A Work Project presented as part of the requirements for the Award of a Masters Degree in Finance from the Nova School of Business and Economics.

BOND FUND RUNS: THE FINANCIAL CRISIS CASE

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A project carried out on the Financial Markets major, under the supervision of:

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January 6th, 2014

Abstract

This paper studies the monthly flows of bond fund geographically focused on Europe and on the United States in the period between 2002 and 2012, with special attention to the effect of the financial crisis of 2008. Through the usage of the panel quantile regression model, this study aims to identify which funds, in terms of their characteristics, are more likely to suffer a run. The main finding is that the impact of the characteristics of fund flows is not equal for all funds, varying with issuer entity, the state of the economy as well as the focus of the fund. During the financial crisis, runs were more pronounced, situation that still affects funds geographically focused on Europe.

Keywords: Runs; Liquidity crisis; Vector Autoregression; Quantile Regressions.

Acknowledgements

I am grateful to every member of the educational system that took part in my academic growth. Sónia Félix and Marta Lopes for the help with the initial support programming and especially Professor Miguel Ferreira for the invaluable guidance during the development period of the presented study.

I dedicate this thesis to my Family.

1. Introduction

Since the global financial crisis in 2008, the global economy has experienced a slow growth, which exposed the unsustainable fiscal policies of many countries around the world namely in Europe. This debt crisis had and still has a negative impact on the global financial markets, where investors' reactions to any bad news coming were fast, leading, in most of the times, to runs of all types of securities and funds.

Nowadays, this is one of the most important problems affecting the world economy and, until now, with no end in sight. This is a crisis that is considered by many economists as the worst after the economic depression that also emerged in the United States at the end of 1920's: The Great Depression of 1929. At that time, the desire to misallocate funds was greater, especially in banks where depositors withdraw their deposits from banks for the fear of the safety of their money. Therefore, runs are a phenomenon that can largely be explained by investors' actions and its empirical evidence started a long time ago. Diamond and Dybvig (1983) is one of the most important literature references about runs that tries to explain how runs propagate in our society, focusing on the problem of the maturity transformation and its relation with the investors' actions. Another important theory, developed by Jacklin and Bhattacharya (1988), is based on the relationship between insolvent banks and runs.

In this paper, I study runs on bond funds in the period between 2002 and 2012, with special focus on the financial crisis of 2008. Bond funds are not all equal, they have their own characteristics that should be taken into account. This study will also be focused on both Sovereign and Corporate bond funds, more specifically on the impact that each bond issuer type has on fund runs, its determinants and how that is linked to the country's credit rating. Though, the goal of this study is to identify which funds, in terms of their characteristics, are more likely to suffer a run.

I use monthly flows of bond funds between 2002 and 2012, geographically focused on the United States and Europe, to determine whether the issuer entity influences or not flows' directions, as well as, the country credit rating. At the end, I will determine which funds' characteristics are the most significant to explain funds flow. To conduct this analysis, I use a panel quantile regression model to better account for the shape of the flows distribution, as well as for the characteristics of fund flows. It is shown that during the financial crisis period runs are more pronounced than in the remaining periods, although, more recently, there are some significant outflows, namely for Europe. Regarding the characteristics of funds, higher funds return tend to have larger outflows and inflows in the left and right tails, respectively, until the crisis period for corporate funds. After crisis, older corporate funds with higher returns tend to have lower outflows in the left tail in the US, but larger outflows in the same tail in Europe. For sovereign funds, before crisis, in the US, the ones with higher TER and owned by institutional investors tend to have low outflows in the left tail, similarly to what happen in Europe in the right tail. During the crisis period, in both regions, funds with higher returns and owned by institutional investors face larger outflows both in the left and right tails. After crisis, large-scale funds have large outflows in the right tail, with institutional investors having lower outflows in the left tail. As a consequence, the impact of the characteristics of fund flows is not equal for all funds, it varies with issuer entity, the state of the economy as well as the focus of the fund.

The remainder paper proceeds as follows[1]. Section 2 describes the importance of bond funds in the United States and Europe, while in Section 3 it is provided a short literature review on runs. Section 4 focuses on the used data set of this empirical study. In Section 5 it is discussed the methodology, whereas in Section 6 it presents the empirical results. Section 7 concludes the study.

2. The importance of Bond funds in the US and Europe

Globalisation is a set of transformations in the global political and economic orders that has been gaining importance since the end of the twentieth century, especially in what concerns to bond

[1] This study contains 25 pages (pp. 1-25). The appendices pages (pp. 26-33) are a complement of the content presented in the main text. All tables and figures are numbered consecutively following their order of appearance. In appendix, the same happens but the numbers are preceded by "*A.*".

markets. Although US has traditionally dominated the world's bond markets, European bond market is now trying to reverse the past history. Table 1 presents the yearly number of Total Net Assets (TNA) of the funds only for the regions under analysis (Europe and the US) until the end of 2012[2]. TNA is defined as the sum of all total fund value (in $ million). TNA have mostly been showing an increasing tendency since 2002, evidencing the increase popularity of bond funds. The exception years are from 2007 to 2009, when the total net assets of funds with geographic investment focus on Europe and the US presented a decrease of almost $1.5 million. This is a decrease that can be easily explained by the liquidity crisis that started affecting both regions in 2007, causing significant reduction to the value of this type of funds. Specifically, this reduction was more pronounced among European countries, namely Portugal, Spain, Italy and France, countries that on average suffer more with the liquidity crisis. After 2009, TNA of European and American bond funds totalled $60.4 million, of which 66% were geographically focused on the US continent. Regarding European countries, Greece was the one that significantly underperformed the European average by presenting a decrease of 52% after 2009.

Table 1: Yearly Number of Total Net Assets (partial)

Region	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	N
Europe	597	5,113	7,228	7,955	8,228	8,436	7,327	6,496	6,881	7,036	6,752	398
U.S.	6,798	8,084	8,399	8,375	8,499	8,945	8,760	9,482	11,800	13,200	14,700	337

Note: The presented numbers are in thousands.

3. Literature Review

Fund Runs are events that have been studied for a long time. One of the most important literature references about runs tries to explain how runs propagate in our society. Through a careful description and analysis, Diamond and Dybvig (1983) (hereafter: DD) constructed a model that analyses the problem of maturity transformation in bank runs in the real economy taking into consideration the relation between the economics of banking and policies' issues. In their

[2] For a complete version of this table, which includes the yearly number of TNA of the funds across European countries, see Table A.3 in the appendix.

equilibrium, they find that financing bank's long-terms loans with short-term deposits can lead to bank runs, since some later depositors withdraw their deposits because of their sense of panic that other late depositors also would withdraw, causing a snow-ball effect that would then result in a possible bank failing. Another important finding of the author is related with deposits' insurance with which the government intervention can eliminate the runs.

Jackelin (1987) used the DD model assumptions to understand what would happen with firms, but instead of using insurance financed by taxes, the author uses dividends and shares, achieving a different equilibrium from DD's one. In his equilibrium, consumers can trade dividends for firm's shares, by giving the option for late consumers to invest their dividends by buying shares at market price, the same shares that early consumers sold after obtaining their dividends, eliminating the possibility of occurrence of a run. Gorton and Pennacchi (1993) try to give a solution for this problem that arises from the maturity gap, proposing the elimination of this gap with narrow banks leaning on short-term securities, which would avoid bank runs.

Another common feature in most of the runs' studies is the relation between funds persistent performance and runs. Brown, Goetzmann, Ibbotson and Ross (1992) used a non-parametric method to study the relation between past and future mutual fund performances. They present numerical examples favoring the evidence of predictable returns between past and future performance in mutual funds. Other important reference on performance and runs is the one from Chen, Goldstein and Jiang (2010) that empirically studied the relationship between payoff complementaries and financial fragility concerning mutual fund outflows. According to this study, illiquid funds tend to have stronger payoff complementaries and, consequently, the outflows are more sensitive to bad performance, a situation that is more common in funds held by retail investors. More recently, Schmidt et al. (2013) studied daily investor flows to and from individual money market mutual funds during September and October of 2008. Using vector autoregression (VAR) models, the authors found that outflows were more concentrated in funds with lower liquidity among institutional investors that moved their money mostly from Commercial Papers into U.S. government's funds.

European literature on runs is very scarce when compared to the American one. Jank and Wedow (2010) investigated the returns and flows of German money market funds over the period of 1996-2008. The main conclusion of the paper is that in liquid times some money market funds' managers enhanced their returns by investing in less liquid assets, outperforming other funds as long as liquidity in the market was high. However, during the liquidity crisis of 2007/2008, illiquid funds experienced runs.

4. Data and initial results

4.1. Sample, Data and Descriptive Statistics

The initial sample includes 70,688 bond funds from 2002 to 2012 collected from the Lipper database. Exchange listed, index-tracking, funds-of-funds and close-end funds were eliminated, as well as funds that were not considered as primary ones, reducing the initial sample to 25,083 bond funds. The fund investment can have different focus which is based on the Lipper geographic focus and it can be a single country, a geographic region or the global one. In order to better organize the sample, five regions are created: Asia-Pacific, Emerging Markets, Europe, Global and North America (hereafter: US), but only the Europe and United States ones are used in this analysis.

Monthly data is used to better analyse both retail and institutional investors' actions across the sample period. In what concerns to the bond issuer, the data set is divided between Sovereign funds and Corporate ones. The variables are then winsorized at the bottom and top in 1% to eliminate extreme outliers of the sample[3].

[3] Table A.1 presents in detail the definition of the variables used in this study.

Because bond funds are not all equal it is important to identify the main variables that had a major impact on current fund flows. Control variables include lagged flow ($LagFlow$), total expense ratio (TER), flow standard deviation ($Flow\ S.D.$), the logarithm of total net assets ($Size$), the cumulative flow ($Cflow$), the total load ($Load$), fund age (Age), the lagged return ($LagRet$) and a dummy variable for the bond issuer type ($Benchmark$). Table A.2 in the appendix provides the descriptive statistics of the stated variables for Europe (panel A) and the US (panel B) regions.

4.2. Fund Flows

One of the main variables of this study is the fund net flow (*Flow*). $Flow_{it}$ is defined as the net growth in TNA of the fund i in the month t, assuming that flows occur at the end of each month:

$$Flow_{it} = \frac{TNA_{it} - TNA_{it-1}(1 + Ret_{it})}{TNA_{it-1}}, \tag{1}$$

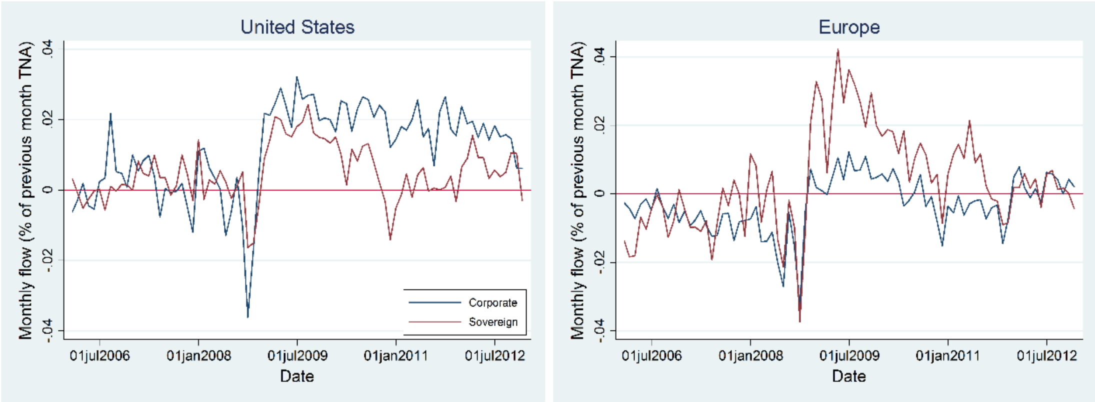
where TNA_{it} is the total net asset value of each fund i (in \$ Million) at the end of the month t, and Ret_{it} is the fund i raw return in month t. Table A.4 of the appendix shows descriptive statistics of fund flows until December of 2012. Specifically, the mean, standard deviation and a range of quantiles during the sample period are presented for each European country and for the US. Through the analysis of the table, we conclude that the average flow from 2002 to 2012 is, in the majority of the countries, nearly zero. It is also interesting to notice that, although the US have a longer history with bond funds, between 2002 and 2012, the number of funds geographically focused on Europe are higher than the ones geographically focused on the US.

4.3. Flow distribution

Figure 1 shows the monthly aggregated flows as a percentage of total assets of both issuing entities to the US (panel A) and Europe (panel B) regions between 2006 and 2012[4].

[4] Note that, because this is a set of funds with geographic focus in the US and Europe, it does not mean that all individual bond funds had exactly the same behaviour as the set during the stated period.

Figure 1: Monthly flows from/to bond funds by issuing entity



Panel A: United States monthly funds **Panel B: European monthly flows**

Depending on the time, the risk associated with each individual (corporate and sovereign) fund varies implying decisive changes in funds' flows. Considering the US case, corporate funds had higher outflows than the sovereign ones during the peak of the liquidity crisis of 2008. More specifically, corporate funds presented a maximum outflow of 3.6% in October 2008, the same month in which sovereign funds also achieved their maximum outflow, of 1.6%. After that month, both types of funds showed a good recovery, specially the corporate ones that in July 2009 presented inflows of 3.2%, similarly to what happened to sovereign funds that also had a good rebound in 2009, by achieving inflows of almost 2.5% in September of that year. This sovereign decrease in 2010 can be seen as the reflex of investors' fear due to the American midterm elections of November 2010, where the Republicans regained the control of the chamber.

European funds' behaviour is somehow related with the US funds' one. Once the US dominates the world's bond markets, a negative impact in the US economy can have consequences all over the world. The collapse of Lehman Brothers in 2008 strongly affected Europe since many of the European countries had funds in dollar currency and experienced large outflows. Like what happened with the US funds in 2008, European geographically focused funds also had the largest outflows since 2006. However, contrarily to the US, in Europe, sovereign funds were the ones that showed the largest outflows, with a maximum of more than 3.7% in October of 2008, against the 3.3% in corporate funds. In 2009, both European sovereign and corporate funds restored their inflows, although the sovereign ones performed better and earlier, achieving a maximum inflow of 4.2% in May, in contrast to the 1.2% accomplishing by corporate funds in July.

We can easily see that Europe and the US differ in time and in issuing entities' runs. In the former, since mid-2008, corporate funds tend to underperform the sovereign ones, contrarily to what happens in the US, where corporate funds tend to outperform the sovereign ones, in the sense that, in Europe, corporate funds tend to have lower inflows and larger outflows than sovereign funds, in opposition to what happens in the US. Note that, in Europe most of the companies are facing financial problems which makes them less appellative for investors and therefore their bond funds face higher outflows. However, for the US, the empirical evidence is the opposite. Because American companies tend to be more financially stable, investors tend to put more of their effort into corporate funds resulting in higher inflows than for sovereign funds. Regarding the time, Europe presented less stability of flows than the US after the peak of 2008, situation that can be explained by the financial difficulties that some of the European countries have constantly been facing since the emergence of the liquidity crisis.

It is also interesting to view what happened in some European countries, namely the comparison between those that have been facing higher financial problems (such as Portugal and Greece) and those that are considered financially stable (such as Germany and Austria). Note that Austria and Germany are countries financially stable, with higher credit ratings than Greece or Portugal. More specifically, according to Standard and Poor's (thereafter: S&P) and Moody's, both Austria and Germany had the highest credit rating possible until the beginning of 2012: AAA and Aaa, respectively given by S&P and Moody's[5]. Regarding Portugal and Greece, the story is much different. Considering only the period between 2002 and 2012, Portugal credit rating had six

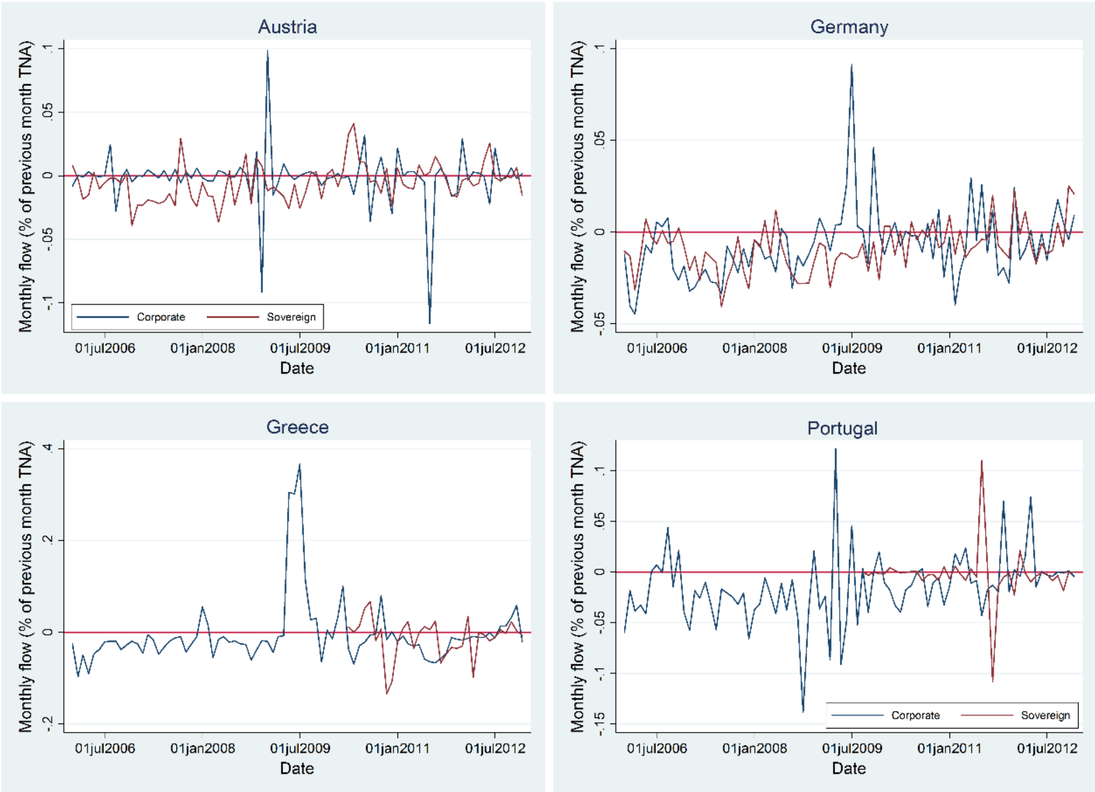
[5] Thereafter, it will only be stated S&P downgrades/upgrades to avoid repeated information, since Moody's downgrades/upgrades tends to coincide with S&P ones.

consecutive downgrades from AA in 2004 to BB in 2012, much better than the Greek situation that on the same period had eight consecutive downgrades, from A+ in 2003 to CCC in 2012.

Due to all these changes, it is important to check if a country credit rating is somehow linked to funds outflows. Figure 2 shows the monthly aggregated flows as a percentage change of total assets for Austria (top left panel), Germany (top right panel), Greece (bottom left panel) and Portugal (bottom right panel). Focusing on the top panel of figure 2, we see that, although Austria and Germany are stable countries, they also tend to have outflows both in corporate and sovereign funds, especially in corporate funds. More specifically, Austria and Germany had a large corporate outflow in mid-2009 that, in Austria, was rapidly compensated by an inflow on the same type of funds months later. Note that the largest outflows and inflows occurred in corporate funds. Sovereign funds also presented months with outflows, but their magnitude was much lower.

If we now focus on the bottom panel, we see that sovereign funds in Greece and Portugal are relatively more recent than the corporate's. However, that fact does not prevent outflows in these countries. More specifically, Greece had large outflows at the end of 2010, contrarily to what happened in Portugal that registered a large inflow at the beginning of 2011, followed then by an equivalent outflow. Regarding the corporate funds, Greece flows alternated between in and outflows with the largest inflow magnitude in July 2009. For Portugal, corporate funds also alternate between in and outflows, but with lower magnitude than in Greece. Therefore, a country credit rating has impact on the fund flows, especially in the sovereign ones.

Figure 2 - Monthly flows from/to Austria, Germany, Greece and Portugal



To get a better picture and a more comprehensive analysis of the extremes situations that happened in the bond funds markets, we should look at the tails of the flow distribution of both regions. More precisely, the percentage outflows of the 10th, 50th (median) and 90th quantiles of funds were studied and the results are presented in figure A.1 of the appendix. Starting with the corporate funds, in Europe (left panel A) the vertical distance between the 10th and 90th quantiles varied across the years. The widest distance was at the time of the emergence of the liquidity crisis, where it was verified the largest outflows in all tails of the distribution. Regarding the median, beyond the outflow in 2008, it had a slightly inflow at the beginning of 2011, that also reached the right tail of the distribution, contrarily to what happened to the left tail, that has been experiencing outflows since mid-2011. Like what happened in Europe, in the US (right panel A) the widest vertical distance between the right and left tails occurred in 2008, when all the tails suffered the largest outflows. After that year the median tended to be stable, contrary to what happened with the right tail of the distribution that experienced larger inflows.

Regarding the sovereign funds, Europe (left panel B) presents a wide vertical distance between right and left tails than the US (right panel B). In the former, this vertical distance increased significantly in 2008, keeping unstable and with an increase trend until 2011, when the left tail presented a larger outflow than the right tail. The median was stable during all periods, except for the emergence of the financial crisis and in 2011, when it experienced a slight outflow. In the US the more pronounced vertical difference occurred, once again, during the liquidity crisis' peak. From then on, there were some instability both on right and left tails, but its vertical distance became tight, compared to what happened in Europe.

Therefore, it is possible to conclude that there is heterogeneity in the behaviour of European and the US' fund flows, independently from the issue entity. This heterogeneity is specially pronounced at the time of the emergency of the liquidity crisis in 2008, when funds had outflows between 10% and 15% both in Europe and in the US.

4.4. Flows persistence

Financial data always exhibits some form of autocorrelation, namely in the conditional variance, showing a strong persistence. This strong persistence has been documented in several studies (Domian & Reichenstein 1998, Jank & Wedow 2010, Schmidt et al. 2013) and it is important to better understand the funds' performance. Persistence in flows in times of large outflows can have a negative impact on funds' performance since large outflows create fear of that fund among investors that eventually will stop to invest in it, leading to a possible run. In this section, the persistency in flows will be studied through a parametric method, based on estimates of panel regressions of the form of an autoregressive model, and a non-parametric method, suggested by Brown et al. (1992), Brown & Goetzmann (1995) and Jank & Wedow (2010).

I first use a parametric method, an AR(1) is estimated based on lagged flow of the monthly funds under analysis between 2002 and 2012:

$$Flow_{it} = \alpha_t + \partial Flow_{it-1} + \varepsilon_{it}, \quad (2)$$

where $Flow_{it}$ is the net growth in TNA of fund i at month t. ∂ represents the persistence measure and captures the common shock across all funds, whereas α_t captures the additional shocks that each fund faced.

Although there will be used two different methods to study the persistence in flows, at the end we should get the same conclusion. The null hypothesis for both methods is the same: past flow performance is unrelated with future flow performance.

Figure A.2 in the appendix shows the coefficients estimates for both corporate (panel A) and sovereign (panel B) bond funds, for the European and the US regions. Focusing on the top left panel, Europe presents an average autocorrelation of 0.25 before the crisis period, value that increases to more than 0.4 at the peak of the 2008 financial crisis. Since then, the average autocorrelation of the European corporate funds decreased but to higher values than the ones that were verified before the emergence of the crisis. Similarly, the US average autocorrelation of corporate bonds funds also increased a lot at the end of 2008, achieving a value of 0.4. However, whereas European corporate funds still face an autocorrelation much higher than the one before crisis, the US average autocorrelation decreased to values similar to the ones before crisis.

About sovereign funds autocorrelation, before crisis both European and the US regions presented an average autocorrelation of 0.3. However, during 2008, the average US sovereign funds autocorrelation more than doubled its value before crisis, contrary to what happened with the European corporate funds that had its increase slightly later and less pronounced. It is important to notice that the behaviour of the after peak period autocorrelations in both regions is slightly different. In the US there was a considerably decrease of the value of the autocorrelation at the beginning of 2011 that was extended until mid-2012, when there was a fast local peak. On the other side of the Atlantic, European sovereign funds' autocorrelation had a significant decrease at the end of 2009, but after that year the autocorrelation tended to increase. Therefore, based on the parametric, we reject the null hypothesis that the past flow is unrelated to future flows.

Alternatively, a non-parametric methodology is performed. In this method, funds are considered as Winners or Losers depending on their performance over consecutive periods. A fund is considered as Winner (Loser) if its performance is above (below) the median performance. This process was done twice, so that in the second time it would be possible to identify repeated winners and losers. Thus, a Winner-Winner (WW) is a fund that was Winner in the previous period and still is Winner in the current period. Loser-Loser (LL), Winner-Loser (WL) and Loser-Winner (LW) follow the same idea of WW. Table A.5 in the appendix summarizes the frequency with which winners and losers repeat, as well as the respective odds-ratio (OR) calculated through the following formula for each year:

$$OR_t = \frac{WW_t \times LL_t}{WL_t \times LW_t} \qquad (3)$$

As previously stated, under the null hypothesis the past flow performance in the previous year is unrelated to the current flow performance. In that case, the odds-ratio equals one and the logarithm of the odds-ratio follows a standard normal distribution:

$$\frac{\ln(OR)}{\sigma_{\ln(OR)}}\text{[6]} \sim N(0,1) \qquad (4)$$

For all years, we reject the null hypothesis at a 1% significance level that consequently means that the winners of the previous year correspond to the winner of the current year. Therefore, we reach the same conclusion both with the parametric and the non-parametric methods that bond fund flows are strongly persistence especially during crises.

4.5. Control Variables

Focusing on table A.2 in the appendix, the main differences between both regions occur in the size, cumulative flow, load and age of bond funds. The US funds presented on average higher total

[6] The standard error of the odds-ratio logarithm was approximated by Brown & Goetzmann (1995) method:

$$\sigma_{\ln(OR)} = \sqrt{\left(\frac{1}{WW} + \frac{1}{LL} + \frac{1}{WL} + \frac{1}{LW}\right)}$$

net assets than European funds, which is visible through the size of funds ($4.37 and $4.06 million, respectively) and the cumulative flows ($680.73 and $435.51 million, respectively). Another important difference is related with the fund age that in the US tends to be larger than in Europe (192.07 against 160.49 months, respectively). On the other hand, load tends to be larger in Europe than in the US ($2.63 against $2.01), as well as the total expense ratio (0.93 for Europe and 0.90 for the US).

Table A.6 shows the cross-sectional correlations of the control variables, for all sample (panel A) and for the largest outflows (panel B), for the European region. Focusing on panel A, flow standard deviation correlates positively with both lagged flow and total expense ratio (0.411 and 0.103 respectively), but negatively with size, age and benchmark (-0.317, -0.552 and -0.355, respectively). As expected, size and cumulative flow have a positive correlation (0.694), as well as load and total expensive ratio (0.475). Regarding panel B, the correlations among the control variables are identical to the top panel ones, but now they tend to have lower values, as is the case of correlation between size and cumulative flow (0.629). In what concerns to the sign of the correlations, the main differences occur with correlations between benchmark and the other control variables that now are more negatively than positively correlated.

Table A.7 provides the correlations among control variables for the US region. In panel A it is shown the correlations for all sample. Similarly to what happen in the European region, size and cumulative flow are highly correlated with each other (0.687). On the other side, cumulative flow is negatively correlated with total expense ratio and flow standard deviation (-0.202 and -0.165, respectively). As expected the latter is also negatively correlated with the size of funds (-0.315). Concerning the bottom panel, the correlations among the variables tended to decrease, but in the majority of the cases keeping its sign. The change in sign occurs mainly in benchmark correlations.

5. Methodology

So far the results are not enough to understand which variables can drive a fund run. Because of that, in this section I will propose a model that might help us to achieve the main variables that explain fund runs.

Funds can be seen as a game in real life. Independently of the type of game, when a game is good and popular it tends to draw the attention of several players that will want to play more time regardless the other players opinion.. However, when a game is not sufficiently good to draw players' attention it will lose its popularity and consequently its players and, at the end, nobody will want to play that game. Financially speaking, whenever a fund has a good flow performance it tends to attract more investors to put part of their effort into this fund. When the fund performance is good, independently of its origin, investors have no fear to invest and do not take into account moves of the other players. However, when the fund performance starts to decrease investors will tend to deviate their investment from this bad fund starting a snow-ball effect, more specifically a fund run.

Due to all those specifications, the model needs to take into consideration both common and specific fund shocks. For that, the model is based on three main conditional quantiles regressions - 10^{th}, 50^{th} and 90^{th} – that will account for the two types of shocks and it will be developed around the mean quantile and then it will diverge for the right and left tails. The advantage of using quantile regression instead of panel OLS is that with the former the whole shape of the distribution is taken into account rather than just the simple mean as it happens with the latter.

The following model was introduced by Koenker & Bassett (1978) and more recently used by Schmidt et al. (2013). Let the dependent variable be Y_{it} and the independent conditioning variables be the matrix X_{it}, in such way that:

$$Y_{it} = f(X_{it}, \beta) + \varepsilon_{it} \tag{5}$$

and satisfies the econometric zero conditional mean assumption that $E[\varepsilon_{it}|X_{i,t}] = 0$, with the restriction that $P[\varepsilon_{it} < 0|X_{it}] = \alpha, \forall\ \alpha \in (0,1)$. In this case, α is associated with the quantile of interest and therefore whenever we change its value we are automatically changing the quantile of interest. In order to account for all quantiles of interest, the following quantiles regressions specifications were taken into consideration:

$$
\begin{aligned}
Y_{it} &= f_0(X_{it}, \beta) = X_{it}'\beta_0 + \varepsilon_{it}^0 & P[\varepsilon_{it}^0 < 0 \big| X_{it}] = 0.5 \\
Y_{it} &= f_1(X_{it}, \beta) = X_{it}'\beta_0 - \exp[X_{it}'\beta_1] + \varepsilon_{it}^1 & P[\varepsilon_{it}^1 < 0 \big| X_{it}] = 0.1 \\
Y_{it} &= f_2(X_{it}, \beta) = X_{it}'\beta_0 + \exp[X_{it}'\beta_2] + \varepsilon_{it}^2 & P[\varepsilon_{it}^2 < 0 \big| X_{it}] = 0.9
\end{aligned} \quad (6)
$$

The different betas captures different shocks. β_0 is responsible for the common shock that affects all funds, whereas β_1 and β_2 capture the additional effect of shocks that affect the left and right tails, respectively, of the distribution.

The stated model can be written in a different way, using positive random variables with $P[\eta_{it} < 1|X_{it}] = 0.8$ and a Bernoulli random variable (D_{it}) that equals one with a probability of 0.5[7]:

$$Y_{it} = X_{it}'\beta_0 - D_{it}\exp[X_{it}'\beta_1]\,\eta_{it} + (1 - D_{it})\exp[X_{it}'\beta_2]\eta_{it} \quad (7)$$

The parameters were then estimated following the process stated in Schmidt (2012). The estimation of β_0 was based on linear quantile regression and only after this estimation had been made it was possible to proceed with the estimation of both β_1 and β_2 by dividing the sample according to the sign of the residuals (positive for β_1 and negative for β_2) and doing additional linear quantile regression on the logarithm of the same residuals[8]. β_0 was then replaced by the estimated one, $\widehat{\beta_0}$, in the median quantile regression. The same was done for both left and right tails, but with a slight difference at the time of estimating the respective standard errors. For both β_1 and β_2, the respective standard errors were estimated through bootstrapping, since the theoretical distribution of the sub-sample was unknown. The bootstrap algorithm drew many independent bootstrap samples through replication and then estimated both β_1 and β_2 standard errors.

[7] To understand why the probability equals 0.5, notice that if $P(\eta_{it} < 1|X_{it}) = 0.8$, then $P(Y_{it} < X_{it}'\beta_0 - \exp[X_{it}'\beta_1]|\, X_{it}) = P(D_{it} = 1|X_{it}) \times P(\eta_{it} > 1|X_{it}) = 0.5 \times (1 - 0.8) = 0.1$

[8] Notice that $\varepsilon_{it} = Y_{it} - X_{it}'\beta_0$ and if $Y_{it} - X_{it}'\beta_0 > 0$ then $Y_{it} - X_{it}\beta_0 = \exp[X_{it}'\beta_2]\,\eta_{it}$. Taking the logs we get $\log[Y_{it} - X_{it}'\beta_0] = X_{it}'\beta_2 + log\eta_{it}$. Because it was assumed that $P(\eta_{it} < 1|X_{it}) = P(log\ \eta_{it} < 0|X_{it}) = 0.8$, the transformed model imposes that $\alpha = 0.8$.

6. Empirical results

The stated model helps us to better understand which funds are more vulnerable to a possible run. In order to figure out both common and specific shocks, the whole sample is firstly evaluated and then divided in three sub-samples that are evaluated individually. The first sub-sample includes monthly observations from year 2002 to 2006 (thereafter: "Before Crisis"), the second from year 2007 to 2011 ("Crisis Period") and the last sub-sample is only composed by year 2012 ("After Crisis") due to the lack of observations after that year. The analysis is repeated for the European and the US regions, taking into consideration both corporate and sovereign funds. For all cases, the dependent variable is the monthly fund flow, calculated as the percentage of lagged Total Net Assets. In the following two tables (2 and 3), there are represented the common shock estimated coefficients ("Common Shock") that in the last section are represented by β_0, as well as the left and right tails estimated coefficients ("Left Tail" and "Right Tail"), respectively denominated by β_1 and β_2 in the last section.

6.1. Corporate funds

6.1.1. All sample

Table 2 provides the estimated coefficients of the quantile regression from equation (6) for corporate funds geographically focused on the US and Europe. From the observation of panel A, it is possible to conclude that the main explanatory variables predict fund flow. The exception is the institutional class that is only statistically significant for the right tail, representing the funds with largest inflows (lowest outflows), meaning that funds owned by institutional investors had lower inflows than retailed ones. Returns have an important statistical significance, since they are the estimator that has the highest coefficient across all shocks, stating that high return in left tail funds tend to have larger outflows. Moreover, regarding the flow standard deviation, although it is always statistically significant, its coefficient increases a lot when we consider left and right tails, reflecting the tendency for capital to enter into those funds. Age coefficient has a small negative impact on fund flows prediction, which means that older funds with high returns tend to have largest outflows in the left tail. Contrarily to what happens with the US, in Europe (panel B) all control variables are statistically significant to predict funds flow. Here, returns have a negative impact in flow prediction in the left tail, having coefficients much lower than in the US case. Flow standard deviation also presents a great coefficient variation when we consider either left or right tails compared to what happens in the common shock. In this case, older funds owned by institutional investors tend to have lower inflows than the ones owned by retail investors in the right tail.

6.1.2. Before Crisis

Through the observation of column "Before Crisis" of panel A it is possible to conclude that funds with high returns have more outflows in the left tail of the distribution, contrarily to what happens with funds with higher returns where, on the right tail, they tend to have the largest inflows. Moreover, funds with higher TER contribute to lower outflows in the left tail and lower inflows in the right tail. Regarding panel B, most of the variables are significant to flow prediction. On average, funds which are owned by institutional investors, tend to have larger outflows in the left tail than in the right tail. In what concerns to the flow standard deviation, it is very strong in both tails, indicating high flow persistence. About the TER, the right tail has lower inflows.

6.1.3. Crisis Period

Panel A tells us that, once again, that larger return funds tend to have the largest outflows in the left tail and larger inflows in the right tail of the distribution. About age, it also has a negative impact in both left and right tails. During this period most investors tend to choose the right tail of the distribution, contrarily to what happened in the period before, where TER coefficient was much higher in the left tail. In the European case (panel B), funds with higher returns tend to face larger outflows in the left tail, contrarily to what happens in the right tail, where high return funds tend to have lower outflows. Once again, the flow standard deviation tends to be stronger in tails than in the median. Those results are in agreement with panel A of figure A.1 in the appendix which shows that in the US investors tend to choose the right tail but in Europe they tend to invest in the left tail.

6.1.4. After Crisis

Focusing now on the "After Crisis" column, in the US, older funds with high returns tend to have lower outflows in the left tail, contrarily to what happens in Europe, where older funds with higher returns tend to have larger outflows. It is important to note that in this period, the effect of the coefficients decreases compared to the crisis period.

Table 2 – Fund Flow Panel Regressions: Corporate bond funds

Variable	Common Shock			
	All sample	**Before Crisis**	**Crisis Period**	**After Crisis**
Return	0.14794***	0.20007***	0.1336***	0.1454***
	[37.2]	[22.8]	[28.2]	[7.5]
TER	-0.00076***	-0.17567***	-0.00055***	0.00219***
	[-4.1]	[-5.9]	[-2.1]	[3.4]
FlowS.D.	0.04629***	0.04528***	0.04589***	0.04955***
	[26.2]	[14.7]	[18.5]	[8.6]
Age	-0.00001***	-0.00001***	-0.00001***	-0.00001***
	[-15.5]	[-9.5]	[-10.0]	[-4.6]
Inst. Class	0.00021	-0.00052	0.00069*	0.00175*
	[0.8]	[-1.3]	[1.7]	[1.7]

Variable	Left Tail			
	All sample	**Before Crisis**	**Crisis Period**	**After Crisis**
Return	-4.33449***	-6.80262***	-3.90074***	1.47043
	[-10.6]	[-10.9]	[-7.9]	[1.1]
TER	0.07036***	0.14438***	0.03061	-0.21623**
	[4.4]	[5.6]	[1.2]	[-2.5]
FlowS.D.	8.07815***	9.15864***	7.78503***	7.48785***
	[42.4]	[27.8]	[30.3]	[21.6]
Age	-0.00098***	-0.00124***	-0.00087***	0.00002
	[-11.3]	[-8.1]	[-6.7]	[0.1]
Inst. Class	0.02856	0.05702	0.00798	-0.03570
	[1.4]	[1.1]	[0.2]	[-0.7]

Variable	Right Tail			
	All sample	**Before Crisis**	**Crisis Period**	**After Crisis**
Return	4.5153***	5.02828***	4.43703***	2.9107*
	[10.0]	[6.2]	[9.5]	[1.9]
TER	0.01318	-0.04498*	0.07717**	0.02679
	[0.8]	[-1.8]	[2.4]	[0.5]
FlowS.D.	11.8211***	13.4069***	11.7718***	9.1782***
	[62.8]	[43.6]	[39.5]	[22.7]
Age	-0.00122***	-0.00105***	-0.00134***	-0.00095***
	[-15.1]	[-8.7]	[-9.5]	[-5.7]
Inst. Class	-0.14418***	-0.20761***	-0.11660***	0.09017
	[-5.2]	[-4.3]	[-3.0]	[0.8]

Panel A: United States

Variable	Common Shock			
	All sample	**Before Crisis**	**Crisis Period**	**After Crisis**
Return	0.01497***	-0.0095***	0.0201364***	0.01617***
	[9.3]	[-2.5]	[8.8]	[3.3]
TER	-0.00397***	-0.00541***	-0.00468***	-0.00170***
	[-29.5]	[-20.7]	[-20.9]	[-4.9]
FlowS.D.	0.00239**	0.01779***	-0.00879***	0.00462*
	[2.1]	[7.6]	[-4.6]	[1.8]
Age	-0.00002***	-0.00003***	-0.00003***	-0.00001***
	[-36.0]	[-20.9]	[-26.9]	[-8.3]
Inst. Class	0.00058***	-0.00149***	0.00128***	0.00273***
	[3.4]	[-4.1]	[4.8]	[6.3]

Variable	Left Tail			
	All sample	**Before Crisis**	**Crisis Period**	**After Crisis**
Return	-1.38841***	0.71650	-1.78379***	-1.32812*
	[-8.7]	[1.5]	[-8.1]	[-1.9]
TER	0.02721	0.07617***	-0.00473	-0.09445
	[1.6]	[2.8]	[-0.2]	[-1.2]
FlowS.D.	10.849***	10.131***	11.79***	7.2916***
	[51.9]	[38.8]	[76.5]	[10.8]
Age	0.00030***	-0.00045***	0.00077***	-0.00082***
	[2.9]	[-2.6]	[6.1]	[-3.2]
Inst. Class	0.06785***	-0.22457***	0.19930***	0.11603*
	[2.8]	[-4.7]	[4.9]	[1.9]

Variable	Right Tail			
	All sample	**Before Crisis**	**Crisis Period**	**After Crisis**
Return	0.76939***	0.46705	1.0031***	1.9246**
	[3.3]	[1.1]	[3.4]	[2.2]
TER	-0.10645***	-0.24612***	-0.05084	-0.04559
	[-5.4]	[-7.2]	[-1.4]	[-0.6]
FlowS.D.	14.3515***	15.1533***	14.5904***	11.7074***
	[62.2]	[40.2]	[76.4]	[19.7]
Age	-0.00069***	-0.00123***	-0.00029***	-0.0011***
	[-6.1]	[-9.9]	[-3.1]	[-5.0]
Inst. Class	-0.19162***	-0.18663***	-0.18913***	-0.1943***
	[-5.6]	[-4.2]	[-5.5]	[-2.7]

Panel B: Europe

Note:

The numbers inside brackets represents the t-values.

, ** and * indicate significance at the 10%, 5% and 1% level, respectively.*

6.2. Sovereign funds

6.2.1. All sample

Table 3 presents the results of the estimated quantile regression of equation (6) for sovereign funds geographically focused on the US and Europe. In most of the cases of panel A, all the variables are statistically important to predict sovereign funds flow. The only exception is for the flow standard deviation in the common shock. Once again, age has a negative impact for all shocks, as well as the fund return in the left tail, meaning that older funds with high returns face higher outflows. However, in the right tail, higher funds return tend to have large inflows if owned by retail investors. Regarding European sovereign funds (panel B), flow standard deviation presents the highest coefficient in both tails, indicating, for the right tail case, the tendency for capital to enter the fund. In the common shock, age and TER have a negative impact on the flow prediction, situation that is not verified in the left tail, where only return coefficient is negative, meaning that funds with higher returns tended to have the largest outflows in the left tail. Similarly to what happens in the US, institutional investors tend to have larger out/inflows than retail investors in all shocks in the left/right tail.

6.2.2. Before Crisis

In this period, for both regions, TER coefficient is much higher in the left than in the right tail (0.138 against -0.034, respectively, for the US and 0.244 against 0.011, for Europe). Regarding funds' age coefficient in both regions, the coefficients are very small and negative for both left and right tails, which means that its contribution to funds' flow prediction has a small impact.

6.2.3. Crisis Period

By the peak of the crisis, in the US, higher return funds have larger outflows than in Europe for the respective left tail of the distribution. Regarding the flow standard deviation, in both regions, it strongly predicts cross-sectional differences in outflows in both left and right tails. In addition, in both regions, institutional investors tend to have lower inflows in the right tail than retail investors.

This fact is more pronounced in the US funds than in the European ones, contrary to what happens in the left tail, which is in agreement with panel B of figure A.1.

6.2.4. After Crisis

After the considered period of crisis, flow standard deviation continues to strongly predict outflows in both tails, contrary to what happens with age in both regions. Regarding TER, that is close to the scale of investment, in both regions, the large-scale funds tend to have larger inflows in the right tail of the distribution. Institutional class is again an important variable for funds flow prediction in both regions, with institutional investors having less outflows than the retail ones in the left tail of the distribution.

Table 3 – Fund Flow Panel Regressions: Sovereign bond funds

Variable	Common Shock			
	All sample	**Before Crisis**	**Crisis Period**	**After Crisis**
Return	0.13072***	0.0711***	0.1904***	0.21148***
	[13.8]	[5.1]	[14.8]	[4.9]
TER	-0.00670***	-0.00618***	-0.00685***	-0.00679***
	[-17.7]	[-12.9]	[-11.0]	[-5.2]
FlowS.D.	0.00413	-0.00574	0.00710	0.0592***
	[1.3]	[-1.4]	[1.4]	[5.7]
Age	-0.00001***	-0.00002***	-0.00001***	-0.00001
	[-12.9]	[-10.8]	[-8.3]	[-2.4]
Inst. Class	-0.00225***	-0.00181***	-0.00265***	-0.00318***
	[-8.1]	[-4.9]	[-6.1]	[-3.6]

Variable	Left Tail			
	All sample	**Before Crisis**	**Crisis Period**	**After Crisis**
Return	-4.67164***	-3.13096	-4.02424***	-4.99736
	[-4.7]	[-1.9]	[-3.8]	[-0.8]
TER	0.17074***	0.13828***	0.14459***	0.18240
	[5.6]	[2.5]	[2.8]	[1.4]
Flow S.D.	8.67483***	9.08335***	8.84643***	6.17624***
	[25.2]	[24.3]	[19.7]	[5.2]
Age	-0.00091***	-0.00140***	-0.00036	-0.00011
	[-6.6]	[-12.9]	[-1.4]	[-0.1]
Inst. Class	0.14350***	0.05199	0.18508***	0.29248***
	[4.9]	[1.3]	[5.3]	[2.9]

Variable	Right Tail			
	All sample	**Before Crisis**	**Crisis Period**	**After Crisis**
Return	7.20362***	6.6417***	6.3429***	1.38876
	[12.2]	[4.1]	[5.6]	[0.4]
TER	-0.09617*	-0.03394	-0.23895***	-0.16882
	[-1.8]	[-0.5]	[-3.2]	[-0.9]
Flow S.D.	12.891***	12.358***	13.587***	12.239***
	[26.8]	[20.3]	[27.7]	[9.0]
Age	-0.00033***	-0.00092***	-0.00010	0.00118***
	[-2.6]	[-6.5]	[-0.6]	[6.3]
Inst. Class	-0.17599***	-0.20645***	-0.16786***	-0.02088
	[-6.4]	[-6.4]	[-3.7]	[-0.2]

Panel A: United States

Variable	Common Shock			
	All sample	**Before Crisis**	**Crisis Period**	**After Crisis**
Return	0.00546***	-0.01032	0.00775***	0.0078**
	[3.1]	[-1.4]	[4.0]	[2.5]
TER	-0.00125***	-0.00361***	-0.00125***	-0.00018
	[-7.9]	[-6.5]	[-6.6]	[-0.8]
FlowS.D.	0.01052***	0.01901***	0.01212***	0.0069***
	[8.8]	[4.1]	[8.3]	[4.3]
Age	-0.00001***	-0.00001***	-0.00002***	0.00000*
	[-14.8]	[-3.1]	[-22.0]	[-1.7]
Inst. Class	0.00176***	0.00020	0.001867***	0.00145***
	[7.9]	[0.3]	[7.1]	[3.8]

Variable	Left Tail			
	All sample	**Before Crisis**	**Crisis Period**	**After Crisis**
Return	-0.58552*	1.89339	-0.96958	0.28939
	[-1.7]	[1.6]	[-1.6]	[0.2]
TER	0.11028***	0.24418*	0.03837	0.1979**
	[2.6]	[1.9]	[0.7]	[2.1]
FlowS.D.	9.18306***	7.80744***	9.40889***	7.13697***
	[32.4]	[10.3]	[31.9]	[8.9]
Age	0.00225***	-0.00178***	0.00350***	0.00212***
	[9.6]	[-6.6]	[6.4]	[4.3]
Inst. Class	0.27901***	-0.20560	0.28795***	0.91373***
	[3.2]	[-1.3]	[3.3]	[2.9]

Variable	Right Tail			
	All sample	**Before Crisis**	**Crisis Period**	**After Crisis**
Return	1.18743*	-1.85177*	2.27370***	0.29794
	[1.7]	[-1.9]	[2.6]	[0.3]
TER	-0.11197**	0.01124	-0.06544	-0.10115
	[-2.2]	[0.2]	[-1.3]	[-1.1]
FlowS.D.	19.6469***	15.358***	20.4961***	18.5317***
	[36.4]	[29.4]	[32.3]	[38.1]
Age	0.00309***	-0.00096**	0.00213***	0.00711***
	[7.1]	[-2.3]	[4.8]	[10.6]
Inst. Class	0.11717	0.15812	-0.10268	0.96967***
	[1.6]	[1.1]	[-1.1]	[3.7]

Panel B: Europe

7. Conclusion

As time goes by, bond funds have been gaining importance in the finance of economies, but there is still a lot of work to do to better understand runs of those types of funds. With this thesis I provide an empirical analysis of runs on bond funds during the period between 2002 and 2012 and its original contribution lies in identifying which funds, in terms of their characteristics, are more likely to suffer a run.

I find that cross-sectional correlations tend to have a similar impact on both US' and European funds, although in the case of the bond issuer entity, it influences more the US' funds than the European ones. Regarding the European case, countries with lower credit rating tend to have, on average, more outflows than countries with higher credit ratings, especially with sovereign funds, which indicates that higher risk level countries tend to face more funds runs.

Based on the panel quantile regressions, during the financial crisis period runs are more pronounced than in the remaining periods. Regarding the characteristics of funds, higher fund return tend to have larger outflows and inflows in the left and right tails, respectively, until the crisis period for corporate funds. After crisis, those older corporate funds with higher returns tend to have lower outflows in the left tail in the US, but larger outflows in the same tail for Europe, which indicates that most of the corporate geographically focused on Europe are still facing significant outflows. Regarding sovereign funds, before crisis, in the US, funds higher TER and owned by institutional investors tend to have low outflows in the left tail, similarly to what happens in Europe in the right tail. During the crisis period, in both regions, funds with higher returns and owned by institutional investors face larger outflows both in the left and right tails. After crisis, large-scale funds have large outflows in the right tail, with institutional investors having lower outflows in the left tail.

To sum up, for the European case, runs continued to be pronounced after the peak crisis period, situation that is not as visible for the US case. Those results are consistent with most of the recent papers about runs during the financial crisis, namely with Schmidt et al. (2013) empirical study.

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Appendices

Table A.1 – Definition of the variables

This table presents the definition of the variables used in this study. All variables were obtained from Lipper database.

Variable	Definition
ID	Lipper ID
Date	Time ID
Name	Fund name
Primary	Dummy that takes the value of one if primary share class
Status	Asset status - active, liquidate or merged
Domicile name	Domicile country name
Currency	Fund currency
Institutional Class	Dummy that takes the value of one if institutional class share
Asset Universe	Asset Universe equals Mutual Funds
Asset Type	Asset type equals Bond
Geographic focus	Geographic focus of the fund
Total Expense Ratio	Total cost of a fund share as percentage of total assets
Total Net Assets	Fund Value (Million) USD
Return	Fund return in USD
Benchmark	Fund bond type
Flow	Fund flows as a percentage of previous period Total Net Assets
Fund age	Number of months since the fund's inception
Size	Logarithm of the Total Net Asset of a fund share
Load	Total load (front- plus back-end load) charged by a fund shares

Table A.2 – Descriptive statistics of the control variables

This table presents the descriptive statistics of the cross-sectional bond funds for Europe (Panel A) and the US (Panel B) regions between 2002 and 2012. LagFlow is the lagged fund flow as a percentage of lagged Total Net Assets, TER represents the total expense ratio of the fund, Flow S.D. is the standard deviation of monthly percentages changes in funds' assets, Size stands for the logarithm of the Total Net Asset of a fund share, Cflow represents the cumulative flow, Load is the total load (front- plus back-end load) charged by a fund shares, Age stands for the fund age calculated since its inception and LagReturn is the lagged fund return.

Panel A: European bond funds

Variable	Mean	S.D.	Min	Quantiles			Max
				0.25	Mdn	0.75	
LagFlow	0.00	0.10	-0.35	-0.02	0.00	0.01	0.62
TER	0.93	0.43	0.04	0.61	0.93	1.19	2.38
Flow S.D.	0.08	0.05	0.00	0.04	0.07	0.11	0.56
Size	4.06	1.82	-2.53	2.97	4.16	5.29	8.16
Cflow	435.51	911.70	0.16	39.68	129.11	401.57	7010.80
Load	2.63	2.31	0.00	0.30	2.50	4.00	11.50
Age	160.49	97.05	0.00	92.37	152.20	217.10	600.67
LagReturn	0.01	0.03	-0.09	-0.01	0.01	0.03	0.09

Panel B: US bond funds

Variable	Mean	S.D.	Min	Quantiles			Max
				0.25	Mdn	0.75	
LagFlow	0.01	0.10	-0.35	-0.02	0.00	0.01	0.62
TER	0.90	0.44	0.04	0.61	0.83	1.08	2.38
Flow S.D.	0.08	0.06	0.00	0.03	0.07	0.11	0.49
Size	4.37	1.97	-2.53	3.21	4.49	5.72	8.16
Cflow	680.73	1330.11	0.16	50.80	180.20	612.40	7010.80
Load	2.01	2.61	0.00	0.00	0.10	4.00	11.50
Age	192.07	120.61	0.93	99.43	186.70	267.87	1362.57
LagReturn	0.00	0.02	-0.09	0.00	0.00	0.01	0.09

Table A.3 – Yearly Number of Total Net Assets (TNA)

The table presents the TNA of the funds across European countries and the US until the end of 2012. TNA is defined as the sum of all total fund value (in $ million). All the values presented below are in $ thousand million.

Country	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	N
Austria	0.158	54.00	77.61	81.68	81.08	74.72	70.50	66.94	62.77	59.58	55.82	6.27
Belgium	5.533	23.71	24.03	19.21	17.29	14.03	14.10	17.38	15.55	13.43	6.902	2.00
Czech Republic	11.79	23.34	28.66	33.74	41.68	47.30	47.86	32.96	35.82	34.17	28.95	3.14
Denmark	2.846	10.83	15.80	18.70	15.92	28.53	43.80	47.92	49.77	74.34	91.86	3.90
Estonia	-	-	-	-	-	0.221	0.941	0.674	0.148	-	-	0.03
Finland	-	0.499	0.460	0.181	0.157	0.023	-	-	-	-	-	0.06
France	1.823	35.85	67.11	75.99	59.79	46.95	44.13	33.23	28.29	26.24	21.18	5.86
Germany	13.38	166.0	247.4	234.5	219.6	181.2	158.6	146.0	147.9	149.6	144.2	8.21
Greece	5.808	9.048	10.64	10.37	5.801	0.844	0.829	0.922	3.135	3.262	1.495	0.90
Hungary	0.586	1.423	0.809	1.194	1.920	25.53	18.42	11.87	19.27	19.34	14.10	3.06
Italy	0.419	34.31	49.85	41.95	54.44	38.61	22.58	25.51	16.75	19.07	25.47	1.07
Lithuania	-	-	0.010	0.003	0.013	0.054	0.136	0.026	0.046	0.000	-	0.08
Netherlands	0.209	1.329	1.168	3.876	6.354	6.272	6.757	6.183	6.101	5.398	4.764	0.94
Norway	0.548	1.914	5.189	9.771	14.59	0.606	26.96	27.40	43.21	0.978	84.88	1.74
Poland	19.44	38.09	24.01	35.38	32.39	30.61	34.24	32.50	45.88	49.26	58.42	3.94
Portugal	7.450	10.66	20.22	23.11	18.36	11.22	9.086	7.058	9.291	10.64	10.78	0.90
Romania	-	-	-	-	-	-	0.210	0.739	2.460	3.155	3.024	0.06
Slovakia	-	0.145	1.250	2.464	2.895	2.720	3.041	2.585	2.626	2.418	1.903	0.61
Spain	19.73	56.58	76.23	82.53	72.28	57.61	51.76	3.382	77.43	214.4	241.1	15.0
Sweden	4.337	37.98	60.53	70.77	80.31	92.87	118.7	115.1	136.2	160.2	174.5	3.84
Switzerland	1.802	157.7	248.7	292.5	379.4	446.1	446.0	420.7	461.9	538.6	533.0	16.2
United Kingdom	26.04	518.5	765.0	931.7	1,177	1,370	1,219	1,098	1,154	1,210	1,286	37.6
Europe	596.6	5,113	7,228	7,955	8,228	8,436	7,327	6,496	6,881	7,036	6,752	398
U.S.	6,798	8,084	8,399	8,375	8,499	8,945	8,760	9,482	11,800	13,200	14,700	337

Table A.4 – Descriptive statistics of funds flows as of December 2012

This table shows the descriptive statistics of funds flows as of December 2012. Specifically, the mean, standard deviation and a range of quantiles during the sample period is presented for each European country and for the US.

Country	N	Mean	S.D.	Min	Quantiles			Max
					0.25	Mdn	0.75	
Austria	3,705	0.00	0.06	-0.35	-0.01	0.00	0.00	0.62
Belgium	1,531	-0.01	0.09	-0.35	-0.02	0.00	0.00	0.62
Czech Republic	2,330	0.00	0.08	-0.35	-0.01	0.00	0.00	0.62
Denmark	2,854	0.01	0.10	-0.35	-0.02	0.00	0.01	0.62
Estonia	33	0.02	0.08	-0.16	0.00	0.00	0.00	0.33
Finland	45	-0.05	0.08	-0.35	-0.05	-0.02	-0.01	0.09
France	5,175	-0.01	0.06	-0.35	-0.02	-0.01	0.00	0.62
Germany	6,961	-0.01	0.07	-0.35	-0.02	-0.01	0.00	0.62
Greece	470	-0.01	0.09	-0.35	-0.02	-0.01	0.00	0.62
Hungary	1,990	0.00	0.10	-0.35	-0.03	-0.01	0.02	0.62
Italy	930	0.01	0.14	-0.35	-0.03	-0.01	0.01	0.62
Lithuania	56	0.04	0.23	-0.35	-0.06	0.00	0.11	0.62
Netherlands	369	-0.02	0.05	-0.33	-0.03	-0.01	0.00	0.17
Norway	1,444	0.02	0.11	-0.35	-0.01	0.00	0.04	0.62
Poland	3,273	0.03	0.15	-0.35	-0.04	0.00	0.05	0.62
Portugal	769	-0.01	0.07	-0.35	-0.02	0.00	0.00	0.62
Romania	58	0.05	0.13	0.00	0.00	0.00	0.03	0.62
Slovakia	499	0.00	0.09	-0.35	-0.02	0.00	0.01	0.62
Spain	13,469	0.00	0.09	-0.35	-0.02	0.00	0.00	0.62
Sweden	2,927	0.01	0.09	-0.35	-0.02	0.00	0.02	0.62
Switzerland	14,409	0.00	0.08	-0.35	-0.01	0.00	0.01	0.62
United Kingdom	30,369	0.01	0.09	-0.35	-0.01	0.00	0.01	0.62
Europe	319,182	0.00	0.10	-0.35	-0.02	0.00	0.01	0.62
U.S.	308,803	0.01	0.10	-0.35	-0.02	0.00	0.01	0.62

Figure A.1 – Quantiles of monthly flows

This figure shows the quantiles of monthly flows for Europe and the US. In Panel A it is shown the quantiles for corporate funds for both regions, whereas in Panel B it is represented the quantiles for sovereign funds.

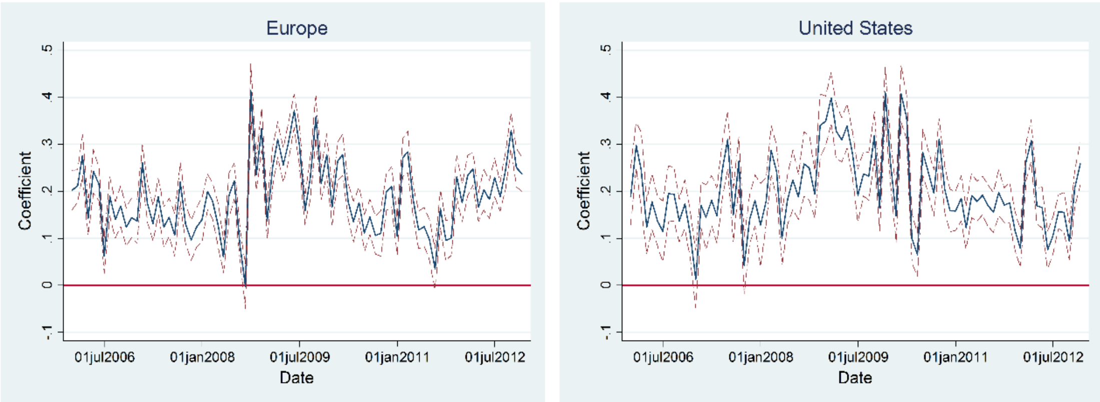
Panel A: Corporate Funds

Panel B – Sovereign Funds

Figure A.2 – AR(1) coefficients

This figure shows the AR(1) coefficients estimates for both corporate (Panel A) and sovereign (Panel B) bond funds, for the European and the US regions.

Panel A – AR(1) coefficients estimates for Corporate funds



Panel B – AR(1) coefficients estimates for sovereign funds

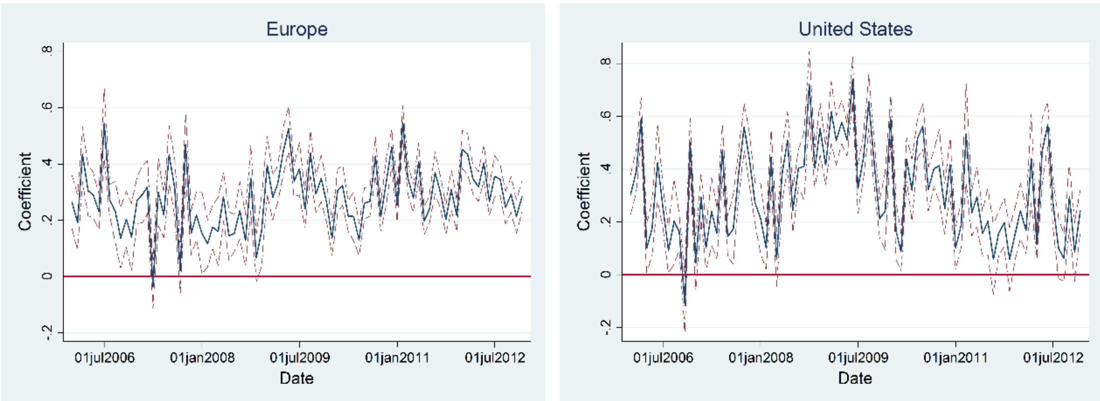


Table A.5 – Performance Persistence of Bond Funds: Repeated Winners and Losers

Funds were classified into winners (annual flow above media) and losers (annual flow below median) for each year between 2002 and 2012. Winner-Winner (WW) shows the number of funds that were winners in the previous period and still are Winner in the current period. Winner-Loser (WL) indicates the number of funds that were winners in the previous period but are not in the current period. The null hypothesis, past flow performance in the previous year is unrelated to the future flow performance, was tested through the odds-ratio: $(WW_t \times LL_t)/(WL_t \times LW_t)$.

Year	Total	Winner-Winner	Winner-Loser	Loser-Winner	Loser-Loser	Odds-ratio	z
2002	5,132	1,526	368	2,302	936	1.7	7.5
2003	5,279	1,136	1,139	1,116	1,888	1.7	9.3
2004	5,320	1,155	1,176	1,001	1,988	2.0	11.8
2005	5,378	1,136	865	1,402	1,975	1.9	10.8
2006	5,340	1,264	990	1,363	1,723	1.6	8.6
2007	5,260	1,315	866	1,606	1,473	1.4	5.8
2008	5,236	1,045	1,253	952	1,986	1.7	9.6
2009	5,599	1,000	1,382	888	2,329	1.9	11.2
2010	6,009	1,274	1,243	1,427	2,065	1.5	7.5
2011	6,454	1,185	1,574	1,080	2,615	1.8	11.4
2012	6,938	1,316	1,666	1,154	2,802	1.9	12.8

Table A.6 – Cross-sectional correlations of the control variables for Europe

This table presents the cross-sectional correlations of the control variables for Europe. The top panel shows the correlations for all sample, whereas the bottom panel presents the same correlations but for the funds that had the largest outflows between 2002 and 2012.

Panel A: All sample correlations

Correlation	LagFlow	TER	Flow S.D.	Size	Cflow	Load	Age	LagReturn	Benchmark
LagFlow	1.000								
TER	-0.013	1.000							
Flow S.D.	0.105	-0.009	1.000						
Size	0.013	-0.184	-0.204	1.000					
Cflow	-0.010	-0.070	-0.111	0.643	1.000				
Load	0.011	0.132	0.028	0.008	-0.022	1.000			
Age	-0.058	0.035	-0.287	0.214	0.148	-0.165	1.000		
LagReturn	0.030	0.001	-0.002	0.015	0.009	-0.002	0.008	1.000	
Benchmark	0.012	-0.016	0.039	-0.052	-0.063	0.149	-0.149	-0.007	1.000

Panel B: Correlations of the bottom tercile

Correlation	LagFlow	TER	Flow S.D.	Size	Cflow	Load	Age	LagReturn	Benchmark
LagFlow	1.000								
TER	0.034	1.000							
Flow S.D.	0.371	0.025	1.000						
Size	-0.089	-0.176	-0.239	1.000					
Cflow	-0.069	-0.059	-0.136	0.629	1.000				
Load	0.009	0.174	0.047	0.007	-0.003	1.000			
Age	-0.105	0.022	-0.303	0.227	0.153	-0.121	1.000		
LagReturn	0.019	0.024	0.002	0.015	0.003	0.003	0.004	1.000	
Benchmark	0.034	-0.019	0.073	-0.034	-0.036	0.067	-0.092	0.018	1.000

Table A.7 – Cross-sectional correlations of the control variables for the US

This table presents the cross-sectional correlations of the control variables for the US. The top panel shows the correlations for all sample, whereas the bottom panel presents the same correlations but for the funds that had the largest outflows between 2002 and 2012.

Panel A: All sample correlations

Correlation	LagFlow	TER	Flow S.D.	Size	Cflow	Load	Age	LagReturn	Benchmark
LagFlow	1.000								
TER	-0.010	1.000							
Flow S.D.	0.140	0.069	1.000						
Size	0.010	-0.312	-0.315	1.000					
Cflow	0.000	-0.202	-0.165	0.687	1.000				
Load	0.021	0.372	-0.042	-0.036	-0.047	1.000			
Age	-0.090	-0.066	-0.542	0.371	0.274	0.038	1.000		
LagReturn	0.048	0.021	0.001	0.028	0.021	0.022	-0.001	1.000	
Benchmark	-0.033	-0.291	-0.378	0.089	0.010	-0.103	0.278	-0.030	1.000

Panel B: Correlations of the bottom tercile

Correlation	LagFlow	TER	Flow S.D.	Size	Cflow	Load	Age	LagReturn	Benchmark
LagFlow	1.000								
TER	0.075	1.000							
Flow S.D.	0.411	0.103	1.000						
Size	-0.169	-0.280	-0.317	1.000					
Cflow	-0.104	-0.178	-0.182	0.694	1.000				
Load	0.021	0.475	-0.004	-0.099	-0.083	1.000			
Age	-0.216	-0.097	-0.552	0.354	0.284	-0.006	1.000		
LagReturn	0.031	0.024	0.006	0.037	0.025	0.015	-0.006	1.000	
Benchmark	-0.155	-0.329	-0.355	0.077	0.008	-0.142	0.262	-0.039	1.000