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Are fund managers rewarded for taking cyclical risks?

by
Ellen Ryan

ESRB
European Systemic Risk Board
European System of Financial Supervision

Abstract

The investment fund sector has expanded dramatically since the crisis of 2008-2009. As the sector grows, so do the implications of its risk-taking for the wider financial system and real economy. This paper provides empirical evidence for the existence of widespread risk-taking incentives in the investment fund sector, with a particular focus on incentives for synchronised, cyclical risk-taking which could have systemic effects. Incentives arise from the positive response of investors to returns achieved through cyclical risk-taking and non-linearities in the relationship between fund returns and fund flows, which may keep managers from fully internalising the effects of adverse outcomes on their portfolios. The fact that market discipline may not be sufficient to ensure prudential behaviour among managers, combined with the externalities of this risk-taking for the wider system, creates a clear case for macroprudential regulatory intervention.

JEL classification: G23; G11; G28

Key words: Financial stability; investment funds; incentive; risk-taking; macroprudential policy

*ellen.ryan@ecb.europa.eu.

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The expansion in the variety of intermediaries and financial transactions has major benefits [...] But along with the opportunities to do good, they have created opportunities to make things worse. The balance between the two is determined by the incentives of players.

The Greenspan Era: Lessons for the Future, Speech by Raghuram G. Rajan, August 27, 2005, Jackson Hole, Wyoming [1]

1 Introduction

The expansion of the non-bank sector has been one of the most notable developments in the global financial system since the crisis of 2008-2009. In the euro area the investment fund sector has tripled in size since 2008.

On one hand this comes with benefits, such as reducing the vulnerability of economies to banking sector shocks. However, policymakers have voiced concerns that a growing investment fund sector has an increasing capacity to create systemic risk. High risk appetite across the fund sector during periods of market exuberance can compress risk premia and (excessively) ease financing conditions in the real economy. During a crisis, funds' demand for risky assets can drop suddenly, as they raise cash to meet rising redemption demand, thus pushing up risk premia and tightening financing conditions. This procyclicality may be amplified where excess risk-taking during "good times" increases the sector's crisis losses or has left funds' liquidity buffers so low they cannot meet redemptions without engaging in firesales. These dynamics were recently observed in March 2020, following the outbreak of the coronavirus crisis in Europe (de Guindos (2020) and ECB (2020)).

These painful consequences for investors and for fund managers beg the question: Why would funds take excess risk in the first place? This paper examines ways the flow-performance relationship can incentivise excess risk-taking by fund managers, with a particular focus on coordinated, cyclical risk-taking which could have systemic implications. We use a large fund-level data set for the euro area to show that the flow-performance relationship for euro area funds does in fact exhibit characteristics associated with cyclical risk-taking incentives. Identifying these adverse incentives not only provides insight into the behaviour of the investment fund sector but also provides further impetus to the expansion of macroprudential policies to this part of the financial system.

In his seminal discussion on the role of incentives in driving risk-taking in modern financial systems, Rajan (2005) argues that competition for investor inflows may push fund managers to take on excessive risk. Competitive behaviour may be particularly problematic where the relationship between fund returns and investor inflows (henceforth the flow-performance relationship) rewards risk-taking. When investors respond to good fund performance with inflows to a greater extent than they respond to poor performance with outflows, managers do not need to fully internalise the downside risks to an investment. Rajan cites Chevalier and Ellison (1997), who show that the flow-performance relationship for US equity funds does exhibit this type of asymmetry and then provide evidence that managers do respond to the incentives this creates.

Our paper adds to the literature on incentives and the flow-performance relationship in a

[1] Available here.

number of ways. Non-linearities in the flow-performance relationship of US equity funds have been extensively examined and a number of papers have carried out analysis for US bond funds. We provide a comprehensive examination for the euro area, covering equity, government bond, corporate bond and high yield funds. By using the same methods across all fund types, we also allow for clean comparison of findings across these four core parts of the fund sector. Through this analysis we confirm the presence of asymmetries in the flow-performance relationship for all categories. This suggests that the flow-performance relationship typically rewards risk-taking across all asset classes in the euro area.

Second, we examine how these asymmetries interact with the wider market environment for each fund type, a question largely ignored due to the microeconomic focus of much of the existing literature. We show that for equity funds the asymmetry of the flow-performance relationship is stronger in times when market prices are rising and when equity funds are receiving net inflows on aggregate. This suggests that general risk-taking incentives for equity fund managers, arising from larger payoffs to good performance than bad performance, may behave procyclically.

However, "cyclical risk-taking" can also occur when managers make investments which are themselves cyclical in nature, purchasing assets which will have very high returns when market prices are rising but very low returns when they fall. Our third contribution is to show that funds across all examined asset classes can in fact attract inflows by making these types of investments. To date, the literature has largely focused on flow response to unsystematic performance, i.e. returns not generated through correlation with the wider market. We decompose fund returns into their systematic (market beta) and unsystematic (alpha) components and show, to our knowledge for the first time, that managers across all asset classes can attract inflows when they generate returns through market-directional investment strategies.

Finally, we identify asymmetries in the strength of the flow performance relationship across market environments. Specifically, we show that performance relative to peers plays a greater role in determining which funds receive inflows during periods of market exuberance than it does outflows during a crisis. This non-linearity is found for performance in general but also for performance derived from correlation with the wider market. Such an asymmetry may further incentivise cyclical risk-taking, which will be rewarded with large inflows as investments perform well in good times but will not result in equivalent "punishment" when the investment underperforms during a crisis. As such, managers do not need to fully internalise the effect of a crisis on their portfolio and in flow terms will always benefit from leaning into (and possibly amplifying) an asset price boom. In this way the actions of fund managers will also amplify the already procyclical tendencies of fund flows. This type of behaviour may be particularly problematic during periods of accommodative monetary policy, where an extended period of rising asset prices results in a build-up of risk among funds.

This type of behaviour among fund investors can be intuitively interpreted as follows: During good times investors choose high-performing funds because they believe the manager has "hot hands" or is highly skilled. During a crisis outflows are instead driven by the wider shock, as opposed to whether or not a fund is underperforming its peers. This type of behaviour among fund investors would be in line with arguments already made about bank investors. Rajan (1994) constructs a model where banks can try boost their reputation by gambling for higher returns in good times. When a crisis occurs and banks post large losses, investors attribute the losses to the crisis itself, as opposed to an individual banker's ability. Rajan shows that this creates the incentive for coordinated, cyclical risk-taking among banks.

The fact that market discipline may not be sufficient to ensure prudential behaviour among managers, combined with the externalities of this risk-taking for the wider system, creates a clear case for regulatory intervention. Moreover, Rajan (1994) shows that where risk-taking arises from competition with peers, policies must be applied to the whole sector. In other words - a macroprudential response is necessary. de Guindos (2020) suggests a number of approaches including macroprudential leverage limits and ex-ante liquidity management tools.

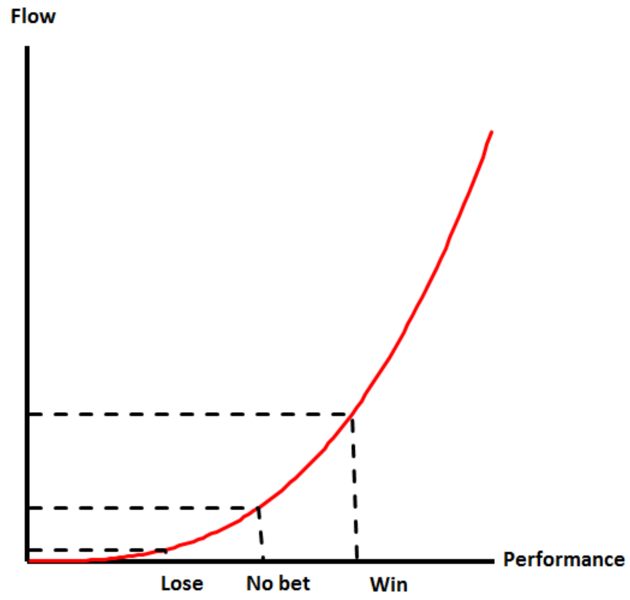
The rest of this paper is structured as follows: Section 2 lays out theoretical links between the flow-performance relationship and risk-taking incentives, with reference to the literature. Section 3 provides an overview of the data set used, the approach taken to classifying funds and introduces the baseline econometric specification. Section 4 augments this baseline specification to address our first two questions about the flow-performance relationship: Do investors respond more to good performance than bad performance and does this asymmetry change with market conditions? Section 5 then examines incentives for managers to take cyclical bets by asking if they can attract flows through cyclical risk-taking and if the flow performance relationship varies across crisis and non-crisis periods. Section 6 discusses policy implications. Section 7 concludes.

2 The Flow Performance Relationship and Risk-Taking Incentives

Under the standard business model of the asset management industry, a fund manager maximises their income by maximising the size of their fund. This is because managers make money from investment fees - as opposed to investment returns - and fees are typically a function of assets under management (AuM). However, investors have been shown to invest more in funds that are performing well and so the relationship between flows into a fund and the fund's performance (henceforth the flow-performance relationship) can be seen as an implicit incentive contract for the manager.

This has given rise to a literature examining the flow-performance relationship's capacity to create adverse incentives when it displays specific characteristics, in particular when it is non-linear. Figure 1 sketches a simple version of this argument, whereby a fund manager considers making an investment which will result in a loss or gain of equal size, with equal likelihood. The expected payoff for the fund's investors is zero but the expected payoff for the manager depends on the shape of the flow-performance relationship. If investors respond more strongly to good performance than bad performance, the flow performance relationship becomes convex. In this case the expected flow payoff to the investment is positive, as the inflow associated with a "win" is larger than the outflow associated with a "loss". This could induce the manager to make investments with negative expected returns, as they are not fully exposed to the downside of their investment decisions. Thus a convex flow-performance relationship can create an incentive for truly "excessive risk-taking", as returns on an investment no longer need to compensate for downside risks. For the rest

Figure 1: Payoffs of an investment to managers and investors with a non-linear flow-performance relationship



of this paper, "excess risk" will refer to investments made by fund managers without full internalisation of downside risk to their investors.

Chevalier and Ellison (1997), the seminal paper in this literature, show that the flow-performance relationship for US equity funds is in fact convex and provide evidence that managers respond to the incentives this creates. The wider literature on this topic examines how various fund or investor features affect these incentives. This includes examining the role of fund age (Chevalier and Ellison (1997)), fund families (Jank and Wedow (2013)), geographic variation in investor base and asset composition (Ferreira et al. (2012)), the number of fund managers and their exposure to termination risk (Qiu (2003)). [2]

However, these papers take a largely microeconomic perspective, ultimately examining agency conflict and incomplete contracts in the mutual fund industry. From a macroeconomic and financial stability perspective, a crucial question is whether risk-taking incentives have a cyclical component. Risk-taking by funds can create systemic risk when all funds raise their risk appetite at the same time, particularly where the fund sector is large enough for the collective behaviour of funds to affect wider risk premia. Moreover, excessive risk-taking during during a market upswing may increase funds' vulnerability to a market reversal and increase the sector's role as an amplifier of market shocks. We examine links between the wider market environment and asymmetries in the flow performance relationship. This will tell us whether general risk-taking incentives, arising from larger payoffs to good performance than bad performance, become more pronounced during periods of wider market exuberance, potentially raising fund managers' risk appetite in a coordinated, procyclical manner.

[2] These papers represent only a sample of a rich wider literature. Also of particular note are Brown et al. (1996) who establish the tournaments method for examining manager response to incentives and Sirri and Tufano (1998) another key paper in the identification of non-linear flow performance relationships for US equity funds.

Once we start thinking about cyclical aspects of these incentives, another form of adverse incentive becomes clear. Fund managers know that the future payoff to assets they purchase is in part state dependent. In particular, assets with cyclical returns will perform well when the market as a whole is rising but very badly during times of crisis. So what if investors care more about a fund's performance (relative to their peers) in good times than during a crisis? In this case fund managers may be incentivised to buy assets with cyclical payoffs. They will benefit from strong inflows during good times as the investment performs well but will not experience equivalent "punishment" during a crisis when it performs badly. Of course such incentives would have clear adverse implications for financial stability, pushing fund managers to always lean into an asset price boom by taking correlated, cyclical bets.

This type of behaviour among fund investors would be in line with arguments already made about bank investors. Rajan (1994) constructs a model whereby bankers care about their long-term portfolio returns but also want to signal their skill to investors through short-term returns. When reputation concerns are strong enough banks may engage in short term gambling, making risky investments to try boost today's return despite their negative long-term expected payoffs. Rajan's bank investors judge the skill of a bank manager by their current returns relative to other banks and this creates cyclical coordination failures. In periods when the banking system as a whole is posting high returns, low returns are attributed to low ability. This creates an incentive for gambling to maintain the appearance of high skill. During a crisis all banks post low returns and so investors attribute poor performance to the wider market shock, as opposed to the skill of an individual manager. Thus banks are incentivised to all increase risk-taking simultaneously and to take correlated, cyclical risks which, if they do not pay off, no individual bank manager can be blamed for. This framework has since been used to motivate and assess the implications of macroprudential policy in the banking system by Haldane (2010) and Aikman et al. (2015).

It would not be surprising if investors buying investment fund shares behaved similarly to those buying bank shares and fund managers have clear incentives to care about their reputation due to their need to attract investor inflows. We can also measure the effect of portfolio performance on a fund manager's reputation by looking at how performance influences investors' decision to give a manager more money - i.e. via the flow-performance relationship. Thus, we can empirically examine whether the incentives which drive cyclical risk-taking in Rajan's model also exist in the fund sector by doing two things. First, we need to show that funds are able to attract inflows with returns which are correlated with the wider market, i.e. by taking cyclical bets. Next we need to show that performance relative to peers plays a stronger role in driving fund-level inflows during good times than during crises.

Previous work examining the flow-performance relationship largely ignores the potential for performance derived from procyclical positioning to attract returns. Indeed, the cyclical or market-correlated component of fund returns is often stripped out before the flow performance relationship is examined. This is due to an implicit or explicit assumption that fund investors are sophisticated enough to look past cyclical returns and only respond to unsystematic fund returns (also referred to as alpha). In this regard, our paper provides novel insights into the capacity of fund managers across a range of asset classes to attract inflows through procyclical positioning. We will discuss this issue in further depth in Section 5.1. Our analysis of non-linearities in this form of the flow-performance relationship is also a novel contribution.

Our work can be seen as complementary to that of Goldstein et al. (2017) and Chen et al. (2010) who also examine how incentives arising from the flow-performance relationship can have financial stability implications. While we examine how the flow-performance relationship may incentivise managers, Goldstein et al. (2017) and Chen et al. (2010) examine how the flow-performance relationship creates incentives for fund investors. Specifically, they examine how concave flow-performance relationships may create incentives for investors to run on funds, thus creating financial fragility where a fund's investments are illiquid and managers are forced to engage in firesales to meet redemptions. Our findings suggest that the flow performance relationship may incentivise managers to take too much risk during periods of market exuberance. Where managers take risk by buying increasingly illiquid assets, this will increase their vulnerability to fund runs during crises, thus amplifying the mechanism studied by Goldstein et al. (2017) and Chen et al. (2010).

Of course there is also a wide literature examining the flow-performance relationship through a lens not related to manager incentives. Work of particular relevance to ours includes Feroli et al. (2014), which examines the flow-performance relationship at the aggregate asset class level for US equity and fixed income funds. The authors find evidence of return-chasing behaviour and evidence that aggregate flows into an asset class can affect market prices, creating a self-fulfilling cycle which can reverse following changes in investor sentiment. At the fund-level, Gruber (2011), Fulkerson et al. (2013) and Chen and Qi (2017) examine the flow-performance relationship of US equity funds, bond funds and corporate bond funds respectively, including potential non-linearities, with the goal of assessing whether flows are "smart".

3 Data Set and Baseline Specification

3.1 Data set and fund categories

We use monthly fund-level data on returns and flows from the commercial provider Lipper, starting in September 2004 and ending in July 2019. To focus on funds whose actions are most relevant for euro area financial stability (i.e. those buying European assets), those with pan-European and global investment mandates are selected. All funds are open ended, actively managed and domiciled within the euro area.

As our paper centres around competition between fund managers for investor inflows, we take care to establish groups of similar funds which could be considered as competing with one another. Typically investors first decide on the type of asset they would like exposure to and then choose among funds providing exposure to this asset. As such, managers are only really competing for flows with other managers whose funds have the same investment universe as they do. Identifying funds which are investing in the same assets, will also help us to identify periods when all funds in a given category are investing in a market with rising or falling prices, thus also simplifying our definitions of procyclical behaviour.

Identifying a fund's investment universe is more complicated than it may first appear. For example, simply selecting funds identified as "Equity" and "European" by Lipper will provide a varied group of funds, many of which invest in only specific segments of the equity market such as financial or real estate firms. These funds are unlikely to be in competition with funds buying solely utility equities, for example, and price dynamics for these sectors will likely be out of sync with each other. Similarly among funds identified as European government bond funds by Lipper, many only invest in specific maturity bonds. Lipper identification for corporate bond funds also inconsistently separates those buying investment grade and high yield securities. To ensure we are comparing funds with similar investment universes, we categorise funds on the basis of the benchmark the fund is managed against. By construction this should align with their investment universe.[3] For example, funds managed against Euro Stoxx can be identified as broad European equity funds and separated from those which are managed against the sectoral subsets of the index. Similarly, funds managed against indices of short maturity government bond funds can also be removed and funds buying high yield securities can be identified by their high yield index. This approach also allows us to easily identify different market environments via price changes to the relevant benchmark.

Alignment between assigned benchmark and investment universe is checked by examining correlation between fund returns and benchmark returns. First, it is found that returns of many European funds associated with government bond indices display a low correlation with the returns of the index. This may be due to the use of government bond indices as a substitute for a risk-free rate, which is then used as a performance benchmark for funds with a wider investment universe. Thus funds managed against government bond benchmarks but not also separately identified by Lipper as government bond funds are dropped.

Second, most euro denominated bond funds identified as "Global" in their investment focus exhibit a low correlation with euro denominated global benchmarks and a much higher correlation with European benchmarks.[4] To allow for mis-identification of benchmarks by Lipper, these funds as re-categorised as European. The paper's overall findings are robust to skipping this cleaning step.

Within each category, flow and return values outside the top and bottom fifth percentile in each period are removed to ensure findings are not driven by outlier or erroneous data entries (this standard in the literature, see for example Fulkerson et al. (2013), Sujing and Jiaping (2014) and Chen and Qi (2017)). Our final sample is made up of almost 8,500 unique funds which are categorised by geographic focus (European, Global) and asset class (equity, government bond, corporate bond, high yield bond). The panel is unbalanced and the total sample size varies across time, in line with trends in the overall investment fund sector. As shown in Figure 2 , the sample grows from approximately 2,000 to 3,000 funds over the fifteen years examined. As expected, the sample size varies substantially across categories. To ensure that results are not driven by dynamics in the larger categories, regression analysis is carried out at asset-class level throughout the paper.[5]

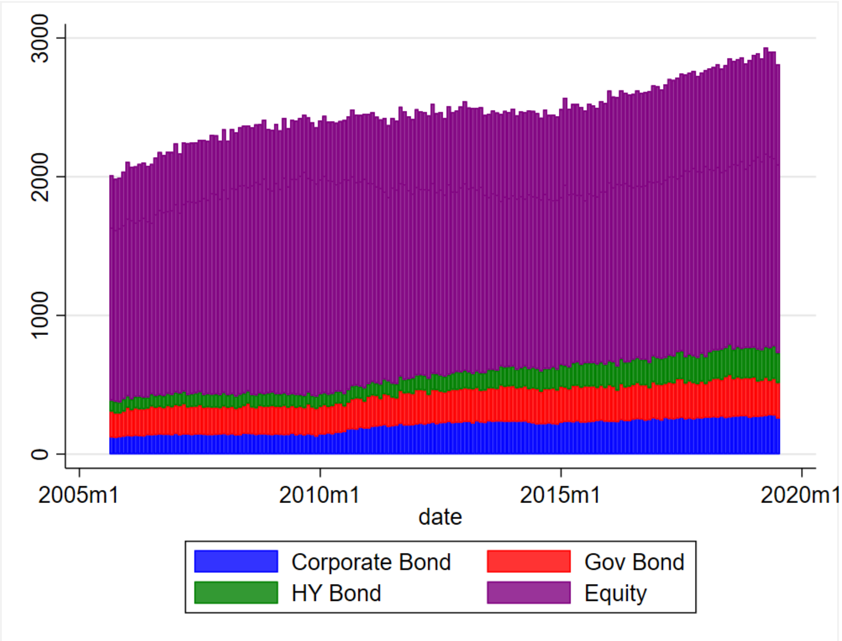
This final sample is predominantly made up of UCITS funds (80 per cent), with a small number of AIFMD funds (7 per cent) and a share of the sample identified as neither (13 per cent). As a result, dynamics reflect the "vanilla", retail end of the market as opposed

[3]Specifically we use the "Technical Benchmark" variable from Lipper as it has superior data quality to the "Manager Benchmark" and is likely to account for different management companies using similar benchmarks compiled by different providers.

[4]A very small minority of European and Global funds are denominated in currencies other than euro or US dollar and these are removed for the sake of simplicity.

[5]Regressions are pooled across geographic focus as global categories for corporate and high yield bond funds are quite small once data cleaning is complete.

Figure 2: Number of funds in sample over time



Note: This chart shows sample where 1 year of performance is available.

to its riskier or more complex segments. Indeed, Lipper identifies only about 1 per cent of the sample as Total Return strategies and Leveraged strategies.

3.2 Baseline specification

The flow-performance relationship in its most simple, linear form is examined before moving on to non-linear methods. As our end goal is to look at actions managers may take to try encourage more flows, it is important to account for types of flows the manager can and cannot influence. A number of factors, such as market price dynamics and investor demand for different types of financial assets, may drive aggregate flows into a given fund category. This is not something the performance of an individual fund can typically influence. However, managers can compete for the share of aggregate inflows (outflows) which they receive. The baseline specification shown in Equation 1 captures this by controlling for total flows into a fund's category.

$$\begin{aligned} \textit{fund flows}_{it} \;=\; a + \theta i + \beta_1 \textit{category flows}_t + \beta_2 \textit{fund performance}_{it-1} \\ + \beta_3 \textit{fund size}_{it-1} + \beta_4 \textit{fund age}_{it} + E_{it} \end{aligned} \tag{1}$$

As a result β_1 will reflect the role of aggregate flows in explaining fund-level flows and β_2 (the main parameter of interest) captures the relationship between a fund's performance and flows into that fund, taking into account the broader flow environment. Flows at fund and category level are expressed as a percentage of the previous month's AuM. Literature standard controls - size (AuM) and age - are also included in log form, with fund size lagged by one period to remove contemporaneous effects of flows on size. θ_i are a series of fund-level fixed effects which will capture time-invariant features of funds not already accounted for by the categorisation process, such as mandate-imposed risk limits or domicile country. While not strictly time invariant, fund fee structures are also typically stable over time (see Sujing and Jiaping (2014)).

Our baseline specification also addresses the two types of endogeneity that can arise in relation to the flow-performance relationship (β_2). First, large flows into an asset class may push up prices for those assets and therefore fund performance. This could lead to flows driving performance instead of vice versa (see Feroli et al. (2014)). Controlling for aggregate flows into a category addresses this problem, as flows into an individual fund are unlikely to impact valuations for an entire asset class. Second, flows in and out of an individual fund may affect its performance. For example, large outflows may require a fund to quickly sell illiquid assets at a loss, thus reducing returns. To avoid this type of endogeneity, fund performance is lagged throughout the paper. Lagging performance measures also captures the tendency for fund investors to respond to its performance with a lag. Errors are also clustered at the fund-level.

3.3 Performance measures

The existing literature uses a range of performance measures when examining the flow-performance relationship. Many papers use risk-adjusted performance measures and Jensen's alpha is a particularly popular choice (see Berkowitz and Kotowitz (2000), Goldstein et al. (2017) and Sirri and Tufano (1998)). In its simplest form, Jensen's alpha is the α_{it} from the CAPM equation below and it is widely used in the mutual fund literature as a measure of fund manager skill. Specifically, it is the part of a fund's performance which is not explained by the fund's correlation with the wider market and so can be interpreted as the manager's capacity to "pick stocks" and generate returns without taking market risk. It can also be referred to as a fund's "unsystematic" return or simply its alpha.

$$\textit{fund return}_{it} - \textit{risk free rate}_t = \alpha_{it} + \beta_{it}(\textit{market return}_t - \textit{risk free rate}_t) \qquad (2)$$

This is clearly a useful measure when analysis is taking a micro-perspective. However from a systemic risk perspective, the component of returns generated through procyclical investment strategies (captured by $\beta_{it}(\textit{market return}_t - \textit{risk free rate}_t)$) is important and is not something we want to remove from our performance measure. Thus we begin by using a fund's ranking relative to its peers as a baseline performance measure, as this will capture both systematic and unsystematic returns. We will study these two components separately in Section 5. We construct our relative ranking variable by ranking funds within each category and period by their rolling 12 month performance and then normalising the variable to give values between 0 and 100.[6] Performance relative to benchmark can also be calculated as the difference between a fund's 12 month returns and the 12 month returns on the benchmark for their category (e.g. Euro Stoxx 50 for European equities).

[6]"Category" refers to a funds' geographic-asset class group, such as European corporate bond. 12 month rolling performance is preferable as month-on-month performance is noisy and not necessarily observable by investors. 12 month performance is also widely used in the existing literature.

Table 1: Baseline results - Fund rank

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Government bonds	(4) High Yield bonds
Category flows (%)	0.202	0.813***	0.299***	0.477***
	(0.141)	(0.0191)	(0.0261)	(0.0729)
Performance rank (lagged)	0.0161***	0.00781***	0.00897***	0.0161***
	(0.00224)	(0.000312)	(0.00101)	(0.00234)
Log(AuM) lagged	-0.127**	-0.0311**	-0.0192	-0.272**
	(0.0590)	(0.0138)	(0.0343)	(0.109)
Log(age)	-0.330***	-0.525***	-0.429***	-0.773***
	(0.116)	(0.0272)	(0.0801)	(0.160)
Constant	0.956	2.071***	1.264***	3.807***
	(0.586)	(0.140)	(0.412)	(0.836)
Observations	25,716	244,115	28,674	16,851
R^2	0.032	0.048	0.027	0.079
Number of funds	613	5,951	743	447

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Baseline results - Performance relative to benchmark

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Government bonds	(4) High Yield bonds
Category flows (%)	0.189	0.760***	0.316***	0.599***
	(0.142)	(0.0206)	(0.0327)	(0.0578)
Rel. perf. (lagged)	0.0388**	1.06e-05	0.0255***	0.00393
	(0.0163)	(9.66e-06)	(0.00799)	(0.0124)
Log(AuM) lagged	-0.157**	-0.0388**	-0.0335	-0.353**
	(0.0718)	(0.0169)	(0.0472)	(0.157)
Log(age)	-0.745***	-0.381***	-0.428***	-1.128***
	(0.184)	(0.0356)	(0.117)	(0.223)
Constant	3.932***	1.812***	1.835***	6.727***
	(0.980)	(0.188)	(0.626)	(1.202)
Observations	19,579	186,457	21,498	12,624
R^2	0.028	0.034	0.023	0.108
Number of funds	533	5,160	641	376

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1 shows results for the baseline specification, using fund ranking as a performance measure. For all asset classes there is a positive and highly statistically significant relationship between a fund's ranking relative to its peers and flows into that fund. This is in line with the flow-performance relationship already well-documented in the literature. Table 2 shows results using a funds' performance relative to its market benchmark, an alternative baseline measure. Coefficients are not statistically significant in all cases, likely due to the greater noisiness of this measure which reduces its effectiveness. Indeed it should be kept in mind that we are using data from a commercial provider as opposed to supervisory data and so erroneous data entries may create some unavoidable noise in our data set. As ranking relative to peers is also more in line with our theoretical argument of fund competition with peers, we keep this as the baseline performance measure.

4 Investor Response to Good and Bad Performance

4.1 The shape of flow-performance relationships in the euro area

To examine non-linearities in the flow-performance relationship, the continuous performance measure from our baseline specification (Equation 1) is replaced with dummy variables for each performance quintile. The third quintile is used as the base category so that coefficients reflect flows to funds in a given performance quintile compared to those in the middle quintile (in that period and in their category). Figure 3 shows coefficients (dots) and confidence intervals (shaded areas) from this specification at category-level. Results are shown in table format in Appendix A.

Asymmetrical, specifically convex, relationships can be seen across all asset classes. For bond funds, the differences between flows to funds in the 3rd performance quintile and those in the 4th and 5th quintiles are either insignificant or barely significant. Moreover, the coefficients for the top quintile are approximately double those for the bottom quintile (in absolute terms). This means there is limited flow downside to under-performance but a clear and positive investor response to out-performance. For equity funds, coefficients on lower quintiles are highly statistically significant, in part due to the larger sample size. However, the payoff to being in the top performance quintile is still double the flow impact of being in the bottom quintile.

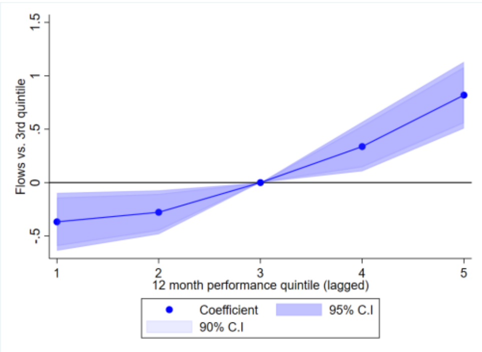
The particularly large impact of being in the top quintile of performers for equity funds reflects findings in the literature on US funds. Of course this raises questions about the behaviour of investors. Chevalier and Ellison (1997) and Sirri and Tufano (1998) suggest that convexity may be produced by the use of fund returns as marketing tools. In particular, top performing funds may appear on published "top performer" lists or receive media attention.

Finding convex flow-performance relationships for corporate bond funds is to some extent at odds with the existing literature. Chen and Qi (2017) find a broadly linear relationship, using piecewise regressions. However, they use multiple factor alphas as performance measures. We construct a two factor alpha by regressing fund returns on aggregate equity and bond indices.[7] We then repeat the exercises shown in Figure 3 with this alternative

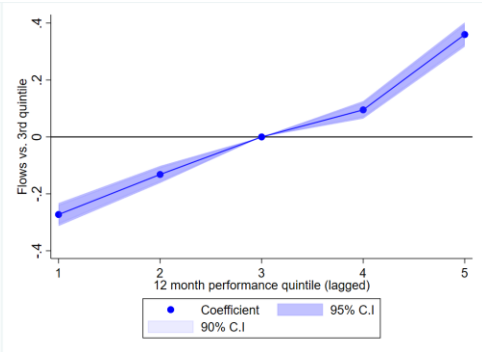
[7]See Sections 5.1 for a more detailed discussion of constructing these types of performance measures.

Figure 3: Non-linearities in the flow-performance relationship

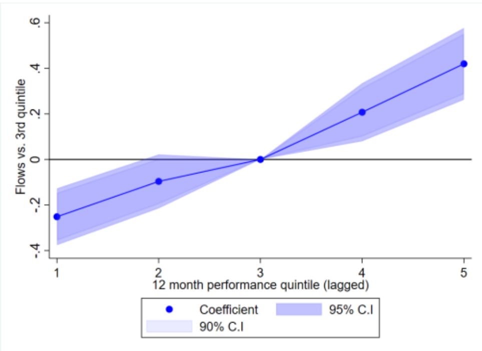
(a) Corporate bonds



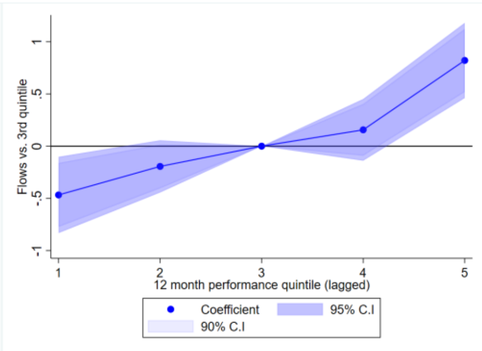
(b) Equities



(c) Government bonds



(d) High yield bonds



measure and, in line with Chen and Qi (2017), find a much smaller difference in the effects of being in the bottom performance quintile (-0.35) versus the top quintile (+0.3). However, we maintain that this performance measure is not entirely relevant to our analysis as it strips out procyclical performance.

Goldstein et al. (2017) primarily use this two factor alpha measure but stress that their findings of a concave relationship are robust to the use of a range of performance measures. When we replicate their main empirical approach - which regresses fund flows on a two factor alpha, a dummy equalling one when this measure is negative and the interaction of both variables - we continue to find weaker flow response to underperformance than overperformance among corporate bond funds. We are able to replicate the Goldstein et al. (2017) result among high yield funds but only with an alpha measure and not our ranking measure, which again we maintain is more relevant to our analysis. It is possible that differences arise from our use of a purely European sample of funds. Indeed, Ferreira et al. (2012) find variation in the shape of the flow-performance relationship across different regions. Goldstein et al. (2017) also find that concavity is less pronounced in funds with an institutional investor base. Thus differences in findings could also be explained by the greater role of institutional investors among the investor base of our sample.

4.2 The market environment and the shape of the flow-performance relationship

Next we examine whether the shape of the flow performance relationship is specific to a given market environment. For example, is the relationship more convex during periods where aggregate inflows are positive or market prices are rising? This would suggest that risk-taking incentives not only exist across the euro area investment fund sector but also have a cyclical element. As a result, changes in the wider macrofinancial environment could result in increasing risk-appetite across the investment fund sector.

The role of the market environment in driving the shape of the flow performance relationship is examined by interacting flow quintile variables with dummies which equal 1 when an asset class is receiving positive net inflows (Table 3) and when aggregate prices for an asset class rose the previous month (Table 4). Aggregate market prices are measured using changes in the value of the relevant benchmark for a given group of funds and this variable is lagged to reflect the lagged relationship between fund performance and fund flows.

Convexity in the flow performance relationship for equity funds appears to have a substantial cyclical component. Specifically, convexity increases in periods with aggregate inflows and when market prices are rising, as shown by the positive and statistically significant interaction terms for higher performance quintiles. This suggests that investors' asymmetric response to good and bad performance may not only incentivise risk-taking among equity fund managers but that these incentives behave procyclically. In "good times", equity managers have more to gain in flow terms from posting high returns compared to the loss they experience if bets don't pay off.

For bond funds results are mixed. For high yield funds convexity weakens in inflow periods, with the flow impact of low returns strengthening. For government bond funds, convexity weakens in periods with aggregate inflows but strengthens in periods when market prices

Table 3: The effect of aggregate inflows on flow-performance convexity

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Government bonds	(4) High Yield bonds
Category flows (%)	0.0985	0.853***	0.213***	0.320***
	(0.0874)	(0.0236)	(0.0273)	(0.0982)
Category inflows dummy	1.686***	-0.0935***	0.440***	1.579***
	(0.253)	(0.0249)	(0.0953)	(0.427)
1st quin. performance lagged	0.0496	-0.271***	-0.194***	-0.104
	(0.142)	(0.0237)	(0.0695)	(0.241)
2nd quin. performance lagged	-0.125	-0.136***	-0.0752	0.169
	(0.108)	(0.0184)	(0.0670)	(0.187)
4th quin. performance lagged	0.142	0.0844***	0.143*	0.0817
	(0.109)	(0.0185)	(0.0753)	(0.212)
5th quin. performance lagged	0.601***	0.339***	0.411***	0.606***
	(0.135)	(0.0243)	(0.0835)	(0.220)
1st quin. perf * Inflows dummy	-0.861***	-0.00545	-0.215*	-0.625**
	(0.166)	(0.0329)	(0.120)	(0.297)
2nd quin. perf * Inflows dummy	-0.328**	0.0111	-0.0708	-0.629**
	(0.157)	(0.0288)	(0.125)	(0.276)
4th quin. perf * Inflows dummy	0.441**	0.0327	0.210	0.125
	(0.193)	(0.0293)	(0.135)	(0.335)
5th quin. perf * Inflows dummy	0.496**	0.0651*	0.0283	0.369
	(0.234)	(0.0352)	(0.149)	(0.334)
Log(AuM) lagged	-0.142**	-0.0285**	-0.0216	-0.297***
	(0.0586)	(0.0138)	(0.0346)	(0.109)
Log(age)	-0.447***	-0.525***	-0.418***	-0.674***
	(0.113)	(0.0273)	(0.0798)	(0.154)
Constant	1.491**	2.486***	1.454***	3.363***
	(0.597)	(0.141)	(0.415)	(0.765)
Observations	25,716	244,115	28,674	16,851
R^2	0.067	0.048	0.029	0.090
Number of funds	613	5,951	743	447

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: The effect of market price dynamics on flow-performance convexity

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Government bonds	(4) High Yield bonds
Category flows (%)	0.197	0.797***	0.293***	0.459***
	(0.140)	(0.0184)	(0.0258)	(0.0739)
Market rising dummy (lagged)	0.516***	0.0701***	0.188***	0.679***
	(0.156)	(0.0160)	(0.0603)	(0.211)
1st quin. performance lagged	-0.262	-0.258***	-0.475***	-0.588**
	(0.227)	(0.0326)	(0.107)	(0.294)
2nd quin. performance lagged	-0.312	-0.111***	-0.195*	-0.0742
	(0.193)	(0.0250)	(0.108)	(0.272)
4th quin. performance lagged	1.100***	0.0253	0.0653	0.463
	(0.363)	(0.0254)	(0.0928)	(0.531)
5th quin. performance lagged	1.117***	0.179***	0.245**	0.329
	(0.423)	(0.0333)	(0.119)	(0.433)
1st quin. perf * Market dummy	-0.108	-0.0247	0.263**	0.129
	(0.202)	(0.0315)	(0.106)	(0.286)
2nd quin. perf * Market dummy	0.0443	-0.0298	0.111	-0.155
	(0.181)	(0.0260)	(0.105)	(0.288)
4th quin. perf * Market dummy	-0.882**	0.0917***	0.176*	-0.357
	(0.349)	(0.0272)	(0.103)	(0.538)
5th quin. perf * Market dummy	-0.352	0.231***	0.222*	0.563
	(0.399)	(0.0339)	(0.124)	(0.440)
Log(AuM) lagged	-0.131**	-0.0381***	-0.0213	-0.317***
	(0.0603)	(0.0138)	(0.0340)	(0.108)
Log(age)	-0.339***	-0.514***	-0.383***	-0.769***
	(0.116)	(0.0272)	(0.0804)	(0.158)
Constant	1.266**	2.369***	1.289***	4.132***
	(0.635)	(0.141)	(0.423)	(0.842)
Observations	25,716	244,115	28,674	16,851
R^2	0.034	0.048	0.028	0.081
Number of funds	613	5,951	743	447

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

are rising. For corporate bond funds convexity weakens in periods with aggregate inflows and when the market is rising, indicated by the greater flow impact of low returns in Table 3 and lower flow impact of high returns in Table 4. While this doesn't provide clear a clear message about convexity in flow performance relationships being cyclical, it does suggest that differences in findings with the existing literature could also be explained by the shape of the flow performance relationship varying across market environments.

5 Investor Response to Cyclical Performance

5.1 Performance measures revisited

Examining how the shape of the flow performance relationship varies across market environments can tell us whether general risk-taking incentives strengthen as the market rises. However, cyclical risk-taking incentives could also operate by incentivising cyclical investment strategies, i.e. investment in assets that perform well when the market performs well but badly during a crisis. A first step towards understanding these types of incentives is to see if managers can attract inflows by taking procyclical bets.

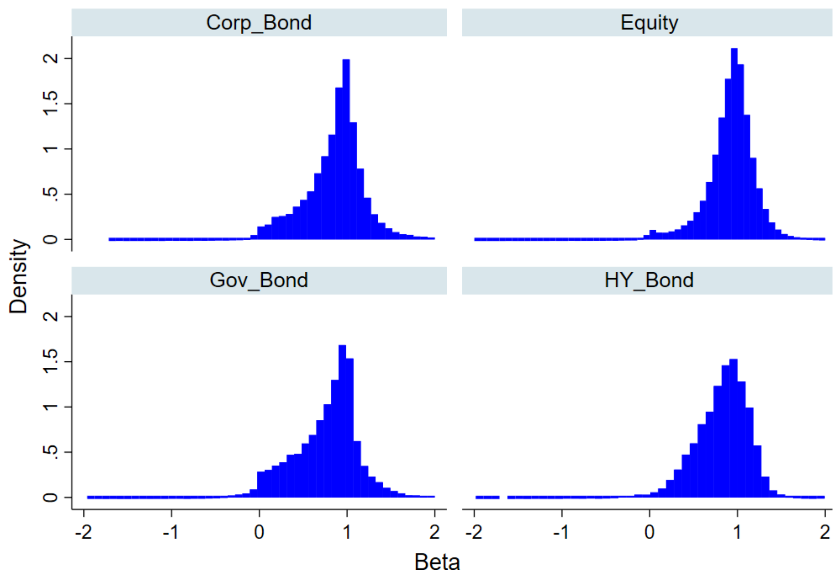
We can decompose a fund's returns into those which are and are not driven by procyclical positioning using the CAPM equation from Section 3.3 (Equation 2). Specifically we estimate α_{it} and β_{it} through 12 month rolling regressions of monthly fund returns in excess of the risk free rate on market returns in excess of the risk free rate. We use the monthly yield on an index of euro area AAA government 1 year bonds from the ECB SDW as our risk free rate, although the ultimate choice of risk-free rate has limited impact on final results. For each category of funds, market return is measured as monthly returns on the benchmark for their category. The distribution of β_{it} for each fund category is shown in Figure 4. Its concentration around 1 for most asset classes reflects the type of funds in our sample, which broadly track specified market indices. However funds can achieve a value higher than one by buying more cyclical assets within their investment universe or lower than one through cash holdings, hedging or holding less cyclical assets.

The component of a fund's returns attributable to the market directionality of its portfolio can then be calculated as shown in Equation 3 and the α_{it} from the CAPM equation will capture the component of returns not achieved through cyclical positioning (its alpha).

$$beta\ performance_{it} = \beta_{it}(monthly\ market\ return_t - risk\ free\ rate_t) \tag{3}$$

We acknowledge that more complex methods are often used to calculate these types of parameters. Fund returns are often regressed on a range of market factors such as returns on stock markets, government bonds and corporate bond risk premia. Indeed many of the papers discussed in Section 2 use alphas produced using this multi-factor approach (see Goldstein et al. (2017), Gruber (2011), Chen and Qi (2017) and Fulkerson et al. (2013) for example). However, for the sake of our analysis the simpler approach yields more relevant metrics. For example, regressing fund returns on factors such as corporate bond spreads and returns on government bonds would let us look at how managers can attract flows by taking tactical positions which will do well in response to developments in these specific

Figure 4: Distribution of β_{it} across categories



Note: This chart shows beta values for all funds in all periods. Large outliers are removed for the sake of readability.

market factors. While this would be an interesting exercise, what we really care about is how investors respond to performance achieved by managers leaning in or out of a trend of rising prices within their mandated investment universe - i.e. procyclical positioning. To examine this we need a simple market beta achieved by regressing fund returns on returns to a fund's market benchmark. Indeed, using other market factors to examine our hypothesis could quickly become very confusing. For example, for a corporate bond fund an investment strategy which benefits from strong returns to government bonds may in fact by a countercyclical position as safe government bonds may perform well while corporate bonds are performing badly. In contrast, for a government bond fund this could potentially be considered a procyclical position.

To our knowledge, our paper is the first to examine investor responses to this type of performance. Chen and Qi (2017) show that macro factors such as the performance of bond benchmarks influence investors' decisions to invest in bond funds but do not examine managers' capacity to attract more inflows that their peers by increasing their correlation with these factors. Sujing and Jiaping (2014) do examine the flow response to performance achieved by equity funds through correlation with a range of market factors such as T-bill returns and spreads between equity market and T-bill returns. But their analysis only examines equity funds, does not specifically examine investor response to procyclical positioning and does not account for different responses when market factors have high and low performance. This final point is crucial for understanding implications for cyclical risk-taking, as we will discuss in Section 5.2.

Table 5 re-runs the baseline specification, replacing ranking relative to peers with both alpha and beta performance measures. In line with the literature, investors respond positively to funds exhibiting a higher alpha across all asset classes. However, in all asset classes there is also a positive and statistically significant relationship between flows and past beta performance.

Table 5: Investor response to alpha and beta performance

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Government bonds	(4) High Yield bonds
Category flows (%)	0.166	0.767***	0.266***	0.443***
	(0.125)	(0.0186)	(0.0256)	(0.0736)
Alpha (lagged)	1.577***	0.303***	0.623***	0.973***
	(0.246)	(0.0156)	(0.107)	(0.201)
Beta perf. (lagged)	0.527***	0.0176***	0.0950***	0.194***
	(0.0835)	(0.00158)	(0.0195)	(0.0309)
Log(AuM) lagged	-0.156**	-0.0387***	-0.0205	-0.278**
	(0.0610)	(0.0139)	(0.0335)	(0.109)
Log(age)	-0.506***	-0.519***	-0.476***	-0.890***
	(0.115)	(0.0274)	(0.0789)	(0.161)
Constant	2.585***	2.432***	1.904***	5.165***
	(0.603)	(0.142)	(0.402)	(0.830)
Observations	25,716	244,115	28,674	16,851
R^2	0.046	0.044	0.026	0.084
Number of funds	613	5,951	743	447

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This is an important finding. The use of alpha performance measures when examining the flow-performance relationship is usually motivated by the (implicit) assumption that investors can identify returns resulting from a fund manager leaning into the a rising market (beta performance) and those resulting from a managers' capacity to identify good investments without taking this type of risk (alpha). Investors are assumed to only reward the latter with inflows. However, investors appear to respond to both.[8] This aligns with behaviour in Rajan's coordination model, whereby high returns boost reputation, regardless of whether they are from prudent investing or gambling.

Our finding that investors allocate money to funds which are performing well due to their market directionality could be interpreted in a number of ways. Investors may believe that fund managers can time the market and intentionally invest in funds where managers are benefiting from their market directionality. Alternatively, investors may not be sophisticated enough to distinguish between good performance achieved through alpha or through beta performance.

In either case, this type of investor behaviour could push fund managers to take cyclical bets in a bid to attract inflows. Of course, the positive and statistically significant coefficient on beta performance does mean that investors also withdraw money from procyclically positioned funds when market performance is negative. However, this may not fully negate the incentive for managers to use cyclical bets to attract inflows. For example, managers may expect asset prices to continue rising for a long time (e.g. due to low for long monetary policy) and believe that they will be able to reverse their position before the market turns. Managers may also simply operate with a short time horizon and care more about immediate inflows than the long term well-being of the fund. Short-termism could be reinforced by asset management companies' approaches to manager compensation.

5.2 The market environment and the strength of the flow-performance relationship

Particularly adverse incentives may arise when managers can attract inflows through cyclical bets *and* the strength of the flow-performance relationship varies with the market environment. If investors disproportionately invest in the best performing funds during good times but do not discriminate across funds in the same way during a crisis, then a manager making large cyclical bets should see much larger inflows than their peers during good times - as the investment performs well - but outflows similar to their peers when the investment performs badly during a crisis.

We empirically examine this issue by comparing the flow performance relationship in crisis and non-crisis periods. Crisis periods for each fund category are identified using aggregate flow and benchmark performance. Specifically, periods where aggregate flows or benchmark performance are below the 10th percentile for the 2004-2019 period are classified as crises. Dummy variables for these periods are then added to the baseline regression and interacted with fund performance. As before dummies for extreme market drops are added at a

[8] Testing for the equality of coefficients on alpha and beta performance coefficients rejects equality in all cases. So a one unit increase in alpha performance will have a bigger impact on flows that a one unit increase in beta performance. However, the finding that investors respond to beta performance at all is still important.

Table 6: Role of rank performance during period with large outflows

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Gov. bonds	(4) HY bonds
Category flows (%)	0.161	0.786***	0.286***	0.380***
	(0.126)	(0.0207)	(0.0294)	(0.0845)
Performance rank (lagged)	0.0180***	0.00758***	0.00884***	0.0177***
	(0.00231)	(0.000307)	(0.00101)	(0.00246)
Flows< 1st decile	-0.545	-0.197***	-0.191	-1.043
	(0.428)	(0.0444)	(0.169)	(0.662)
Flows< 1st decile*Perf. rank (lagged)	-0.0171***	0.00234***	0.00156	-0.0159**
	(0.00344)	(0.000789)	(0.00284)	(0.00781)
Log(age)	-0.453***	-0.530***	-0.439***	-0.891***
	(0.117)	(0.0271)	(0.0790)	(0.167)
Log(AuM) lagged	-0.125**	-0.0302**	-0.0178	-0.279***
	(0.0585)	(0.0138)	(0.0341)	(0.107)
Constant	1.523**	2.102***	1.318***	4.464***
	(0.599)	(0.140)	(0.408)	(0.900)
Observations	25,716	244,115	28,674	16,851
R^2	0.042	0.048	0.027	0.086
Number of funds	613	5,951	743	447

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Role of beta performance following large market drops

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Gov. bonds	(4) HY bonds
Category flows (%)	0.162	0.800***	0.289***	0.438***
	(0.122)	(0.0188)	(0.0263)	(0.0741)
Beta perf. (lagged)	0.506***	0.00989***	0.0835***	0.198***
	(0.0879)	(0.00178)	(0.0207)	(0.0451)
Bench < 1st dec. (lag.)	-0.649***	0.00539	-0.334**	-0.488**
	(0.213)	(0.0459)	(0.141)	(0.219)
Bench < 1st dec. (lag.)*Beta perf. (lagged)	-0.370***	0.0110*	-0.186**	-0.115*
	(0.127)	(0.00667)	(0.0938)	(0.0623)
Log(age)	-0.489***	-0.556***	-0.464***	-0.871***
	(0.117)	(0.0280)	(0.0798)	(0.167)
Log(AuM) lagged	-0.135**	-0.0293**	-0.0122	-0.277***
	(0.0608)	(0.0140)	(0.0337)	(0.106)
Constant	2.364***	2.598***	1.837***	4.993***
	(0.613)	(0.144)	(0.408)	(0.865)
Observations	25,716	244,115	28,674	16,851
R^2	0.041	0.041	0.023	0.081
Number of funds	613	5,951	743	447

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Role of alpha performance following large market drops

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Gov. bonds	(4) HY bonds
Category flows (%)	0.194	0.783***	0.273***	0.459***
	(0.138)	(0.0190)	(0.0262)	(0.0742)
Alpha (lagged)	1.158***	0.294***	0.519***	0.766***
	(0.268)	(0.0157)	(0.110)	(0.203)
Bench < 1st dec. (lag.)	-0.994***	-0.153***	-0.215***	-0.952***
	(0.234)	(0.0191)	(0.0655)	(0.187)
Bench < 1st dec. (lag.)*Alpha (lagged)	0.744	-0.0484	0.293	0.805
	(0.636)	(0.0321)	(0.183)	(0.589)
Log(age)	-0.488***	-0.518***	-0.460***	-0.935***
	(0.116)	(0.0274)	(0.0792)	(0.166)
Log(AuM) lagged	-0.143**	-0.0390***	-0.0224	-0.299***
	(0.0607)	(0.0139)	(0.0338)	(0.110)
Constant	2.673***	2.455***	1.880***	5.584***
	(0.612)	(0.142)	(0.405)	(0.861)
Observations	25,716	244,115	28,674	16,851
R^2	0.034	0.044	0.024	0.080
Number of funds	613	5,951	743	447

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

lag, reflecting the lagged response of flows to performance. As we are regressing lagged fund performance on flows this also ensures that the periods used for fund and market performance align. There is substantial but not complete overlap between dates identified via extreme flows and those identified via extreme market price drops.

First, Table 6 shows that the coefficient for the interaction between rank performance and the outflow crisis dummy is negative and statistically significant for corporate and high yield funds. Corporate and high yield funds are arguably the fund categories with the greatest propensity to create the financial stability risks. Funds hold a larger share of outstanding euro area corporate and high yield bonds than they do government bonds or equities, increasing the sector's capacity to influence market pricing. Corporate and high yield bonds are also much less liquid than government bonds or equities, increasing these funds' likelihood to engage in firesale activity during periods of large outflows.

For periods associated with large drops in asset values, we interact the crisis dummy with performance due to a fund's beta (Table 7) and then with a fund's alpha (Table 8). The coefficient for the interaction between beta performance and a crisis period is negative and statistically significant for all types of bond fund. In contrast, the interaction with alpha performance in Table 8 is never statistically significant. So investors treat non-systematic (or "non-cyclical") returns equally across market conditions but are more forgiving of losses arising from the market drop itself (beta performance).

Taken together this suggests that incentives facing bond fund managers may be captured by two quotes used in Haldane (2010). If investors reward beta performance during good times but do not equally punish it when the market turns then, to paraphrase Keynes, "*A sound [fund manager], alas, is not one who foresees danger and avoids it, but one who, when he is ruined, is ruined in a conventional and orthodox way with his fellows, so that no one can really blame him*". As a result, in the period preceding crises, procyclical investing may be driven more by competition with peers than by a genuine belief by fund managers that asset prices will continue to rise. Or as stated in 2006 by then Citibank CEO Chuck Prince *"As long as the music is playing, you've got to get up and dance. We're still dancing"*. Notably, the overall effect on market pricing will act out alongside the effect of aggregate flows, which are also typically procyclical (see Feroli et al. (2014)).

Of course, this doesn't mean that during a crisis period risky funds are not experiencing outflows or that outflows during a crisis period are not a problem. In particular, our findings do not negate concerns around fund firesales during crisis periods raised in papers like Goldstein et al. (2017). First, our findings do not refer to the sensitivity of flows in and out of an *asset class* to the performance of that asset class but instead refer to flows at the fund-level relative to peers. Feroli et al. (2014) documents that flows to given asset classes are highly sensitive to their returns. So during periods where an asset class performs badly most funds will be experiencing outflows but the role of past performance in determining how flows are distributed across funds will be weaker than in normal periods.

Second, the negative interaction term suggests that at the fund-level the *sensitivity* of flows to performance weakens during a crisis. Funds with very procyclical positioning who are posting much larger losses than their more conservative peers will likely also be experiencing larger outflows in absolute terms. It is the marginal effect that is weaker and it is this marginal effect which can incentivise risk-taking in the upswing.

In contrast, the interaction coefficients are positive for equity funds in both Table 6 and 7, although they are smaller in absolute size than for corporate and high yield funds. This suggests that while cyclical risk-taking incentives also exist for equity funds, they arise from changes in the shape of the flow-performance relationship as studied in Section 4.1 as opposed to its intensity as examined here.

To ensure that our findings are robust to variation in the cut-off point used in crisis definition, we repeat the exercises from Tables 6 to 8, defining a crisis as periods in the bottom 5th, 15th and 20th percentile of months across our 15 year sample. Full results can be found in Appendix B. For crises characterised by large outflows, the interaction of rank performance and the crisis dummy remains negative and statistically significant for both high yield and corporate bond funds across all cut-off points.

For periods with large market drops, significance of the beta performance interaction term is lost for bond funds only when a 20th percentile cut-off is used and for government bonds with a 5th percentile cut-off. However, coefficients remain negative in all cases. Interestingly, the alpha-crisis interaction is statistically significant and positive for high yield and corporate bond funds when the 20th percentile cut-off is used and for high yield funds when the 15th percentile cut-off is used. This suggests that in some cases investors are not only less sensitive to losses arising from pro-cyclical positioning during crisis but also more sensitive to non-systematic losses during these periods. Again, this supports our (and Rajan's) argument that during a crisis investors treat market-directional (pro-cyclical) and non-market-directional returns differently.

6 Policy Implications

Our empirical analysis has shown that the flow performance relationship for euro area funds exhibits characteristics associated with cyclical risk-taking incentives. Overall this suggests that the flow performance relationship *does* reward fund managers for taking cyclical risks.While this is bad news for funds' investors, it also has serious implications for the wider financial system and the real economy. Excess risk-taking among investment funds can have externalities for the wider system and as the fund sector grows so does its capacity to create systemic risk.

The fact that market discipline, as imposed by funds' investors, may not be sufficient to ensure prudential behaviour among managers, combined with the externalities of this risk-taking for the wider system, creates a clear case for regulatory intervention. This argument has already been comprehensively made for banks, resulting in extensive prudential supervision of the sector, which has grown further since the global financial crisis. Parallels between incentives identified in our analysis and in the banking literature suggests that these arguments also apply to funds. For example, Hellmann et al. (2000) and Rochet (1992) illustrate that regulatory intervention in the face of convex payoff structures can be welfare improving in the banking sector. When Rajan (1994) takes into account the effects of competition between agents, he shows that regulation applied to only parts of a sector can increase risk-taking incentives but that policy applied to all agents can be beneficial. This further highlights the importance of a macroprudential approach in the funds sector, a task which has been a high priority among policy makers for a number of years.

Understanding the incentives driving risk-taking can also assists in the design of policies aiming to mitigate it. Examining policy response to convex payoff structures, Hellmann et al. (2000) suggests two complementary approaches: Increase agent's exposure to their own investments and limit the capacity of agents to engage in risk-taking which has negative long term consequences for their own profits. Building on Rajan's model, Haldane (2010) puts forward two similar suggestions: Increase the cost of gambling for the gamblers and use credible policy to push agents to coordinate at lower risk levels. In particular, Haldane (2010) emphasises that credible policy can also work via an expectations channel, whereby agents expect their peers to take less risk and so do not need to take as much risk themselves.

In theory, fund managers' exposure to their own investments (and thus the cost of gambling) could be increased by applying principles already used in corporate renumeration packages to fund fees. In many parts of the corporate and financial sector it is now commonplace for bonuses to be paid partially in company equity, which cannot be sold for a specified period of time after the bonus payment. The goal is to incentivise employees through performance-linked compensation, while also ensuring that employees do not boost short term performance metrics through actions which ultimately undermine the well-being of the company. Similarly, fund fee payments by investors could be subject to a lock-up and only received by fund managers after a specified period, if the fund has performed well over the cycle or has met some set of medium-term performance metrics. This could also be framed simply as a performance fee which includes a fee rebate for investors in the event of severe underperformance.

This type of policy would increase fund managers and management companies' exposure to the downside of their own risk-taking and discourage managers from boosting short term returns to the detriment of the funds' longer term performance. In the context of Rajan's model, this would make the benefits derived from a good reputation also subject to the cost of gambling. Of course these tools are subject to the Lucas critique, in that changing fee structures could change investor flow behaviour, and are not currently available in regulatory legislation.

Tools which limit risk-taking capacity are more readily available, with de Guindos (2020) suggesting a number of suitable options. First he suggests the use of ex-ante liquidity management tools, such as minimum liquidity buffers and redemption notice periods. Both would primarily reduce the externalities of funds' behaviours during crisis periods, by increasing their capacity to meet large redemptions without engaging in firesales. However, by requiring that funds hold some share of their portfolio in safe, highly liquid assets, minimum liquidity buffers would also reduce their capacity to take excess risk in the first place. Increased regulation of redemption notice periods would also reduce funds' capacity to attract flows by offering short notice redemptions, which ultimately results in substantial liquidity risk-taking when funds' assets are illiquid.

de Guindos (2020) also suggests that existing leverage regulation be reconsidered. The use of leverage by funds, through either derivatives or borrowing can increase the cyclicality of their returns, allowing them to boost returns during good times but also requiring them to rapidly exit large positions during crises. Again, where effectively and credibly applied across funds, leverage limits could reduce the capacity for cyclical, systemic risk to build-up in the fund sector.

Finally, our findings regarding cyclicality in risk-taking incentives suggest that these tools could benefit from countercyclical implementation, similarly to countercyclical capital buffers in the banking sector. In practice this would involve tightening liquidity and leverage requirements during periods of market exuberance but then loosening them during crises, to allow funds to respond to large redemptions and to avoid funds collectively deleveraging and exiting positions.

7 Conclusions

To understand the behaviour of the financial system, we need to understand the incentives faced by its participants. Where incentive structures reward agents for making decisions which are to the detriment of the system as a whole, this creates fundamental instability. It also justifies regulatory intervention.

This paper has provided empirical evidence for the existence of wide-spread risk-taking incentives in the investment fund sector. Incentives arise from the positive response of investors to returns achieved through cyclical risk-taking and non-linearities in the relationship between fund returns and fund flows, which may keep managers from fully internalising the effects of adverse outcomes on their portfolios.

Our findings mirror the drivers laid out in the existing literature on bank-driven credit booms, pointing to broad, destabilising effects. However, understanding these incentives also allows for effective policy design to mitigate their effects. As the incentives arise from competition between funds, it is crucial that policies are applied across the sector, i.e. that a macroprudential approach is taken, and that they directly tackle the coordination problem. The need for these types of policies may be particularly pronounced during extended periods of accommodative monetary policy, where long periods of rising asset prices result in a build-up of risk among funds.

These findings raise a number of questions for further research. Most obviously, can we measure funds' response to these incentives? Such analysis would not be straightforward and would need to account for increased fund demand for risky assets manifesting in increased fund holdings and, in cases where funds are the dominant buyer of a security, in pricing effects. It would also likely require holdings-level data for a large number of funds over an extended period of time.[9] The examination of fund incentives could also be extended to sources other than the flow-performance relationship.

Finally, Goldstein et al. (2017) highlight that the growing role of ETFs may change the way the flow-performance relationship affects the investment fund sector. In relation to this paper's analysis, growth in passive products may reduce the share of the fund sector which can choose to take excess risk but could also increase investors' expectation of strong returns from actively managed products, amplifying the flow-performance dynamics shown here.

[9] See Barbu et al. (2020) who use this type of data to examine institutional funds.

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Appendices

A Results in Table Format

Table 9: Flow-performance non-linearity - 12 month rank performance

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Government bonds	(4) High Yield bonds
Category flows (%)	0.202	0.813***	0.300***	0.478***
	(0.141)	(0.0191)	(0.0262)	(0.0729)
1st quin. performance lagged	-0.367***	-0.273***	-0.252***	-0.467**
	(0.138)	(0.0207)	(0.0635)	(0.186)
2nd quin. performance lagged	-0.278***	-0.132***	-0.0964	-0.194
	(0.105)	(0.0154)	(0.0603)	(0.127)
4th quin. performance lagged	0.337***	0.0951***	0.207***	0.156
	(0.118)	(0.0158)	(0.0649)	(0.151)
5th quin. performance lagged	0.819***	0.360***	0.420***	0.821***
	(0.159)	(0.0219)	(0.0803)	(0.184)
Log(AuM) lagged	-0.127**	-0.0303**	-0.0176	-0.271**
	(0.0590)	(0.0138)	(0.0342)	(0.109)
Log(age)	-0.335***	-0.525***	-0.433***	-0.783***
	(0.116)	(0.0273)	(0.0801)	(0.160)
Constant	1.682***	2.451***	1.673***	4.594***
	(0.601)	(0.141)	(0.413)	(0.822)
Observations	25,716	244,115	28,674	16,851
R^2	0.032	0.047	0.026	0.079
Number of funds	613	5,951	743	447

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

B Varying Crisis Definitions

Table 10: Outflows below 5th percentile- performance rank

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Gov. bonds	(4) HY bonds
Category flows (%)	0.175	0.771***	0.308***	0.411***
	(0.132)	(0.0191)	(0.0280)	(0.0788)
Performance rank (lagged)	0.0167***	0.00773***	0.00894***	0.0174***
	(0.00225)	(0.000308)	(0.000996)	(0.00238)
Flows< 5th percentile	-0.929	-0.286***	0.113	-0.791
	(0.582)	(0.0676)	(0.236)	(0.888)
Flows< 5th percentile*Perf. rank (lagged)	-0.0149**	0.00182	0.000606	-0.0264**
	(0.00588)	(0.00121)	(0.00408)	(0.0129)
Log(age)	-0.428***	-0.530***	-0.423***	-0.893***
	(0.118)	(0.0272)	(0.0793)	(0.165)
Log(AuM) lagged	-0.124**	-0.0306**	-0.0197	-0.277**
	(0.0590)	(0.0138)	(0.0343)	(0.108)
Constant	1.408**	2.091***	1.241***	4.394***
	(0.601)	(0.140)	(0.410)	(0.873)
Observations	25,716	244,115	28,674	16,851
R^2	0.038	0.048	0.027	0.084
Number of funds	613	5,951	743	447

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 11: Outflows below 15th percentile- performance rank

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Gov. bonds	(4) HY bonds
Category flows (%)	0.151	0.796***	0.256***	0.337***
	(0.121)	(0.0215)	(0.0297)	(0.0869)
Performance rank (lagged)	0.0183***	0.00761***	0.00901***	0.0184***
	(0.00232)	(0.000311)	(0.00102)	(0.00250)
Flows< 15th percentile	-0.704*	-0.103***	-0.276**	-1.190**
	(0.362)	(0.0367)	(0.136)	(0.595)
Flows< 15th percentile*Perf. rank (lagged)	-0.0131***	0.00127**	-0.000328	-0.0180***
	(0.00269)	(0.000631)	(0.00238)	(0.00654)
Log(age)	-0.428***	-0.528***	-0.453***	-1.017***
	(0.115)	(0.0272)	(0.0791)	(0.173)
Log(AuM) lagged	-0.128**	-0.0306**	-0.0150	-0.272**
	(0.0582)	(0.0138)	(0.0341)	(0.108)
Constant	1.472**	2.094***	1.383***	5.086***
	(0.590)	(0.140)	(0.406)	(0.950)
Observations	25,716	244,115	28,674	16,851
R^2	0.045	0.048	0.027	0.091
Number of funds	613	5,951	743	447

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 12: Outflows below 20th percentile- performance rank

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Gov. bonds	(4) HY bonds
Category flows (%)	0.145	0.822***	0.238***	0.326***
	(0.118)	(0.0225)	(0.0287)	(0.0900)
Performance rank (lagged)	0.0186***	0.00769***	0.00903***	0.0190***
	(0.00235)	(0.000317)	(0.00104)	(0.00259)
Flows< 1st quintile	-0.717**	-0.0120	-0.337***	-1.034**
	(0.336)	(0.0305)	(0.116)	(0.525)
Flows< 1st quintile*Perf. rank (lagged	-0.0120***	0.000603	-0.000318	-0.0162***
	(0.00255)	(0.000524)	(0.00210)	(0.00550)
Log(age)	-0.430***	-0.524***	-0.469***	-0.973***
	(0.115)	(0.0272)	(0.0795)	(0.169)
Log(AuM) lagged	-0.128**	-0.0311**	-0.0146	-0.269**
	(0.0582)	(0.0138)	(0.0340)	(0.106)
Constant	1.511**	2.072***	1.472***	4.929***
	(0.591)	(0.140)	(0.408)	(0.940)
Observations	25,716	244,115	28,674	16,851
R^2	0.046	0.048	0.028	0.091
Number of funds	613	5,951	743	447

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 13: Market drop below 5th percentile (lagged) - beta performance

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Gov. bonds	(4) HY bonds
Category flows (%)	0.163	0.798***	0.289***	0.436***
	(0.123)	(0.0188)	(0.0263)	(0.0737)
Beta perf. (lagged)	0.503***	0.0116***	0.0739***	0.195***
	(0.0953)	(0.00164)	(0.0198)	(0.0413)
Bench < 5th percentile (lag.)	-1.354***	0.0391	-0.293**	-1.030***
	(0.272)	(0.0965)	(0.139)	(0.379)
Bench < 5th percentile (lag.)*Beta perf. (lagged)	-0.583***	0.0126	-0.0934	-0.161**
	(0.138)	(0.0107)	(0.0762)	(0.0642)
Log(age)	-0.489***	-0.556***	-0.463***	-0.877***
	(0.116)	(0.0279)	(0.0799)	(0.163)
Log(AuM) lagged	-0.137**	-0.0288**	-0.0119	-0.281***
	(0.0611)	(0.0140)	(0.0337)	(0.106)
Constant	2.373***	2.593***	1.832***	5.044***
	(0.610)	(0.144)	(0.408)	(0.841)
Observations	25,716	244,115	28,674	16,851
R^2	0.042	0.041	0.022	0.081
Number of funds	613	5,951	743	447

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Market drop below 15th percentile (lagged) - beta performance

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Gov. bonds	(4) HY bonds
Category flows (%)	0.162	0.798***	0.290***	0.440***
	(0.122)	(0.0188)	(0.0263)	(0.0740)
Beta perf. (lagged)	0.515***	0.0117***	0.0865***	0.214***
	(0.0926)	(0.00201)	(0.0228)	(0.0499)
Bench < 15th percentile (lag.)	-0.352**	0.0699**	-0.284***	-0.205
	(0.158)	(0.0272)	(0.105)	(0.148)
Bench < 15th percentile (lag.)*Beta perf. (lagged)	-0.275**	0.0151***	-0.181**	-0.111*
	(0.118)	(0.00514)	(0.0799)	(0.0631)
Log(age)	-0.475***	-0.557***	-0.463***	-0.847***
	(0.116)	(0.0279)	(0.0798)	(0.163)
Log(AuM) lagged	-0.137**	-0.0289**	-0.0118	-0.272**
	(0.0610)	(0.0140)	(0.0337)	(0.106)
Constant	2.303***	2.596***	1.831***	4.844***
	(0.612)	(0.144)	(0.407)	(0.851)
Observations	25,716	244,115	28,674	16,851
R^2	0.041	0.041	0.023	0.081
Number of funds	613	5,951	743	447

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Market drop below 20th percentile (lagged) - beta performance

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Gov. bonds	(4) HY bonds
Category flows (%)	0.163	0.801***	0.290***	0.437***
	(0.122)	(0.0188)	(0.0261)	(0.0738)
Beta perf. (lagged)	0.488***	0.00807***	0.0690***	0.167***
	(0.0967)	(0.00237)	(0.0242)	(0.0535)
Bench < 1st quin. (lag.)	-0.247**	-0.00537	-0.204***	-0.514***
	(0.113)	(0.0176)	(0.0749)	(0.127)
Bench < 1st quin. (lag.)*Beta perf. (lagged)	-0.164	0.0109**	-0.0996	-0.0898
	(0.106)	(0.00449)	(0.0696)	(0.0653)
Log(age)	-0.488***	-0.556***	-0.467***	-0.822***
	(0.117)	(0.0279)	(0.0799)	(0.163)
Log(AuM) lagged	-0.137**	-0.0294**	-0.0115	-0.285***
	(0.0609)	(0.0140)	(0.0337)	(0.106)
Constant	2.384***	2.605***	1.869***	4.904***
	(0.619)	(0.145)	(0.409)	(0.858)
Observations	25,716	244,115	28,674	16,851
R^2	0.041	0.041	0.023	0.082
Number of funds	613	5,951	743	447

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 16: Extreme market drop (lagged) - alpha

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Gov. bonds	(4) HY bonds
Category flows (%)	0.202	0.778***	0.272***	0.461***
	(0.141)	(0.0189)	(0.0261)	(0.0737)
Alpha (lagged)	1.157***	0.292***	0.574***	0.776***
	(0.272)	(0.0155)	(0.104)	(0.196)
Bench < 5th percentile (lag.)	-1.258***	-0.187***	-0.316***	-1.264***
	(0.208)	(0.0269)	(0.0893)	(0.262)
Bench < 5th percentile (lag.)*Alpha (lagged)	0.865	-0.0564	0.0912	1.190
	(0.784)	(0.0496)	(0.393)	(0.950)
Log(age)	-0.458***	-0.521***	-0.453***	-0.911***
	(0.116)	(0.0275)	(0.0791)	(0.164)
Log(AuM) lagged	-0.148**	-0.0388***	-0.0229	-0.305***
	(0.0614)	(0.0139)	(0.0337)	(0.110)
Constant	2.521***	2.460***	1.843***	5.473***
	(0.608)	(0.142)	(0.405)	(0.847)
Observations	25,716	244,115	28,674	16,851
R^2	0.033	0.044	0.024	0.080
Number of funds	613	5,951	743	447

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 17: Extreme market drop (lagged) - alpha

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Gov. bonds	(4) HY bonds
Category flows (%)	0.193	0.786***	0.270***	0.463***
	(0.137)	(0.0191)	(0.0262)	(0.0741)
Alpha (lagged)	1.127***	0.296***	0.524***	0.728***
	(0.269)	(0.0160)	(0.113)	(0.204)
Bench < 15th percentile (lag.)	-0.847***	-0.109***	-0.207***	-0.635***
	(0.197)	(0.0148)	(0.0531)	(0.143)
Bench < 15th percentile (lag.)*Alpha (lagged)	0.560	-0.0376	0.246	0.846*
	(0.408)	(0.0263)	(0.176)	(0.501)
Log(age)	-0.463***	-0.516***	-0.463***	-0.855***
	(0.115)	(0.0274)	(0.0791)	(0.162)
Log(AuM) lagged	-0.151**	-0.0379***	-0.0212	-0.300***
	(0.0614)	(0.0139)	(0.0337)	(0.110)
Constant	2.619***	2.444***	1.896***	5.250***
	(0.609)	(0.142)	(0.404)	(0.839)
Observations	25,716	244,115	28,674	16,851
R^2	0.034	0.044	0.025	0.080
Number of funds	613	5,951	743	447

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Extreme market drop (lagged) - alpha

VARIABLES	(1) Corporate bonds	(2) Equities	(3) Gov. bonds	(4) HY bonds
Category flows (%)	0.190	0.781***	0.268***	0.453***
	(0.135)	(0.0190)	(0.0257)	(0.0737)
Alpha (lagged)	1.113***	0.298***	0.511***	0.672***
	(0.251)	(0.0164)	(0.115)	(0.212)
Bench < 1st quin. (lag.)	-0.837***	-0.113***	-0.233***	-0.786***
	(0.169)	(0.0117)	(0.0438)	(0.133)
Bench < 1st quin. (lag.)*Alpha (lagged)	0.754*	-0.0223	0.266	0.937**
	(0.443)	(0.0207)	(0.172)	(0.378)
Log(age)	-0.527***	-0.518***	-0.473***	-0.816***
	(0.116)	(0.0274)	(0.0790)	(0.162)
Log(AuM) lagged	-0.146**	-0.0386***	-0.0206	-0.302***
	(0.0607)	(0.0139)	(0.0337)	(0.110)
Constant	2.964***	2.468***	1.969***	5.194***
	(0.618)	(0.142)	(0.404)	(0.839)
Observations	25,716	244,115	28,674	16,851
R^2	0.037	0.044	0.025	0.082
Number of funds	613	5,951	743	447

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Ellen Ryan
European Central Bank, Frankfurt am Main, Germany; email: **ellen.ryan@ecb.europa.eu**

Postal address	60640 Frankfurt am Main, Germany
Telephone	+49 69 1344 0
Website	**www.esrb.europa.eu**

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