The impact of return shocks on the mutual funds' flows: an example based on the 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 on 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 proving that mutual funds can be at the origin of financial instability. Indeed, the possibility that negative shocks impacting the short-term returns generate outflows can result in a loop between funds' flows and their returns. Our model authorizes the presence of nonlinear effects in the shape of the relationship between flows and performances. The results demonstrate that mutual funds presenting very negative short-term returns experience superior outflows compared to funds presenting less negative short-term returns (this effect appears at the bottom negative return quintile). Conversely, this nonlinear effect is not present on the positive short-term returns' segment. Irrespective of mutual funds' returns, the 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 biggest shares and thus whose decisions will pose more for the mutual fund), the nonlinear effect appears starting with the second negative return quintile. We hence confirm the presence of a potential source of fragility and risk coming from negative shocks on bond mutual funds' short-term returns.

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1. Introduction

The recent growth of shadow banking and most importantly of mutual funds raised concerns for the regulatory institutions. Since the year 2000, mutual funds have attracted many investors seduced by the diversification and the liquidity of the proposed investments. According to the IMF (2015), the biggest 500 mutual funds had assets under management worth of 35 trillion in 2000, compared to 79 trillion in 2013. Despite a decline during the financial crisis of 2007-2008, the asset management sector remained particularly dynamic. In France, bond funds have showed a growth of almost 40% of assets under management between 2011 and 2016, passing from 184 billion euro(s) to 257 billion euro(s) according to AMF (2017). This growth of bond funds' assets under management is explained by a more accommodative stance of monetary policy translated by both a decline in key interest rates, and bond purchase programme having for purpose to lower the middle-long term interest rates. The fall of interest rates has had a positive effect on bonds' prices and has contributed to a gain of attractivity for bond mutual funds compared to their equity counterparties.

Given the importance of assets managed by this industry (the bond funds being a privileged support for pension savings? around the world) and its sway on financial markets, the understanding of investment choices made by the agents is fundamental both for academic world and regulatory institutions. Different studies carried by regulatory institutions (OFR (2013), FSB (2017), IMF (2015) have underlined the fact that mutual funds' activities are subject to multiple risks, including a particularly pronounced liquidity risk[2]. In case of a shock exerting a negative impact on the funds' returns, the investors may be tempted to redeem their shares, which is synonym of outflows. Mutual funds may be constrained to rapidly sell bonds in order to honour the demands. Hence, the flow-performance relationship can transform in a vicious circle if bonds' sells were inducing transaction costs or were exerting a negative pressure on the assets' prices (a case that is particularly plausible on the less liquid part of the bond funds' portfolios, as is shown by Coudert et Salakhova (2019) for French bond funds).

Consequently, for open-ended mutual funds, the 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 it may impair global financial stability.

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

From a theoretical point of view, the link that exists between flows and performance has its origins in the principal-agent relationship that exists between mutual funds' managers and final investors. As the investors are unable to directly observe the aptitudes of the funds' managers, they will try to infer it by examining past funds' returns (Berk and Green (2004)). They will thus use past returns in order to take their investment decisions.

The flow-performance relationship has constituted the subject of numerous articles in the case of equity open-end funds. The literature (Sirri and Tufano (1998), Chevalier and Ellison (1997) for American open-ended mutual funds, Bellando and Tran-Dieu (2011) for French open-ended mutual funds) has proved the existence of a convex relationship between flows and performances: investors do not redeem more their shares of a fund that has showed a bad performance, but performing funds seem to attract inflows. This convex form may encourage mutual funds' managers to engage in a risk-taking behaviour, but at the same time it does not suggest the existence of a fragility for equity funds, as they would not face massive outflows in response to a bad 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 the segments of return: the investors will redeem their shares if the return has been negative. In addition, Goldstein et al (2017) demonstrate that a fund which possesses more illiquid assets will show an even sharper positive flow-performance relationship, because the costs that will have to be bared by investors remaining in the fund will be higher. Therefore, the remaining investors will be encouraged to redeem before the others. Finally, these funds may be particularly sensitive to shocks on monetary policy (Banegas et al (2016)), which may constitute the starting point of a vicious loop between flows and returns.

It is thus important to study the fragilities posed by bond mutual funds. In this purpose, the present article will empirically study bond mutual funds using a database including bond mutual funds domiciliated in France between January 2005 and December 2017. More specifically, we are interested in what may trigger the mechanism exposed earlier: do negative short-term returns prompt massive outflows?

The majority of articles studying the shape of the flow-performance relationship is considering a long-term relative return: the funds are ranked according to their one-year or longer performance and the rank 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 in order to correctly display the funds' fragilities in response to a shock. Hence, we propose to introduce the short-term absolute return to 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 do not consider only the ranking of funds (constructed according by the model of Sirri and Tufano (1998)), but they also take into account 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, the investors redeem their shares more of funds having showed the most negative one-month returns. This effect is additive to the other responses on flows of relative and absolute returns. In this respect, it constitutes the first indication of fragilities posed by bond funds regarding a negative loop between flows and performances.

We are also interested in studying the effect of uncertainty or financial crisis on our results. Indeed, crisis periods are susceptible to increase caution, and even the mistrust of investors towards mutual funds (Goldstein et al (2017) among others). The results confirm a negative effect of financial stress periods on the funds' flows. This effect is again adding up to the others previously mentioned, and it seems to confirm a global fragility presented by the bond mutual funds market. This shows that our initial result is not induced by periods of crisis or uncertainty: un isolated fund presenting a very negative short-term return will still suffer more outflows, even if this bad return occurs during a « stress » period or not.

Lastly, we analyse the possibility of a certain behaviour difference between investors of different types. The literature has shown a certain interest to this kind of questions (Ferreira et al (2012), 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 the investors' type, we show that both investors are sensitive to very negative short-term returns. The results show that in the case of institutional funds, their reaction to poor returns takes place for a larger range of negative returns: their outflows are superior starting from less negative levels of short-term returns and thus may happen more often. As institutional investors are characterised by more important shares' detention, the effect on the flows as described earlier may be strengthened.

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

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

2. Hypothesis development

The hypothesis that we propose to test are based on the presumption that short-term return is an investment's criteria for investors.

The majority of studies carried until the present (based on equity or bond mutual funds) have demonstrated that long-term relative return (the ranking of the funds at a one-year horizon) is influencing the agents' investment choices. We suggest that is important to also integrate in the model past short-term return.

The first reason motivating our suggestion is that the change of a funds' position in the ranking doesn't capture the intensity of the short-term return that a fund was subject to. 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 his short-term return has suffered a shock. By integrating only the ranking concerning the long-term performance, we may ignore the effect of a brutal decline or improvement of the short-term performance of a fund. Moreover, if two funds are simultaneously subject to a shock, their ranking may not be affected, whereas flows can take place. Thus, irrespective of its ranking's evolution, a mutual fund that presents a strong short-term return may be subject to important flows.

Given the results of the studies that have integrated in their models measures of short-term performance (for example Del Guercio and Reuter (2014) for equity mutual funds, or 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 level of the individual short-term performance of a fund. As long as a majority of funds has been subject to a decline of their returns (which affects the median of short-term funds' returns) it is possible that investors redeem their shares out of a fund even if it presents a strong past return. The reason to this is that investors may be aware of a possible contagion effect from the market towards the individual funds.

Indeed, the investors can consider that the individual return of a fund is composed by two elements: one term reflecting the more general return of the market (here we measure if by the median of short-term returns) and an idiosyncratic term, specific to each fund (that reflects the risk level taken by a fund among other factors). For these reasons, we think it is important to integrate in the model the median of short-term funds' returns, in order to take into account the effect of the global market performance.

The first hypothesis can be expressed as follows:

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

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

The following hypothesis are seeking to authorize nonlinear effects of 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 performances or their reaction may not be similar to more or less negative returns.

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

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

As we intend to study the fragilities that can be presented by bond mutual funds, we are particularly interested in studying the situations susceptible to generate massive outflows. Indeed, the recent literature is drawing attention to possible liquidity problems that mutual funds can be subject to in case of important outflows.

In order to take into account this effect, we suppose that there could be an asymmetric impact of various signals represented by different levels of short-term returns. We would like to authorize nonlinear effects for « extreme » values of short-term returns, particularly on the negative segment. By doing so, we evaluate the plausibility of situations where certain mutual funds would see their initial difficulties (materialized by very low returns) enhanced by important outflows. This can indeed expose mutual funds to liquidity problems: Coudert and Salakhova (2019) show that massive outflows have important negative impact on corporate bonds' yields. Galanti and Le Quéré (2016) confirm that flows affect the yields of corporate bonds as well as those of sovereign bonds. In total, we enrich the model detailed in the second hypothesis, by allowing an asymmetric effect whose purpose is 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 superior outflows.

To complete the study, we would like to examine if flows are sensitive to financial conjuncture. Indeed, the investors' behaviour change according to different situations of financial conjuncture, as Goldstein et al (2017), or the IMF (2015) have demonstrated.

Furthermore, according to the previous hypothesis, we can imagine important negative outflows for the funds whose short-term returns were showing an extreme value. Or by using this empirical model, we can capture a simple effect of financial crisis periods, especially because these periods exist in our sample. Therefore, we are looking to examine if this crisis' effect coincides with extreme returns or if it is additive to it. More precisely, we try to analyse if superior flows take place during periods of financial stress irrespective of the performance of each fund. Therefore, the fourth hypothesis can be phrased as follows :

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

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

The last hypothesis that we examine aims at clarifying the origin of a possible different reaction to short-term returns between distinct types of investors. The distinction between retail investors and institutional investors is generally considered in the literature. We use the minimum initial investment requirement in each part in order to separate the two types of clientele. As institutional investors detain larger shares, their redeeming decisions are susceptible to impact the mutual funds more severely.

Institutional clients are considered to be more sophisticated, less subject to inertia or to a strong reaction to a signal. The literature demonstrates (Ferreira et al (2012), 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 compared to their retail counterparties. Furthermore, according to the IMF (2015), institutional investors seem to react less to recent returns compared to retail investors. This behaviour can be explained by the fact that for example contractual engagements of institutional investors towards their principal constrains them to a certain management[3]. In contrast, two types of arguments can explain a greater reactivity of institutional investors to recent performance. Firstly, keeping their shares in a bad performing fund can lead to a reputational loss and can harm future activity. Hence, following a similar choice as the one presented in a window-dressing context, institutional investors would redeem their least performing shares in order to not appear as that they have made a bad choice in their investment decisions. Secondly, a sensitivity of clients to short-term performance can be justified if these returns were having a certain 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 cleanings

We use data from Datastream about shares of OPCVM (open-end 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 initial investment, the purchase fees, redemption fees, and management fees can differ. Because these fees impact the returns (because they are net of fees in the database), which are a central variable in this article, it is important to study returns at the share level and not at the fund level.

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

More precisely, we have worked on shares with a "bond" classification made by Datastream. Unfortunately, some shares classified as "bonds" by Datastream are classified as "diversified" or have a different classification by the AMF[4]. We choose to retain shares for every month in which they also are classified "bonds" by the AMF, and thus drop the months in which shares are labelled "diversified" or other by the AMF. We drop observations for which a funds' total net asset is below 300,000 euros, because, according to AMF rules, the fund has the obligation to be liquidated when net asset falls below this threshold. We also drop observations of funds with an age of less than one year, in order to have sufficient time length. Finally, share prices (net asset value per shares) have been adjusted for splits.

As we study flows of shares, we do not retain closed-end funds (that have a fixed number of shares), nor ETF funds (whose shares are traded on an Exchange, and whose price can differ from its intrinsic value), nor feeder funds (whose returns follow these 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 is not available), and shares not labelled in euros (as the returns could capture movements on the foreign exchange market).

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

3.2 The definition of variables:

Measurement of flows:

In accordance to the majority of studies, our variable of interest is the percentage net fund flows ($Flow_{i,t}$), which corresponds to the difference, of inflows minus outflows, between t and t-1, in percentage of total net assets at the 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 in using the monthly total net assets and the growth of the share's net asset value (NAV) between t and t-1:

[4] The AMF (Autorité des Marchés Financiers) is the financial market regulatory authority, which is in charge of supervising Mutual Funds domiciled in France.

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

As we can see below, the evolution of the share's total net assets can be separated into two terms: a first effect being synonym of a « valuation » effect and the second term being synonym of 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:

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

The definition of explanatory variables:

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

The long-term relative performance:

The model used by Sirri and Tufano (1998) is usually applied to define relative performance. This model takes into account the effect on the flows of the shares' ranking 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 authorises the presence of a nonlinear slope between flows and performance rank[6].

Hence, by using their model, we authorise the slope of the relationship to differ between 3 groups of relative performances: the first group LowPerf varies only for funds whose performance is in the first performance quintile, the second group MidPerf represents funds

[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

whose rank is comprised between 0.2 et 0.8 and the variable HighPerf corresponds to the highest performance quintile:

$LowPerf_{i,t}$ = Min (0,2 ; $Rank_{i,t-1}$)

$MidPerf_{i,t}$ = Min (0,6 ; $Rank_{i,t-1}$ - $LowPerf_{i,t}$)

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

The 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 usually used in the existing studies (for example by Goldstein et al (2017), Chen and Qin (2017) for bond mutual funds, or by 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 of more marketing following its creation. This can attract new investors irrespective of the share's performance. Even if the definition of this variable varies between different articles, we adopt the measure used by Goldstein et al (2017). Consequently, the natural logarithm of the share's age measured in years since inception is used as a control variable.

The size of each share:

According to the literature, the size of each share is calculated as being the natural logarithm of past month assets under management. Previous studies have demonstrated that if net flows are not proportional to the share's size, percentage net flows should be smaller as shares grow in size. Given the fact that our dependent variable is percentage net flows, we expect the results to show a negative relationship between the dependent variable and the share's size.

[7] Aside from raw monthly returns, other definitions of short-term returns may be used. Indeed, a short-term performance may be calculated differently depending on the period's risk-free rates for example. 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 an usual practice in the literature, this variable is calculated as the standard deviation of the past 12 monthly returns. We explain the use of this variable as a standard control variable because net flows can be influenced by the fact that investors may be sensitive to the risk level taken by the manager in his portfolio decisions.

3.3. Descriptive statistics:

The assets under management, as well as the number of shares, follow an increasing trend during the 2005-2017 period (cf. Figure 1).

Figure 1

Assets under management (monthly, 2007-2017, million euros)

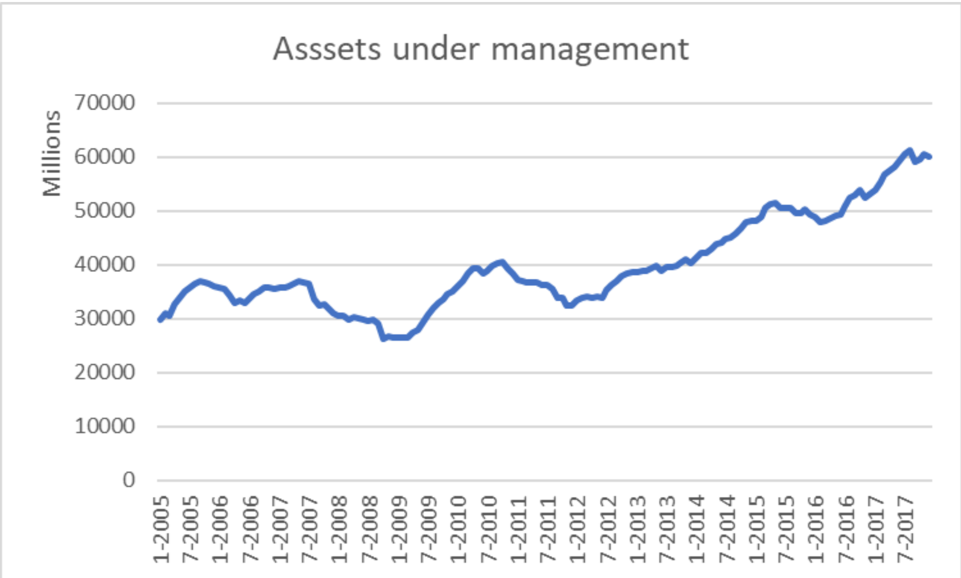
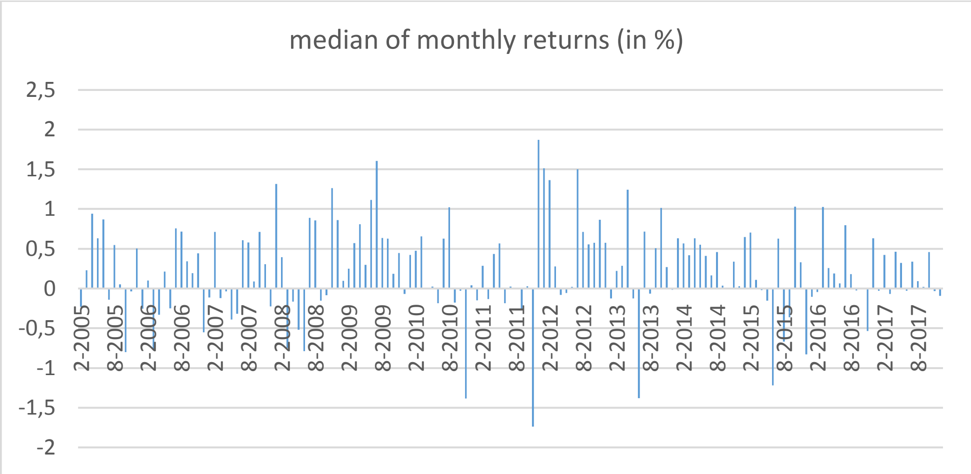


Figure 1 shows that between January 2005 and December 2017, assets under management (AuM) increased by roughly 100%. The effect of two major crisis appear: the global financial crisis (AuM decreased by 26% between June 2007 and April 2009), and the European sovereign debt crisis (AuM decreased by 20% between October 2010 to December 2011).

These crises are also affecting our sample, but in a slighter way, as it is shown by Figure 2, which represents the evolution of the median of the monthly shares' returns in the sample.

Figure 2

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



Finally, in Table 1, we present the mean, standard deviation, and the 5%,25%, 50%, 75% and 95% percentile of the distributions of the variables used in our models, as long as 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	53433
Lagged monthly return	0,003	0,014	-0,016	-0,002	0,002	0,008	0,022	53433
Ln(lagged TNA)	17,27	1,59	14,468	16,286	17,376	18,396	19,62	53433
Ln(age)	2,04	0,894	0,47	1,364	2,104	2,777	3,333	53433
Standard deviation of the past 12 monthly returns	0,01	0,01	0,001	0,004	0,008	0,013	0,024	53433
Median of lagged monthly returns	0,002	0,006	-0,008	-0,001	0,002	0,006	0,012	154

We remark that more than the half of observations corresponds to outflows (negative net flows). The monthly returns are positive on average (0.3%), and amount to an annual return of around 3.7%. However, for 5% of observations, the monthly return is at most –1.6%, which corresponds to around –18% per year. Finally, we remark that the median of Asset under Management is approximately 35 Million euros, while the average age of a share is around 7 years and a half.

4. Model and results

4.1. The Model :

In this subsection we present our modelling choices.

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

In every model, we add share fixed effects, because we want to take into account the characteristics that are constant in time and could be correlated with other variables in the model. Notably, we think about management fees, which can be unchanged through the life time of the share, but can be 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, in order to authorize 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 synonym to testing whether β_4 is significantly different superior to zero.

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

[8] Because we study situations which are prone to provoke important outflows, dropping the extreme 1% percentiles of flows could have an impact on the results. However, we have tested other truncations (0,5%, 2.5%, 5%) and the results are qualitatively similar.

[9] As a robustness check we have also introduced 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 this article.

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

Results are given in the first column of Table 2. We first comment control variables, and 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 them here.

Table 2: Hypothesis 1-a and 1-b: reaction to short-term absolute returns, at the individual and market level

	(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 99^{th} percentile and below the 1^{st} percentile of the distribution). *LowPerf, MidPerf, HighPerf* are indicators of relative long-term performance (12 months), built as in Sirri and Tuffano (1998). *Lagged raw return* is the past month share raw return. *Median* is the median of past month share returns on all funds. Control variables include: the natural logarithm of net assets under management of past month (*log(TNA)*), the natural log of the number of years since inception of the share (*log(age)*) and past standard deviation of monthly returns (on the 12 past months: *Std dev*). We use fixed effects at the share level, and clustered errors by fund. Stars indicate the p-values of statistics (*** p<0,01, ** p<0,05, * p<0,1).

Concerning long-term relative returns, Wald tests indicate that LowPerf and HighPerf are statistically different from MidPerf (99% level), whereas LowPerf and HighPerf coefficients are not different from each other. This is interpreted as a concave relation between low returns and middle returns, and as a convex relation between middle returns and high returns.

In other words, whatever the initial rank of the fund, a rise in the ranking is rewarded with inflows, and a lowering of its rank is punished by outflows. However, if the initial position of the share's rank is in the middle segment, the impact of rank on flows is weaker (the coefficient of MidPerf is lower). This flow-performance relationship confirms the one found by Chen and Qin (2017) for US bond funds. The convex form in the right side of the relationship (for high relative returns) can cause risk-taking incentives, or tournament phenomenon, as Chevalier and Ellison (1997), Ferreira et al (2012) or Kim (20l7) showed for equity funds. On the side of middle and low performances, the concave shape indicates a sanction for poor performances. This effect indicates a precautionary behavior from investors and joins up with the results of Chen and Qin (2017) and IMF (2015) for US bond funds. However, it also indicates that investors react strongly to poor relative performances, and this effect could complement the one on absolute short-term returns[11].

Results in Table 2 indicate that the raw short-term return is an important determinant of flows, and confirm the interest of introducing this variable besides the Sirri-Tuffano effects. A fund with a 1 percentage point increase in past month raw return will have, all else equal, a surplus inflow of 0.38%. This positive and significant relation between flows and lagged short-term returns confirms those of 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' performances, the global return of the funds' market could influence flows. We thus add the "*Median*" variable, the median of past month shares' returns. The aim is to capture positive (negative) shocks on numerous funds, which could increase (lower) the monthly median of performances. 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].

[11] For example, a fund suddenly lowering its ranking can experiment outflows which could trigger a negative flow-performance feedback.

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

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

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

Comparatively with the first regression, the results are globally similar. The *"Median"* variable has a positive and statistically significant coefficient. Investors are thus also reacting to the global performance of bond funds[13]. This points to the fragility of a fund when confronted to a global decrease in the bond fund market. Hypothesis 1-b seems to be validated.

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

We now try to capture non-linear effects of short-term returns. First, we hypothesize that investors may not react the same when confronted with negative or 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.

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

Previously defined variables are the same. ($I(ret_{neg})$ *and* $I(med_{neg})$ are equal to 1 when past individual, or median, return was negative. If the reaction is stronger when the signal is negative, we expect coefficients β_5 and β_7 to be positive. Besides, β_8 and β_9 are susceptible to capture an additional negative effect on net flows. Table 3 shows the results.

Investors seem to react identically to an increase or decrease of past individual positive or 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

[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 by its return in excess of the median return, and results do not qualitatively change. Investors both react to the individual, and to the global, component of the short-term return.

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 the same to a decrease in returns. However, when a decrease happens for already negative returns, there is a supplementary outflow of 0.9%, compared with a decrease that happens for initially positive returns. Put differently, 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 given to the median is no longer sizable when the initial sign of past month share's return is taken into account.

Table 3: Hypothesis 2: difference of 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 99th percentile and below the 1st percentile of the distribution). *LowPerf, MidPerf, HighPerf* are indicators of relative long-term performance (12 months), built as in Sirri and Tuffano (1998). *Lagged raw return* is the past month share raw return. *Median* is the median of past month share returns on 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*, respectively between $I(med_{neg})$ and *Median* have been introduced in order to allow the presence of different slopes between the positive/negative segments of lagged return and median returns. Control variables include: the natural logarithm of net assets under management of past month (*log(TNA)*), the natural log of the number of years since inception of the share (*log(age)*) and past standard deviation of monthly returns (on the 12 past months: *Std dev*). We use fixed effects at the share level, and clustered errors by fund. Stars indicate the p-values of statistics (*** 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 exists a difference in the intercepts of the model depending on the fact that the raw short-term return is negative or positive. As a preamble to testing hypothesis 3, we indicate in appendix 3 results of a regression authorizing intercepts to differ according to the quintiles of negative returns and quintiles of positive returns. The bounds of the quintiles are defined on the whole sample. We define IN-0-20 a variable equal to 1 if the individual raw return of the previous month is below the 20% of the worst negative returns, and zero otherwise. IN-20-40 takes the value 1 if the individual raw return of the previous month is within the 20th percentile and 40th percentile of negative returns, etc. Similarly, we build dummy variables in the positive side: IP-0-20 takes value 1 if the raw return of the previous month is below the 20th percentile of positive returns, etc. We choose the highest quintile of positive returns as the reference, i.e. IP-80-100. Results are given in appendix 3.

We observe that the coefficients of all negative quintiles are significantly negative. We test the difference between these coefficients and show that the coefficient of the worst negative returns, IN-0-20, is significantly inferior to the other coefficients. The other four quintile coefficients are not statistically different from one another, hence, they can be grouped into one only dummy variable, IN-20-100.

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

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

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

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's 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)
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, HighPerf* are indicators of relative long-term performance (12 months), built as in Sirri and Tuffano (1998). *Lagged raw return* is the past month share raw return. *Median* is the median of past month share returns on all funds. *IN-0-20* = 1 if the individual raw return of the previous month is below the 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 of past month (*log(TNA)*), the natural log of the number of years since inception of the share (*log(age)*) and past standard deviation of monthly returns (on the 12 past months: *Std dev*). We use fixed effects at the share level, and clustered errors by fund. Stars indicate the p-values of statistics (*** p<0,01, ** p<0,05, * p<0,1).

The results for control variables and performance rankings remain identical. 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 flow-performance short term 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 statistically different (at the 95% level), with the greatest outflows for the worst returns. It is noteworthy to remark that these effects add up with the linear effect of returns. In a nutshell, investors present a specific sensitivity to returns when they are particularly negative, with greater outflows for the worst returns. Appendix 3 shows that it is not equivalent for positive returns, as the flow-performance relationship on the positive side is linear and does not exhibit shifts.

Furthermore, we remark that the coefficients for the median variable is no longer significant[15]. We attempt to explain this by the fact that the global effect of the median is dominated by these 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 20st percentile of negative return is high. We remark that these 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 adds up with the effect of a general context of crisis, not necessarily specific to the bond funds sector. This is the point 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 being in a period of financial stress or not. 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 mixed with those of the decrease of the fund's returns. We aim at considering the general effect of financial stress at large on investors' behavior. We run the following regression:

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

The new variable here is a dummy *I(Crisis)* taking the value of 1 if the indicator is superior to the 90th percentile of its distribution (high stress). As advocated earlier, variable IN-0-20 is related with crisis on the bond market, and the coefficient of *I(Crisis)* will tell us whether the general financial stress substitutes, or is a complement to, the effect of individual fund returns on fund flows.

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

If the crisis dummy is significant and the shift in intercepts for very negative returns does not appear anymore, it means that the shift we observed was simply the consequence of a general financial distress. 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 negative share's return, investors redeem their shares from funds more in times of stress (around +0.6% in terms of outflows, as indicated by *I(Crisis)* coefficient for the VIX case) compared to normal times.

However, we observe that the "shift" in returns is still significant (at the 95% level) throughout all three models. It means that, independently of the general financial context, investors redeem more, all else equal, from funds which exhibit the worst negative returns. Furthermore, during periods of stress, funds suffer from important outflows, independently 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 ("slope" effect) and with 2) with the worst negative returns ("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)
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 99th percentile and below the 1st percentile of the distribution). *LowPerf, MidPerf, HighPerf* are indicators of relative long-term performance (12 months), built as in Sirri and Tuffano (1998). *Lagged raw return* is the past month share raw return. *Median* is the median of past month share returns on all funds. *I(Crisis)* = 1 if the indicator is superior to 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 below the 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 of past month (*log(TNA)*), the natural log of the number of years since inception of the share (*log(age)*) and past standard deviation of monthly returns (on the 12 past months: *Std dev*). We use fixed effects at the share level, and clustered errors by fund. Stars indicate the p-values of statistics (*** p<0,01, ** p<0,05, * p<0,1).

4.6 Results concerning hypothesis 5: types of investors

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

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

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

Results are given in Table 6, in which we recall the results on the whole sample.

Concerning long-term performance, institutional investors behavior differs from retail investors' one in that they do not seem to react to a good relative performance (the coefficient for HighPerf is not significantly different from 0). This result joins up with this of Ferreira et al. (2012) for which 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 bad relative performance. We attempt to explain it by the mandatory obligations that concern institutional investors *vis-à-vis* their own clients (maintaining certain ratings class proportion in portfolio, investment policy statements), independently of returns, financial context, or state of the funds market.

Concerning their sensitivity to short term raw returns, institutional investors also differ from retail ones, in that they react less to short term returns (the coefficient are both positive but with a 10%-level significance vs. 1%-level, respectively).

[16]We also check robustness using a threshold of 100,000 euros. This does not change 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 the type of investor

	Retail shares	Institutional shares	Total sample
LowPerf	0.056***	0.049*	0.053***
	(0.000)	(0.060)	(0.000)
MidPerf	0.008**	0.020***	0.012***
	(0.012)	(0.003)	(0.000)
HighPerf	0.085***	0.015	0.064***
	(0.000)	(0.557)	(0.000)
Lagged raw return	0.181***	0.098*	0.148***
	(0.000)	(0.099)	(0.000)
Median	0.164*	0.040	0.128
	(0.089)	(0.820)	(0.137)
Log(TNA)	-0.006***	-0.005***	-0.006***
	(0.000)	(0.001)	(0.000)
Std Dev	0.013	-0.283**	-0.080
	(0.913)	(0.015)	(0.365)
Log(age)	-0.007***	-0.007**	-0.007***
	(0.001)	(0.023)	(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)
Intercept	0.094***	0.096***	0.096***
	(0.000)	(0.001)	(0.000)
Observations	37,966	15,152	53,433
R-squared	0.021	0.016	0.019

The sample has been separated between 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 results for the total sample (according to Table 4). 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, HighPerf* are indicators of relative long-term performance (12 months), built as in Sirri and Tuffano (1998). *Lagged raw return* is the past month share raw return. *Median* is the median of past month share returns on all funds. *IN-0-20* = 1 if the individual raw return of the previous month is below the 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 of past month (*log(TNA)*), the natural log of the number of years since inception of the share (*log(age)*) and past standard deviation of monthly returns (on the 12 past months: *Std dev*). We use fixed effects at the share level, and clustered errors by fund. Stars indicate the p-values of statistics (*** p<0,01, ** p<0,05, * p<0,1).

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

The test of difference between the two coefficients (unreported) confirm 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 ones. It seems that institutional investors do not react to the same level of negative returns. In order to check this point, appendix 5a and 5b show that institutional investors the supplementary outflows happen for a less negative level of returns –they react as soon as the return lies below the 40% worst negative returns, instead of 20%. It means that they react for negative returns which 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 important also for funds dedicating a large fraction of their portfolios to institutional clientele.

5. Conclusion (work in progress)

Negative shocks affecting bond funds' returns may trigger a negative loop between flows and returns, which could be unfavourable 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 prospect: the effect of very negative short-term returns does not cause a change in the slope of the relationship between returns and flows, but it leads to nonlinear effects (if returns get below a specific threshold, additional outflows will occur. The crises or financial stress periods contribute as well to supplementary outflows. Lastly, for shares with a higher minimum initial requirement (synonym of institutional shares), additional outflows seem to take place for less negative levels of short-term returns.

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Appendix :

Appendix 1 : The effect on flows of past month raw share's return, in 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, HighPerf* are indicators of relative long-term performance (12 months), built as in Sirri and Tuffano (1998). *Lagged raw return* is the past month share raw return. Control variables include: the natural logarithm of net assets under management of past month (*log(TNA)*), the natural log of the number of years since inception of the share (*log(age)*) and past standard deviation of monthly returns (on the 12 past months: *Std dev*). We use fixed effects at the share level and at the month level, and clustered errors by fund. Stars indicate the p-values of statistics (*** 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 99th percentile and below the 1st percentile of the distribution). *LowPerf, MidPerf, HighPerf* are indicators of relative long-term performance (12 months), built as in Sirri and Tuffano (1998). *Excess_median* is the past month individual share raw return in excess of the past month median return. *Median* is the median of past month share returns on all funds. Control variables include: the natural logarithm of net assets under management of past month (*log(TNA)*), the natural log of the number of years since inception of the share (*log(age)*) and past standard deviation of monthly returns (on the 12 past months: *Std dev*). We use fixed effects at the share level, and clustered errors by fund. Stars indicate the p-values of statistics (*** p<0,01, ** p<0,05, * p<0,1).

Appendix 3: investors' reactions depending on the level of short-term raw share's 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)
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, HighPerf* are indicators of relative long-term performance (12 months), built as in Sirri and Tuffano (1998). *Lagged raw return* is the past month share raw return. *Median* is the median of past month share returns on all funds. *IN-0-20* = 1 if the individual raw return of the previous month is below the 20% of the worst negative returns, and zero otherwise. *IN-20-40* = 1 if the individual raw return of the previous month is between the 20th percentile and the 40th percentile of negative returns and 0 otherwise etc. *IP-0-20* = 1 if the raw return of the previous month is below the 20th percentile of positive returns, etc. 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 of past month (*log(TNA)*), the natural log of the number of years since inception of the share (*log(age)*) and past standard deviation of monthly returns (on the 12 past months: *Std dev*). We use fixed effects at the share level, and clustered errors by fund. Stars indicate the p-values of statistics (*** 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, HighPerf* are indicators of relative long-term performance (12 months), built as in Sirri and Tuffano (1998). *Lagged raw return* is the past month share raw return. *Median* is the median of past month share returns on 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*, respectively between *I(Med-0-10)* and *Median* have been introduced in order to allow 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 of the previous month is below the 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 and 0. Control variables include: the natural logarithm of net assets under management of past month (*log(TNA)*), the natural log of the number of years since inception of the share (*log(age)*) and past standard deviation of monthly returns (on the 12 past months: *Std dev*). We use fixed effects at the share level, and clustered errors by fund. Stars indicate the p-values of statistics (*** p<0,01, ** p<0,05, * p<0,1).

Appendix 5-a : 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)
Observations	15,152
R-squared	0.016

The sample has been separated between 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, HighPerf* are indicators of relative long-term performance (12 months), built as in Sirri and Tuffano (1998). *Lagged raw return* is the past month share raw return. *Median* is the median of past month share returns on all funds. *IN-0-20* = 1 if the individual raw return of the previous month is below the 20% of the worst negative returns, and zero otherwise. *IN-20-40* = 1 if the individual raw return of the previous month is between the 20th percentile and the 40th percentile of negative returns and 0 otherwise etc. Control variables include: the natural logarithm of net assets under management of past month (*log(TNA)*), the natural log of the number of years since inception of the share (*log(age)*) and past standard deviation of monthly returns (on the 12 past months: *Std dev*). We use fixed effects at the share level, and clustered errors by fund. Stars indicate the p-values of statistics (*** p<0,01, ** p<0,05, * p<0,1).

Appendix 5-b : differential sensitivity for institutional investors

LowPerf	0.049*
	(0.059)
MidPerf	0.020***
	(0.003)
HighPerf	0.015
	(0.549)
Lagged raw return	0.079
	(0.164)
Median	0.020
	(0.909)
Log(TNA)	-0.005***
	(0.001)
Std Dev	-0.273**
	(0.018)
Log(age)	-0.008**
	(0.021)
IN-0-40	-0.016***
	(0.000)
IN-40-100	-0.009***
	(0.000)
Intercept	0.097***
	(0.001)
Observations	15,152
R-squared	0.016

The sample has been separated between 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 99^{th} percentile and below the 1^{st} percentile of the distribution). *LowPerf, MidPerf, HighPerf* are indicators of relative long-term performance (12 months), built as in Sirri and Tuffano (1998). *Lagged raw return* is the past month share raw return. *Median* is the median of past month share returns on all funds. *IN-0-40* = 1 if the individual raw return of the previous month is below the 40% of the worst negative returns, and zero otherwise. *IN-40-100* = 1 if the individual raw return of the previous month is between the 40th percentile and 0. Control variables include: the natural logarithm of net assets under management of past month (*log(TNA)*), the natural log of the number of years since inception of the share (*log(age)*) and past standard deviation of monthly returns (on the 12 past months: *Std dev*). We use fixed effects at the share level, and clustered errors by fund. Stars indicate the p-values of statistics (*** p<0,01, ** p<0,05, * p<0,1).