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

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Abstract

We study the shape of the relationship between French bond mutual funds' returns and their flows by using data for the period 2005-2017. Beyond considering the effect of relative performance, we are mainly interested by 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. We show 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 non-linear effect appears more frequently, starting from the fourth quintile of negative returns. 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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The recent growth of shadow banking and, in particular, of mutual funds has raised concerns for regulatory institutions. According to the EFAMA (2019), European investment funds increased their Assets under Management (AuM) from 7.1 trillion euros in 2007 to 12.9 trillion euros at the end of 2017. The growth in bond funds is particularly salient. In France, AuM grew from 184 billion euros in 2011 to 297 billion euros in 2017 (AMF (2017, 2018)). This is explained primarily by the more accommodative monetary policy stance in recent years. 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.

This surge has prompted regulatory institutions (OFR (2013), FSB (2017), IMF (2015, 2019)) to focus on the liquidity risk borne by mutual funds (see also Roncalli and Weisang (2015)). In the event of a negative shock to the funds' returns, investors may be tempted to redeem their shares. These outflows could force the mutual funds may to rapidly sell bonds. Hence, the flow-performance relationship can lead to 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. Because this loop can be self-perpetuating and may impair global financial stability, regulators have taken measures to reduce the "first-mover advantage" that arises when funds face liquidity problems (e.g. introduction of side pockets or swing pricing rules; see AFG (2016), and AMF (2013)).

Overall, in a context of historically low interest rates, there is a renewed interest in the flow-performance relationship in the bonds mutual funds case.

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 decide to buy fund shares (inflow) or sell fund shares (outflow).

In the empirical literature, the flow-performance relationship is the subject of numerous articles examining open-ended equity mutual funds. The literature (see Sirri and Tufano (1998), and Chevalier and Ellison (1997), for American funds and Bellando and Tran-Dieu (2011), for French 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. By contrast, in the case of bond mutual funds, more recent studies (Chen and Qin (2017), Goldstein and 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 particular, Goldstein and 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.

It is thus important to study the resulting fragilities for bond mutual funds. The empirical literature has for the majority analyzed the influence of funds' long-term relative returns (or rankings) on flows, following the seminal article of Sirri and Tuffano (1998). Nevertheless, long-term performance measures do not seem to be adequate to correctly display funds' fragilities in response to a sudden shock. Hence, this article proposes to also study the impact of short-term absolute negative returns on flows.

To do so, we empirically study bond mutual funds using a database including bond mutual funds domiciled in France between January 2005 and December 2017. Our main hypothesis is that investors are sensitive to short-term signals, particularly very negative signals.

The results are as follows. Although we confirm the long-term impact of funds' rankings (using the same variables as in Sirri and Tufano (1998)), we show that the short-term return of a fund also affects its net flows and that this effect is even stronger for the most negative returns[2]. In order to take into account the general performance of the bond funds market, we also show that investors' flows in one particular fund can be influenced by the median of past short-term returns of all bond funds.

This result is also robust to variants in the model: taking into account the influence of crisis or stress at the macroeconomic level or the heterogeneity among investors. First, crisis periods are susceptible to increased

[2] This result is also consistent with Li and al. (2017), who demonstrate that mutual fund investors are sensitive to performance measures assessed at different horizons and that they are more sensitive to the worst performance estimation.

investors' caution and even mistrust toward mutual funds (see Goldstein and al. (2017), among others). We confirm a negative effect of periods of financial stress on funds' flows, again without altering our main result. Second, several articles show that the behaviors of institutional and retail customers differ (Chen and al., (2010)). Institutional investors are supposed to be more sophisticated and hence to react more to risk-adjusted fund performance rather than to raw returns (Evans and Fahlenbrach (2012)). Furthermore, due to agency conflicts (Del Guercio and Tkak (2002)), institutional investors may implement a "scapegoating" strategy (James and Karceski (2006), Jones and Martinez (2017)), resulting in selling fund shares when short-term returns are negative, even if their sophistication would entice them not to overreact to recent past returns[3]. We find that both types of investors are sensitive to negative short-term returns; however, institutional investors are more sensitive in the sense that the effect of poor returns is observed for a larger range of negative short-term returns and thus may occur more often.

In sum, our results show that short-term negative returns are clearly interpreted as negative signals and thus could have a significant effect on flows. 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.

1. Hypothesis development

Hypotheses H1 to H3 develop our main research question, while hypotheses H4 and H5 are extensions and robustness checks.

[3] As Jones and Martinez (2017, p.2756) argue, institutional investors "have reasons to value manager characteristics that are easily justified to superiors or a trustee committee. One important characteristic is an asset manager's past performance, which is readily observable by the stakeholders".

Most studies conducted thus far demonstrate that the long-term relative return (the ranking of funds at a one-year horizon) influences agents' investment choices (i.e., net flows). Following Del Guercio and Reuter (2014) and IMF (2015), 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, by including only the ranking of long-term performance, we may understate the effect of a substantial decline or improvement in the short-term performance of a fund and, as a result, fail to detect financial fragility. 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.

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 are 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.

Indeed, investors could behave as if 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 in order to account for the effect of global market performance. The first hypothesis can be expressed as follows:

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

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

Next, we consider the possibility of the existence of a non-linearity in the relationship. It is indeed possible that investors do not react in the same way to positive or negative individual or median performance.

The second hypothesis is thus defined as follows:

H2: The relation between flows and short-term returns is not strictly linear and 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, which could indeed expose mutual funds to liquidity problems: Coudert and Salakhova (2019) show that massive outflows have an important positive impact on corporate bond yields. Galanti and Le Quéré (2016) confirm that flows affect the yields of both corporate and sovereign bonds.

Thus, we want to capture nonlinear effects of "extreme" values of short-term returns, particularly on the negative segment. 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 strictly linear and very negative returns lead to larger outflows.

To complete the study, as financial crisis periods are present in our sample, we examine whether flows are sensitive to financial conditions. As Goldstein and al. (2017) and the IMF (2015) have demonstrated, investors' behavior changes with financial conditions.

Furthermore, our previous model could capture through the effect of negative short-term fund returns the effect of financial crisis periods. 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. 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 negative short-term returns.

The last hypothesis that we examine is intended to study the potential different reactions to short-term returns of distinct types of investors. The distinction between retail investors and institutional investors is widely considered in the literature. Because of the weight of institutional investor holdings in fund assets, their redemption decisions have the potential to more severely affect mutual funds. Even though institutional investors are more sophisticated, they face agency conflicts with their own clients that may drive them to follow

a “scapegoating” strategy (Del Guercio and Tkak (2002), James and Karceski (2006), Jones and Martinez (2017)). If their clients look closely at recent returns, institutional investors are constrained to react quickly to poor short-term returns by selling shares of the fund, even if their sophistication would advise them not to over-react to recent returns.

We present the final hypothesis in the following terms:

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

2. Data and sample

2.1. Database cleaning

We use data from Thomson Reuters Eikon (TRE) on shares of OPCVM (open-ended mutual) funds domiciled in France from January 2005 to December 2017.

Different shares may compose a mutual fund. Each share has its own AuM, and shares can present different returns if they display different management fees. We concentrate on fund shares because they can have different characteristics: the amount of the initial investment, purchasing fees, redemption fees, and management fees can differ between the shares of the same fund. Because returns, which represent a central variable in this article, are displayed net of fees in the database, it is important to study returns at the share level and not at the fund level. For ease of readability, we sometimes use the words “fund” and “share” interchangeably when the context allows it; however, all variables and results are at the share level.

Specifically, we consider shares with a “bond” classification in the TRE database. Unfortunately, some shares classified as “bonds” in our database are classified as “diversified” or have a different classification according to the AMF database OPC-Geco[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 total net assets (TNA) are below 300,000 euros because too small assets under

[4] The AMF is the French financial markets authority, responsible for supervising mutual funds domiciled in France. Its website gives access to the GECO database, where one can find information relating to UCI under French law.

management may lead to extreme values of flows.[5] We also drop observations of shares 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.

Furthermore, we have excluded shares for which coupons are distributed (because their returns do not include the distributed coupons, for which data are not available), and shares not denominated in Euro (as their returns could capture movements in the foreign exchange market).

The final sample includes 883 different shares from 576 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.

2.2. Variable definitions

We present here the variables of our empirical model. Annex 1 presents some basics statistics: 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.

Measurement of the dependent variable: 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, denoted $R_{i,t}$:

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

The change in a share's TNA can be separated into two terms: a valuation effect (or return effect) and a "volume" effect linked to net inflows:

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

[5] The main results are unchanged if we drop observations for which the TNA is below 500,000 or below 1,000,000 euros.

Hence, net inflows between t and t-1 are computed here using the following formula:

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

In annex 1, we can observe that more than half of the share-month observations correspond to outflows (negative net flows).

Definitions of explanatory variables

The explanatory variables used in this study are performance measures: long-term relative performance and short-term raw returns.

Long-term relative performance

The method proposed 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 ranking is computed on performance measure at long-term horizons. The article[6] presents results measured with raw returns (at a one-year horizon) computed as:

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

Within a category, namely those classified by the AMF as "European bonds" and those classified as "International bonds", 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[7]. The specification of Sirri and Tufano (1998) allows for the presence of a nonlinear relationship between flows and performance rank[8]. In our estimations, the slope of the relationship can differ

[6] To check the robustness of our results, we have considered, as in the literature, different measures of performances. Investors may also react to risk-adjusted measures of returns (as demonstrated in the case of bond mutual funds by Goldstein and al. (2018) or by Chen and Qin (2017), among others). We build two other rankings based on risk-adjusted performances, namely the Sharpe ratio and the alphas generated by a factor model. In unreported results, we find no qualitative difference among performances measured with raw returns, Sharpe ratios, or alphas from factor models.

[7] If during month t, 10% of shares have a lower performance than share X, then $Rank_{i,t}$ for X will be equal to 0.1.

[8] That is, for low returns, there is no effect on flows, whereas high returns attract inflows: there is a convex shape of the flow-relative performance relationship. This result for equity mutual funds is confirmed by subsequent research.

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[9].

Short-term raw returns

The return of 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 monthly returns (see table 1) 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.

The control variables

The following variables are widely used in the existing literature (for example, Goldstein and al. (2017) and Chen and Qin (2017) for bond mutual funds and Ferreira and 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 and al. (2017). Consequently, the natural logarithm of the share's age measured in years since its creation is used as a control variable. We expect flows to decrease as the share grows older.

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

[9] For a technical presentation of the Sirri and Tufano variables see for example, Bellando and Tran Dieu (2011)

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.

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 months of returns. We include this as a standard control variable because net flows could be influenced by investors' sensitivity to risk. We expect flows to be negatively related to standard deviations of returns.

3. Model and results

3.1. Empirical Specifications

To limit the influence of outliers, we drop observations above the 99th percentile and below the 1st percentile of the distribution of flows.

In every estimation, we add share fixed effects 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 negatively correlated with the share's return. We also cluster errors at the fund level to allow for the autocorrelation of residuals within a given fund.

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

We first investigate whether short-term returns influence investors' decisions. In the following equation, H1-a implies that 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 1. 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 only comment on them here.

INSERT TABLE 1 HERE

In accordance with the literature results, bigger and older shares present lower net flows. By contrast, while the majority of articles display a negative and significant relationship between the standard deviation of monthly returns and flows, this variable is insignificant in our estimations.

Concerning long-term relative returns, tests indicate that LowPerf and HighPerf are significantly different from MidPerf (at the 1% level), whereas the LowPerf and HighPerf coefficients are not different from one another. Whatever the initial ranking of a fund, an increase in the ranking is rewarded with inflows, and a decrease in the ranking is punished with outflows. However, within the middle segment, the impact of rank on flows seems weaker (the coefficient of MidPerf is lower). This concave then convex 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 and al. (2012) and Kim (2019) 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. Note that it also indicates that investors in bond funds react strongly to poor relative performance, and this effect could complement that on absolute short-term returns.

The results in Table 1 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-Tufano 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 seems 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 shares' returns. It is intended to capture positive (negative) shocks affecting numerous funds, which could increase (decrease) the

monthly median of performance. To a certain extent, the *Median* variable is a way to introduce time fixed effects[10].

We thus proceed to this second regression, the results of which are reported in the second column of Table 1.

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

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 global performance of bond funds[11]. 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.

We now attempt to capture the nonlinear effects of short-term returns. First, we hypothesize that investors may not react in the same way 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 is 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 independent of the level of the variables. Column 3 of Table 1 presents the results.

Investors seem to react identically to an increase or 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 $I(Ret_{neg})$ is significant and

[10] The results are unchanged when we test hypothesis 1a including time fixed effects (results not reported).
[11] In unreported results, we replace the individual return with its return in excess of the median return, and the results do not qualitatively change.

negative. The slope seems to be the same for negative and positive returns, but there is a supplementary outflow of 0.9% when the short-term return is negative.

Furthermore, we observe that the coefficient for the median loses significance and that there is no additional effect (β_9 is not significant). It seems that the importance accorded to the median is no longer sizable when the initial sign of the past-month share return is taken into account.

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 have made estimations whose results are not reported here (but available upon request) to allow the intercepts to differ according to the quintiles of negative returns and quintiles of positive returns, the bounds of the quintiles being defined over the whole sample. On the positive side of past individual returns, the coefficients of the dummies are insignificant, while the dummies of negative quantiles have significant negative coefficients and seem to be different. We show that the coefficient of the worst negative returns, IN-0-20 (a dummy equal to 1 if the individual raw return in the previous month is in the bottom 20% of the short-term negative returns and zero otherwise) 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 (that takes a value of 1 if the individual raw return in the previous month is between the 20th and 100th percentiles of negative returns). 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:

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

The results for the control variables and performance rankings remain unchanged[12]. Investors are still sensitive to past-month raw short-term performance (the coefficient of 0.148 is significantly positive at the 1% level).

[12] Note also that introducing year fixed effects does not significantly change the results.

By 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 5% level), with the greatest outflows observed for the worst returns. Note that these effects are cumulative with the linear effect of returns. Our results mean that outflows could be particularly severe for funds with low short-term raw returns (the "slope" effect) and the worst negative returns (the "shift in constant" effect).

Although the difference between the two 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), 121 shares 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 approximately 33,000,000 euros for those shares.

Furthermore, the coefficients for the median variable are no longer significant[13]. Our explanation for this finding is that the global effect of the median may be 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 and not necessarily specific to the bond funds sector. This is the aim of the next subsection.

Complementary regressions (available upon request) show that the use of risk-adjusted measures (Sharpe and factor-based alphas) at different horizons of the 3 variables of Sirri and Tufano specification of long-term performance does not significantly change our results[14]. Investors are still sensitive to poor long-term results, and the shift on the negative side of short-term returns is still present.

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

[14] We still use the share's raw return as the past-month share return, as we consider that after observing a poor 1-month return, investors will not have the necessary 12-month horizon to calculate the risk-adjusted returns mentioned earlier. Therefore, the lagged 1-month raw return can be considered as a more direct short-term performance signal.

3.3 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 global financial stress. We take the CISS, the VIX and the VSTOXX as indicators of financial stress. Our aim is to check whether our results are driven by the impact of general financial stress or not. 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) that takes value 1 if the indicator is above the 90th percentile of its distribution (high stress). Since the effect of IN-0-20 could be linked to a bond market crisis, the introduction of a crisis dummy allows us to examine whether general financial stress is adding to or replacing the effect of the returns of individual funds on the flow of funds: if 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 2. 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.

INSERT TABLE 2 HERE

However, we observe that the "shift" in returns is still significant (at the 5% 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 effects seem to be additive.

3.4 Results concerning hypothesis 5: types of investors

Finally, we want to determine whether investors react differently according to their type. As our database does not provide information on whether the client of the fund is a retail investor or an institutional investor, we use

the minimum initial investment requirement in each part to identify the two types of clients. We suppose, as a proxy, that a fund with a minimum initial investment above the 10,000-euro threshold is mainly dedicated to institutional investors[15].

We apply the same regression as model (3) 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 3, where we also restate the full-sample results.

INSERT TABLE 3 HERE

Institutional investors' behavior differs from retail investors' behavior in several ways. First, institutional investors 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 and al. (2012), who find that institutional investors are less sensitive than retail investors to very good relative performance. Second, institutional investors also react less than retail investors to short-term returns (the coefficients are both positive but at the 10% and 1% levels, respectively), but unlike retail investors, they seem to be significantly sensitive to the standard deviation of funds returns.

However, 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, unreported results 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 to negative returns that are closer to zero. In sum, we show that institutional investors are sensitive to past returns, which is consistent with the literature related to agency conflicts concerning institutional clients of mutual funds (James

[15]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.

and Karceski (2006), Jones and Martinez (2017))[16]. As James and Karcesky (2006) argue, "pension fund sponsors, corporate treasurers and trustees may delegate money management to outside managers in order to avoid responsibility for poor performance. This can lead to the selection of money managers based on prior performance – similar to the way retail customers appear to select mutual funds."[17]

We confirm the literature in showing that the behaviors of retail and institutional investors differ. Moreover, we add to that literature by showing that institutional investors are in fact more sensitive to negative signals, especially concerning short-term absolute raw returns of bond mutual funds. This result is important in that the stronger and more frequent reaction of institutional investors could increase the magnitude of outflows. Furthermore, in unreported results, we show that this effect is additive to that of financial stress periods, as retail and institutional investors will withdraw more during stress periods.

4. 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: very negative short-term returns do not change the slope of the relationship between returns and flows but lead to nonlinear effects (if returns fall below a specific threshold, additional outflows will occur). Crises or periods of financial stress 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

[16] Building the long-term performances based not on raw returns but on risk-adjusted returns (Sharpe and alphas) does not significantly change the results. The shift in short-term performance still occurs at less negative levels for institutional shares, and the investors in those shares are still less sensitive to good long-term performances and past-month raw share returns. The results are not reported but are available upon request.

[17] James and Karcesky (2006, p. 2788)

outflows exert a negative pressure on the prices of traded securities (as showed by Coudert and Salakhova (2019)), which negatively impacts the returns of funds, causing future outflows to take place.

However, mutual funds could take measures to alleviate the possibility of arrival of such a loop. A solution might be to hold more liquid assets and sell them in the first place in order to satisfy redemptions. Some recent studies show on the contrary that in the current context of low interest rates, international fixed income funds and the euro area bond funds have reduced the share of liquid products (cash, government bonds) and have increased their exposures to high-yield corporate debt in order to boost their returns (IMF (2019), ECB (2019)) [18]. This risk-taking behavior could make them more fragile in the event of a shock. Another possibility would be to charge investors a higher redemption fee in order to discourage redemptions. However, the growing competition in the mutual funds industry could discourage funds from setting up more restrictive measures on redemptions.

To conclude, our results are in line with regulators' concerns about the fragility of bond funds upon adverse market events and underline the interest in strengthening mechanisms that remain optional in Europe, such as the introduction of an anti-dilution tax or swing pricing rules for fund shares[19].

[18] See also Choi and Kronlund (2016) for an empirical estimation of this behavior of US corporate bonds funds.

[19] The extent to which mutual funds take such precautionary measures remains to be determined, as such protection mechanisms can only be activated if they are mentioned in the fund's prospectus and if investors are aware of their existence.

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Table 1: Hypotheses H1a, H1b, H2 and H3: reaction to short-term absolute returns at the individual and market levels

	(1 a)	(1 b)	(2)	(3)
LowPerf	0.053***	0.054***	0.053***	0.053***
	(0.000)	(0.000)	(0.000)	(0.000)
MidPerf	0.013***	0.014***	0.012***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)
HighPerf	0.063***	0.065***	0.064***	0.064***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged raw return	0.380***	0.309***	0.235***	0.148***
	(0.000)	(0.000)	(0.000)	(0.000)
Median		0.369***	0.076	0.128
		(0.000)	(0.556)	(0.137)
Log(TNA)	-0.006***	-0.006***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
Std Dev	-0.129	-0.144	-0.127	-0.080
	(0.151)	(0.110)	(0.171)	(0.365)
Log(age)	-0.007***	-0.007***	-0.007***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged raw return*I(Ret_neg)			-0.078	
			(0.439)	
Median*I(Med_neg)			0.273	
			(0.193)	
I(Ret_neg)			-0.009***	
			(0.000)	
I(Med_neg)			0.001	
			(0.417)	
IN-0-20				-0.013***
				(0.000)
IN-20-100				-0.009***
				(0.000)
Intercept	0.093***	0.092***	0.096***	0.096***
	(0.000)	(0.000)	(0.000)	(0.000)
H0: IN-0-20 = IN-20-100				0.016**
Observations	53,433	53,433	53,433	53,433
R-squared	0.016	0.017	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

Tufano (1998). *Lagged raw return* is the past month's raw share return. *Median* is the median of past-month share returns on all funds. $I(ret_{neg})$ = 1 if the share 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. *IN-0-20* = 1 if the individual share 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 share 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 for 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. P-values are given in parentheses. Asterisks indicate p-values (*** p<0.01, ** p<0.05, * p<0.1).

Table 2: 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***	0.144***
	(0.000)	(0.000)	(0.000)
Median	0.147*	0.136	0.154*
	(0.086)	(0.112)	(0.069)
I(crisis)	-0.006***	-0.007***	-0.005***
	(0.000)	(0.000)	(0.005)
Log(TNA)	-0.006***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)
Std Dev	-0.039	-0.024	-0.034
	(0.661)	(0.783)	(0.703)
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***	-0.008***
	(0.000)	(0.000)	(0.000)
Intercept	0.098***	0.099***	0.098***
	(0.000)	(0.000)	(0.000)
H0: IN-0-20 = IN-20-100	0.0319**	0.0388**	0.0326**
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, and HighPerf* are indicators of relative long-term performance (12 months), constructed as in Sirri and Tufano (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. P-values are given in parentheses. Asterisks indicate p-values (*** p<0.01, ** p<0.05, * p<0.1).

Table 3: 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 3). 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 Tufano (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. P-values are given in parentheses. Asterisks indicate p-values (*** p<0.01, ** p<0.05, * p<0.1)

Annex 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