000)
IN-0-20	-0.013***
	(0.000)
IN-20-100	-0.009***
	(0.000)
Intercept	0.096***
	(0.000)
H0: IN-0-20 = IN-20-100	0.016**
Observations	53,433
R-squared	0.019

The dependent variable is the net flows in % (truncation of observations above the 99th percentile and below the 1st percentile of the distribution). *LowPerf, MidPerf, and HighPerf* are indicators of relative long-term performance (12 months), constructed as in Sirri and Tuffano (1998). *Lagged raw return* is the past-month raw share return. *Median* is the median of past-month share returns of all funds. *IN-0-20* = 1 if the individual raw return of the previous month is in the bottom 20% of the worst negative returns and zero otherwise. *IN-20-100* = 1 if the individual raw return of the previous month is between the 20th percentile of negative returns and 0. Control variables include the natural logarithm of net assets under management in the past month (*log(TNA)*), the natural log of the number of years since the inception of the share (*log(age)*) and the past standard deviation of monthly returns (over the past 12 months: *Std dev*). We use fixed effects at the share level and clustered errors by fund. Stars indicate p-values (*** p<0.01, ** p<0.05, * p<0.1).

The results for the control variables and performance rankings remain unchanged. Investors are also again sensitive to past-month raw short-term performance (the coefficient of 0.148 is significantly positive at the 99% level).

In contrast, the short-term flow-performance relationship exhibits shifts on the negative side of returns. The coefficients of the dummy variables IN-0-20 and IN-20-100 are both significantly negative and significantly different (at the 95% level), with the greatest outflows being observed for the worst returns. Note that these effects are cumulative with the linear effect of returns. In essence, investors present a particular sensitivity to returns when they are substantially negative, with greater outflows being observed for the worst returns. Appendix 3 shows that an equivalent relationship is not observed for positive returns, as the flow-performance relationship on the positive side is linear and does not exhibit shifts.

Although the difference between the 2 dummy coefficients may not seem considerable (only 0.004 in value), they still predict important outflows during crisis periods. For example, during the taper tantrum (between June and July 2013), 125 shares have passed from the group of less negative short-term returns (namely IN-20-100) to the group of very low short-term returns (namely IN-0-20). The seemingly low difference between the two coefficients still predicts surplus outflows worth of approximately 35 000 000 euros for those shares.

Furthermore, the coefficients for the median variable are no longer significant[15]. Our explanation for this finding is that the global effect of the median is dominated by that of the very negative returns (IN-0-20). Indeed, a complementary analysis (not reported) shows that when the median return is very low, the fraction of shares below the 20th percentile of negative returns is large. Such periods coincide with periods of stress in the bond market (during the sovereign debt crisis at the end of 2011 or during the *taper tantrum* of 2013). It is thus interesting to check whether the effect of very low returns is cumulative with that of a general context of crisis, not necessarily specific to the bond funds sector. This is the aim of the next subsection.

4.5 Results concerning hypothesis 4: the impact of financial stress periods

We now investigate whether investors behave in a different manner depending on whether they are in a period of financial stress. We take the CISS, the VIX and the VSTOXX as indicators of financial stress. We deliberately avoid indicators based on bond markets because their effect on the funds' outflows may be contaminated with those of the decrease in a fund's returns. Our aim is to consider the general effect of financial stress at large on investors' behavior. We run the following regression:

$$Flow_{i,t} = \beta_0 + \beta_1 LowPerf_{i,t} + \beta_2 MidPerf_{i,t} + \beta_3 HighPerf_{i,t} + \beta_4 R_{i,t-1} + \beta_5\, Median_t + \beta_6\, I(crisis) + \beta_7\, IN-0-20 + \beta_8\, IN-20-100 + \beta_9 Controls_{i,t} + \gamma_i + \varepsilon_{i,t} \quad (4)$$

[15] We also tested whether investors differ according to the level of median returns when the median is negative or very negative, but the results, reported in appendix 4, do not reveal any such sensitivity.

The new variable here is a dummy *I(Crisis)* that takes value 1 if the indicator is above the 90th percentile of its distribution (high stress). As argued earlier, variable IN-0-20 is related to a crisis in the bond market, and the coefficient of *I(Crisis)* indicates whether such general financial stress substitutes for, or compliments, the effect of individual fund returns on fund flows.

If the crisis dummy is significant and the shift in intercepts for very negative returns no longer appears, this means that the shift we observed was simply the consequence of general financial distress. The results are presented in Table 5. We confirm that periods of financial stress generate supplementary outflows from funds, in line with the literature (IMF 2015). Controlling for the level of a negative share return, investors redeem more of their shares from funds in times of stress (approximately +0.6% in terms of outflows, as indicated by the *I(Crisis)* coefficient in the VIX case) than in normal times.

However, we observe that the "shift" in returns is still significant (at the 95% level) throughout all three models. This means that, independent of the general financial context, investors redeem more, all else being equal, from funds that exhibit the worst negative returns. Furthermore, during periods of stress, funds suffer from substantial outflows, independent of the level of their returns. This could constitute a major concern for regulators to the extent that these two effects are additive. Indeed, in periods of stress, outflows could be particularly severe for funds with 1) low short-term raw returns (the "slope" effect) and 2) the worst negative returns (the "shift in constant" effect).

Table 5: Hypothesis 4: the role of financial stress periods

	VIX	VSTOXX	CISS
	1	2	3
LowPerf	0.054***	0.055***	0.054***
	(0.000)	(0.000)	(0.000)
MidPerf	0.012***	0.012***	0.012***
	(0.000)	(0.000)	(0.000)
HighPerf	0.064***	0.064***	0.064***
	(0.000)	(0.000)	(0.000)
Lagged raw return	0.142***	0.142***	0.143***
	(0.000)	(0.000)	(0.000)
Median	0.147*	0.136	0.128
	(0.086)	(0.112)	(0.137)
I(crisis)	-0.006***	-0.007***	-0.003**
	(0.000)	(0.000)	(0.045)
Log(TNA)	-0.006***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)
Std Dev	-0.039	-0.024	-0.054
	(0.661)	(0.783)	(0.547)
Log(age)	-0.007***	-0.008***	-0.007***
	(0.000)	(0.000)	(0.000)
IN-0-20	-0.013***	-0.012***	-0.013***
	(0.000)	(0.000)	(0.000)
IN-20-100	-0.009***	-0.008***	-0.009***
	(0.000)	(0.000)	(0.000)
Intercept	0.098***	0.099***	0.097***
	(0.000)	(0.000)	(0.000)
H0: IN-0-20 = IN-20-100	0.0319**	0.0388**	0.0197**
Observations	53,433	53,433	53,433
R-squared	0.019	0.019	0.019

The dependent variable is the net flows in % (truncation of observations above the 99^{th} percentile and below the 1^{st} percentile of the distribution). *LowPerf, MidPerf, and HighPerf* are indicators of relative long-term performance (12 months), constructed as in Sirri and Tuffano (1998). *Lagged raw return* is the past-month raw share return. *Median* is the median of past-month share returns of all funds. *I(Crisis)* = 1 if the indicator is above the 90th percentile of its distribution (high stress) and 0 otherwise. *IN-0-20* = 1 if the individual raw return of the previous month is in the bottom 20% of the worst negative returns and zero otherwise. *IN-20-100* = 1 if the individual raw return in the previous month is between the 20th percentile of negative returns and 0. Control variables include the natural logarithm of net assets under management in the past month (*log(TNA)*), the natural log of the number of years since the inception of the share (*log(age)*) and the past standard deviation of monthly returns (over the past 12 months: *Std dev*). We use fixed effects at the share level and clustered errors by fund. Stars indicate p-values (*** p<0.01, ** p<0.05, * p<0.1).

4.6 Results concerning hypothesis 5: types of investors

Finally, we want to determine whether investors react differently according to their type or the previous results remain general. To this end, we split the sample in two, depending on the minimum initial investment requirement of the funds' shares. However, our database does not have information on whether the client of the fund is a retail investor or an institutional investor. We suppose, as a proxy, that a fund with a minimum investment above the 10,000-euro threshold is dedicated to institutional investors[16].

We apply the same regression as model (3), applied to each of the two subsamples.

$$Flow_{i,t} = \beta_0 + \beta_1 LowPerf_{i,t} + \beta_2 MidPerf_{i,t} + \beta_3 HighPerf_{i,t} + \beta_4 R_{i,t-1} + \beta_5 Mediane_{\ t} + \beta_6 \text{ IN-0-20-} + \beta_7 \text{ IN-20-100} + \beta_8 Controls_{i,t} + \gamma_i + \varepsilon_{i,t} \quad (3)$$

The results are presented in Table 6, where we also restate the full-sample results.

Concerning long-term performance, institutional investors' behavior differs from retail investors' behavior in that the former do not seem to react to good relative performance (the coefficient for HighPerf is not significantly different from 0). This result echoes that of Ferreira et al. (2012), who find that institutional investors are less sensitive than retail investors to very good relative performance. However, our results also indicate that institutional investors are less sensitive to poor relative performance. Our proposed explanation for this is the mandatory obligations that concern institutional investors *vis-à-vis* their own clients (maintaining a certain proportion of ratings classes in the portfolio, investment policy statements), independent of returns, financial context, or the state of the funds market.

Institutional investors also differ from retail investors in their sensitivity to short-term raw returns, as the former react less to short-term returns (the coefficients are both positive but at the 10% and 1% levels, respectively).

[16]We also check the robustness of these results using a threshold of 100,000 euros. This does not change the results for the "retail" subsample, but for the "institutional" subsample, LowPerf and past raw returns become non-significant.

Table 6: Hypothesis 5: differential sensitivity according to investor type

	Retail shares	Institutional shares	Institutional shares	Total sample
LowPerf	0.056***	0.049*	0.050*	0.053***
	(0.000)	(0.060)	(0.053)	(0.000)
MidPerf	0.008**	0.020***	0.020***	0.012***
	(0.012)	(0.003)	(0.003)	(0.000)
HighPerf	0.085***	0.015	0.015	0.064***
	(0.000)	(0.557)	(0.572)	(0.000)
Lagged raw return	0.181***	0.098*	0.108*	0.148***
	(0.000)	(0.099)	(0.053)	(0.000)
Median	0.164*	0.040	0.026	0.128
	(0.089)	(0.820)	(0.882)	(0.137)
Log(TNA)	-0.006***	-0.005***	-0.005***	-0.006***
	(0.000)	(0.001)	(0.001)	(0.000)
Std Dev	0.013	-0.283**	-0.292**	-0.080
	(0.913)	(0.015)	(0.011)	(0.365)
Log(age)	-0.007***	-0.007**	-0.008**	-0.007***
	(0.001)	(0.023)	(0.019)	(0.000)
IN-0-20	-0.012***	-0.015***		-0.013***
	(0.000)	(0.000)		(0.000)
IN-20-100	-0.007***	-0.011***		-0.009***
	(0.000)	(0.000)		(0.000)
IN-0-80			-0.013***	
			(0.000)	
IN-80-100			-0.006**	
			(0.026)	
Intercept	0.094***	0.096***	0.097***	0.096***
	(0.000)	(0.001)	(0.001)	(0.000)
H0: IN-0-20 = IN-20-100	0.0319**	0.188		0.016**
H0: IN-0-80 = IN-80-100			0.0315**	
Observations	37,966	15,152	15,152	53,433
R-squared	0.021	0.016	0.016	0.019

The sample has been separated into retail shares (with a minimum initial investment requirement lower than 10,000 euros) and institutional shares (with a minimum initial investment requirement higher than 10,000 euros). The third column shows the results for the full sample (from Table 4). The dependent variable is the net flows in % (truncation of observations above the 99th percentile and below the 1st percentile of the distribution). *LowPerf, MidPerf, and HighPerf* are indicators of relative long-term performance (12 months), constructed as in Sirri and Tuffano (1998). *Lagged raw return* is the past-month raw share return. *Median* is the median of the past month's share returns of all funds. *IN-0-20* = 1 if the individual raw return in the previous month is in the bottom 20% of the worst negative returns and zero otherwise. *IN-0-80* = 1 if the individual raw return in the previous month is in the bottom 80% of the worst negative returns and zero otherwise *IN-20-100* = 1 if the individual raw return in the previous month is between the 20th percentile of negative returns and 0. *IN-80-100* = 1 if the individual raw return in the previous month is between the 80th percentile of negative returns and 0 Control variables include the natural logarithm of net assets under management in the past month (*log(TNA)*), the natural log of the number of years since the inception of the share (*log(age)*) and past standard deviation of monthly returns (over the past 12 months: *Std dev*). We use fixed effects at the share level and clustered errors by fund. Stars indicate p-values (*** p<0.01, ** p<0.05, * p<0.1).

However, and contrary to the retail investor subsample, the effect of intermediate negative returns (IN-20-100) is slightly stronger.

The test of the difference between the two coefficients confirms that, in line with previous tests, there is a shift (the IN-0-20 coefficient is different from the IN-20-100 coefficient) for retail investors. Interestingly, this is not the case for institutional investors. It seems that institutional investors do not react to the same level of negative returns. To check this point, appendix 5 and the third column of table 6 show that institutional investors' supplementary outflows occur at a less negative level of returns – they react as soon as the return falls into the 80% worst negative returns, instead of 20%. This means that they react for negative returns that are closer to zero.

This result is important in that the stronger and more frequent reaction of institutional investors is prone to foster the magnitude of outflows. It is also important for funds dedicating a large fraction of their portfolios to an institutional clientele.

5. Conclusion

Negative shocks affecting bond funds' returns may trigger a negative feedback loop between flows and returns, which could be unfavorable for investors, mutual funds and markets. In this paper, we focus on the first part of the loop: the effect of returns on flows.

Several results confirm this proposition: the effect of very negative short-term returns does not change the slope of the relationship between returns and flows, but it leads to nonlinear effects (if returns fall below a specific threshold, additional outflows will occur). Crises or periods of financial stress periods also contribute to supplementary outflows. Finally, for shares with a higher minimum initial investment requirement (used as a proxy for institutional shares), additional outflows seem to occur at less negative levels of short-term returns.

The existence of a negative relation between returns and outflows represents the first step in demonstrating the presence of a negative loop between flows and performance. The second step would be to demonstrate that outflows exert a negative pressure on the prices of traded securities, which negatively impacts the returns of funds, causing future outflows to take place. But mutual funds can take measures to alleviate the possibility of arrival of such a loop. One of the possible solutions would be to hold more liquid assets and to sell them in the first place in order to satisfy redemptions. Another possibility would be to charge investors a higher redemption fee in order to discourage them from redeeming. The degree to which mutual funds take such precautionary measures is yet to be determined. Indeed, the growing competition in the mutual funds industry discourages them from setting up more restrictive measures on redemptions, while holding a very liquid portfolio negatively impacts their returns. Regulatory authorities should be aware of the presence of such industry risks, especially in the case of bond mutual funds, for which liquidity is more difficult to assess.

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Appendix:

Appendix 1: The effect on flows of the past month's raw share return in the presence of month fixed effects:

LowPerf	0.055***
	(0.000)
MidPerf	0.014***
	(0.000)
HighPerf	0.066***
	(0.000)
Lagged raw return	0.280***
	(0.000)
Log(TNA)	-0.006***
	(0.000)
Std Dev	-0.151
	(0.166)
Log(age)	-0.010***
	(0.000)
Intercept	0.107***
	(0.000)
Observations	53,433
R-squared	0.027

The dependent variable is the net flows in % (truncation of observations above the 99th percentile and below the 1st percentile of the distribution). *LowPerf, MidPerf, and HighPerf* are indicators of relative long-term performance (12 months), constructed as in Sirri and Tuffano (1998). *Lagged raw return* is the past month's raw share return. Control variables include the natural logarithm of net assets under management in the past month (*log(TNA)*), the natural log of the number of years since the inception of the share (*log(age)*) and the past standard deviation of monthly returns (over the past 12 months: *Std dev*). We use fixed effects at the share level and at the month level and clustered errors by fund. Stars indicate p-values (*** p<0.01, ** p<0.05, * p<0.1).

Appendix 2: The effect on flows of the gap between a share's return and the global median return of funds:

LowPerf	0.054***
	(0.000)
MidPerf	0.014***
	(0.000)
HighPerf	0.065***
	(0.000)
Excess_median	0.309***
	(0.000)
Median	0.678***
	(0.000)
Log(TNA)	-0.006***
	(0.000)
Std Dev	-0.144
	(0.110)
Log(age)	-0.007***
	(0.000)
Intercept	0.092***
	(0.000)
Observations	53,433
R-squared	0.017

The dependent variable is the net flows in % (truncation of observations above the 99^{th} percentile and below the 1^{st} percentile of the distribution). *LowPerf, MidPerf, and HighPerf* are indicators of relative long-term performance (12 months), constructed as in Sirri and Tuffano (1998). *Excess_median* is the past month's individual raw share return in excess of the past month's median return. *Median* is the median of the past month's share returns of all funds. Control variables include the natural logarithm of net assets under management in the past month (*log(TNA)*), the natural log of the number of years since the inception of the share (*log(age)*) and the past standard deviation of monthly returns (over the past 12 months: *Std dev*). We use fixed effects at the share level and clustered errors by fund. Stars indicate p-values (*** p<0.01, ** p<0.05, * p<0.1).

Appendix 3: Investors' reactions depending on the level of short-term raw share return

LowPerf	0.052***
	(0.000)
MidPerf	0.012***
	(0.000)
HighPerf	0.064***
	(0.000)
Lagged raw return	0.122***
	(0.003)
Median	0.102
	(0.244)
Log(TNA)	-0.006***
	(0.000)
Std Dev	-0.085
	(0.344)
Log(age)	-0.007***
	(0.000)
IN-0-20	-0.015***
	(0.000)
IN-20-40	-0.011***
	(0.000)
IN-40-60	-0.009***
	(0.000)
IN-60-80	-0.010***
	(0.000)
IN-80-100	-0.010***
	(0.000)
IP-0-20	-0.003
	(0.176)
IP-20-40	0.000
	(0.865)
IP-40-60	-0.002
	(0.172)
IP-60-80	-0.000
	(0.801)
Intercept	0.098***
	(0.000)
H0: IN-0-20 = IN-20-40	0.0244**
Observations	53,433
R-squared	0.019

The dependent variable is the net flows in % (truncation of observations above the 99th percentile and below the 1st percentile of the distribution). *LowPerf, MidPerf, and HighPerf* are indicators of relative long-term performance (12 months), constructed as in Sirri and Tuffano (1998). *Lagged raw return* is the past month's raw share return. *Median* is the median of the past month's share returns of all funds. *IN-0-20* = 1 if the individual raw return of the previous month is in the bottom 20% of the worst negative returns and zero otherwise. *IN-20-40* = 1 if the individual raw return in the previous month is between the 20th percentile and the 40th percentile of negative returns and 0 otherwise, and so forth. *IP-0-20* = 1 if the raw return in the previous month is below the 20th percentile of positive returns, and so forth. We choose the highest quintile of positive returns as the reference, i.e., *IP-80-100*. Control variables include the natural logarithm of net assets under management in the past month (*log(TNA)*), the natural log of the number of years since the inception of the share (*log(age)*) and the past standard deviation of monthly returns (over the past 12 months: *Std dev*). We use fixed effects at the share level and clustered errors by fund. Stars indicate p-values (*** p<0.01, ** p<0.05, * p<0.1).

Appendix 4: Differential sensitivity for negative or very negative levels of median returns:

LowPerf	0.053***	0.053***
	(0.000)	(0.000)
MidPerf	0.012***	0.012***
	(0.000)	(0.000)
HighPerf	0.064***	0.064***
	(0.000)	(0.000)
Lagged raw return	0.150***	0.157***
	(0.000)	(0.000)
Median	0.129	0.039
	(0.312)	(0.734)
Median*I(Med_neg)	0.109	
	(0.610)	
Median*I(Med-0-10)		-0.107
		(0.734)
Log(TNA)	-0.006***	-0.006***
	(0.000)	(0.000)
Std Dev	-0.079	-0.078
	(0.370)	(0.377)
Log(age)	-0.007***	-0.007***
	(0.000)	(0.000)
IN-0-20	-0.013***	-0.012***
	(0.000)	(0.000)
IN-20-100	-0.009***	-0.008***
	(0.000)	(0.000)
I(Med_neg)	0.001	
	(0.418)	
I(Med-0-10)		-0.004
		(0.180)
Intercept	0.096***	0.097***
	(0.000)	(0.000)
Observations	53,433	53,433
R-squared	0.019	0.019

The dependent variable is the net flows in % (truncation of observations above the 99th percentile and below the 1st percentile of the distribution). *LowPerf, MidPerf, and HighPerf* are indicators of relative long-term performance (12 months), constructed as in Sirri and Tuffano (1998). *Lagged raw return* is the past month's raw share return. *Median* is the median of the past month's share returns of all funds. $I(med_{neg})$ = 1 if the median of lagged monthly returns is negative and 0 otherwise. *I(Med-0-10)* = 1 if the median of lagged monthly returns is below the 10th percentile of its distribution. Interaction terms between $I(med_{neg})$ and *Median* and between *I(Med-0-10)* and *Median* have been introduced to allow for the presence of different slopes between the positive/negative and the lowest/ higher segments of median returns. *IN-0-20* = 1 if the individual raw return in the previous month is in the bottom 20% of the worst negative returns and zero otherwise. *IN-20-100* = 1 if the individual raw return in the previous month is between the 20th percentile and 0. Control variables include the natural logarithm of net assets under management in the past month (*log(TNA)*), the natural log of the number of years since the inception of the share (*log(age)*) and the past standard deviation of monthly returns (over the past 12 months: *Std dev*). We use fixed effects at the share level and clustered errors by fund. Stars indicate p-values (*** p<0.01, ** p<0.05, * p<0.1).

Appendix 5: Differential sensitivity for institutional investors

LowPerf	0.050*
	(0.056)
MidPerf	0.020***
	(0.003)
HighPerf	0.015
	(0.568)
Lagged raw return	0.066
	(0.270)
Median	0.007
	(0.969)
Log(TNA)	-0.005***
	(0.001)
Std Dev	-0.267**
	(0.021)
Log(age)	-0.008**
	(0.019)
IN-0-20	-0.017***
	(0.000)
IN-20-40	-0.016***
	(0.000)
IN-40-60	-0.012***
	(0.000)
IN-60-80	-0.011***
	(0.003)
IN-80-100	-0.006**
	(0.020)
Intercept	0.097***
	(0.001)
H0: IN-0-20 = IN-40-60	0.21
H0': IN-0-20 = IN-80-100	0.02**
Observations	15,152
R-squared	0.016

The sample has been separated into retail shares (with a minimum initial investment requirement lower than 10,000 euros) and institutional shares (with a minimum initial investment requirement higher than 10,000 euros). Here, only the results for the institutional shares are reported. The dependent variable is the net flows in % (truncation of observations above the 99th percentile and below the 1st percentile of the distribution). *LowPerf, MidPerf, and HighPerf* are indicators of relative long-term performance (12 months), constructed as in Sirri and Tuffano (1998). *Lagged raw return* is the past month's raw share return. *Median* is the median of the past month's share returns of all funds. *IN-0-20* = 1 if the individual raw return in the previous month is in the bottom 20% of the worst negative returns and zero otherwise. *IN-20-40* = 1 if the individual raw return in the previous month is between the 20th percentile and the 40th percentile of negative returns and 0 otherwise, and so forth. Control variables include the natural logarithm of net assets under management in the past month (*log(TNA)*), the natural log of the number of years since the inception of the share (*log(age)*) and the past standard deviation of monthly returns (over the past 12 months: *Std dev*). We use fixed effects at the share level and clustered errors by fund. Stars indicate p-values (*** p<0.01, ** p<0.05, * p<0.1).