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Mutual funds' exits, financial crisis and Darwin

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ABSTRACT

It is recognized in the literature that there is a negative relationship between fund performance and fund exit. This paper analyses the performance of 6600 U.S. mutual funds that exited the market in the 2000–2014 period and nearly twice as many U.S. mutual funds that remained operational, to provide evidence on whether the negative exit – performance relationship existed during the 2008 financial crisis. We confirm the general relationship but show that, in contrast to all the other periods, there was no statistically significant exit – performance relationship during the financial crisis. We also show that the impact of expenses and loads on fund exit increased during the crisis. This is consistent with our argument that when some active investors leave the market, the passive ones become important to fund–families, albeit the investors may lose out as a result. We also show that the mergers that occurred in the years following the financial crisis resulted in statistically significantly worse post–merger performance of both the acquirers and of the targets in comparison with their pre–merger performance.

1. Introduction

The mutual fund market, like many markets, exhibits Darwinian forces that tend to remove weak performers and promote better ones. To keep current and to attract future mutual fund members, fund–families have incentives to open new funds as well as to close poor performing funds and transfer members (especially active ones) to better performing funds rather than see them leave to other fund–families. This ensures that the mutual fund industry remains attractive, competitive, and of benefit to investors (even, to a degree, for those investors who are not active or financially savvy). This effect is well documented (e.g. Carhart et al. 2002; Jayaraman et al. 2002; Zhao 2005; Khorana et al. 2007; Namvar and Phillips 2013; Park 2013). However, the argument depends on active investors moving within the market in response to signals. In a period when more active investors than usual are choosing to leave the mutual fund market and fund redemptions are high, this driver of the Darwinian argument is lost, and the Darwinian effect may be weakened or entirely absent. This paper explores this hypothesis by investigating the exit – performance relationship in a sample of the 6600 U.S. mutual funds that exited the market in the 2000–2014 period and a matched sample of surviving funds.

During the 2008 financial crisis a great number of investors left the market entirely and fund redemptions were abnormally high to meet this increase in exodus (Itzhak et al. 2011; Cella et al. 2013). As a result, the Darwinian story outlined above suggests that the exit – performance relationship that defines 'normal' periods should have been different during the financial crisis. We confirm this hypothesis by showing that the exit – performance relationship was strongly statistically significant before and after, but not during the financial crisis.

Furthermore, in periods when keeping active investors is harder, the importance of passive investors increases. To the extent that

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fee structure (notably load fees which tend to act as a transaction cost and expenses) affects the balance of active and passive investors in a fund (e.g. Morey 2003; Friesen and Sapp 2007; Houge and Wellman 2007), we should also expect that the impact of loads and expenses may be different during the financial crisis than in other periods. We show that this is indeed the case. Specifically, we find strong and robust evidence that during the financial crisis funds with back–end loads were less likely to exit the market, and that having a back–end load had a greater impact on reducing the probability of exit than having a front–end load. We also show that having back–end loads was more detrimental to stopping fund exits than the size of the back–end loads. The opposite was true for front–end loads. We also find that expenses had a much greater impact on the reduction of the probability of liquidations than mergers.

Moreover, to shed more light on the distortion of Darwinian forces, we analyze the pre– and post–merger performance of acquiring funds for mergers that took place during the financial crisis and outside of the financial crisis. If the decline of the exit – performance relationship during the financial crisis resulted in, on average, lower quality funds being present in the market at the end of the crisis period, then the mergers that took place at the start of the post–financial crisis period would likely be poorer than in other periods. We find strong evidence in support of the conjecture.

The results contribute to several strands of the literature. First, they contribute to the literature devoted to understanding mechanisms and practices of the mutual fund industry. It broadens our understanding of factors determining fund exits (e.g. Elton et al. 1996; Carhart et al. 2002; Jayaraman et al. 2002; Zhao 2005; Khorana et al. 2007; Namvar and Phillips 2013; Park 2013) and of specifics of fee structures (e.g. Ivković and Weisbenner 2009; Bailey et al. 2011; Cumming et al. 2019) by showing that their impact may change with market conditions.

Second, our findings expose yet another form of the conflict of interest between fund–families and investors. Numerous papers document that fund–families do not always act in the best interest of their investors (e.g. Najand and Prather 1999; Hillion and Suominen 2004; Cooper et al. 2005; Goriaev et al. 2008; Ortiz et al. 2012; Bucher–Koenen and Ziegelmeyer, 2013; Chalmers et al. 2013; Shirley and Stark 2016, Guiso and Viviano 2015; Grinblatt et al. 2015). We add to this strand of the literature by showing that during the financial crisis fund performance stopped being a statistically significant factor in determining fund exit.

Third, the paper contributes to the literature on the impact of the financial crisis on the business environment and practices. The literature concentrates on the link between the business environment and practices (e.g. Ivashina and Scharfstein 2010; Thakor 2012; DeYoung and Torna 2013; Brown and Petersen 2015; Homar and van Wijnbergen 2017; Chen et al. 2018), and the link between different corporate governance structures and practices (e.g. Erkens et al. 2012). This research shows that governance practices worsened during the financial crisis because fund–families did not act in the best interests of investors.[1]

Fourth, the research contributes to the growing literature on pension investments. As a result of the severe underfunding experienced by the defined–benefit pension industry[2] and the growing reliance on defined–contribution schemes,[3] the understanding of the mutual fund industry's investment strategies and ethical standards has become more important than ever. The U.S. mutual fund industry is the largest in the world with $17.71 trillion of assets under management in 2018.[4] It plays a major role in the U.S. pension market as 93% of the 56 million American households that invest in mutual funds use them as retirement savings (ICI, 2019). Given that differences in the performance – exit relationship at different times may have a material long–term impact on the state of retirement accounts of millions of Americans, our findings are of particular relevance.

Finally, the paper also contributes to the M&A literature. The M&A research is mainly focused on corporate issues (see Renneboog and Vansteenkiste 2019, for an excellent literature review) and less is known about M&A in the context of mutual funds. Yet the mutual fund industry, given its specifics (e.g. high frequency data in comparison with corporations, fund–family structure, etc.) can provide unique opportunities to understand the M&A decision making processes and effects. Even though it is recognized that returns on M&As vary with waves, and that the nature of M&As changed after the financial crisis (e.g. Grave et al. 2012), the impact of the financial crisis on the factors determining M&As and the post–merger performance is not well understood.

The results have broad regulatory implications. It is well documented that financial advice and regulatory protection is particularly important for not-so-financially savvy investors (e.g. Allen and Gale 1999; Bhattacharya et al. 2012; Inderst and Ottaviani 2012; Gaudecker, 2015; Guiso and Viviano 2015; Foerster et al. 2017; Bianchi 2018; Dahlquist et al. 2018). Our results strongly support this notion, and also suggest that the fee structure may work against the not so financially savvy investors by reducing fund–families incentives to close poorly performing funds, both of which highlight the importance of regulatory protection.

2. Related literature review and hypothesis development

2.1. Brief literature review

Mutual fund investors are a source of investment money and fees to the funds they invest in. Hence, any exodus of investors is unwelcome and mutual funds pay great attention to advertising their services to attract new investors and to maintain existing ones

[1] In the case of mutual funds, it is common to refer to their shareholders as investors. To stay consistent with this tradition we refer to mutual funds' shareholders as investors throughout the paper.

[2] According to the Federal Reserve Board, the funding gap of the state and local government pension funds in the U.S in 2016 was $8433 billion. https://www.federalreserve.gov/releases/z1/dataviz/pension/funding_status/table/

[3] More than 97 million Americans were covered by DC schemes in 2017 (Vanguard, 2018)

[4] https://www.statista.com/statistics/255518/mutual-fund-assets-held-by-investment-companies-in-the-united-states/

(e.g. Jain and Wu 2000; Aydogdu and Wellman 2011). But not all their efforts to attract/retain investors seem fair. There is considerable evidence that mutual funds misinform investors about their investment strategies, performance, and risks taken (e.g. Najand and Prather 1999; Hillion and Suominen 2004; Cooper et al. 2005; Ortiz et al. 2012; Shirley and Stark 2016). Moreover, mutual funds take advantage of investors' financial illiteracy by exploiting their low performance–fees sensitivity and low mobility (e.g. Christoffersen and Musto 2002; Houge and Wellman 2007; Gil–Bazo and Ruiz–Versy, 2009).

There is a substantial body of the literature that documents that poor performance is an important factor in determining mutual fund exits (e.g. Makadok and Walker 1996; Jain and Wu 2000; Jayaraman et al. 2002; Zhao 2005; Khorana et al. 2007; Rohleder et al. 2010; Wang and Huang 2013; Cogneau and Hübner 2015).[5] There is also evidence that funds with high 12b–1 (i.e. distribution and services fees) and management fees are liquidated more slowly than funds with low or no 12b–1 fees, and that funds with high 12b–1 and management fees are merged within the fund–family more quickly (e.g. Dukes et al. 2006; English et al., 2011). This suggests that the exit decisions may not always be driven by the best interest of investors (i.e. the quality of investment opportunities offered to them) but by how much fees they generate for the fund–family. Indeed, Evans et al. (2017) find evidence that at times fund–families may maximize the fund–family's fee revenues at the expense of investors who hold poorly performing funds. They do not, however, consider whether such behavior may be more pronounced under certain market conditions. Intuitively, one might suspect that some market conditions can create an environment more prone for mutual funds to take advantage of some investors.

There is convincing evidence that the financial crisis impacted the business environment and practices (e.g. Ivashina and Scharfstein 2010; Erkens et al. 2012; Carlson et al. 2013; DeYoung and Torna 2013; Flannery et al. 2013; Calomiris and Missim, 2014; Brown and Petersen 2015; Ritz and Walther 2015; Grout and Zalewska 2016; Homar and van Wijnbergen 2017; Rice and Rose 2016; Anginer et al. 2017; Chen et al. 2018; Huang et al. 2018), and that the propensity towards maintaining high ethical standards weakened during the financial crisis as it often does in periods of weak financial performance (Campbell 2007). Indeed, there is some evidence that corporations took advantage of informational opaqueness and chaos in the markets during the financial crisis (e.g. Fassin and Gosselin 2011; Harrison and Berman 2016). Yet, there does not seem to be much evidence on whether and how fund–families responded to the outflow of investors,[6] or how an outflow of investors may have affected fund exit decisions.

2.2. The basic intuition

To build our intuition of how market conditions impact fund–families' decisions of whether or not to exit poorly performing funds, let us assume that in a two–period world a profit–maximizing fund–family has two funds, A and B. The funds are run by different managers but have the same expectations with regard to their performance.[7] Let us also assume that both funds have the same proportion of active investors (i.e. investors sensitive to their fund performance and likely to move if they are dissatisfied with their fund's performance) and of passive investors (i.e. investors who stay with the fund regardless of its performance). Denote the proportion of the active investors by α. At the start of period 1, it is expected that funds A and B will deliver the same returns. At the end of period 1, the fund–family observes the performance of the funds before the information is released to investors. Let us assume that fund A performed as expected (i.e. it delivered the expected return), but fund B performed below expectation. The fund–family realizes that the active investors of fund A will be satisfied with the fund's performance and certain to invest in it in period 2. The fund–family also realizes that the active investors of fund B will be disappointed with the fund's performance and likely to withdraw their investments at the end of period 1. A small fraction of them may move to fund A. The remaining ones will move to other fund–families.

To increase the proportion of fund B's investors moving to fund A, the fund–family can merge fund B with fund A or liquidate it.[8] If fund B is merged with fund A, then all investors of fund B move to fund A. If it is liquidated, a fraction, larger than the one if the fund–family did not take any action, would move to fund A. To keep the explanation simple, both liquidations and mergers will be referred to as exits. Whether the fund–family prefers to exit funds or do nothing depends on the cost of exit relative to the loss in fees if they do nothing, which itself depends on the proportion of investors that are active.[9]

At one extreme, if all the investors in the funds are passive (i.e. $\alpha = 0$), then no investors would leave the funds. In this case, the fund–family would not be interested in exit, because the fund–family would incur the cost of exit with no gain in fees. At the other extreme, if all the investors in the funds are active ($\alpha = 1$), then the fund–family would lose almost all investors in fund B (and their fees) if they do not exit fund B from the market. In this case, the fees kept in the fund–family by choosing, say, to exit fund B and merge it with fund A, would be large relative to the cost of exit, so it is likely that the exit of fund B is the fund–family's best strategy. It follows that between these two extremes there will be a critical proportion, α’, of active investors. If the proportion of active investors is greater than α’, then it is optimal to exit fund B, but if the proportion of active investors is less than α’, then it makes sense to retain the two funds separately.

[5] It is also documented that funds' flows, age, size, and expense ratios play a role in determining mutual funds' exits (e.g. Brown and Goetzmann 1994; Elton et al. 1996; Jayaraman et al. 2002) so does the probability of managerial turnover (e.g. Bryant 2012).

[6] Cella et al. (2013) and Itzhak et al. (2011) document a substantial reduction of hedge and mutual fund portfolios due to redemptions.

[7] We assume that there are many fund–families like the one we consider.

[8] To ensure that some investors of fund B move to fund A, the fund–family could make considerable efforts to advertise fund A. The advertisement costs would be counted as part of the cost of exit.

[9] The cost of exit may not be purely direct financial costs. Fund board costs, business disruption costs, psychic costs, reputational issues, knock-on salary increases for those running larger funds, even behavioral aspects, are some of the many things that may enter in the calculus of an exit decision.

The above situation describes a market in which investors can find attractive, alternative investment opportunities if they are dissatisfied with the performance of fund *B*. But now, let us imagine that the market crashes and both funds perform worse than investors expected, although fund *A* still outperforms fund *B*. Let us assume that some active investors may leave the market entirely, i.e. the fund–family is aware that some active investors will leave the funds regardless of the fund–family's actions.[10] What effect does this have on the incentive to exit fund *B*? Imagine in the new situation that there are exactly α' active investors, i.e. the previous critical cut off point. At this point, if fund *B* exits, the costs of exit will have to be paid but the fees gained as a result is less because some of the active investors who would have stayed will now leave the market entirely. Hence, the cost of exit does not justify the fees gained at α'. The proportion of active investors, therefore, needs to be higher if exit is to provide enough 'saved' fees to cover the exit costs. The new critical level, call this α", will be higher than α'. The mathematical representation of the model is presented in Appendix 1.

2.3. Hypothesis development

In summary, the higher the proportion of active investors that leaves the market, all other things being equal, the more incentive fund–families have to 'milk' the remaining investors, i.e. the departure of active investors from the market reduces fund–families' incentives to exit poorly performing funds. This means that in times of active investors' outflow, the exit – performance relationship may be weaker than in times when incentives to keep active investors induce competition for active investors and keep the Darwinian forces at work. A weak exit – performance relationship may result from relatively better performing funds exiting the market (if they have a relatively high proportion of active investors) or poorly performing funds not exiting the market (if they have a relatively high proportion of passive investors).

The investor composition at fund level is unknown, but the past literature shows that the existence and form of loads and expenses convey some information about investors' financial literacy and passivity/activity. Less sophisticated investors are prone to choose funds that have loads (Morey 2003; Friesen and Sapp 2007; Houge and Wellman 2007). If so, funds with loads are more likely to have a higher proportion of passive investors than funds with low or no loads. Consequently, the existence of loads may be negatively associated with the probability of a fund's exit during a market crash.

It is also well documented that load size, and whether this is a front–end or back–end load, carries information about investors' sophistication (Ivković and Weisbenner 2009; Bailey et al. 2011; Cumming et al. 2019). If investors have already paid a front–end load, the decision to leave the fund does not generate any additional expense, unless one wishes to reinvest the money in another load–fund. However, if investors face a back–end load, the decision to leave means that this charge must be paid. Thus, one can conjecture that a decision whether to leave a fund or to stay will be more influenced by the existence of back–end loads than by front–end loads. Back–end loads imply, other things being equal, a smaller proportion of active investors, which as the previous sub–section suggests, makes exit less likely, particularly during a crisis period, since higher proportions of active investors are needed for exit to be the best strategy. Consequently, during a market crash we should observe a stronger negative relationship between the existence of back–end loads and the probability of exit than between the existence of front–end loads and the probability of exit. However, if the size of front–end loads is negatively correlated with investors' sophistication (e.g. Bailey et al. 2011), we should observe that there is a strong negative relationship between the quantum of the front–end loads and the probability of exit.

Loads may also contribute differently to how funds exit the market. One can assume that merge–or–liquidate decisions are complex, but if a fund–family considers a fund liquidation it may matter whether the fund has front–end or back–end loads. While liquidating a fund will result in losing the back–end loads of any remaining investors (hence the higher back–end loads, the lower probability of liquidation), front–end loads cannot be lost as they have already been paid. Thus, front–end loads may have lower explanatory power in explaining liquidation decisions than back–end loads.

It is well documented in the corporate literature that the post–merger performance of acquirers worsens in comparison with their pre–merger performance while the opposite is true for targets. The drop in the performance of acquirers is often attributed to their restructuring costs and/or cost of improving poorly performing targets. Similar conclusions have been drawn for the mutual fund industry (e.g. Khorana et al. 2007; Zhao 2005).

Therefore, if it is true that funds that exited the market during the financial crisis were relatively good performers, the impact of mergers that took place during the financial crisis might be less negative than the impact of mergers that took place outside the period of the financial crisis. In other words, one may expect that the weakening of the Darwinian forces during the financial crisis may have reduced the negative impact of mergers on the acquirers in comparison with the other periods.

Does this mean that it is good policy to leave poorly performing funds operational? The absence of a negative exit – performance relationship suggests that some fund families of poorly performing funds chose to let them 'sit back on the passive investors', having lost many of their active ones. As a result, the passive investors missed out on the chance of joining a better fund, either through merger or liquidation (in the latter case having to find another fund).

Moreover, the pool of funds left on the market was worse (on average) than if the Darwinian forces worked as 'normal'. Thus, after the financial crisis when the Darwinian forces strengthen and poorly performing funds start exiting the market, the mergers may be of poorer quality than they would be if the Darwinian forces worked during the financial markets. Thus, we conjecture that the

[10] This a plausible assumption as Johnson (2010) shows that some investors' decisions to sell/retain their holdings in current funds are driven by the existence of better investment opportunities rather than the poor performance. Schmidt et al. (2016) show that sophisticated investors redeemed more than unsophisticated ones in response to negative shocks to the fundamentals in September 2008.

performance of post–financial crisis mergers should be worse than the performance of mergers that took place in the other periods.

3. Data and methodology

Data about (i) 7814 funds that stopped operating between January 2000 and December 2014, and (ii) 10,887 funds that have not exited the market or were not the result of mergers between January 2000 and June 2015 was collected from the Centre for Research in Security Price (CRSP) Survivor–Bias Free U.S. Mutual Fund Database to create the base for the empirical analysis.[11] Before we discuss the properties of the sample, we specify non–crash and crash markets as these are fundamental for the organization and analysis of the data. We then discuss characteristics of the sample.

3.1. Non–crash and crash markets

It is important that the separation into crash and non–crash markets is objective in the sense that it is not based on characteristics of the mutual funds themselves. A crash market is more than just a bear market. It is a market of dramatic decline across a wide range of sectors, and is therefore a market of considerably reduced investment opportunities and greater outflow of investors. In contrast, a non–crash market offers a range of investment opportunities that are potentially attractive to investors.

During the 2000–2015 period, there were two prolonged periods of market index decline and two periods of market index growth. These, according to the lowest and the highest values of the market index were: January 2000 – March 2003, the decline following the burst of the dotcom bubble (referred to it as the post–dotcom decline), followed by the raising market of April 2003 – August 2007 (referred to as the pre–crisis period), which in turn is followed by the September 2007 – March 2009 period of the market's decline following the collapse of Lehman Brothers. This period is referred to as the financial crisis. The last period, April 2009 – December 2014, is the period of market recovery with an upward trending market index and is referred to as the post–financial crisis period. Below we compare the two periods of market decline and explain why we only consider the financial crisis as a market crash.

During the post–dotcom market decline, the S&P 500 index lost 40.7%, with the technology sector index declining 73.4%, but the tradable real estate index gaining 98.7%. The post–dotcom decline clearly separated high–tech and "old–economy" stocks, providing savvy investors with positive investment opportunities.[12] During the financial crisis, the market index lost 43.8%, but not a single sector index ended up with a positive return during that period. The heaviest losses were recorded for the financial sector (−66.6%), while the smallest losses were recorded for the tradable real estate sector (−21.8%). Bekaert et al. (2014) find strong evidence of domestic contagion during the financial crisis, but not during the bust of the dotcom bubble.

The severity of the financial crisis and its unique character in comparison with the post–dotcom decline is also visible in the changes in sentiment of the market as well as investors. At the start of the financial crisis in 2008, the Chicago Board Options Volatility Index (VIX) was already as high as at the highest peak of the post–dotcom decline period and in 2010 it hit an all–time high. The two periods also differ considerably in how much consumer confidence changed. According to Gros and Alcaide (2010), the U.S. Standardized Happiness Index (US–SHI) that measures consumer confidence declined from around 1 in 1999 to −0.5 in 2002 before it started to rise again. The same index declined from around 1 in 2006 to −3 in 2009 before it started to increase.[13] Numerous papers discuss the severity of the financial crisis, its unprecedented impact on the U.S. market and economy, and its distinguishing features in comparison with previous periods of market distress (e.g. Ivashina and Scharfstein 2010; Friewald et al. 2012; Cella et al. 2013; Jagannathan et al. 2013; Kahle and Stulz 2013; Bekaert et al. 2014; Loh and Stulz 2018).

Thus, given that during the financial crisis, in contrast to the other periods, investment opportunities were severely limited, we expect to observe that if any distortion of the Darwinian exit forces should be observed, it would be more likely to happen during the financial crisis than during the post–dotcom decline.

3.2. Sample of the exit funds

According to CRSP, 7814 mutual funds from 824 fund–families exited the market between January 2000 and December 2014.[14] This sample was screened for funds with incomplete information of monthly returns (only the primary classes were used in the analysis). A fund was removed from the sample if its time series of returns had two or more consecutive months missing. This filter

[11] There also is a small group of funds that were subject to across–family mergers. These were excluded from the analysis given that it can be expected that across–family merger decisions may depend considerably on the characteristics of the fund/fund–family that acquires an exiting fund, and as such are 'exogeneous' to the characteristic of the pre–merger fund–family.

[12] Grout and Zalewska (2006) document changes in market risk between the old and the new economy stocks during the dotcom bubble. Grout and Zalewska (2016) provide the discussion of the changes of market risk between financials, utilities and industrial stocks during the financial crisis.

[13] The Conference Board's Consumer Confidence Index reached its historically lowest level of 26 in early 2008. The lowest value of the index during the dotcom bubble correction was 61. The average value of the index for the 2003–2007 period was just above 100. Differences in consumer confidence and its co–movement with market indexes are discussed in Ferrer et al. (2016).

[14] Only liquidations and within–family mergers are used in the analysis. The information about the funds that exited the market through across–family mergers was also collected. However, given the insufficient number of across–family merger funds, they have been excluded from the analysis. The decision was further supported by the fact that performance is not a significant determinant of across–family mergers (Jayaraman et al. 2002).

was applied to ensure that the sample funds had return observations prior to their exit and to secure continuity of quarterly returns that are used in the analysis.

The way of exiting the market was not specified by CRSP for 1660 funds. Using the webpages of the U.S. Securities and Exchange Commission (SEC)[15] and of the Bloomberg Company Overview (BCO), the funds whose form of exit was not specified were manually checked. In this way, the form of exit was determined for an additional 824 funds. Thus, the final sample consists of 6600 exit funds of which 1140 exited in January 2000 – March 2003, 1604 in April 2003 – August 2007, 734 in September 2007 – March 2009, and 3122 in April 2009 – December 2014.

The previous literature documents that fund characteristics (e.g. age, size, etc.) play a role in determining whether funds exit the market or not. Therefore, to ensure that like–with–like funds were compared, the following information was collected for each exit fund: investment objective classification, age, size, flows and turnover ratio, expense ratio, front–end and back–end fees. The investment objectives were determined by the objective codes provided by CRSP. For each calendar month, a fund's age was calculated as the number of years that the fund was in operation. A fund's size was determined by the reported amount of its total net assets (in millions of U.S. dollars). A fund's flow was calculated as the difference between current-month fund size and the product of last–-month size and current–month net return, divided by last–month fund size, and a fund's turnover was corroborated as the minimum of aggregated sales or purchases of securities, divided by the average 12–month total net assets of the fund. These monthly statistics were used to calculate quarterly statistics. In the regression analysis, Age and Size were defined as averages of the corresponding monthly statistics within each quarter. Flows were defined as the cumulative quarterly flows and Turnover – as the quarterly–reported value of the turnover ratio. Expense, Load-f-e, Load-b-e and Load refer to quarterly values of the expense ratios, front–end loads, back–end loads and the sum of back–end and front–end loads, respectively. Moreover, for each fund three dummy variables were defined: $D_{\text{Load-b-e}}$ took the value of one if a fund had back–end loads and zero otherwise; $D_{\text{Load-f-e}}$ took value of one if a fund had front–end load, and zero otherwise; and D_{Load} took value of one if a fund charged back–end or front–end loads, and zero otherwise.[16] Returns were defined as cumulative quarterly returns of monthly net returns.[17]

In addition, two fund–family variables were defined. Fund–family size is the sum of the market values of the funds within the fund–family for every calendar month. Fund–family specialization is the ratio of the number of funds belonging to a given style over the total number of funds the fund–family provided for every calendar month. Again, these monthly statistics were used to calculate quarterly averages, which are referred to as FF-size and FF-spec, respectively.

Quarterly returns were adopted as the base for the analysis because a quarter is the shortest period of managerial performance (Ma et al. 2019). Quarterly returns also smooth away potential monthly 'spikes' in the data, and they automatically remove all funds that exited within the first couple of months of each period considered. This partially deals with the issue that if it takes a few months to implement an exit decision, the decision to exit funds that left the market at the start of each of the four periods would be taken outside the period in question. Removing the funds that exited within the first few months of each period increases the probability that the performance of and the decision to exit funds is period specific.

Table 1 shows the means, medians and standard deviations of the key variables except for the investment objectives (there are 56 investment objectives in the sample) for the whole period and for the four sub–periods. It shows that over the whole 2000–2015 period the mean and the median exit funds delivered 0.802% and 1.276% quarterly returns, respectively. They also were on average 9.4 years old and experienced negative flows. However, the separation into the four sub–periods shows a much more complex picture.

The comparison of the mean and the median Return shows that there are considerable differences between the periods of market growth and decline, and that the financial crisis was particularly tough. During the periods of market growth both the mean and median returns were positive, suggesting that the funds that exited the market did not necessarily lose money. The distributions of Return are skewed to the right during the periods of market growth. In contrast, they are skewed to the left during the periods of market decline. Yet, there are considerable differences between the post–dotcom decline and the financial crisis periods. The average fund that exited the market during the post–dotcom decline delivered a negative quarterly return of −1.568%, even though the median exit fund's return was still positive (0.686%). The financial crisis statistics show that the mean and the median returns of the exit funds were − 6.035% and − 4.034%, respectively. The financial crisis is the only period considered in this analysis that has a negative median return.

Table 1 also shows that the mean and the median Age of the exit funds increased over time. The mean (median) Age was 3.4 years (2.7 years) higher during the post–financial crisis period than during the post–dotcom decline period. The size of the exit funds has a different pattern. The mean Size of the exit funds was considerably larger during the periods of market growth than it was during the periods of market decline. This is, however, not confirmed for the medians. While the median Size was much bigger during the pre–financial crisis period ($26.9mln) than during the post–dotcom decline ($16.3mln) and the financial crisis ($11.1mln), the lowest median Size was in the post–financial crisis period ($9.3mln). Yet, in all the four periods Size was heavily skewed to the right. In contrast, the Flows variable was skewed to the left. Moreover, the magnitudes of the mean and the median Flows were largest during

[15] http://www.sec.gov/cgi–bin/srch–edgar

[16] We have also defined a load dummy based on a class share specification, i.e. D_{Load} was equal to one if fund's name had a suffix A, B or M and zero otherwise. Load was then defined as the value of the load as reported in CRSP when D_{Load} was one and zero otherwise. There are numerous issues with this definition of loads (e.g. institutional share classes, such as Y, I, K, Z etc. may charge limited loads, single–share do not include any share-class suffixes, etc.), so it is not discussed in the paper in detail, but some results are provided in Appendix 2.

[17] According to CRSP, monthly returns are calculated as a change in NAV including reinvested dividends from one period to the next. NAVs are net of all management expenses and 12b-fees.

Table 1
Descriptive statistics of the exit funds for the whole period and the four sub-periods. The statistics are based on all quarters within the period specified in the top row. Returns and flows are cumulative 3–monthly observations. Age is the number of years a fund was in operation at the end–month of each quarter. Size ($mln), FF-size ($bln) and FF-spec are the quarterly means of the corresponding statistics. Turnover, Expense, Load-f-e, Load-b-e and Load are the quarterly values of the turnover ratios, expense ratios, front–end loads, back–end loads and the sum of back–end and front–end loads, respectively. D_{Load} is a dummy indicating whether a fund has a load or not. $D_{Load\text{-}b\text{-}e}$, $D_{Load\text{-}f\text{-}e}$, are dummies indicating whether a fund has a back–end load or front–end load, respectively.

	1/2000–12/2014			1/2000–3/2003			4/2003–8/2007			9/2007–3/2009			4/2009–12/2014		
	Mean	Median	St dev	Mean	Median	St dev	Mean	Median	St dev.	Mean	Median	St dev.	Mean	Median	St dev.
Returns	0.802	1.276	9.113	−1.568	0.686	10.433	3.558	1.898	6.134	−6.035	−4.034	7.684	3.960	3.660	9.144
Age	9.371	7.671	7.911	6.940	6.082	5.428	9.426	7.671	7.452	9.063	8.507	6.040	10.315	8.838	8.332
Size	165.740	24.200	776.339	71.281	16.250	256.248	119.450	26.867	398.831	60.621	11.133	213.756	148.397	9.300	956.761
Flows	−1.632	−2.604	17.736	−3.113	−3.028	19.547	−3.300	−3.262	15.127	−6.336	−4.930	21.102	−4.430	−3.657	17.479
Turnover	0.966	0.640	1.106	1.107	0.800	1.178	0.963	0.660	0.980	1.136	0.780	1.330	0.914	0.570	1.109
Expense	1.374	1.300	1.145	1.395	1.300	0.689	1.434	1.320	0.751	1.393	1.325	0.693	1.296	1.260	0.736
Load	0.943	0.000	1.622	1.360	0.000	1.673	0.951	0.000	1.587	0.239	0.000	0.834	0.725	0.000	1.563
Load-b-e	0.463	0.000	1.389	0.545	0.000	1.429	0.428	0.000	1.323	0.080	0.000	0.576	0.455	0.000	1.405
Load-f-e	0.479	0.000	1.061	0.813	0.000	1.254	0.522	0.000	1.090	0.159	0.000	0.625	0.270	0.000	0.840
D_{Load}	0.298	0.000	0.457	0.459	0.000	0.498	0.320	0.000	0.467	0.092	0.000	0.289	0.210	0.000	0.408
$D_{load\text{-}b\text{-}e}$	0.124	0.000	0.329	0.158	0.000	0.365	0.128	0.000	0.335	0.028	0.000	0.166	0.114	0.000	0.318
$D_{load\text{-}f\text{-}e}$	0.185	0.000	0.388	0.309	0.000	0.462	0.215	0.000	0.411	0.064	0.000	0.244	0.101	0.000	0.302
FF-size	82.978	30.220	167.316	52.009	16.844	73.353	59.913	41.321	75.193	75.002	32.696	132.591	120.984	26.443	260.490
FF-spec	0.146	0.096	0.170	0.156	0.086	0.192	0.146	0.090	0.182	0.159	0.111	0.181	0.166	0.112	0.195
Funds	6600	6600	6600	1140	1140	1140	1604	1604	1604	734	734	734	3122	3122	3122
Obs	101,204	101,204	101,204	5234	5234	5234	10,095	10,095	10,095	1242	1242	1242	23,569	23,569	23,569

Table 2

Descriptive statistics of the surviving funds for the whole period and the four sub–periods. The statistics are based on all quarters within the period specified in the top row. Quarterly returns/flows are (not annualised) cumulative, percentage 3-month returns/flows. Age is the number of years a fund was in operation at the end-month of each quarter. Size ($mln), FF-size ($bln) and FF-spec are the quarterly means of the corresponding statistics. Turnover, Expense, Load-f-e, Load-b-e and Load are the quarterly values of the turnover ratios, expense ratios, front–end loads, back–end loads and the sum of back–end and front–end loads, respectively. D_{Load} is a dummy indicating whether a fund has a load or not. $D_{Load\text{-}b\text{-}e}$, $D_{Load\text{-}f\text{-}e}$, are dummies indicating whether a fund has a back–end load or front–end load, respectively.

	1/2000–12/2014			1/2000–3/2003			4/2003–8/2007			9/2007–3/2009			4/2009–12/2014		
	Mean	Median	St dev	Mean	Median	St dev	Mean	Median	St dev	Mean	Median	St dev	Mean	Median	St dev.
Returns	1.827	1.845	8.449	−0.991	0.789	9.656	3.390	2.127	5.494	−7.024	−4.837	9.449	3.307	2.709	7.865
Age	12.234	10.005	10.480	9.584	7.173	9.585	11.192	9.173	9.612	11.490	9.926	9.811	12.840	11.005	10.581
Size	994.44	137.07	4045.2	693.01	87.933	3069.2	823.93	112.20	3479.7	783.69	87.733	3496.4	955.14	116.53	4085.3
Flows	2.446	−0.492	18.658	2.940	−0.425	18.024	2.191	−0.691	17.744	0.848	−1.686	19.196	1.974	−0.696	19.024
Turnover	0.823	0.500	1.076	0.970	0.630	1.120	0.871	0.530	1.109	0.840	0.530	1.069	0.798	0.470	1.073
Expense	1.063	0.990	0.590	1.231	1.120	0.684	1.188	1.100	0.642	1.104	1.020	0.606	1.042	0.970	0.590
Load	0.915	0.000	1.405	1.253	0.000	1.644	0.996	0.000	1.502	0.887	0.000	1.444	0.796	0.000	1.332
Load-b-e	0.244	0.000	0.933	0.484	0.000	1.367	0.335	0.000	1.133	0.287	0.000	1.050	0.194	0.000	0.822
Load-f-e	0.668	0.000	1.184	0.762	0.000	1.238	0.658	0.000	1.177	0.599	0.000	1.141	0.600	0.000	1.144
D_{Load}	0.356	0.000	0.479	0.439	0.000	0.496	0.367	0.000	0.482	0.330	0.000	0.470	0.314	0.000	0.464
$D_{load\text{-}b\text{-}e}$	0.099	0.000	0.299	0.149	0.000	0.257	0.114	0.000	0.318	0.102	0.000	0.302	0.085	0.000	0.279
$D_{load\text{-}f\text{-}e}$	0.266	0.000	0.442	0.305	0.000	0.461	0.264	0.000	0.441	0.238	0.000	0.426	0.236	0.000	0.424
FF-size	171.30	40.173	310.72	92.265	45.168	157.05	128.15	44.338	228.14	158.501	38.310	287.11	192.99	37.736	350.53
FF-spec	0.144	0.092	0.174	0.138	0.083	0.167	0.132	0.086	0.151	0.139	0.094	0.162	0.151	0.099	0.183
Funds	10,499	10,499	10,499	7661	7661	7661	8011	8011	8011	9313	9313	9313	10,499	10,499	10,499
Obs	290,084	290,084	290,084	57,497	57,497	57,497	95,908	95,908	95,908	39,633	39,633	39,633	157,304	157,304	157,304

the financial crisis (−6.3% and − 4.9% respectively), but the second largest mean and median Flows were during the post–financial crisis period (−4.4% and − 3.6%, respectively). Flows observed for the post–dotcom decline period were comparable with those observed for the pre–financial crisis period. In contrast, the periods of market decline had much higher average and median Turnover than the periods of market growth. Yet, Turnover observed for the post–dotcom decline was comparable to the turnover observed for the financial crisis. Loads were lowest during the financial crisis. The lowest expenses were during the post–financial crisis period.

The FF-size statistics show that the average fund–family size increased over time, and that the FF-spec statistics were comparable across the four sub–periods considered.

3.3. Sample of the surviving funds

To assure that like–with–like funds were compared, funds were classified as surviving in a given period if they stayed operational for at least two quarters after a period in question ended. For example, for the funds that exited the market between January 2000 – March 2003 the surviving equivalent funds were defined as those that were operational between January 2000 – September 2003. Other definitions of the surviving funds are discussed in Section 4.3 Robustness tests. Table 2 shows the summary statistics for the samples of the surviving funds.

The statistics show that the surviving funds came from bigger and less specialized families, were on average older, bigger, had better cash flows and smaller turnover than the exit funds. Moreover, they had lower expenses than their exit counterparts. Yet, when it comes to the comparison of loads and returns, the picture is not that uniform.

The 2000–2014 statistics show that the surviving funds earned higher returns than the exit funds, but this is not necessarily true for the individual sub–periods. In fact, the exit funds earned lower returns than the surviving funds only during the post-dotcom decline period. Their front–end loads were bigger, except for the post–dotcom decline period, and the back–end loads were smaller except for the financial crisis period. The t–tests of the differences of the means of the exit and of the surviving samples are shown in Appendix 2 (Table A2.1). The statistics document considerable differences in the distributional properties of the exit and of the surviving samples.

To reduce the possibility that the results are driven by distributional differences across the populations, it is important to reduce differences across the covariates of the exit and the surviving samples. To do so, the nearest neighbor matching (NNM) with replacement was adopted.[18]

The NNM was tested for various specifications of how many nearest neighbors were considered, and what covariates should be used in the matching algorithm. The quality of the matching, and thus its suitability for further analysis, was assessed using the standardized differences in the means and the variance ratios of the initial and the matched samples. To satisfy the assumption of ignorability, i.e. that there are no unobserved differences between the exit and the surviving funds, conditional on observed covariates, the matching should be based on all variables known to be related to the fund performance and the decision of exit (Rubin and Thomas 1996; Heckman et al., 1998; Glazerman et al. 2003; Hill et al. 2004). Based on the past literature, fund size and age are associated with the performance and exit decisions (e.g. Jayaraman et al. 2002) and, therefore, were selected as the matching criteria. One can also expect that performance may be related to investment objectives as, for example, passive domestic equity funds may perform differently to, and/or face different demand than, active funds investing in emerging markets equity. Thus, funds were matched on their age, size, and investments objectives.

Fig. 1 shows the standardized differences in means (SDMs, Panel A) and the variance ratios (VRs, Panel B) for each sub–period, for each non–binary variable (i.e. Age and Size). The statistics show that the matching produced the SDMs close to zero for both Size and Age for all four sub–periods. There is also a considerable improvement in the VRs. All the after–matching VRs are within the expected range of 0.5–2 (Rubin 2001).

Table 3 shows the summary statistics of the core variables calculated for the exit and the surviving funds after matching. The matching reduced the differences across many variables, even those that were not used for matching (e.g. FF-size, FF-spec). Interestingly, the financial crisis is the only period for which the exit funds have a higher mean Return than the matched surviving funds.

3.4. Market risk factors

To assess any potential differences in the post– and the pre–acquisition performance of the acquirers and of their targets, we compared funds' alphas estimated from a multifactor risk model following Fung and Hsieh (1997). For this purpose, we collected data on the three Fama–French factors (Fama and French, 1992, 1993),[19] the U.S. Benchmark 10–year DataStream Government Bond total return index, JPMorgan Global Government Bond total return index and the S&P GSCI Gold total return index. The bond and gold indexes were downloaded from DataStream. The three Fama–French factors replaced the three equity market indexes (the domestic equity index, the developed markets' equity index and the emerging markets' equity index) used by Fung and Hsieh (1997). This was done to avoid the high correlation of the U.S. domestic and foreign equity indexes. Table A2.2 in Appendix 2 shows the summary statistics for the factors during the whole period and for the four sub–periods.

[18] We also adopted propensity score matching with the nearest neighbor matching and the propensity score matching with the kernel matching. We have not used them for further research as their matched samples had inferior properties in comparison with the matched sample produced by the simple nearest–neighbor matching.

[19] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

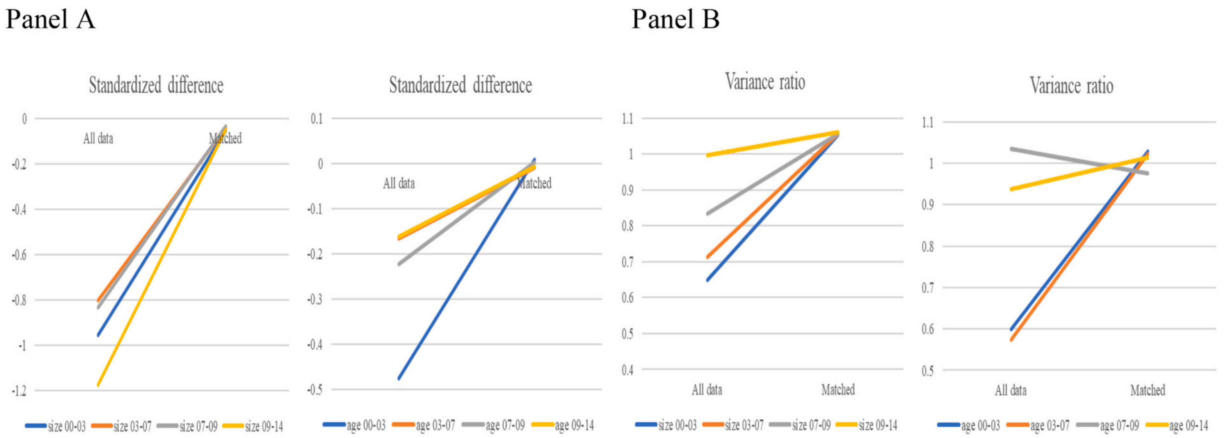

Fig. 1. Standardized differences in means (Panel A) and the variance ratios (Panel B) for the Nearest-Neighbor matching; matching by investment objectives, Age, and Size.

4. Results

4.1. Did the Darwinian forces weaken during the financial crisis?

To test whether the role of performance in explaining mutual funds' exits weakened during the financial crisis logit regressions we adopted in which the dependent variables took value of one for the exit funds and zero for the surviving funds. All regressions control for fund age, size, flows, turnover, expenses, fund–family size, and specialization. They differ in how loads are accounted for. All regressions have the investment objective dummies and time dummies and are clustered by investment objectives.

Table 4 Panel A shows marginal effects obtained from the regressions when the dummy D_{Load} was used to control for whether funds had loads.[20] Table 4 Panel B shows results for the regressions that replaced the D_{Load} dummy with the values of loads (Load). The first column of Table 4 shows the results for the 2000–2014 period. The following four columns show the results for the four sub–periods separately (columns 2–5).

To start with Table 4 Panel A, the results confirm what has been known from the literature, i.e. funds' returns and flows covary negatively with the probability of exit, and that funds with higher turnover and expenses are more likely to exit the market. Moreover, load–funds are less likely to exit the market.

The individual sub–period regressions show that the marginal effects estimated for Return remain negative and highly statistically significant for the post–dotcom decline, the pre–crisis and the post–crisis periods. However, the financial crisis marginal effects are statistically insignificant confirming the hypothesis that the significance of performance in determining fund exits declined during the financial crisis. Interestingly, the other two variables of interest, i.e. expenses and loads, are also statistically significant during the financial crisis. The financial crisis is the only sub–period for which the marginal effects of Expense are statistically significant. Their negative sign indicates that funds with higher expenses were less likely to exit the market. If higher expenses are associated with passive investors, the result is consistent with our conjecture that funds with passive investors were less likely to exit the market during the financial crisis. The marginal effect of D_{Load} is also highly statistically significant for the financial crisis period, and although the marginal effect of the post financial crisis period is also statistically significantly negative, the financial crisis' marginal effect is over four times greater.

Table 4 Panel B confirms the exit – performance relationship findings of Table 4 Panel A: all marginal effects are negative and highly statistically significant except the one for the financial crisis. In contrast, the marginal effects of Expense and Load are highly statistically significant only for the financial crisis period. Both are negative which is consistent with the conjecture that higher loads and expenses are associated with greater passivity of investors which in turn would reduce funds' probability of exit during the financial crisis.

We have conjectured that because previous research shows that investors' sophistication is related to what load contracts they enter, it may be informative to test whether the probability of fund exits covaries differently with front–end and back–end loads.

Table 5 shows the marginal effects of regression specifications similar to those presented in Table 4, but this time the D_{Load} dummy was replaced by two dummies, $D_{Load\text{-}b\text{-}e}$ and $D_{Load\text{-}f\text{-}e}$ (Panel A), and the Load variable was replaced by Load-b-e and Load-f-e (Panel B).

Table 5 confirms that the exit – performance relationship was strong in all the periods except during the financial crisis. It also

[20] Appendix 2 (Table A2.3) shows the equivalent table obtained for the alternative definition of loads as defined in Footnote 16. They strongly confirm the main hypothesis of the exit – performance weakening during the financial crisis. It also supports the hypothesis that the role of expenses and fees changes during the financial crisis. The changes in sign of loads are likely to be the consequence of classifying many load funds as no load funds.

Table 3
Descriptive statistics of the exit and of the surviving funds determined by the Nearest–Neighbor matching for the whole period and the four sub–periods specified in the top row. The exit funds are defined by the periods specified in the top row. The matching funds were selected from the funds that remained operational for at least two quarters after the end of period specified in the top row. The matching is by Size, Age, and investment objective. Returns and flows are cumulative 3–monthly observations. Age is the number of years a fund was in operation at the end-month of each quarter. Size ($mln), FF-size ($bln) and FF-spec are the quarterly means of the corresponding statistics. Turnover, Expense, Load-f-e, Load-b-e and Load are the quarterly values of the turnover ratios, expense ratios, front–end loads, back–end loads and the sum of back–end and front–end loads, respectively. D_{Load} is a dummy indicating whether a fund has a load or not. $D_{Load\text{-}b\text{-}e}$, $D_{Load\text{-}f\text{-}e}$, are dummies indicating whether a fund has a back–end load or front–end load, respectively.

		1/2000–12/2014		1/2000–3/2003		4/2003–8/2007		9/2007–3/2009		4/2009–12/2014	
		Exit	Surviving	Exit	Surviving	Exit	Surviving	Exit	Surviving	Exit	Surviving
Returns	Mean	0.758	1.271	−1.560	−0.657	3.604	3.853	−5.478	−5.304	4.056	4.317
	Median	1.300	1.565	0.701	1.098	1.961	2.135	−3.366	−2.831	3.726	3.903
	St Dev.	9.325	9.010	10.500	9.680	6.225	6.196	7.279	7.747	9.264	9.098
Age	Mean	9.051	9.880	6.923	7.024	8.693	8.978	9.007	9.036	9.803	10.372
	Median	7.175	7.838	6.167	6.167	7.088	7.334	8.258	8.090	7.753	8.255
	St Dev.	7.875	8.830	5.274	5.765	6.397	6.629	6.362	6.676	8.274	9.026
Size	Mean	163.80	170.76	63.149	64.134	105.62	98.902	48.051	61.388	189.24	184.24
	Median	24.567	30.267	16.333	16.300	26.733	24.067	9.400	9.017	10.000	12.600
	St Dev.	754.35	962.44	167.08	158.91	299.57	283.89	171.94	344.53	1168.1	1596.4
Flows	Mean	−1.279	1.440	−3.053	2.488	−3.373	1.076	−6.817	0.276	−3.584	1.087
	Median	−2.417	−1.232	−3.058	−0.708	−3.192	−1.272	−5.744	−2.596	−3.189	−1.467
	St Dev.	18.205	19.790	19.483	21.640	15.181	19.228	23.166	23.186	17.498	21.131
Turnover	Mean	1.012	0.941	1.109	1.055	0.979	0.958	1.120	1.029	0.978	0.911
	Median	0.680	0.610	0.790	0.710	0.680	0.660	0.770	0.650	0.590	0.580
	St Dev.	1.139	1.124	1.186	1.150	1.002	1.060	1.250	1.218	1.199	1.149
Expense	Mean	1.355	1.297	1.399	1.400	1.425	1.395	1.391	1.444	1.279	1.280
	Median	1.270	1.240	1.300	1.300	1.330	1.330	1.440	1.480	1.240	1.210
	St Dev.	0.749	0.646	0.696	0.709	0.725	0.644	0.577	0.634	0.781	0.685
Load	Mean	1.241	1.109	1.392	1.309	1.243	0.958	0.298	0.775	1.070	0.869
	Median	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	St Dev.	1.769	1.585	1.680	1.681	1.713	1.498	0.936	1.408	1.797	1.469
Load-b-e	Mean	0.628	0.524	0.559	0.616	0.557	0.401	0.124	0.416	0.678	0.412
	Median	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	St Dev.	1.584	1.354	1.446	1.454	1.489	1.210	0.726	1.189	1.665	1.213
Load-f-e	Mean	0.611	0.584	0.830	0.687	0.684	0.554	0.173	0.359	0.392	0.457

(*continued on next page*)

Table 3 (*continued*)

		1/2000–12/2014		1/2000–3/2003		4/2003–8/2007		9/2007–3/2009		4/2009–12/2014	
	Median	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	St Dev.	1.165	1.120	1.262	1.198	1.203	1.098	0.626	0.928	0.989	1.024
D_{Load}	Mean	0.390	0.412	0.469	0.462	0.415	0.362	0.115	0.310	0.311	0.327
	Median	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	St Dev.	0.488	0.492	0.499	0.499	0.493	0.481	0.319	0.463	0.463	0.469
$D_{Load\text{-}b\text{-}e}$	Mean	0.168	0.191	0.163	0.221	0.166	0.147	0.041	0.173	0.171	0.154
	Median	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	St Dev.	0.374	0.393	0.369	0.415	0.372	0.354	0.197	0.379	0.377	0.361
$D_{Load\text{-}f\text{-}e}$	Mean	0.236	0.240	0.315	0.288	0.282	0.236	0.075	0.145	0.148	0.179
	Median	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	St Dev.	0.425	0.427	0.465	0.453	0.450	0.425	0.263	0.352	0.355	0.384
FF-size	Mean	81.678	95.085	52.507	61.460	60.423	75.188	57.252	107.47	129.15	129.82
	Median	28.694	20.522	17.232	17.232	35.512	18.832	22.004	30.220	26.443	24.480
	St Dev.	174.16	212.89	73.959	125.95	82.879	157.70	81.377	225.46	286.22	281.15
FF-spec	Mean	0.150	0.155	0.153	0.161	0.154	0.154	0.148	0.134	0.173	0.162
	Median	0.097	0.103	0.086	0.093	0.087	0.100	0.111	0.097	0.115	0.109
	St Dev.	0.179	0.172	0.188	0.188	0.197	0.168	0.171	0.154	0.202	0.185
Funds		4445	2360	1017	740	1136	883	420	357	1885	1357
Obs.		66,537	43,430	5079	4250	7361	6463	768	710	15,340	11,705

Table 4

Marginal effects of logit regressions clustered by investment objectives after matching by Age, Size and investment style. The dependent variable is equal to one for every quarter for funds that exited within the window specified at the top of the columns, and it is equal to zero for every quarter for funds that have not exited the market before the end of the periods as specified at the top of the columns. Returns and flows are cumulative 3–monthly observations. Age is the number of years a fund was in operation at the end–month of current quarter. Size, FF-size and FF-spec are quarterly means. Turnover and Expense are the quarterly values of the turnover ratios and expense ratios, respectively. D_{Load}, is a dummy indicating whether a fund has a load or not. Load is the load value. All regressions have time and investment style fixed effects. P–values are shown in brackets. *** - 1% statistical significance, ** - 5% statistical significance, * - 10% statistical significance.

	1/2000–12/2014	1/2000–3/2003	4/2003–8/2007	9/2007–3/2009	4/2009–12/2014
Panel A					
Return	−0.107***	−0.201***	−0.348***	−0.127	−0.080**
	(0.000)	(0.000)	(0.000)	(0.342)	(0.020)
Flow	−0.194***	−0.312***	−0.398***	−0.456***	−0.301***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	−0.006	−0.003	0.005	−0.003	−0.002
	(0.105)	(0.516)	(0.294)	(0.731)	(0.558)
Age	−0.001	−0.002*	−0.003**	−0.000	−0.001
	(0.184)	(0.082)	(0.015)	(0.848)	(0.271)
Turnover	0.016***	0.022	0.006	0.005	0.015
	(0.010)	(0.189)	(0.591)	(0.842)	(0.182)
Expense	2.341*	−2.390	−0.741	−8.614**	−1.907
	(0.087)	(0.461)	(0.811)	(0.027)	(0.283)
FF-size	0.008	−0.021***	−0.016	−0.014	0.011*
	(0.123)	(0.010)	(0.162)	(0.441)	(0.068)
FF-spec	−0.052	−0.252	−0.106	−0.119	0.153
	(0.435)	(0.102)	(0.597)	(0.537)	(0.141)
D_{Load}	−0.077***	0.016	0.007	−0.322***	−0.077**
	(0.001)	(0.551)	(0.815)	(0.000)	(0.012)
Pseudo-R^2	0.0187	0.0266	0.0214	0.0940	0.0232
Obs.	100,821	9323	11,578	1420	24,681
Panel B					
Return	−0.104***	−0.200***	−0.349***	−0.079	−0.079**
	(0.000)	(0.000)	(0.000)	(0.557)	(0.019)
Flow	−0.199***	−0.309***	−0.399***	−0.426***	−0.307***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	−0.006*	−0.002	0.005	−0.007	−0.003
	(0.081)	(0.691)	(0.314)	(0.511)	(0.470)
Age	−0.002*	−0.002*	−0.004**	0.001	−0.001
	(0.089)	(0.066)	(0.011)	(0.722)	(0.182)
Turnover	0.017***	0.020	0.006	0.004	0.015
	(0.007)	(0.224)	(0.580)	(0.870)	(0.166)
Expense	1.118	−2.563	−0.824	−10.111***	−2.962*
	(0.384)	(0.430)	(0.782)	(0.008)	(0.083)
FF-size	0.007	−0.021***	−0.016	−0.014	0.010*
	(0.220)	(0.008)	(0.153)	(0.467)	(0.093)
FF-spec	−0.044	−0.244	−0.104	−0.107	0.157
	(0.508)	(0.125)	(0.601)	(0.606)	(0.128)
Load	−0.850	1.006	0.911	−14.171***	−1.110
	(0.272)	(0.140)	(0.395)	(0.001)	(0.344)
Pseudo-R^2	0.0155	0.0267	0.0215	0.0885	0.0206
Obs.	100,821	9323	11,578	1420	24,681

shows that the financial crisis was the only period during which funds with higher expense ratios, back–end loads and front–end loads were less likely to exit. Table 5 Panel A shows that the marginal effect of $D_{Load\text{-}b\text{-}e}$ is −0.385 (statistically significant at 1%) whereas the marginal effect of $D_{Load\text{-}f\text{-}e}$ is −0.236 (statistically significant at 5%). Thus, having a back–end load created a stronger barrier to exit than having a front–end load.

The importance of loads in reducing the probability of exit is also confirmed by the negative and statistically significant coefficients of Load-b-e and Load-f-e (Table 5 Panel B). The results show that the relative size of the front–end loads played a bigger role in reducing the probability of exits than the size of the back–end loads. This is consistent with evidence documented in the literature that the size of front–end loads is positively associated with investors' financial unsavvy. That is, it is not just having front–end loads that matters but also how big they are. The effect is opposite for back–end loads. It is more important that back–end loads simply exist than how big they are. This is further magnified by the fact that back–end loads are smaller than the front–end loads.

To complete the discussion, Tables 6 and 7 show the equivalent results to those presented in Table 5 but for liquidations and mergers, respectively. Both tables confirm that there was no statistically significant exit – performance relationship during the financial crisis while it was strong in all other sub–periods. Moreover, although the results are statistically insignificant, the marginal

Table 5

Marginal effects of logit regressions clustered by investment objectives after matching by Age, Size and investment style. The dependent variable is equal to one for every quarter for funds that exited within the window specified at the top of the columns, and it is equal to zero for every quarter for funds that have not exited the market before the end of the periods as specified at the top of the columns. Returns and flows are cumulative 3–monthly observations. Age is the number of years a fund was in operation at the end–month of current quarter. Size, FF-size and FF-spec are quarterly means. Turnover and Expense are the quarterly values of the turnover ratios and expense ratios, respectively. $D_{Load\text{-}b\text{-}e}$, $D_{Load\text{-}f\text{-}e}$, are dummies indicating whether a fund has a back–end load or front–end load, respectively. Load-b-e, Load-f-e, are values of back–end load and front–end load, respectively. All regressions have time and investment style fixed effects P–values are shown in brackets. *** - 1% statistical significance, ** - 5% statistical significance, * - 10% statistical significance.

	1/2000–12/2014	1/2000–3/2003	4/2003–8/2007	9/2007–3/2009	4/2009–12/2014
Panel A					
Return	−0.107***	−0.185***	−0.348***	−0.131	−0.074**
	(0.000)	(0.000)	(0.000)	(0.326)	(0.025)
Flow	−0.199***	−0.309***	−0.399***	−0.470***	−0.326***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	−0.011***	−0.004	0.005	−0.003	−0.008**
	(0.002)	(0.542)	(0.316)	(0.676)	(0.038)
Age	−0.002***	−0.002	−0.004***	−0.001	−0.002*
	(0.001)	(0.254)	(0.009)	(0.687)	(0.099)
Turnover	0.013**	0.021	0.006	0.012	0.014
	(0.046)	(0.223)	(0.553)	(0.695)	(0.167)
Expense	5.561***	0.218	−0.773	−6.013*	−0.862
	(0.001)	(0.950)	(0.813)	(0.097)	(0.627)
FF-size	0.014**	−0.018**	−0.016	−0.015	0.017**
	(0.012)	(0.020)	(0.152)	(0.421)	(0.012)
FF-spec	−0.002	−0.246	−0.104	−0.117	0.214*
	(0.974)	(0.119)	(0.602)	(0.536)	(0.058)
$D_{Load\text{-}b\text{-}e}$	−0.127***	−0.084	−0.009	−0.385***	−0.028
	(0.000)	(0.300)	(0.863)	(0.000)	(0.535)
$D_{Load\text{-}f\text{-}e}$	−0.021	0.009	0.041*	−0.236**	−0.039
	(0.339)	(0.719)	(0.100)	(0.024)	(0.210)
Pseudo-R^2	0.0229	0.0315	0.0220	0.0979	0.0229
Obs.	109,543	8488	11,578	1465	26,693
Panel B					
Return	−0.103***	−0.188***	−0.348***	−0.115	−0.077**
	(0.000)	(0.000)	(0.000)	(0.353)	(0.017)
Flow	−0.198***	−0.323***	−0.399***	−0.473***	−0.312***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	−0.012***	−0.002	0.005	−0.006	−0.007*
	(0.001)	(0.751)	(0.313)	(0.471)	(0.059)
Age	−0.002***	−0.004***	−0.004**	0.000	−0.002*
	(0.001)	(0.000)	(0.012)	(0.877)	(0.050)
Turnover	0.015**	0.017	0.006	0.010	0.015
	(0.016)	(0.307)	(0.584)	(0.730)	(0.139)
Expense	1.732	1.040	−0.681	−9.271**	−3.224**
	(0.205)	(0.772)	(0.837)	(0.012)	(0.043)
FF-size	0.009*	−0.017**	−0.016	−0.015	0.013**
	(0.074)	(0.026)	(0.162)	(0.426)	(0.045)
FF-spec	0.003	−0.210	−0.104	−0.103	0.206*
	(0.961)	(0.151)	(0.602)	(0.607)	(0.062)
Load-b-e	−0.087	−0.176	0.109	−8.192***	2.002
	(0.924)	(0.890)	(0.981)	(0.005)	(0.132)
Load-f-e	0.700	2.237*	0.987	−10.648**	−0.354
	(0.382)	(0.068)	(0.350)	(0.014)	(0.769)
Pseudo-R^2	0.0180	0.0308	0.0215	0.0819	0.0242
Obs.	109,543	8488	11,578	1465	26,693

effects estimated for Return in the merger sample (Table 7) are positive.

The results also indicate differences in the role played by expenses, back–end loads and front–end loads in explaining the form of exit. Liquidations, even if they result in some investors staying with the fund–family, are likely to be associated with a larger decline in the numbers of investors than if a fund is merged with another (typically better performing) fund. Following from this, the intuition suggests that fund–families may be more sensitive to giving up any potential future fees (i.e. expenses and back–end loads) that they would be entitled to if a fund stayed operational than to the fees that have already been collected (front–end loads) when making liquidation decisions. This is congruent with the results presented in Table 6 which show that several marginal effects estimated for Expense are statistically significantly negative, and those estimated for the financial crisis are larger than for the other periods.

Table 6
Marginal effects of logit regressions clustered by investment objectives after matching by Age, Size and investment style. The dependent variable is equal to one for every quarter for funds that exited the market through liquidations within the window specified at the top of the columns, and it is equal to zero for every quarter for funds that have not exited the market before the end of the periods as specified at the top of the columns. Returns and flows are cumulative 3–monthly observations. Age is the number of years a fund was in operation at the end–month of current quarter. Size, FF-size and FF-spec are quarterly means. Turnover and Expense are the quarterly values of the turnover ratios and expense ratios, respectively. $D_{Load\text{-}b\text{-}e}$, $D_{Load\text{-}f\text{-}e}$, are dummies indicating whether a fund has a back–end load or front–end load, respectively. Load-b-e, Load-f-e, are values of a back–end load and front–end load, respectively. All regressions have time and investment style fixed effects. P–values are shown in brackets. *** - 1% statistical significance, ** - 5% statistical significance, * - 10% statistical significance.

	1/2000–12/2014	1/2000–3/2003	4/2003–8/2007	9/2007–3/2009	4/2009–12/2014
Panel A					
Return	−0.122***	−0.166***	−0.392***	−0.143	−0.111**
	(0.000)	(0.000)	(0.000)	(0.518)	(0.047)
Flow	−0.215***	−0.241***	−0.397***	−0.561***	−0.284***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.004	−0.001	0.007	−0.040***	0.004
	(0.261)	(0.916)	(0.540)	(0.009)	(0.373)
Age	−0.003	−0.008*	−0.004	−0.005	−0.004
	(0.247)	(0.073)	(0.241)	(0.242)	(0.139)
Turnover	0.015	0.025	−0.009	0.049**	0.027
	(0.145)	(0.212)	(0.563)	(0.029)	(0.121)
Expense	−1.859	−4.544	−13.440***	−16.760**	−4.451
	(0.349)	(0.243)	(0.001)	(0.012)	(0.216)
FF-size	−0.015**	−0.063***	−0.058***	−0.024	−0.002
	(0.017)	(0.000)	(0.000)	(0.294)	(0.812)
FF-spec	−0.010	−0.343**	0.126	0.099	0.085
	(0.878)	(0.015)	(0.418)	(0.716)	(0.372)
$D_{Load\text{-}b\text{-}e}$	−0.224***	−0.301***	−0.070	−0.250*	−0.101
	(0.000)	(0.006)	(0.435)	(0.084)	(0.188)
$D_{Load\text{-}f\text{-}e}$	−0.015	−0.075*	0.044	0.071	−0.060
	(0.755)	(0.090)	(0.604)	(0.620)	(0.308)
Pseudo-R2	0.0431	0.137	0.158	0.149	0.0382
Observations	37,577	3213	3747	541	12,745
Panel B					
Return	−0.121***	−0.159***	−0.396***	−0.138	−0.112**
	(0.000)	(0.000)	(0.000)	(0.527)	(0.039)
Flow	−0.225***	−0.255***	−0.398***	−0.558***	−0.285***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.004	0.001	0.007	−0.038***	0.005
	(0.258)	(0.944)	(0.535)	(0.009)	(0.314)
Age	−0.002	−0.008*	−0.003	−0.005	−0.004
	(0.467)	(0.089)	(0.282)	(0.247)	(0.130)
Turnover	0.017	0.029	−0.009	0.048**	0.030*
	(0.102)	(0.143)	(0.573)	(0.028)	(0.096)
Expense	−4.557*	−6.580*	−14.085***	−16.471**	−6.498
	(0.060)	(0.078)	(0.001)	(0.013)	(0.105)
FF-size	−0.019***	−0.067***	−0.059***	−0.023	−0.004
	(0.004)	(0.000)	(0.000)	(0.321)	(0.667)
FF-spec	−0.001	−0.351**	0.126	0.099	0.089
	(0.989)	(0.015)	(0.407)	(0.726)	(0.355)
Load-b-e	−2.877	−9.505	0.247	−24.118*	1.735
	(0.421)	(0.140)	(0.977)	(0.075)	(0.651)
Load-f-e	0.246	−1.425	0.962	3.388	−1.477
	(0.883)	(0.489)	(0.820)	(0.595)	(0.440)
Pseudo-R2	0.0331	0.122	0.156	0.152	0.0364
Observations	37,577	3213	3747	541	12,745

Table 6 also confirms that the relationship between the probability of liquidation and back–end loads is much stronger than between the probability of liquidation and front–end loads.

Interestingly, Table 7 shows that expenses are much less important in explaining merger decisions than they are in the case of liquidations. This is consistent with the notion that when investors of a merged fund are 'transferred' to an acquirer, they will still pay expenses. The significance and size of the marginal effects estimated for the back–end and the front–end loads are consistent with the arguments and evidence presented in Table 5.

Table 7

Marginal effects of logit regressions clustered by investment objectives after matching by Age, Size and investment style. The dependent variable is equal to one for every quarter for funds that exited the market through merger within the window specified at the top of the columns, and it is equal to zero for every quarter for funds that have not exited the market before the end of the periods as specified at the top of the columns. Returns and flows are cumulative 3–monthly observations. Age is the number of years a fund was in operation at the end–month of current quarter. Size, FF-size and FF-spec are quarterly means. Turnover and Expense are the quarterly values of the turnover ratios and expense ratios, respectively. $D_{Load\text{-}b\text{-}e}$, $D_{Load\text{-}f\text{-}e}$, are dummies indicating whether a fund has a back–end load or front–end load, respectively. Load-b-e, Load-f-e, are values of a back–end load and front–end load, respectively. All regressions have time and investment style fixed effects. P–values are shown in brackets. *** - 1% statistical significance, ** - 5% statistical significance, * - 10% statistical significance.

	1/2000–12/2014	1/2000–3/2003	4/2003–8/2007	9/2007–3/2009	4/2009–12/2014
Panel A					
Return	−0.082***	−0.218***	−0.355***	0.042	−0.059*
	(0.000)	(0.000)	(0.000)	(0.848)	(0.065)
Flow	−0.138***	−0.320***	−0.297***	−0.340***	−0.333***
	(0.000)	(0.000)	(0.000)	(0.009)	(0.000)
Size	−0.002	−0.005	0.006	0.016*	−0.004
	(0.647)	(0.263)	(0.428)	(0.091)	(0.646)
Age	−0.002**	−0.001	−0.003*	0.002	−0.002
	(0.024)	(0.402)	(0.096)	(0.401)	(0.173)
Turnover	0.010	0.031*	0.009	−0.077***	−0.008
	(0.226)	(0.066)	(0.626)	(0.010)	(0.445)
Expense	12.887***	4.658	5.976	0.532	5.350
	(0.000)	(0.368)	(0.213)	(0.905)	(0.208)
FF-size	0.036***	0.018	0.021	−0.006	0.030***
	(0.000)	(0.164)	(0.156)	(0.811)	(0.001)
FF-spec	−0.205**	−0.127	−0.595***	−0.512	0.272
	(0.038)	(0.580)	(0.005)	(0.268)	(0.252)
$D_{Load\text{-}b\text{-}e}$	−0.251***	−0.054	0.005	−0.621***	−0.106**
	(0.000)	(0.350)	(0.947)	(0.000)	(0.025)
$D_{Load\text{-}f\text{-}e}$	−0.011	0.042	0.022	−0.415**	−0.025
	(0.637)	(0.283)	(0.513)	(0.020)	(0.571)
Pseudo-R2	0.0443	0.0314	0.0524	0.140	0.0236
Observations	67,870	6192	8055	889	13,824
Panel B					
Return	−0.075***	−0.215***	−0.355***	0.100	−0.061*
	(0.000)	(0.000)	(0.000)	(0.551)	(0.054)
Flow	−0.147***	−0.312***	−0.298***	−0.334***	−0.330***
	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)
Size	−0.002	−0.005	0.006	0.016	−0.003
	(0.613)	(0.275)	(0.424)	(0.138)	(0.663)
Age	−0.001*	−0.001	−0.003	0.003	−0.001
	(0.066)	(0.337)	(0.101)	(0.155)	(0.194)
Turnover	0.009	0.032*	0.009	−0.077**	−0.007
	(0.234)	(0.066)	(0.643)	(0.013)	(0.478)
Expense	9.882***	1.219	6.256	−2.370	2.154
	(0.000)	(0.797)	(0.192)	(0.606)	(0.614)
FF-size	0.033***	0.016	0.021	−0.010	0.025***
	(0.000)	(0.230)	(0.150)	(0.710)	(0.003)
FF-spec	−0.210**	−0.126	−0.596***	−0.616	0.270
	(0.030)	(0.598)	(0.006)	(0.194)	(0.247)
Load-b-e	−9.039***	1.368	0.144	−13.718**	−0.255
	(0.000)	(0.295)	(0.980)	(0.040)	(0.856)
Load-f-e	0.533	3.343*	0.684	−20.440**	0.215
	(0.563)	(0.055)	(0.594)	(0.016)	(0.895)
Pseudo-R^2	0.0377	0.0338	0.0523	0.123	0.0203
Obs.	67,870	6192	8055	889	13,824

4.2. Darwinian forces and post-merger performance

Our results in Section 4.1. document that some of the poorer performing funds that would normally have exited during the financial crisis period did not do so because the Darwinian forces were not strong enough. This suggests that on average the quality of the pool of funds at the end of the crisis period would have been worse than if the conventional Darwinian processes had occurred. If this is true one might conjecture that the mergers at the start of the post–financial crisis period would be poorer than in other periods,

Table 8

The alpha estimates from the six-factor model for the target funds and their acquirers for year one (−1), year two (−2) before the merger and year one (1) and year two (2) after the merger, as well as *t*-tests for the significance of their differences. The periods of mergers are indicated in bold headings. *P*-values are in brackets. *** - 1% statistical significance, ** - 5% statistical significance, * - 10% statistical significance.

	−2	−1	1	2	1-(−1)	2-(−1)	1- (−1)	2-(−1)
2000–2014								
Target	−0.106	−0.124						
Acquirer	−0.015	−0.045	−0.088	−0.094				
Acquirer–Target	0.091***	0.078***					0.026	0.024
	(0.000)	(0.000)					(0.246)	(−0.302)
Acquirer - Acquirer					−0.049**	−0.052**		
					(0.033)	(0.028)		
Obs.	2076	2238	2159	2057	2060	1962	2151	2049
1/2000–3/2003								
Target	−0.633	−0.416						
Acquirer	−0.453	−0.268	−0.348	−0.356				
Acquirer–Target	0.180***	0.148***					0.064	0.051
	(0.001)	(0.000)					(0.452)	(0.555)
Acquirer - Acquirer					−0.035	−0.042		
					(0.696)	(0.643)		
Obs.	314	357	381	372	353	344	379	370
4/2003–8/2007								
Target	−0.132	−0.105						
Acquirer	−0.027	−0.064	−0.093	−0.083				
Acquirer–Target	0.104***	0.040**					0.017	0.026
	(0.000)	(0.017)					(0.588)	(0.410)
Acquirer - Acquirer					−0.019	−0.022		
					(0.558)	(0.500)		
Obs.	567	616	621	603	598	584	621	603
9/2007–3/2009								
Target	−0.123	−0.123						
Acquirer	−0.075	−0.008	0.137	0.131				
Acquirer–Target	0.048	0.114**					0.273***	0.273***
	(0.177)	(0.017)					(0.004)	(0.006)
Acquirer - Acquirer					0.161	0.183		
					(0.121)	(0.124)		
Obs.	160	166	170	162	162	154	170	162
4/2009–12/2014								
Target	0.071	−0.048						
Acquirer	0.158	0.033	−0.046	−0.062				
Acquirer–Target	0.087***	0.080***					−0.034	−0.048*
	(0.000)	(0.000)					(0.204)	(0.091)
Acquirer - Acquirer					−0.128***	−0.138***		
					(0.000)	(0.000)		
Obs.	992	1048	938	869	900	831	933	864
4/2009–6/2011								
Target	0.209	0.152	0.032	0.022				
Acquirer	0.319	0.226						
Acquirer–Target	0.110***	0.074***					−0.136***	−0.147***
	(0.000)	(0.001)					(0.000)	(0.000)
Acquirer - Acquirer					−0.208***	−0.216***		
					(0.000)	(0.000)		
Obs.	439	462	479	455	461	437	476	452
7/2011–12/2014								
Target	−0.039	−0.205	−0.128	−0.154				
Acquirer	0.031	−0.12						
Acquirer–Target	0.070***	0.085***					0.071*	0.06
	(0.000)	(0.000)					(0.057)	(0.128)
Acquirer - Acquirer					−0.045	−0.052		
					(0.201)	(0.159)		
Obs.	553	586	459	414	439	394	457	412

whereas the opposite would be true if the pool of funds coming into the post–financial crisis period were better than at other times. If we find that the post–merger performance of funds in the post–financial crisis period was worse than at any other point in the sample, this would lend additional weight to the view that fewer poorly performing funds were exited during the financial crisis.

There is an extensive literature showing that mutual fund mergers bring considerable benefits to the shareholders of the target funds but are not so beneficial to the shareholders of the acquirers (e.g. Elton et al. 1996; Carhart et al. 2002; Jayaraman et al. 2002; Khorana et al. 2007; Namvar and Phillips 2013; Park 2013). Building up on this literature and, in particular, following Jayaraman et al. (2002), the post-merger performance of the acquirers is compared (i) against their pre–merger performance and (ii) against the pre-merger performance of the target funds, i.e. funds that were referred to as merged funds in the previous sections. Funds' performance is measured by their alphas obtained from regressing the funds' excess returns (relative to the one-month Treasury bill rate) against the six factors specified in Section 3.4, i.e. the Fama–French three factors, returns on two bond indexes and on the gold index. The performance of the acquirers and of the targets was assessed for the sample of all the mergers that occurred in 2000–2014, and for each of the four sub–periods separately.

Table 8 shows the results of the analysis. The first two columns show the average pre–merger alphas of the targets, of the acquirers and the results of the t–tests for whether the acquirers' alphas were statistically significantly different from those estimated for the targets (rows named 'Acquirer–Target'). The alphas were calculated for year one before the mergers (column headed '-1'), and for year two before the mergers (column headed '-2'). Consistent with the literature, the results confirm that the pre–merger performance of the acquirers was statistically superior to the performance of the targets.

The next two columns of Table 8 show the average alphas for year one (column '1') and year two (column '2') of the post-merger funds. The following four columns compare the post–merger and the pre–merger performance. First, the differences in the post– and the pre–merger performance of the acquirers are shown. Then, the differences in the post–merger performance of the acquirers and of the targets are shown. The differences in the performance are calculated as the differences between year one after the merger and year one before the merger (columns headed '1-(−1)'), and between year two after the merger and year one before the merger ('2-(−1)').

The results obtained for the sample of all the mergers that took place between 2000 and 2014 are consistent with the literature, i.e. mergers, on average, are not good news for the shareholders of the acquirers. The post–merger alphas of the acquirers are statistically significantly lower than their pre–merger alphas. There is no statistically significant benefit to the shareholders of the target funds, although their differences between the post– and the pre–merger alphas are positive.

The separation of the mergers into those that occurred during the growing and the declining markets sheds new light on the benefits of the mergers. The differences between the post– and the pre–merger alphas of the acquirers are negative for all the non–financial crisis periods, and those obtained for the post–financial crisis period are highly statistically significant. In contrast, the differences obtained for the financial crisis mergers are positive even though they are not statistically significant.

The differences between the post–merger alphas of the acquirers and the pre-merger alphas of the targets are positive over the whole period, and for the first three sub–periods. Those obtained for the financial crisis are highly statistically significant. In contrast, the differences obtained for the post–financial crisis period are negative, and one of them is statistically significant at 10%.

To further understand the properties of the post–financial crisis mergers, we split the post–financial crisis period into two sub–periods. If clearing of the market from poorly performing funds that survived the financial crises was to happen, it is more likely that it would happen at the start of the post–financial crisis period, i.e. in 2009, 2010 and maybe even 2011, rather than several years after the market had lifted itself up from the bottom of the financial crisis.

The last two sets of results in Table 8 show the results when the April 2009 – December 2014 period was split into two sub–-periods, April 2009 – June 2011 and July 2011 – December 2014. Thus, the five–year and eight–month period was split into two years and three months, and three years and six months. This allowed for a nearly even split of the number of the mergers that took place in the post–financial crisis period.

The separation of the post–financial crisis period into two sub–periods shows that the first years after the financial crisis were very different from the latter years. While the results obtained for 2011–2014 are comparable with those obtained for the pre–financial crisis periods (i.e. negative but statistically insignificant), those obtained for the years following the financial crisis are statistically significantly negative. Thus, the post–merger performance of both the acquirers and of the target funds was statistically significantly worse than their pre–merger performance.

4.3. Robustness tests

To test the robustness of the findings, we applied several definitions of surviving funds in combination with different matching criteria. More precisely, we defined the exit funds as having stayed operational (i) within a given sub–period, and (ii) over the whole period. This did not affect the results in the sense that, regardless of the definition of the surviving funds, the relationship between exit and performance remained insignificant during the financial crisis.

We also repeated the analysis changing the matching criteria by imposing that in addition to age, size and investment strategy, matched funds should be from the same family, although it is unlikely that when investors want to leave one fund they will only look to invest in funds within the same family. The restriction of having both the exit and the matching funds from the same fund family greatly reduces the number of possible matches and worsened the matching quality (the standardized differences and variance ratios remained within the expected boundaries, but sometimes they were worse than those before matching). Interestingly, the marginal effects of Return became statistically significantly positive during the financial crisis but remained negative for the remaining periods. This result may be slightly surprising, but it provides additional evidence that poorly performing funds were not more likely to exit than other funds during the financial crisis.

Table 9

Marginal effects for logit regressions for a sample of exit institutional funds and surviving funds obtained from matching by Age, Size and investment style. All regressions were clustered by investment objectives. The dependent variable is equal to one for every quarter for funds that exited within the window specified at the top of the columns, and it is equal to zero for every quarter for funds that have not exited the market before the end of the periods as specified at the top of the columns. Returns and flows are cumulative 3–monthly observations. Age is the number of years a fund was in operation at the end–month of current quarter. Size, FF-size and FF-spec are quarterly means. Turnover and Expense are the quarterly values of the turnover ratios and expense ratios, respectively. D_{Load}, is a dummy indicating whether a fund has a load or not. Load is the load value. All regressions have time and investment style fixed effects P–values are shown in brackets. *** - 1% statistical significance, ** - 5% statistical significance, * - 10% statistical significance.

	1/2000–12/2014	1/2000–3/2003	4/2003–8/2007	9/2007–3/2009	4/2009–12/2014
Panel A					
Return	−0.136***	−0.318***	−0.429***	0.101	−0.034
	(0.000)	(0.000)	(0.000)	(0.677)	(0.510)
Flow	−0.205***	−0.353***	−0.412***	−0.520***	−0.269***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.005	0.014	0.009	0.012	−0.005
	(0.234)	(0.119)	(0.521)	(0.528)	(0.350)
Age	−0.002	−0.007**	0.004	−0.020***	−0.003*
	(0.357)	(0.040)	(0.411)	(0.000)	(0.087)
Turnover	0.011	0.053**	−0.056*	0.022	0.021*
	(0.129)	(0.036)	(0.088)	(0.473)	(0.062)
Expense	6.216	9.686	8.833	26.919**	−2.972
	(0.256)	(0.338)	(0.278)	(0.043)	(0.600)
FF-size	0.008	−0.034**	−0.025*	−0.032	0.026**
	(0.267)	(0.048)	(0.052)	(0.291)	(0.025)
FF-spec	0.022	−0.030	0.146	0.988	0.221
	(0.875)	(0.879)	(0.396)	(0.186)	(0.304)
D_{Load}	0.023	0.099	0.122	−0.247***	0.056
	(0.816)	(0.305)	(0.537)	(0.000)	(0.621)
Pseudo-R^2	0.0146	0.0747	0.0690	0.168	0.0271
Obs.	32,394	2307	2386	466	10,084
Panel B					
Return	−0.135***	−0.316***	−0.437***	0.101	−0.036
	(0.000)	(0.000)	(0.000)	(0.677)	(0.492)
Flow	−0.205***	−0.346***	−0.409***	−0.519***	−0.265***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.004	0.015	0.009	0.011	−0.005
	(0.290)	(0.104)	(0.523)	(0.540)	(0.373)
Age	−0.002	−0.007**	0.004	−0.020***	−0.002
	(0.477)	(0.038)	(0.233)	(0.001)	(0.213)
Turnover	0.011	0.053**	−0.056*	0.022	0.021*
	(0.130)	(0.039)	(0.088)	(0.474)	(0.053)
Expense	6.181	8.315	8.284	26.846**	−3.677
	(0.273)	(0.390)	(0.318)	(0.044)	(0.549)
FF-size	0.009	−0.038**	−0.024*	−0.031	0.024**
	(0.234)	(0.027)	(0.073)	(0.297)	(0.031)
FF-spec	0.022	−0.057	0.147	0.988	0.207
	(0.875)	(0.771)	(0.389)	(0.186)	(0.332)
Load	−2.690	8.295**	5.007	−13.592***	−5.080
	(0.499)	(0.048)	(0.643)	(0.000)	(0.309)
Pseudo-R^2	0.0148	0.0800	0.0682	0.169	0.0266
Obs.	32,391	2307	2386	466	10,098

Finally, given that sophistication of investors plays an important role in our story, we split the sample into institutional and retail funds and repeated the analysis (in these regressions the matching of institutional funds was also restricted to institutional funds, and of retail funds to retail funds). The results obtained for the retail funds were practically identical to those presented above for the whole sample and to save space we do not report them. However, given that institutional funds are designed to attract both institutional investors and wealthy individuals, we can safely assume that the level of financial savvy is higher among institutional funds' investors than it is among the retail ones. The results presented in Table 9 show that, while institutional investors might not be easily fooled by expenses (the marginal effects of Expense are positive and statistically significant), the exit – performance relationship weakened during the financial crisis, and although not statistically significant, Return's marginal effects became positive. Moreover, Table 9 shows that the marginal effects estimated for D_{Load} and Load are statistically significantly negative, as in other regressions. There is no separation between back–end loads and front–end loads as the institutional funds in our samples only had front–end loads (hence, Load is in fact Load-f-e).

5. Conclusions

Darwinian forces that tend to remove weak performers and promote better ones are an important mechanism of ensuring markets' sound growth and development. Yet the strength of these forces may vary with market conditions, as may the responsiveness of agents to the signals they receive. In this paper, we analyze the exit – performance relationship in the U.S. mutual fund industry over the 2000–2014 period to assess whether the exit – performance relationship weakened during the 2008 financial crisis. We hypothesize that the exit – performance relationship might weaken during the financial crisis because with the particularly acute outflow of investors from the market (e.g. Schmidt et al. 2016), fund–families' incentives to prevent investors from moving to competitors might have weakened. In addition, passive investors might have become more important; as long as they paid fees, there was no immediate need to exit funds they held.

We find a strong and robust support for our hypothesis. After controlling for numerous fund and fund–family characteristics, we find that there was a negative and strongly statistically significant relationship between fund performance and the probability of fund exit in three periods (January 2000 – March 2003, April 2003 – August 2007 and April 2009 – December 2014), but not during the financial crisis (September 2007 – March 2009). We also find that while during the financial crisis the role of performance in determining exits decreased, the role of expenses and loads increased.

Given that numerous studies support the notion that expenses and loads are negatively associated with investors' financial savvy, these results are consistent with the conjecture that passiveness of investors became particularly important in helping funds survive the financial crisis.

We also show that the consequences of not exiting poor performers during the financial crisis may have stretched beyond the financial crisis. The years following the financial crisis were the only period during which the post–merger performance of both the targets and of the acquirers statistically significantly deteriorated in comparison with their pre–merger performance.

In summary, the paper finds support for the hypothesis that Darwinian forces are not always strong enough to eliminate the weak, and consequently fund–families' behavior changes with market conditions in a way that is likely to benefit fund–families rather than investors.

Given the importance of mutual fund investments for household finances and the position of the mutual fund industry on the global financial stage, it is important to understand the industry's practices and specifics in order to inform the debate on best practices and to improve the design of regulation that aims to protect investors. This paper contributes to the debate. This is particularly important as the regulatory pressure to improve the asset management's transparency has been increasing (e.g. MiFiD II, creation of Independent Governance Committees to oversee investment governance of workplace pension funds in the UK, etc.).

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Appendix 1

Let us assume a two–period world in which a fund–family offers two funds, A and B, at the start of period 1. These funds are run by different managers, who differ in their ability to perform, but neither the investors nor the fund–family know the quality of the managers at the start of period 1. Hence, the funds have the same expected return, $R > 0$. Furthermore, we assume that when the funds open, they attract the same number of investors, N, and the same mix of investors. There are two types of investors, those who are sensitive to whether the fund delivers the expected return in period 1 (and decide whether to stay with the fund or not based on the observed returns), and those investors who keep their investment through period 2 regardless of the return in period 1. We refer to the first type of the investors as "active", and they comprise α of the investor population, $0 < \alpha < 1$. The second type of investors is referred to as "passive" and, by construction, they comprise $1-\alpha$ of the investor population. Their probability of continuing investing in period 2 is one regardless of the outcome of the fund performance, if the fund remains operational in period 2.

We assume that both funds, A and B, charge investors the same per period fee $f > 0$, and that funds are subject to a fixed cost $F > 0$ and a variable cost per investor $c > 0$. The fees are assumed high enough to compensate for the fund's costs.

The timeline is as follows. (1) Managers make investments at the start of period 1. (2) At the end of period 1 the (profit maximizing) fund–family observes the realized return. (3) In light of the returns, the fund–family decides whether to exit poorly performing funds (e.g. merge them with better performing funds or liquidate them) or to leave them as they are. (4) The investors observe the returns and any exit decision, and active investors decide whether to stay with the fund for period 2 or move. (5) Those managers still in place invest in period 2. (6) Period 2 returns are observed at the end of period 2. Our primary interest is in steps (3) and (4), and how these may differ in a non–crash market from a crash. We consider these in turn.

A non–crash market

This is a partial equilibrium model but implicitly we assume that in the background, there are many similar fund–families and funds, although we are not directly concerned with their issues.[21] To understand the fund–family's decision to reorganize the existing funds or not, let us assume that fund *A* performs at least as well as expected, i.e. earns at least return *R*, but fund *B* underperforms and earns less than *R*. Given that the return on fund *A* is at least as expected, all the active investors investing in fund *A* will infer that it is more probable that the fund's/manager's quality is good and will extend their investment with fund *A* into period 2.[22] Thus, both passive and active investors who invested in fund *A* in period 1 will also invest in period 2.

In contrast, the fund–family realizes that the active investors investing in fund *B* will be disappointed, will infer that it is more probable that the fund's/manager's quality is less good, and are likely to leave the fund upon observing the return. For simplicity of argument, let us assume that there are many comparable funds offered by other fund–families, so fund *B*'s active investors have no difficulties in finding alternative investments with other fund–families once they decide to leave fund *B*. Some of them, of course, may opt to invest in fund *A*. The probability of fund *B*'s active investors moving to fund *A* is denoted as φ ($0 \leq \varphi < < 1$). Thus, the fund–family's profits from operating fund *A*, π_A, and fund *B*, π_B, are respectively:

$$\pi_A = (f - c)N + \varphi\alpha(f - c)N - F,$$

$$\pi_B = (1 - \alpha)(f - c)N - F,$$

and the return to the fund–family from operating both funds is:

$$\pi = \pi_A + \pi_B = (f - c)N(2 - \alpha + \varphi\alpha) - 2F. \tag{1}$$

Anticipating a considerable loss of fund *B*'s active investors, the fund–family may decide to exit fund *B* by merging it with fund *A* or liquidating it entirely. We assume that when fund *B* is merged with fund *A*, all fund *B*'s investors move to fund *A*. We also assume that when fund *B* is liquidated, only a fraction of fund *B*'s active investors will move to fund *A*. This fraction is denoted as γ, where $0 \leq \gamma < 1$. Thus, the fraction of fund *B*'s investors that stays with the fund–family after fund *B* exits the market is equal to $0 \leq \gamma \leq 1$, where $\gamma = 1$ corresponds to a merger. It is also assumed that all the passive investors will move to fund *A*, instead of searching for alternative investments outside the fund–family. Exiting fund *B* brings additional costs $\rho > 0$ that are an increasing function of γ. To simplify the notation, ρ does not bear any subscript linking it to γ. It is also assumed that $\varphi < \gamma$, i.e. the effort put into the restructuring process (e.g. advertising fund *A* to investors as an alternative investment opportunity, plus all the other costs related to closing down or merging the funds) results in more active investors from fund *B* moving to fund *A* than if no action had been taken and the active investors of fund *B* had just left. Intuition also suggests that it is sensible to assume that $\rho > F$.

Putting it all together, if fund *B* exits the market, the fund–family's expected profit in period 2 is:

$$\pi_E = (f - c)N(2 + \gamma\alpha - \alpha) - F - \rho \tag{2}$$

Whether the fund–family prefers to run or exit fund *B* depends on whether π is greater or smaller than π_E. Thus, the comparison of (1) and (2) produces the critical value of α, α', that for all $\alpha > \alpha'$ the fund–family prefers to exit fund *B*, and for all $\alpha < \alpha'$ the fund–family prefers to not take any action. Simple algebraic calculations give

$$\alpha' = \frac{\rho - F}{(f - c)N(\gamma - \varphi)} \tag{3}$$

A crash market

We now repeat the exercise, under the assumption that the market performed badly during period 1, i.e. it is not only fund *B* that performed badly, but also fund *A* and the funds run by the fund–family's competitors also performed below the investors' expectations set at the start of period 1. We allow for the possibility that some of the active investors may leave the market completely, even if their fund performed better than other funds. In this scenario, the fund–family is aware that some active investors will leave regardless of the fund–family's actions.[23] We denote the fraction (or probability) of the active investors staying with fund *A* by p ($0 < p < 1$). As previously, all passive investors of fund *A* stay with fund *A*.

The actions of fund *B*'s investors will once more depend of whether the fund–family exits fund *B* or not. If the fund–family decides to run fund *B* in period 2, all its passive investors will stay. The active investors will leave, and some of them will leave the market entirely, while some will move to better performing funds. Some of the investors from the latter group will move to fund *A*. There will be $p\varphi$ of them. Thus, the expected profits from fund *A*, ${\pi_A}^C$, and from fund *B*, ${\pi_B}^C$ during a crash market, are

$$\pi_A^C = (f - c)N(p\alpha + 1 - \alpha + \varphi p\alpha) - F,$$

$${\pi_B}^C = (f - c)N(1 - \alpha) - F,$$

The expected profit from operating both funds is

[21] One way of looking at the situation would be to assume that the market offers an infinite number of funds/fund–families who have earned at least *R* in period 1, so the probability of investors moving their investments to another fund–family, if they wish to leave the current fund, is one.

[22] The argument is consistent with Gervais et al. (2005) who show that it is optimal for fund-families to fire the worse performing fund managers.

[23] This is a plausible assumption as Johnson (2010) shows that some investors' decisions to sell/retain their holdings in current funds are driven by the existence of better investment opportunities rather than the poor performance.

$$\pi^C = \pi_A^C + \pi_B^C = (f - c)N(2 - \alpha(2 - p(1 + \varphi)) - 2F \tag{4}$$

If the fund–family decides to exit fund B in an attempt to retain some of fund B's active investors, the fund–family's expected profit is:

$$\pi_E^C = (f - c)N(p\alpha + 1 - \alpha) + (\gamma p\alpha + 1 - \alpha)(f - c)N - F - \rho = (f - c)N(2 - 2\alpha + (1 + \gamma)p\alpha) - F - \rho \tag{5}$$

where, as previously, ρ denotes the cost of exiting fund B.

By equating (4) and (5) we obtain the critical value α^C

$$\alpha^C = \frac{\rho - F}{(f - c)Np(\gamma - \varphi)} \tag{6}$$

such that for all $\alpha > \alpha^C$ the fund–family prefers to exit fund B and for all $\alpha < \alpha^C$ the fund–family prefers not to take any action. Moreover, a bit of algebra shows that

$$\alpha^C = \frac{1}{p}\alpha' > \alpha'.$$

for any combination of the parameters.

To visualize the model, Fig. 1 shows how the outflow of investors affects exit decisions during a crash by plotting the fund–family's expected profits as a function of α. The lines π, π^C, π_E and $\pi_E{}^C$ are graphical representations of (1), (2), (4) and (5) respectively. Given that $\pi|_{\alpha=0} = 2(f - c)N - 2F > 2(f - c)N - F - \rho = \pi_E|_{\alpha=0}$, and the derivation of (1) and (2) respectively give $\frac{d\pi}{d\alpha} = -(f - c)N(1 - \varphi)$ and $\frac{d\pi_E}{d\alpha} = -(f - c)N(1 - \gamma)$, the intercept of line π with the vertical axis is larger than that of line π_E, and its slope is steeper than that of π_E.The crossing point of the two lines is marked as α'.

Analogously, $\pi^C|_{\alpha=0} = \pi|_{\alpha=0} > \pi_E|_{\alpha=0} = \pi_E{}^C|_{\alpha=0}$ and $\frac{d\pi^C}{d\alpha} = -(f - c)N(2 - p(1 + \varphi))$, and $\frac{d\pi_E^C}{d\alpha} = -(f - c)N(2 - p(1 + \gamma))$. Thus, even though π and π^C have the same intercept with the vertical axis, as do π_E and $\pi_E{}^C$, they become steeper than their pre–crisis counterparts.

For notational simplicity, we have so far assumed that fees f paid by the investors were the same in both states of the world. However, in a more realistic scenario the fees paid during a crash would be reduced as the value of assets under management declines. If we assume that the fees paid during the market crash are f^C, such that $f > f^C$, then the results are even stronger. If $\alpha^{C'}$ denotes the critical value of α as in (6) but for f^C, i.e.

$$\alpha^{C'} = \frac{\rho - F}{(f^C - c)Np(\gamma - \varphi)},$$

then $\alpha' < \alpha^C < \alpha^{C'}$. Thus, the critical value of the active investors must be even higher than when we assume that $f > f^C$.

Fig. A1 shows the position of the fund-family's profits during the crash market when we assume that $f > f^C$. The crossing point, $\alpha^{C'}$, marks the critical value of α above which it is more financially beneficial for the fund–family to exit fund B than to leave it operational.

Thus, market crash conditions cause some funds (those with α between α' and $\alpha^{C'}$) that would have been exited in non–crash market to continue operating even if they performed worse than their counterparts.

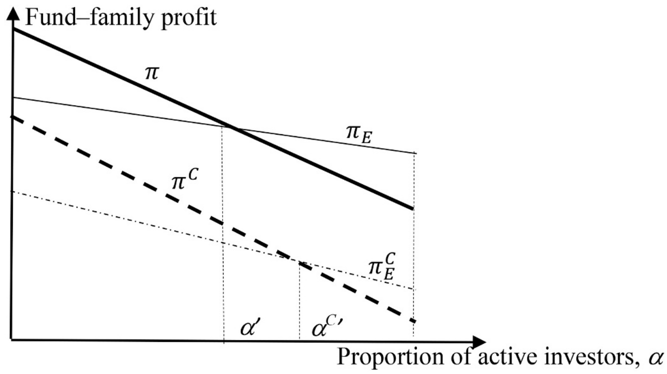

Fig. A1. Relationship between the proportion of active investors (α) and the fund–family's profit in a non–crash market (when the worst performing fund does not exit the market, π, and when it does, π_E), and in a crash market (when the worst performing fund does not exit the market, π^C, and when it does, $\pi_E{}^C$).

Appendix 2

Table A2.1
t-test of the differences in the means of fund and fund-family characteristics between exit funds and surviving funds for the whole and the four sub–periods.

	1/2000–12/2014			1/2000–3/2003			4/2003–8/2007			9/2007–3/2009			4/2009–12/2014		
	Surviving	Exit	S-E	Surviving	Exit	S-E	Surviving	Exit	S-E	Surviving	Exit	S-E	Surviving	Exit	S-E
Returns	1.827	0.802	1.025***	−0.991	−1.568	0.577***	3.390	3.558	−0.168***	−7.024	−6.035	−0.989***	3.307	3.960	−0.653***
Age	12.234	9.371	2.863***	9.584	6.940	2.644***	11.192	9.426	1.766***	11.490	9.063	2.427***	12.840	10.315	2.524***
Size	994.435	165.740	828.695***	693.011	71.281	621.731***	823.933	119.450	704.483***	783.687	60.621	723.066***	955.144	148.397	806.748***
Flow	2.446	−1.632	4.078***	2.940	−3.113	6.054***	2.191	−3.300	5.490***	0.848	−6.336	7.184***	1.974	−4.430	6.404***
Turnover	0.823	0.966	−0.143***	0.970	1.107	−0.137***	0.871	0.963	−0.093***	0.840	1.136	−0.296***	0.798	0.914	−0.116***
Expense	1.063	1.374	−0.310***	1.231	1.395	−0.164***	1.188	1.434	−0.246***	1.104	1.393	−0.290***	1.042	1.296	−0.254***
Load	0.915	0.943	−0.028***	1.253	1.360	−0.106***	0.996	0.951	0.045***	0.887	0.239	0.648***	0.796	0.725	0.070***
Load-b-e	0.244	0.463	−0.219***	0.484	0.545	−0.060***	0.335	0.428	−0.093***	0.287	0.080	0.208***	0.194	0.455	−0.261***
Load-f-e	0.668	0.479	0.190***	0.762	0.813	−0.051***	0.658	0.522	0.135***	0.599	0.159	0.440***	0.600	0.270	0.330***
D_{Load}	0.356	0.298	0.058***	0.439	0.459	−0.020***	0.367	0.320	0.047***	0.330	0.092	0.238***	0.314	0.210	0.103***
$D_{Load\text{-}b\text{-}e}$	0.099	0.124	−0.024***	0.149	0.158	−0.009*	0.114	0.128	−0.015***	0.102	0.028	0.074***	0.085	0.114	−0.029***
$D_{Load\text{-}f\text{-}e}$	0.266	0.185	0.082***	0.305	0.309	−0.003	0.264	0.215	0.048***	0.238	0.064	0.174***	0.236	0.101	0.134***
FF–size	171.299	82.978	88.321***	92.265	52.009	42.256***	128.151	59.913	68.238***	158.501	75.002	84.499***	192.987	120.984	72.003***
FF–spec	0.144	0.146	−0.002***	0.138	0.156	−0.018***	0.132	0.146	−0.019***	0.139	0.159	−0.021***	0.151	0.166	−0.015***
Funds	10,499	6600		7661	1140		8011	1604		9313	734		10,499	3122	
Obs.	290,084	101,204		57,497	5234		95,908	10,095		39,633	1242		157,304	23,569	

Table A2.2
Summary statistics of the monthly returns of the risk factors (in %). MRTRF, SMB and HML are returns on the three Fama–French factors, US gov bond are returns on the US Benchmark 10-year DataStream Government Bond total return index, Global gov bond are returns on the JPMorgan Global Government Bond total return index and Gold are returns on S&P GSCI Gold total return index.

2000–2014	Mean	Median	Std. dev	Min	Max	Obs
MKTRF	0.333	1.130	4.568	−17.230	11.350	180
SMB	0.441	0.190	3.231	−14.910	18.320	180
HML	0.107	0.015	3.282	−11.100	12.900	180
US gov bond	0.513	0.523	2.226	−6.432	11.496	180
Global gov bond	0.440	0.408	2.007	−5.145	6.456	180
Gold	0.882	0.733	5.127	−18.027	13.843	180
1/2000–3/2003						
MKTRF	−1.457	−1.940	5.415	−10.720	7.940	39
SMB	1.003	0.550	5.333	−14.910	18.320	39
HML	1.463	1.690	5.233	−9.930	12.900	39
US gov bond	0.835	0.991	1.997	−3.339	3.885	39
Global gov bond	0.586	0.453	2.075	−3.949	5.466	39
Gold	0.546	−0.258	3.543	−5.914	9.432	39
4/2003–8/2007						
MKTRF	1.068	1.400	2.594	−4.060	8.220	53
SMB	0.451	0.080	2.265	−4.030	5.780	53
HML	0.503	0.230	1.503	−3.340	4.100	53
US gov bond	0.202	0.383	2.009	−6.432	4.614	53
Global gov bond	0.431	0.467	2.120	−4.654	6.426	53
Gold	1.258	1.035	4.310	−9.554	11.485	53
9/2007–3/2009						
MKTRF	−2.849	−0.930	6.360	−17.230	8.950	19
SMB	−0.053	0.030	2.309	−3.890	3.670	19
HML	−0.978	−0.960	4.248	−11.100	6.330	19
US gov bond	1.192	0.711	3.206	−3.585	11.496	19
Global gov bond	0.657	0.391	2.710	−3.796	6.456	19
Gold	2.010	5.079	7.929	−18.027	13.843	19
4/2009–12/2014						
MKTRF	1.657	2.520	3.979	−7.890	11.353	69
SMB	0.253	0.130	2.442	−4.780	6.730	69
HML	0.117	−0.210	2.297	−4.500	7.760	69
US gov bond	0.384	0.424	2.174	−4.242	5.713	69
Global gov bond	0.305	0.277	1.666	−5.145	3.979	69
Gold	0.473	0.202	5.534	−11.060	13.734	69

Table A2.3
(Equivalent to Table 4). Marginal effects of logit regressions clustered by investment objectives after matching by Age, Size and investment style. The dependent variable is equal to one for every quarter for funds that exited within the window specified at the top of the columns, and it is equal to zero for every quarter for funds that have not exited the market before the end of the periods as specified at the top of the columns. Returns and flows are cumulative 3–monthly observations. Age is the number of years a fund was in operation at the end–month of current quarter. Size, FF-size and FF-spec are quarterly means. Turnover and Expense are the quarterly values of the turnover ratios and expense ratios, respectively. D_{Load}, is a dummy indicating whether a fund has a load or not, based on the share class specification. Load is the load value. P–values are shown in brackets. *** - 1% statistical significance, ** - 5% statistical significance, * - 10% statistical significance.

	1/2000–12/2014	1/2000–3/2003	4/2003–8/2007	9/2007–3/2009	4/2009–12/2014
Panel A					
Return	−0.105***	−0.155***	−0.330***	−0.145	−0.089***
	(0.000)	(0.004)	(0.005)	(0.402)	(0.004)
Flow	−0.166***	−0.306***	−0.436***	−0.399***	−0.319***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	−0.017***	0.000	−0.004	−0.014	−0.019***
	(0.001)	(0.951)	(0.394)	(0.101)	(0.002)
Age	−0.000	−0.002	0.000	0.005	0.001
	(0.490)	(0.186)	(0.845)	(0.316)	(0.350)
Turnover	0.012	0.010	−0.005	0.006	0.016*
	(0.159)	(0.612)	(0.631)	(0.844)	(0.098)
Expense	1.889	−3.595	7.323**	−14.528***	0.122
	(0.208)	(0.404)	(0.013)	(0.000)	(0.944)
FF-size	−0.001	−0.021*	−0.002	−0.029	0.006
	(0.913)	(0.075)	(0.890)	(0.154)	(0.442)

(continued on next page)

Table A2.3 (*continued*)

	1/2000–12/2014	1/2000–3/2003	4/2003–8/2007	9/2007–3/2009	4/2009–12/2014
FF-spec	−0.054	−0.302	−0.216	0.037	0.250*
	(0.522)	(0.304)	(0.363)	(0.918)	(0.053)
D_{Load}	0.096***	0.066**	0.078**	−0.059	0.084***
	(0.000)	(0.039)	(0.043)	(0.255)	(0.000)
Pseudo-R^2	0.0302	0.0358	0.0483	0.0647	0.0405
Obs.	77,594	6246	9683	1129	18,893
Panel B					
Return	−0.106***	−0.151***	−0.341***	−0.136	−0.093***
	(0.000)	(0.005)	(0.002)	(0.399)	(0.002)
Flow	−0.170***	−0.306***	−0.435***	−0.359***	−0.326***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	−0.016***	−0.001	−0.008**	−0.007	−0.019***
	(0.001)	(0.921)	(0.049)	(0.502)	(0.002)
Age	0.000	−0.002	0.000	0.005	0.002
	(0.595)	(0.163)	(0.881)	(0.294)	(0.144)
Turnover	0.011	0.011	−0.003	0.006	0.014
	(0.199)	(0.581)	(0.770)	(0.849)	(0.150)
Expense	3.441***	−4.475	6.510**	−13.614***	1.243
	(0.008)	(0.302)	(0.029)	(0.001)	(0.450)
FF-size	−0.001	−0.022*	−0.006	−0.036*	0.006
	(0.917)	(0.056)	(0.608)	(0.079)	(0.501)
FF-spec	−0.072	−0.311	−0.233	−0.151	0.232*
	(0.423)	(0.302)	(0.265)	(0.635)	(0.086)
Load	0.778	2.581***	4.207***	−8.097***	1.125
	(0.254)	(0.001)	(0.000)	(0.000)	(0.313)
Pseudo-R^2	0.0246	0.0392	0.0595	0.0890	0.0371
Obs.	77,580	6253	9683	1129	18,884

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