Management of flow risk in mutual funds

Martin Rohleder[1] · **Dominik Schulte**[1] · **Marco Wilkens**[1]

Abstract This paper is the first to relate the investment practices of U.S. equity mutual funds to their management of flow risk, defined as the adverse effect of investor in- and outflows on fund performance. Using a comprehensive merged sample of 2585 actively managed U.S. domestic equity funds from the CRSP mutual fund database and the SEC's regulatory N-SAR filings, we are the first to detect differences in funds' responses to flow risk. We find that funds using derivatives, such as options and futures on indices as well as individual stocks, have higher performance than non-using funds. We further show that this outperformance is the result of superior flow risk management using these derivatives and not a result of derivatives based stock-picking or market-timing activities. Overall, our findings document that superior flow management ability is valuable when managing open-end mutual funds and should be considered by investors and researches when evaluating fund performance.

Keywords Mutual fund performance · Mutual fund flows · Derivatives

JEL Classification G11 · G20 · G23

Martin Rohleder
martin.rohleder@wiwi.uni-augsburg.de

Dominik Schulte
dominik.schulte@wiwi.uni-augsburg.de

Marco Wilkens
marco.wilkens@wiwi.uni-augsburg.de

[1] Chair of Finance and Banking, University of Augsburg, Universitaetsstr. 16, 86159 Augsburg, Germany

1 Introduction and literature overview

This is the first paper to relate the derivatives use of equity mutual funds to their management of flow risk, defined as the adverse effect of investor flows on fund performance. This is important because differential ability in managing flow risk and the identification of funds successfully managing flow risk may create value for investors. Our results indicate that (1) mutual fund flow risk is generally associated with lower performance, (2) derivative using funds have higher performance on average than their non-using peers and (3) this higher performance is based on the superior flow management ability of derivative users. Hence, stricter regulation of mutual fund derivatives use as currently discussed by the SEC may interfere with funds' ability to cope with adverse investor flows.[1]

U.S. equity funds have faced investor gross in- and outflows of 2.9 trillion USD per year on average over the last decade.[2] This has led to a vast amount of research analyzing the relation between investor flows and performance of mutual funds. Next to the analyses of the smart money effect and of performance chasing by fund investors, there has been growing interest in flow risk, i.e. in the potentially negative impact of investor flows on performance. This effect results from the nature of open-end mutual fund investments. Mutual funds collect money from shareholders, invest this money in securities, and promise to issue and redeem fund shares at net asset value (NAV) on a daily basis. Thus, funds' trading activities in securities are not perfectly aligned with investors' trading activities in fund shares. Therefore, in order to fulfill their promise to redeem (issue) shares, funds are forced to sell (buy) assets. Alternatively, a fund may choose not to trade and instead hoard excess cash or pay for the service of external liquidity providers, such as "ReFlow", to meet investor purchases and redemptions.[3] In this paper, we analyze funds' use of derivatives to manage adverse investor flows.

In a related study, Rakowski (2010) argues that flow-induced trading leads to decreasing performance due to increased trading costs, such as brokerage commissions and bid-ask spreads. He finds a negative and economically significant adverse impact of daily flow risk on performance in a cross-section of fund share classes. Edelen (1999) states that flow-induced and thus uninformed trading also leads to trading losses of funds to informed traders and empirically confirms that investor flows influence fund trading activity. This relation consequently leads to underperformance of equity funds. Li and Ma (2010) find that newly raised funds, which have by nature higher cash flows through more intense advertising, underperform seasoned funds due to flow risk. Furthermore, fund trades can lead to additional costs from higher taxes due to unexpected capital gains and losses (Chordia 1996) and to severe price impact, especially for trades of illiquid securities. Using holdings data, Alexander et al. (2007) find that fund's flow-induced trades on average underperform valuation-motivated trades. Coval and Stafford (2007) also find a negative effect of net flows on performance by analyzing fund's asset fire sales.

However, the majority of existing studies do not analyze how flow risk differs between funds, if such differences are due to differential abilities in managing flow risk, and which strategies funds use to manage flow risk. Only Frino et al. (2009) and Dubofsky (2010) investigate how the differential use of index futures influences flow risk. Dubofsky (2010) does not find a significant impact of index futures on the relationship between investor

[1] http://www.wsj.com/articles/sec-preps-mutual-fund-rules-1410137113 (accessed 04/13/2015).

[2] See Table 20 of Investment Company Institute Fact Book, 2014.

[3] ReFlow is a company offering so-called NAV swaps to its clients to help them manage the adverse impact of investor flows on performance. http://www.reflow.com/.

flows and trading behavior of U.S. funds. Further, he does not link the use of index futures to fund performance. Frino et al. (2009) show that funds using index futures are less adversely affected by investor flows compared to non-using funds. However, they use a relatively small sample of Australian funds, leaving the relation unexplored for the U.S. fund market. Overall, there are good reasons to assume that derivatives offer benefits as they can be used to gain quick and comparably cheap exposure to equity markets when funds face adverse in- or outflows. Hence, using derivatives should allow funds to invest more independently from investor flows. This, in turn, should lower the adverse effect of flows on fund performance.

Our study contributes to the existing literature in several ways. First, we use a comprehensive sample of 2585 actively managed U.S. domestic equity funds during the period 1998–2013 obtained from the CRSP Survivor-Bias-Free Mutual Fund Database merged with regulatory information from 15,771 individual N-SAR filings obtained from the SEC's EDGAR database. The information available in the N-SAR filings allows us to analyze actual monthly gross fund flows and actual fund investment practices in detail. Particularly, by using gross flows instead of net flows, we are able to better control for the potentially endogenous relation between performance and investor flows. The related seminal study by Edelen (1999) also uses data from N-SAR, however only for a very small sample of 166 funds in the short period from 1985 to 1990. In contrast, our dataset represents, to our knowledge, the largest merged CRSP/N-SAR sample using gross flows and investment practices to date. Based on this sample we show that flow risk affects mutual fund performance negatively as funds with higher flow risk have lower risk-adjusted performance on average.

Second, we contribute to the literature on derivatives used by mutual funds. Previous studies focus on the direct relation between derivatives and performance. For instance, Lynch-Koski and Pontiff (1999), Cao et al. (2011), as well as Cici and Palacios (2015) show that derivatives do not have a strong influence on fund performance and risk characteristics. However, these studies use information on funds' derivative use from telephone interviews (Lynch-Koski and Pontiff 1999) or from holdings reports (Cici and Palacios 2015) whereas we can use regulatory information directly reported to the SEC. Thus, we identify 36 % of our sample funds as derivative users (23 % option users) whereas, e.g., Cici and Palacios (2015) identify only about 10 % as option users.[4] Based on this superior information, we show that derivatives use in general is positively related with performance as user funds have higher risk-adjusted performance on average.

Moreover, prior studies analyzing mutual fund derivative use do not consider how these instruments might influence other risks, such as flow risk. Therefore, third and most importantly, we extend the flow risk literature by investigating differences between individual funds based on differences in derivatives usage. We show that the relation between adverse investor flows and fund performance is less pronounced for funds using options and futures compared to nonuser funds. Moreover, the direct impact of derivatives use on fund performance vanishes once we introduce a proxy for flow management. Instead, we observe a significant relation between fund performance and flow management via derivatives. To the best of our knowledge, we are the first to show that funds using derivatives can at least partly mitigate the adverse influence of investor flows on risk-adjusted fund performance. This is a very interesting finding as, according to Berk and Green (2004), there is no superior performance even by skilled mutual funds in equilibrium

[4] Cao et al. (2011) also use N-SAR data on derivatives use. However, they use a very short time interval from June 1996 to January 1998.

since performance induced inflows cause decreasing returns to scale. Our findings suggest that this negative flow impact is mitigated to some extent by successful flow risk management.

Our results are independent of the type of derivatives used as funds seem to equally manage flow risk using index options, options on individual stocks and index futures. The results are more pronounced for heavy and medium derivative users compared to light users. Moreover, these findings are robust to the use of different performance models, for different proxies for flow risk, and different methodological approaches.

The rest of the paper is structured as follows. Section 2 develops our research hypotheses. Section 3 describes the institutional environment and introduces our dataset. Our results and interpretations are reported in Sect. 4. Section 5 displays our robustness checks. Section 6 concludes.

2 Hypotheses development

Because fund investors' purchases and redemptions of their fund shares are not perfectly aligned with funds' trading decisions, mutual funds may suffer performance losses. The studies of Edelen (1999), Frino et al. (2009), and Rakowski (2010) support this notion as they find significant flow risk for mutual funds. Hence, as starting point of our analysis of flow risk management, the first hypothesis we test is that the mutual funds in our sample suffer from flow risk (*flow risk hypothesis*).

As our ultimate objective is to relate the use of derivatives to funds' management of flow risk, we first test the direct effect of derivative use on mutual fund performance. The literature so far has found only weak evidence of a direct effect. However, in this literature the arguments in favor of a positive effect, e.g., option traders being more informed (DeLisle et al. 2015), outweigh the arguments in favor of a negative effect (for a lengthy discussion see, e.g., Cici and Palacios 2015). Having a more comprehensive dataset compared to other studies, we therefore hypothesize that using derivatives leads to higher risk-adjusted returns (*performance hypothesis*).

Finally, besides the direct effect of derivatives use on performance, there are several arguments in favor of derivatives dampening the relation between adverse investor flows and fund performance. Deli and Varma (2002) argue that derivatives are able to mitigate flow risk as they enable funds to maintain stable exposure to equity markets in times of adverse flows. Options and futures facilitate cash equitization strategies, i.e. investing net inflows into equity exposure without severe transaction costs and price impact. For example, instead of investing new investor money directly in new securities, funds can (temporarily) hold excess cash and use it as collateral for derivatives such as futures and options, thereby avoiding price impact and extensive transaction costs.[5] Due to these effects we hypothesize that risk-adjusted performance of derivatives users is less affected by adverse investor flows than nonuser funds' risk-adjusted performance (*flow management hypothesis*).

[5] We elaborate on the regulation of mutual fund derivative use in Sect. 3.1 to provide a more detailed understanding of how such strategies work.

3 Data

3.1 Institutional environment

Mutual funds are regulated by the SEC via the Investment Company Act (ICA) of 1940. Their use of derivatives is governed by Section 18(f), which generally prohibits the issuance of senior securities. The SEC has established a broad definition of senior securities, such that it includes the use of derivatives. Mutual funds nevertheless are able to use derivative securities if they comply with Section 18(f) of the ICA 1940 by maintaining an asset coverage ratio above 300 %.[6] Alternatively, a fund can hold liquid assets, such as cash, U.S. treasuries, high-grade debt, or liquid stocks covering the senior securities' market value in segregated accounts. New investor money, for example, may be invested in highly liquid securities and stored in segregated accounts. These accounts are then used to trade index derivatives or call options providing funds with equity exposure in positive market climates. In negative market climates put options can be traded to gain an appropriate market exposure.

The SEC further requires funds to disclose their investment practices in a very detailed fashion via semiannual N-SAR filings. This makes these filings the perfect and natural data source for our empirical analysis.[7]

3.2 Sample construction

To test our hypotheses, we use mutual fund data from two different sources, namely the CRSP Survivor-Bias-Free Mutual Fund Database and the SEC's regulatory N-SAR filings. Information on fund returns and other characteristics such as size, turnover, fee structure, and age are from CRSP. As CRSP variables are reported at the share class level, we aggregate them by value-weighting each share class by its respective total net assets (TNA), except for TNA, age, and load information. Fund TNA is the sum of all individual share class TNA,[8] fund age is the logarithm of the oldest share class age, and load information is based on the largest share class. Following Rakowski (2010), we discard funds with TNA of less than $ 10 million.[9] To obtain reliable performance estimates, we also eliminate all funds with less than 24 monthly observations.[10]

Information on monthly gross in- and outflows (Item 28) and semiannual investment practices (Item 70) are extracted from the N-SAR filings.[11] These mandatory reports are stored in single text filings and must be downloaded and parsed separately before being

---

[6] The asset coverage ratio is defined as the ratio of fund total net assets plus the market value of senior securities to the market value of senior securities.

[7] For a detailed description of mutual fund investment practice regulation, see Chen et al. (2013).

[8] We fill missing entries for TNA in CRSP similar to the procedure laid out in Rohleder et al. (2011).

[9] Our results are robust to changing this threshold to $25 million.

[10] Our results are robust to changing this threshold to 48 monthly observations.

[11] N-SAR filings from the SEC are used in several other studies. Edelen (1999) investigates the impact of investor flows on fund trading behavior. Deli and Varma (2002) and Almazan et al. (2004) analyze fund investment restrictions. O'Neal (2004) studies gross investor flows. Reuter (2006) investigates the relation between underwriter commissions and initial public offerings, while Kuhnen (2009) and Warner and Wu (2011) analyze investment advisory contracts. Edelen et al. (2012) examine brokerage commissions. Cashman et al. (2012, 2014), Clifford et al. (2013), and Fulkerson et al. (2013) analyze the effect of performance on future gross investor flows. Christoffersen et al. (2013) focus on the relationship between gross investor flows and fees. Chen et al. (2013) investigate mutual funds using short sales. Evans et al.

condensed in a consistent database.[12] Specifically, we download 106,357 individual N-SAR filings from the SEC's EDGAR database. We begin our analysis in 1998, as the repealing of the "short–short" rule with the Taxpayer Relief Act of 1997 enabled mutual funds to use derivatives more easily (Bae and Yi 2008). A common identifier between N-SAR and CRSP does not exist. Therefore, the data has to be matched using fund names. Since many N-SAR fund name entries are erroneous, we correct them manually and then match them to CRSP fund names via algorithmic string matching techniques. Finally, we eliminate potential entry errors in the N-SAR reports and false matches with rigorous data screening techniques (see "Appendix").

Our final merged dataset, which is to our knowledge the most comprehensive NSAR/CRSP sample using monthly gross flows and semiannual investment practices, contains 15,771 filings of 2585 U.S. actively managed domestic equity funds in the period from 1998 to 2013. As can be seen in Table 12 in the Appendix, there are no substantial differences in main fund characteristics between our merged sample and the complete actively managed domestic equity fund sample from CRSP. Moreover, the correlations between CRSP and N-SAR calculated for variables available in both sources are very high with 99 % for TNA and 93 % for turnover. Thus, we can rule out any sampling bias.

3.3 Variable definition

The main variables of interest in our empirical analysis are fund performance, flow risk, and derivatives use. We measure our dependent variable, fund performance, with the Carhart (1997) 4-factor model as it is the widest spread model to date.[13] We elaborate on the robustness of our findings with regard to other performance models in Sect. 5.3.

Regarding flow risk, there are several ways to measure adverse investor flows. Some authors, such as Rakowski (2010) use flow surprises. However, this might not be appropriate as expected as well as unexpected flows lead to noise trading and a priori cash hoarding. The standard deviation of daily flows alternatively used by Rakowski (2010) is also a biased proxy for adverse investor flows. Consider the following two scenarios: First, a fund experiences a net flow of zero. Obviously, this causes no liquidity motivated trading. The standard deviation, however, falsely assumes flow risk if a fund has non-zero net flow on average, which is the case for most funds in our sample. In the second scenario, the fund attracts net inflows in accordance with average net flows. In this case, the standard deviation falsely assumes this fund free of flow risk, although it has to trade in response to these investor flows. Therefore, we follow Frino et al. (2009) and define our main independent variable *flow_risk* as the time-series mean of fund monthly absolute net flows.[14] This measure thus considers the adverse impact of both net investor inflows and outflows. In contrast to Frino et al. (2009) and Rakowski (2010), however, we use actual net flows, defined as gross inflows minus gross outflows, from N-SAR filings (Item 28) instead of implied net flows calculated from fund size (TNA). Thereby, we mitigate potential biases

---

Footnote 11 continued
(2014) analyze security lending by mutual funds and Clifford et al. (2014) analyze the determinants of investment practice permission.

[12] The N-SAR filings are available for download at http://www.sec.gov/edgar.shtml.

[13] We thank Kenneth R. French for providing data on risk free rate, market, size, book-to-market, and momentum factors at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[14] Results are qualitatively the same when we use mean squared net flow instead of mean absolute net flows as a proxy for adverse investor flows.

caused by strong assumptions about the timing of flows during the month required for the calculation of implied net flows. Following the existing literature, we scale dollar flow variables by beginning of month TNA to consider percentage flows (henceforth "flows").

By using monthly net flows, we also circumvent problems that might arise with daily flow data as used by, e.g., Rakowski (2010), Greene et al. (2007) and Rakowski and Wang (2009). Qian (2011) states that implied daily fund flows are inaccurate because funds do not provide precise end-of-day information about their TNA. Thus, the exact timing of flows remains unknown even with daily data. Furthermore, some funds pay out redemptions with time lags of several days. This gives them time to accumulate inflows to set off the redemptions. Rakowski and Wang (2009) also argue that daily fund flows have different dynamics compared to monthly fund flows.

Moreover, we examine flow risk at the fund level and not at the share class level. Many existing studies (e.g., Rakowski 2010) focus on the effect of flows on share class performance. Performance of different share classes, however, is based on a common portfolio of assets. Therefore, it does not matter to which share class new money flows as flow risk impacts all share classes equally. Opposing flows to different share classes of the same fund also offset each other at the fund portfolio level and therefore do not lead to flow risk. Thus, our measure of flow risk is superior to those used in the existing literature, as it combines actual fund level investor in- and outflows.

Regarding mutual fund derivative use, we use information based on Item 70 of the N-SAR filings. Item 70 reports whether or not the respective investment practice is permitted by the fund's investment policy and whether or not the fund is actually engaged in this activity during the reporting period. Specifically, our indicator variable *futures* is employed to measure the effect of index futures on flow risk similar to Frino et al. (2009) and Dubofsky (2010). *futures* is equal to one if a fund invests in "stock index futures" (Item 70F) at least once over the entire sample period for our cross-sectional analysis. For our Fama–MacBeth analysis (Fama and MacBeth 1973), *futures* is equal to one if a fund invests in stock index futures at least once in the respective year.

As of yet, the use of options has not been studied in the context of flow risk. Therefore, we investigate the relation between option use and flow risk by introducing the dummy variable *options*. This indicator variable equals one for funds that use options at least once during the entire period (the respective year) and zero otherwise. To obtain this indicator variable we aggregate information on questions regarding the writing of or investment in individual stock options (Item 70B "equity options" and Item 70G "options on futures"), and index options (Item 70D "options on stock indices" and Item 70H "options on stock index futures"). For our Fama–MacBeth analysis, *options* is equal to one if a fund invests in such instruments at least once in the respective year. To examine both options and futures at the same time, we combine the respective dummies into the dummy variable *derivatives*.[15]

As control variables for other differences between funds, we use the natural logarithm of total net assets (*size*), the annual turnover ratio (*turnover*), a dummy for funds charging front loads or back loads (*load*), yearly expense ratios (*expense*), the percentage of assets held in cash (*cash*), the age of the oldest share class (*age*), the fund's return volatility (*ret_vola*), and the natural logarithm of total family net assets (*family_size*). To control specifically for the potential endogenous performance-flow relation caused by investor's

[15] In alternative specifications, the cross-sectional dummy *derivatives* is one if a fund uses derivatives at least 10, 25, 50, or 75 % of the time, respectively. The results remain the same. For brevity, these analyses are not reported in the main text, but available from the authors upon request.

performance chasing behavior, we further incorporate the gross flow variables *inflow* and *outflow* from N-SAR (Item 28). Additionally, we control for the performance effect of different fund investment styles and potential time effects by using style and time dummies.

3.4 Summary statistics

Table 1 presents summary statistics for our dataset. Fund performance is in line with the existing literature, as funds on average have negative after fee Carhart (1997) alphas. The mean (median) total net assets managed by our sample funds are $968 million ($194 million) with an average age of 10 years (median 7 years). This implies many small and few very large funds. The annual turnover ratio averages 93.4 % with huge dispersion among funds (standard deviation of 132.8 %), suggesting that funds substantially differ in their trading behavior. The majority of our sample funds charge front or back loads. Annual expense ratios are around 1.2 %. Average monthly net flow is positive with 0.66 % of TNA. Average gross flows, however, are vastly larger, with inflows averaging 3.76 % of TNA per month and outflows 3.10 %. This is in line with findings by O'Neal (2004), Cashman et al. (2012, 2014), and Christoffersen et al. (2013), who find that the majority of monthly in- and outflows offset each other. Our measure of flow risk, mean absolute net flow, has a cross-sectional mean of 2.94 % and a standard deviation of 1.87 %.

Table 1 Summary statistics

	Mean	Median	Standard deviation
Excess net return	0.0042	0.0047	0.0063
Return volatility	0.0516	0.0502	0.0147
CAPM alpha	−0.0003	−0.0004	0.0032
Fama–French alpha	−0.0008	−0.0007	0.0028
Carhart alpha	−0.0008	−0.0007	0.0027
Carhart and liquidity factor alpha	−0.0009	−0.0009	0.0026
Ferson Schadt alpha	−0.0007	−0.0007	0.0027
TNA ($mil)	967.8	193.9	3195.4
Family TNA ($mil)	108,560.0	16,741.2	278,929.0
Age (years)	10.2	7.2	9.5
Turnover ratio (% TNA, p.a)	0.9337	0.6870	1.3283
Load dummy	0.6747	1.0000	0.4686
Expense ratio (% TNA, p.a)	0.0119	0.0119	0.0047
Cash (% TNA)	0.0411	0.0267	0.0866
Inflow (% TNA)	0.0376	0.0301	0.0410
Outflow (% TNA)	0.0310	0.0263	0.0377
Net flow (% TNA)	0.0066	0.0043	0.0204
Abs. net flow (% TNA)	0.0294	0.0255	0.0187

This table presents descriptive statistics for actively managed US domestic equity funds with entries in N-SAR filings and the CRSP mutual fund database during the period 1998–2013. All variables are per month except where noted

Table 2 Derivative permission and use

	Permission	Use	# Months	% Months
Derivatives	0.9431	0.3636	81.32	0.7179
Options	0.9389	0.2309	67.55	0.6101
Stock options	0.9369	0.2054	68.27	0.6046
Index options	0.9176	0.0797	48.74	0.5197
Futures	0.8867	0.2275	82.44	0.7328

This table shows the percentage of actively managed US domestic equity funds, which are permitted at least once during the period 1998–2013 to use the respective derivative and the percentage of active domestic equity funds, which actually use the respective derivative at least once during this period based on their answers to Item 70 of the semiannual N-SAR filings. # Months (% Months) denotes the average number of months (fraction of usage months to total months) for which a user fund employs the respective derivative

Summary statistics for fund derivatives use are shown in Table 2. While most of the funds are permitted to use derivatives, only a fraction of funds make use of this permission. This is rooted in the fact that funds permit a broad scope of investment practices as it is difficult to change permissions over time. Nevertheless, many fund managers face self-imposed restrictions (Almazan et al. 2004).[16] While 94 % of all funds are allowed to invest in derivatives, only 36 % of funds actually use derivatives. Those funds investing in derivatives do so for most of the time, as the average usage time is 81 months. Derivatives usage consists of futures usage and options usage, which is further separated into the use of individual stock options and stock index options. Stock options are the most commonly used option type as 20.5 % of all funds have employed them at least once. Options on stock indices are less common, as 8.0 % of funds use them. Index futures are used by 22.8 % of our sample funds.

Summary statistics displayed in Deli and Varma (2002) and Almazan et al. (2004) show stronger restrictions of mutual fund investment practices before 2001. Hence, there has been substantial growth in the number of funds being allowed to use derivatives over the past decade. Figure 1 confirms this finding, but at the same time shows that the actual usage of derivatives is rather stable over time. Overall, many funds use some kind of derivative instrument. This underlines the importance of analyzing their relation to flow risk and fund performance.

4 Empirical results

4.1 Statistics on users and nonusers of derivatives

Table 3 displays summary statistics for users and nonusers of derivatives separately. There are 940 user funds and 1645 nonuser funds. User funds are larger by 81 %, older by about 2 years and belong to larger families. On average, they hold more cash (4.67–3.79 %) and trade more often (turnover ratio of 114.40 % to 81.36 %). Users have significantly higher

[16] To control for any self-selection bias arising from these self-imposed restrictions we use an additional propensity score matching analysis. The results to this test are in line with our main findings and presented in Sect. 5.1.

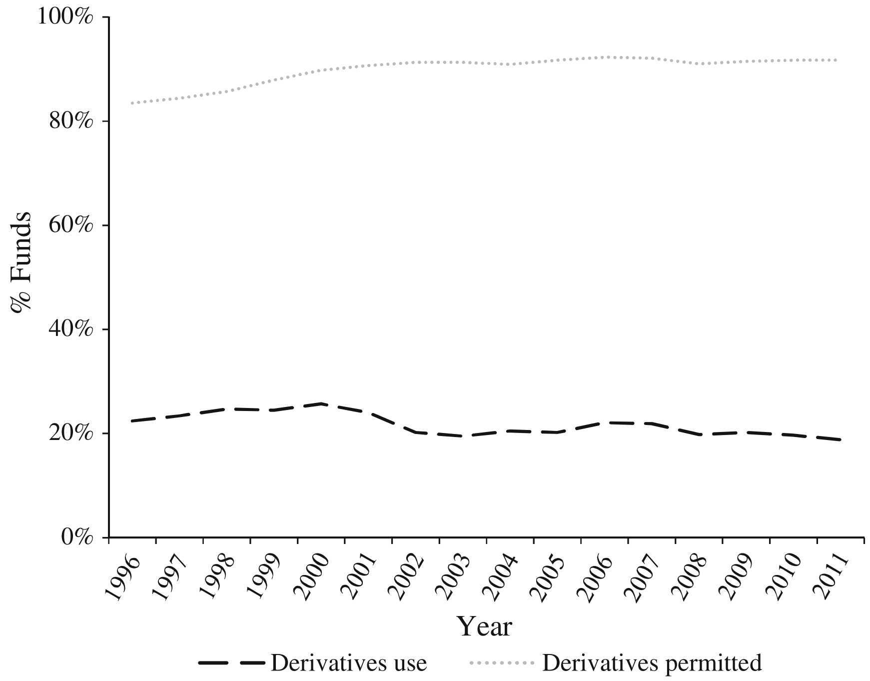

Fig. 1 Derivatives permitted and use over time. This figure shows the proportion of actively managed US domestic equity funds, which are permitted to use (actually use) derivatives at least once in the respective year during the period 1998–2013, based on Item 70 of the semiannual N-SAR filings

expense ratios (1.23 %) than nonusers (1.16 %). Although user funds experience just 0.62 % of their TNA in monthly net flows compared to 0.95 % for nonusers, they have a similar amount of flow risk (2.86–2.99 %) as measured by their mean absolute net flows. This difference in monthly net flows is driven by investor outflows. While new investor money flows into user and nonuser funds at the same rate of 3.76 %, outflows are significantly higher for users than for nonusers (3.32–2.97 %). This underlines the importance of incorporating gross flow data into our analysis. To ensure that these cross-sectional differences between users and nonusers of derivatives do not drive our results, we control for these fund characteristics in our regression analyses.

4.2 Overall flow risk

To test our *flow risk hypothesis* that mutual funds face diminished performance due to absolute net flows, we use two different regression approaches, namely cross-sectional OLS regressions as well as yearly cross-sectional Fama–MacBeth two-stage least squares (2SLS) instrument variable regressions (e.g., Angrist and Imbens 1995; Wang 2015). Both approaches are suitable to control for the strong endogeneity in the relation between investor flows and fund performance documented in the literature. Regarding this endogeneity, there is extensive evidence that performance influences ensuing investor flows. Among others, Ippolito (1992), Sirri and Tufano (1998), as well as Del Guercio and Tkac (2002) find a positive relationship between performance and subsequent monthly net flows. Rakowski and Wang (2009) confirm this finding for daily net flows while O'Neal (2004), Ivkovic and Weisbenner (2009), Shrider (2009), and Cashman et al. (2012, 2014) all find similar results for the impact of performance on ensuing gross flows. Furthermore, there exists some evidence for a smart money effect (Gruber 1996; Zheng 1999), i.e. a positive

Table 3 Summary statistics for derivative users and nonusers

	Mean			Median		
	Nonusers	Users	Users–Nonusers	Nonusers	Users	Users–Nonusers
Excess net return	0.0044	0.0038	−0.0006***	0.0050	0.0044	−0.0006***
Return volatility	0.0514	0.0521	0.0007	0.0498	0.0509	0.0010***
CAPM alpha	−0.0005	0.0000	0.0005***	−0.0006	−0.0003	0.0003***
Fama–French alpha	−0.0010	−0.0006	0.0004***	−0.0008	−0.0005	0.0003***
Carhart alpha	−0.0010	−0.0006	0.0003***	−0.0008	−0.0006	0.0002***
Carhart & liquidity factor alpha	−0.0010	−0.0008	0.0002***	−0.0009	−0.0008	0.0001
Ferson Schadt alpha	−0.0008	−0.0005	0.0004***	−0.0008	−0.0006	0.0001***
TNA ($mil)	748	1352	604***	141	329	188***
Family TNA ($mil)	82,263	154,580	72,318***	11,163	42,473	31,310***
Age (Years)	9.4626	11.4591	1.9965***	6.3750	8.3197	1.9447***
Turnover ratio (% TNA, p.a)	0.8136	1.1440	0.3304***	0.6002	0.8211	0.2209***
Load dummy	0.6359	0.7426	0.1067***	1.0000	1.0000	0.0000***
Expense ratio (% TNA, p.a)	0.0116	0.0123	0.0007***	0.0117	0.0120	0.0003***
Cash (% TNA)	0.0379	0.0467	0.0088***	0.0258	0.0283	0.0025***
Inflow (% TNA)	0.0376	0.0376	0.0000	0.0311	0.0281	−0.0030***
Outflow (% TNA)	0.0297	0.0332	0.0035***	0.0254	0.0273	0.0018***
Net flow (% TNA)	0.0095	0.0062	−0.0034***	0.0055	0.0026	−0.0029***
Abs. net flow (% TNA)	0.0299	0.0286	−0.0014	0.0260	0.0248	−0.0013***

This table presents descriptive statistics for actively managed US domestic equity funds with entries in N-SAR filings and the CRSP mutual fund database during the period 1998–2013. Users (940) are funds, which at least once use derivatives during the entire sample period. Nonusers (1645) are funds, which do not use any derivatives over the entire sample period. All variables are per month except where noted. ***, **, * denote significant difference of mean (median) at the 1, 5 and 10 % level, respectively. Differences are tested with the standard *t* test (means) and Wilcoxon rank-sum test (medians)

relation between past flows and performance.[17] Loon (2011) shows that flow-performance relation and smart money effect are independent of each other. Moreover, fund flows impact stock prices (e.g., Lou 2012; Maher et al. 2008), and subsequently may effect fund performance. Thus, the relation between flows and performance suffers from endogeneity. In addition, the precise timing of flows and ensuing fund performance is not observable. This is true for all kinds of flow data including monthly gross flows due to low data frequency as well as for daily flows, due to the imprecisions in reporting described by Qian (2011).

Our baseline model, represented by Eq. (1), is based on the approach used by Rakowski (2010). The independent variable, α_i, is the Carhart (1997) 4-factor alpha of each fund i.

[17] While Sapp and Tiwari (2004) argue that these findings are due to these studies not controlling for stock momentum, Keswani and Stolin (2008) show that even when controlling for momentum a smart money effect exists.

$$\alpha_i = \beta_0 + \beta_1\, inflow_i + \beta_2\, outflow_i + \beta_3 flow\_risk_i + \sum_{j=1}^{J} \beta_j Controls_{j,i} + \varepsilon_i. \qquad (1)$$

To isolate the effect of flows on performance in our cross-sectional approach, we control for the endogeneity described above by including additional flow variables as in Rakowski (2010). However, in contrast to Rakowski (2010) we use the means of gross flow variables *inflow* and *outflow* instead of mean net flows. This is grounded in the fact that the influence of performance on subsequent net flows appears asymmetric as documented by Chevalier and Ellison (1997), Sirri and Tufano (1999), and Huang et al. (2007). Once gross flows are analyzed, however, performance significantly affects both in- and outflows (Ivkovic and Weisbenner 2009; Cashman et al. 2012 and 2014; Clifford et al. 2013). Thus, our Eq. (1) including gross investor flows controls better for the potentially endogenous and asymmetric impact of performance on flow than existing studies on flow risk. The explanatory variables are as described in Sect. 3.2. To control for style effects, we use style dummies.

To further control for endogeneity, and to avoid potential biases arising from different market climates, our second regression approach represents a yearly cross-sectional Fama–MacBeth two stage least squares regression (2SLS) methodology similar to the two studies closest to ours, namely Frino et al. (2009) and Rakowski (2010). As instruments, we use lagged values of all independent variables and of fund performance. To control for differential performance of funds with different investment objectives and over time, we also include investment style fixed effects and time fixed effects into our regressions.

The results reported in Table 4 support our *flow risk hypothesis* that flow risk, measured by mean absolute net flows, is significantly and negatively related to performance. This is in line with Rakowski's (2010) findings for daily flows. The effect is stronger when using our 2SLS approach. Mean in- and outflows show significant coefficients across different estimation specifications. As expected, the relation of performance with average fund inflows is positive, whereas its relation with outflows is negative. This confirms the findings of Cashman et al. (2012, 2014) and Clifford et al. (2013).

4.3 Derivatives, performance, and flow risk

To test our *performance hypothesis*, that the use of derivatives leads to superior risk-adjusted fund performance, we augment our baseline regression with the *derivatives* dummy as an additional explanatory variable. The respective coefficient is positive and significant for the OLS approach whereas it is positive and mostly insignificant for our 2SLS approach displayed in Table 5. Coefficients range from 0.0001 to 0.0003. Funds using derivatives thus earn abnormal risk-adjusted returns between 0.12 and 0.36 % per year in excess of their non-using peers, all else being equal. This lends weak support to our *performance hypothesis*.

We find further evidence in favor of our *performance hypothesis* for different types of derivatives using separate regressions with dummies for the individual components of *derivatives* instead of the overall dummy. Table 6 displays the results and shows positive relations between performance and most types of derivatives. Especially, index futures and individual stock options are associated with higher fund performance. The coefficient on index options is only significant in our OLS approach. This positive performance impact of options and futures is in contrast to the findings of Lynch-Koski and Pontiff (1999) as well as Cici and Palacios (2015), who do not find a significant influence of derivatives and options usage on fund performance, respectively. Their findings, however, could be based

Table 4 Regressions of performance on flow risk

	Panel A: OLS		Panel B: 2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)
flow_risk	−0.0109*	−0.0118*	−0.0761***	−0.0724***	−0.0849***	−0.0795***
	(0.0063)	(0.0064)	(0.0133)	(0.0132)	(0.0133)	(0.0132)
inflow	0.0408***	0.0412***	0.0765***	0.0742***	0.0826***	0.0796***
	(0.0052)	(0.0052)	(0.0073)	(0.0073)	(0.0074)	(0.0073)
outflow	−0.0378***	−0.0376***	−0.0568***	−0.0558***	−0.0589***	−0.0576***
	(0.0042)	(0.0042)	(0.0045)	(0.0044)	(0.0044)	(0.0044)
size	0.0002***	0.0002***	−0.0001**	−0.0001**	−0.0002***	−0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
turnover	−0.0002**	−0.0002**	−0.0001**	−0.0001**	−0.0001**	−0.0001**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
load	−0.0000	0.0000	0.0001	0.0001	0.0001	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
expense	−0.0212	−0.0381***	−0.0181	−0.0301*	0.0101	−0.0060
	(0.0144)	(0.0145)	(0.0159)	(0.0164)	(0.0157)	(0.0159)
cash	0.0010	0.0009	−0.0001	−0.0000	−0.0007	−0.0007
	(0.0010)	(0.0010)	(0.0009)	(0.0008)	(0.0009)	(0.0009)
age	0.0005***	0.0005***	0.0001*	0.0002**	0.0002***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ret_vola	−0.0043	−0.0113*	0.0116***	0.0094**	−0.0101	−0.0190***
	(0.0058)	(0.0064)	(0.0036)	(0.0037)	(0.0063)	(0.0070)
family_size	−0.0001***	−0.0001***	0.0000	0.0000	0.0001**	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
intercept	−0.0016***	0.0011	0.0002	0.0000	−0.0014***	−0.0012
	(0.0004)	(0.0012)	(0.0005)	(0.0007)	(0.0005)	(0.0008)
Style FE	No	Yes	No	Yes	No	Yes
Time FE	No	No	No	No	Yes	Yes
Adj. R^2	0.12	0.14	0.00	0.01	0.11	0.13
N	2585	2585	16,380	16,380	16,380	16,380

This table shows results of OLS and 2SLS regressions of fund performance on flow risk. The sample consists of actively managed US domestic equity funds over the period 1998–2013. The dependent variable is the Carhart (1997) 4-factor alpha. *flow_risk* is defined as mean absolute net flow. In Panel A, all variables are time-series means per fund. In Panel B, all variables are averages per fund-year. The endogenous variable is *flow_risk* and the instruments used in the 2SLS model include lagged values of all independent variables and lagged fund performance. ***, **, * denote significance of the coefficient at the 1, 5 and 10 % level, respectively. Heteroskedasticity consistent standard errors are given in parentheses (White 1980)

on a different sample period (Lynch-Koski and Pontiff 1999) or on different data sources (Cici and Palacios 2015). Holdings data, for example, could be biased by window dressing as it only shows options used on the respective reporting date and not over the entire reporting period (e.g., Agarwal et al. 2014).

Table 5 Regressions of performance on flow risk and derivatives use

	Panel A: OLS		Panel B: 2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)
flow_risk	−0.0111*	−0.0120*	−0.0762***	−0.0724***	−0.0850***	−0.0796***
	(0.0063)	(0.0063)	(0.0133)	(0.0132)	(0.0133)	(0.0132)
derivatives	0.0004***	0.0004***	0.0002	0.0002*	0.0001	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
inflow	0.0413***	0.0418***	0.0766***	0.0743***	0.0828***	0.0797***
	(0.0052)	(0.0052)	(0.0074)	(0.0073)	(0.0074)	(0.0073)
outflow	−0.0383***	−0.0380***	−0.0568***	−0.0559***	−0.0590***	−0.0577***
	(0.0042)	(0.0043)	(0.0045)	(0.0044)	(0.0044)	(0.0044)
size	0.0002***	0.0002***	−0.0001**	−0.0001**	−0.0002***	−0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
turnover	−0.0002**	−0.0002**	−0.0001**	−0.0002**	−0.0001**	−0.0001**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
load	−0.0000	−0.0000	0.0001	0.0001	0.0001	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
expense	−0.0258*	−0.0430***	−0.0186	−0.0311*	0.0096	−0.0068
	(0.0144)	(0.0145)	(0.0159)	(0.0163)	(0.0157)	(0.0159)
cash	0.0008	0.0007	−0.0002	−0.0001	−0.0007	−0.0008
	(0.0010)	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
age	0.0005***	0.0005***	0.0001*	0.0002**	0.0002***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ret_vola	−0.0041	−0.0113*	0.0116***	0.0094**	−0.0099	−0.0188***
	(0.0058)	(0.0064)	(0.0036)	(0.0037)	(0.0063)	(0.0070)
family_size	−0.0001***	−0.0001***	0.0000	0.0000	0.0001**	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
intercept	−0.0014***	0.0013	0.0002	0.0001	−0.0014***	−0.0011
	(0.0004)	(0.0012)	(0.0005)	(0.0007)	(0.0005)	(0.0008)
Style FE	No	Yes	No	Yes	No	Yes
Time FE	No	No	No	No	Yes	Yes
Adj. R^2	0.12	0.14	0.00	0.01	0.12	0.13
N	2585	2585	16,380	16,380	16,380	16,380

This table shows results of OLS and 2SLS regressions of fund performance on flow risk and the derivatives use dummy. The sample consists of actively managed US domestic equity funds over the period 1998–2013. The dependent variable is the Carhart (1997) 4-factor alpha. *flow_risk* is defined as mean absolute net flow, *derivatives* is equal to 1 if a fund uses any derivative at least once in the given period and 0 otherwise. In Panel A, all variables are time-series means per fund. In Panel B, all variables are averages per fund-year. The endogenous variable is *flow_risk* and the instruments used in the 2SLS model include lagged values of all independent variables and lagged fund performance. ***, **, * denote significance of the coefficient at the 1, 5 and 10 % level, respectively. Heteroskedasticity consistent standard errors are given in parentheses (White 1980)

Table 6 Regression of performance on flow risk and different aspects of derivatives use

	Panel A: OLS				Panel B: 2SLS			
	Options	Index options	Individual options	Index futures	Options	Index options	Individual options	Index futures
flow_risk	−0.0123**	−0.0124**	−0.0121*	−0.0118*	−0.0795***	−0.0796***	−0.0800***	−0.0795***
	(0.0063)	(0.0063)	(0.0063)	(0.0063)	(0.0132)	(0.0132)	(0.0133)	(0.0132)
derivatives	0.0005***	0.0005***	0.0005**	0.0003**	0.0000	0.0001	0.0006*	0.0003**
	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0002)	(0.0002)	(0.0004)	(0.0001)
inflow	0.0413***	0.0412***	0.0411***	0.0418***	0.0796***	0.0796***	0.0797***	0.0798***
	(0.0051)	(0.0051)	(0.0052)	(0.0052)	(0.0073)	(0.0073)	(0.0073)	(0.0073)
outflow	−0.0375***	−0.0374***	−0.0376***	−0.0382***	−0.0576***	−0.0576***	−0.0577***	−0.0578***
	(0.0042)	(0.0042)	(0.0043)	(0.0043)	(0.0044)	(0.0044)	(0.0044)	(0.0044)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	Yes	Yes	Yes	Yes
Adj. R^2	0.14	0.14	0.14	0.14	0.13	0.13	0.13	0.13
N	2585	2585	2585	2585	16,380	16,380	16,380	16,380

This table shows results of OLS and 2SLS regressions of fund performance on flow risk and the derivatives use dummy. The sample consists of actively managed US domestic equity funds over the period 1998–2013. The dependent variable is the Carhart (1997) 4-factor alpha. *flow_risk* is defined as mean absolute net flow, *derivatives* is equal to 1 if a fund uses the respective derivative at least once in the given period and 0 otherwise. In Panel A, all variables are time-series means per fund. In Panel B, all variables are averages per fund-year. The endogenous variable is *flow_risk* and the instruments used in the 2SLS model include lagged values of all independent variables and lagged fund performance

***, **, * denote significance of the coefficient at the 1, 5 and 10 % level, respectively. Heteroskedasticity consistent standard errors are given in parentheses (White 1980)

4.4 Flow management

Our findings that funds using derivatives outperform nonusers could be due to a direct effect of derivatives allowing funds to use proprietary information more efficiently. Another possible explanation is superior flow risk management ability of derivative users. To test this *flow management hypothesis*, we analyze the relation between derivatives, flow risk, and performance by employing the following regression:

$$\alpha_i = \beta_0 + \beta_1\, inflow_i + \beta_2\, outflow_i + \beta_3 flow\_risk_i + \beta_4 flow\_mgmt_i + \beta_5\, derivatives_i + \sum_{j=1}^{J} \beta_j Controls_{j,i} + \varepsilon_i, \tag{2}$$

where *flow_mgmt* is calculated as the interaction variable between the indicator variable *derivatives* and *flow_risk*. In this way, *flow_mgmt* represents the amount of flow risk that fund i avoids by employing derivatives. Table 7 reports the results for the respective OLS and 2SLS regressions. Supporting our *flow management hypothesis*. The coefficient on *flow_mgmt* is significant and positive with coefficients between 0.0256 and 0.0545. *flow_risk*, on the other hand, is significant and negative for all specifications. This implies that funds utilize derivatives to at least partly mitigate flow risk.

Interestingly, the direct relation between *derivatives* and performance becomes negative once the *flow_management* interaction variable is incorporated. This proves that our results are not driven by funds using derivatives to enhance performance directly via stock picking or market timing activities. Rather, the coefficients of the *derivatives* dummy now measure the negative impact of costs associated with managing flow risk on fund performance.

To gain a better understanding of the underlying mechanism between derivatives usage, flows, and fund performance, we examine options and futures separately. Therefore, Table 8 breaks down the *derivatives* dummy into its components. For all of the individual derivatives, the results are consistent with our *flow management hypothesis*. Specifically, funds use options on stock indices, options on individual stocks and index futures to manage their flow risk. While the *flow_mgmt* coefficient is 0.0333 for index options and 0.0359 for individual stock options, it is 0.0257 for index futures. For the 2SLS specifications the coefficients are even higher. Thus, we can also alleviate concerns that our findings are merely a result of funds using index futures as analyzed by Frino et al. (2009) for Australian funds. This shows that derivatives enable fund managers to better manage their flow risk by employing cash equitization strategies more easily and cost-efficiently.

5 Robustness

5.1 Propensity score test

Another explanation for our results could be the existence of a self-selection bias. Funds deciding to use derivatives may do so because of specific reasons besides flow risk management. To lessen this concern we follow Evans et al. (2015) and apply a propensity score matching technique. This type of analysis selects a non-using control fund for each derivatives user fund so that the control fund is the non-using fund that most closely resembles the respective user fund. This way, we ensure that our group of user funds and the control group of propensity score matched nonuser funds differ only in their decision to employ derivatives but are similar regarding all other fund characteristics.

Table 7 Regressions of performance on flow risk, derivative use and flow management

	Panel A: OLS		Panel B: 2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)
flow_risk	−0.0197***	−0.0213***	−0.0837***	−0.0797***	−0.0930***	−0.0871***
	(0.0067)	(0.0068)	(0.0145)	(0.0144)	(0.0144)	(0.0143)
flow_mgmt	0.0256***	0.0278***	0.0510***	0.0501***	0.0545***	0.0529***
	(0.0075)	(0.0076)	(0.0107)	(0.0107)	(0.0105)	(0.0105)
derivatives	−0.0004*	−0.0004**	−0.0011***	−0.0010***	−0.0012***	−0.0011***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
inflow	0.0411***	0.0415***	0.0746***	0.0723***	0.0806***	0.0775***
	(0.0052)	(0.0051)	(0.0071)	(0.0070)	(0.0071)	(0.0070)
outflow	−0.0390***	−0.0387***	−0.0571***	−0.0561***	−0.0593***	−0.0579***
	(0.0043)	(0.0043)	(0.0044)	(0.0043)	(0.0044)	(0.0043)
size	0.0002***	0.0002***	−0.0001**	−0.0001*	−0.0002***	−0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
turnover	−0.0002***	−0.0002***	−0.0002**	−0.0002**	−0.0001**	−0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
load	−0.0001	−0.0000	0.0001	0.0001	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
expense	−0.0269*	−0.0450***	−0.0191	−0.0324**	0.0079	−0.0092
	(0.0142)	(0.0144)	(0.0159)	(0.0163)	(0.0157)	(0.0159)
cash	0.0010	0.0009	−0.0002	−0.0001	−0.0008	−0.0008
	(0.0010)	(0.0010)	(0.0008)	(0.0008)	(0.0009)	(0.0009)
age	0.0005***	0.0005***	0.0002**	0.0002**	0.0003***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ret_vola	−0.0033	−0.0108*	0.0118***	0.0094**	−0.0095	−0.0188***
	(0.0058)	(0.0063)	(0.0037)	(0.0038)	(0.0064)	(0.0071)
family_size	−0.0001***	−0.0001***	0.0000	0.0000	0.0001**	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
intercept	−0.0012***	0.0016	0.0004	0.0003	−0.0012**	−0.0009
	(0.0004)	(0.0013)	(0.0005)	(0.0008)	(0.0005)	(0.0008)
Style FE	No	Yes	No	Yes	No	Yes
Time FE	No	No	No	No	Yes	Yes
Adj. R^2	0.13	0.15	0.00	0.01	0.11	0.13
N	2585	2585	16,380	16,380	16,380	16,380

This table shows results of OLS and 2SLS regressions of fund performance on flow risk, derivatives use, and flow management. The sample consists of actively managed US domestic equity funds over the period 1998–2013. The dependent variable is the Carhart (1997) 4-factor alpha. *flow_risk* is defined as mean absolute net flow, *derivatives* is equal to 1 if a fund uses any derivative at least once in the given period and 0 otherwise, *flow_mgmt* is given by the interaction of flow risk with the derivatives dummy. In Panel A, all variables are time-series means per fund. In Panel B, all variables are averages per fund-year. The endogenous variable is *flow_risk* and the instruments used in the 2SLS model include lagged values of all independent variables and lagged fund performance. ***, **, * denote significance of the coefficient at the 1, 5 and 10 % level, respectively. Heteroskedasticity consistent standard errors are given in parentheses (White 1980)

Table 8 Regression of performance on flow risk, derivative use and different aspects of flow management

	Panel A: OLS				Panel B: 2SLS			
	Options	Index options	Individual options	Index futures	Options	Index options	Individual options	Index futures
flow_risk	−0.0181***	−0.0181***	−0.0135**	−0.0168**	−0.0834***	−0.0834***	−0.0836***	−0.0827***
	(0.0064)	(0.0064)	(0.0062)	(0.0065)	(0.0138)	(0.0138)	(0.0138)	(0.0136)
flow_mgmt	0.0334***	0.0333***	0.0359**	0.0257***	0.0394***	0.0394***	0.0456***	0.0481***
	(0.0091)	(0.0094)	(0.0141)	(0.0095)	(0.0109)	(0.0109)	(0.0109)	(0.0116)
derivatives	−0.0005**	−0.0005*	−0.0006*	−0.0004**	−0.0010***	−0.0010***	−0.0011***	−0.0009***
	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
inflow	0.0390***	0.0390***	0.0392***	0.0422***	0.0785***	0.0785***	0.0784***	0.0786***
	(0.0052)	(0.0051)	(0.0053)	(0.0052)	(0.0072)	(0.0072)	(0.0072)	(0.0072)
outflow	−0.0358***	−0.0356***	−0.0373***	−0.0401***	−0.0571***	−0.0571***	−0.0570***	−0.0587***
	(0.0044)	(0.0044)	(0.0044)	(0.0045)	(0.0043)	(0.0043)	(0.0043)	(0.0044)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	Yes	Yes	Yes	Yes
Adj. R^2	0.15	0.15	0.15	0.15	0.15	0.13	0.13	0.13
N	2585	2585	2585	2585	16,380	16,380	16,380	16,380

This table shows results of OLS and 2SLS regressions of fund performance on flow risk, derivatives use, and flow management. The sample consists of actively managed US domestic equity funds over the period 1998–2013. The dependent variable is the Carhart (1997) 4-factor alpha. *flow_risk* is defined as mean absolute net flow, *derivatives* is equal to 1 if a fund uses the respective derivative at least once in the given period and 0 otherwise, *flow_mgmt* is given by the interaction of flow risk with the respective derivatives dummy. In Panel A, all variables are time-series means per fund. In Panel B, all variables are averages per fund-year. The endogenous variable is flow_risk and the instruments used in the 2SLS model include lagged values of all independent variables and lagged fund performance. ***, **, * denote significance of the coefficient at the 1, 5 and 10 % level, respectively. Heteroskedasticity consistent standard errors are given in parentheses (White 1980)

Table 9 Probit regression of propensity to use derivatives

	Derivatives
size	0.1480***
	(0.0224)
turnover	0.1355***
	(0.0409)
load	0.1322**
	(0.0628)
expense	35.2523***
	(7.2619)
cash	0.7085*
	(0.3723)
age	0.0330
	(0.0367)
ret_vola	−0.9575
	(1.9336)
family_size	0.0836***
	(0.0138)
Intercept	−2.5989***
	(0.1843)
Pseudo R^2	0.08
N	2585

This table shows results of a cross-sectional probit regression of derivatives use on fund characteristics. The sample consists of actively managed US domestic equity funds over the period 1998–2013. The dependent variable, derivatives use, is a dummy equal to 1 if a fund uses any derivative at least once and 0 otherwise. All variables are time-series means per fund. ***, **, * denote significance of the coefficient at the 1, 5 and 10 % level, respectively. Heteroskedasticity consistent standard errors are given in parentheses (White 1980)

First, we calculate a propensity score for each fund. The propensity score is based on a probit model where *derivatives* is the binary dependent variable and fund characteristics are the explanatory variables. The results, presented in Table 9, can be interpreted as the determinants driving a fund's decision to use derivatives. Fund size and fund family size have a positive impact on the decision to use derivatives. This is in line with our summary statistics in Table 3 and with the existing literature arguing that there are fixed costs associated with implementing derivatives. Lynch-Koski and Pontiff (1999) find that funds trading more frequently are more inclined to use derivatives. Turnover and loads have a significantly positive impact on the decision to employ derivatives. Higher expense ratios and cash holdings also correlate with a higher propensity to use derivatives.

Following the probit regression, we match each derivatives user fund to its nearest non-using neighbor fund, i.e. to a fund not employing derivatives with the closest propensity score. Table 10 displays results for our OLS and 2SLS regressions on a sample containing only user funds and their propensity score matched control funds. Supporting our previous results the *derivatives* dummy is positive in Model (1) and becomes negative in Model (2) once flow management is considered. The *flow_mgmt* coefficient in Model (2) is positive and significant alleviating concerns that our results are solely driven by a fund's decision to use derivatives. These results consequently confirm our findings that derivatives play a prominent role in mitigating the adverse impact of investor flow on fund performance and lend further support to our *flow management hypothesis*.[18]

[18] Additional propensity score analyses for the individual components of *derivatives* show similar results. For brevity, they are not reported in the paper but available from the authors upon request.

Table 10 Regression of performance on flow risk, derivatives use, and flow management—propensity score matched sample

	Panel A: OLS		Panel B: 2SLS	
	(1)	(2)	(1)	(2)
flow_risk	−0.0236***	−0.0416***	−0.0697***	−0.1043***
	(0.0078)	(0.0089)	(0.0180)	(0.0279)
flow_mgmt		0.0347***		0.0761***
		(0.0083)		(0.0218)
derivatives	0.0004***	−0.0005**	0.0002	−0.0016***
	(0.0001)	(0.0002)	(0.0001)	(0.0005)
inflow	0.0564***	0.0568***	0.0821***	0.0752***
	(0.0066)	(0.0065)	(0.0096)	(0.0085)
outflow	−0.0504***	−0.0516***	−0.0618***	−0.0621***
	(0.0056)	(0.0056)	(0.0059)	(0.0057)
Controls	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes
Adj. R^2	0.17	0.18	0.15	0.15
N	1880	1880	8978	8978

This table shows results of OLS and 2SLS regressions of fund performance on flow risk, derivatives use, and flow management. The sample consists of actively managed US domestic equity user and control funds over the period 1998–2013. User funds are funds that use any kind of derivative at least once. Control funds are funds with the closest propensity score to the user fund based on the propensity scores determined by the probit regression in Table 9. The dependent variable is the Carhart (1997) 4-factor alpha. *flow_risk* is defined as mean absolute net flow, *derivatives* is a dummy variable equal to 1 if a fund uses derivatives at least once in the given period and 0 otherwise, *flow_mgmt* is given by the interaction of flow risk with the derivatives dummy. In Panel A, all variables are time-series means per fund. In Panel B, all variables are averages per fund-year. The endogenous variable is *flow_risk* and the instruments used in the 2SLS model include lagged values of all independent variables and lagged fund performance. ***, **, * denote significance of the coefficient at the 1, 5 and 10 % level, respectively. Heteroskedasticity consistent standard errors are given in parentheses (White 1980)

5.2 Different user types

Our definition of users as those funds that use derivatives at least once may be too coarse. Hence, we partition the users into different types to estimate piecewise linear regressions where the effect of flow management on performance is allowed to depend on the frequency of derivatives use. Funds that only seldom employ the respective derivative, i.e. less than one-third of the time, are grouped into the *light* user group. *Medium* users are funds that use the respective derivative between one-third and two-thirds of the time. *Heavy* users are funds that use the respective derivative at least two-thirds of the time. *flow_mgmt_light, flow_mgmt_medium,* and *flow_mgmt_heavy* accordingly represent the amount of flow risk these user types mitigate with their employment of derivatives. The results in Table 11 clearly indicate that *medium* and *heavy* users are able to mitigate more flow risk via derivatives compared to *light* users thereby further supporting our *flow management hypothesis*.

Table 11 Regression of performance on flow risk and flow management—different user types

	Derivatives	Options	Index options	Individual options	Index futures
flow_risk	−0.0213***	−0.0177***	−0.0180***	−0.0135**	−0.0175***
	(0.0068)	(0.0064)	(0.0062)	(0.0063)	(0.0065)
flow_mgmt_light	0.0220**	0.0219**	0.0285**	0.0200*	0.0060
	(0.0108)	(0.0107)	(0.0120)	(0.0103)	(0.0105)
flow_mgmt_medium	0.0183*	0.0485***	0.0454***	0.0455*	0.0761*
	(0.0104)	(0.0158)	(0.0162)	(0.0255)	(0.0435)
flow_mgmt_heavy	0.0323***	0.0322*	0.0276	0.0276	0.0237**
	(0.0094)	(0.0188)	(0.0202)	(0.0510)	(0.0095)
light	−0.0005**	−0.0002	−0.0000	−0.0008	−0.0005*
	(0.0002)	(0.0004)	(0.0004)	(0.0018)	(0.0003)
medium	−0.0003	−0.0002	−0.0004	−0.0004	0.0000
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
heavy	−0.0003	−0.0010**	−0.0009*	0.0010	−0.0016*
	(0.0003)	(0.0004)	(0.0005)	(0.0017)	(0.0009)
inflow	0.0418***	0.0388***	0.0389***	0.0394***	0.0425***
	(0.0051)	(0.0051)	(0.0050)	(0.0053)	(0.0052)
outflow	−0.0391***	−0.0360***	−0.0354***	−0.0377***	−0.0395***
	(0.0044)	(0.0044)	(0.0044)	(0.0044)	(0.0044)
intercept	0.0016	0.0016	0.0016	0.0012	0.0012
	(0.0013)	(0.0013)	(0.0013)	(0.0012)	(0.0012)
Controls	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No
Adj. R^2	0.15	0.15	0.15	0.15	0.15
N	2585	2585	2585	2585	2585

This table shows results of cross-sectional OLS regressions of fund performance on flow risk, derivatives use, and flow management for different user types. The sample consists of actively managed US domestic equity funds over the period 1998–2013. The dependent variable is the Carhart (1997) 4-factor alpha. *flow_risk* is defined as mean absolute net flow, *light* (*medium, heavy*) is a dummy variable equal to 1 if a fund uses the respective derivative up to a third (a third to two-thirds, or more than two-thirds) of the time and 0 otherwise, *flow_mgmt_light* (*flow_mgmt_medium, flow_mgmt_heavy*) is given by the interaction of flow risk with the respective dummy. All variables are time-series means per fund. ***, **, * denote significance of the coefficient at the 1, 5 and 10 % level, respectively. Heteroskedasticity consistent standard errors are given in parentheses (White 1980)

5.3 Further tests

We verify the robustness of our results with several different specifications of our methodology. For brevity, the respective tables are not reported in the paper, but are available from the authors upon request. Specifically, when repeating our calculations with gross returns instead of net returns, results remain the same. Moreover, we measure fund performance with several alternative models. We employ the CAPM (Jensen 1968), Fama and French's (1993) 3-factor model, and the Carhart model with Ferson and Schadt (1996) conditional market betas.[19] To control for potential benchmark misspecifications by using the benchmark factors from French's data library, we repeat our analyses with the index-based four-factor model introduced by Cremers et al. (2013).[20] The respective results are similar to those using the Carhart (1997) 4-factor alpha.

Adverse investor flows may affect funds with more illiquid trading strategies more heavily, as they cannot trade as easily (Chen et al. 2010). Due to the holding of illiquid securities, they may also earn higher returns via a liquidity premium (Acharya and Pedersen 2005). To control for these effects we alternatively measure fund performance by using the Carhart model augmented with the liquidity factor from Pástor and Stambaugh (2003).[21] The results are the same as in our main analysis.

Mutual funds' use of derivatives may depend on the general economic environment. Therefore, we divide our sample into different sub-periods based on the crisis years 2001, 2002, 2007, and 2008 and on the remaining non-crisis years. The permission to use (91.62 vs. 92.85 %) and the actual usage of derivatives (35.32 vs. 34.65 %) are more or less the same during crisis and non-crisis periods. Furthermore, results stay the same as in our main analysis, so that flow management has a positive and significant relation to fund performance during crisis years as well as during the non-crisis years.

To further test whether derivatives use is different during different market regimes, we also divide our sample months with positive and months with negative market returns. The permission to use (92.23 vs. 93.29 %) is similar during both market regimes. The actual use of derivatives is somewhat lower during months with positive market returns (38.07 %) than in months with negative market returns (41.06 %). However, in both regimes our results of a significant positive relation between flow management and performance hold. In addition, we also partition our sample into two equally long sub-periods from 1998 to 2005 and from 2006 to 2013 to check if the relation intensified or weakened over time. This also does not materially affect our results as our hypotheses hold in both periods.

6 Conclusion

Using a large and comprehensive sample of active U.S. domestic equity mutual funds merged between the CRSP Survivor-Bias-Free Mutual Fund Database and the SEC's semi-annual N-SAR filings, we analyze differences between mutual funds with respect to flow risk, which is the adverse impact of investor flows on fund performance. Specifically, we are the first using detailed information on funds' investment practices to analyze the drivers of these cross-sectional differences.

Overall, we find that funds using derivatives generate yearly abnormal risk-adjusted returns in excess of their non-using peers. We attribute this to the fact that user funds are able to maintain adequate market exposure in times of adverse investor inflows or outflows

[19] The conditioning variables are the S&P 500 dividend yield obtained from Thomson Reuters Datastream, the term spread (yield spread between 10-year treasury bond yield and 3-month treasury bill yield), the default spread (yield spread between BAA-rated and AAA-rated corporate bonds), and the 3-month treasury bill yield. We obtain all yield time-series from the St. Louis Federal Reserve website.

[20] We thank Antii Petajisto for providing the data. http://www.petajisto.net/data.html.

[21] We thank Robert F. Stambaugh for providing the time-series of the Pástor and Stambaugh (2003) liquidity factor on his website at http://finance.wharton.upenn.edu/~stambaugh/liq_data_1962_2012.txt.

Table 12 Comparison of CRSP and N-SAR samples

	Panel A: NSAR matched data			Panel B: CRSP data		
	Mean	Median	Standard deviation	Mean	Median	Standard deviation
TNA ($mil)	967	194	3194	883	164	3462
Expense ratio (% TNA, p.a)	0.0119	0.0119	0.0047	0.0120	0.0120	0.0050
Turnover ratio (% TNA, p.a)	0.9334	0.6867	1.3276	0.9828	0.6917	1.4246
Age (Years)	10.20	7.19	9.47	9.36	6.50	8.91
Implied net flow (% TNA)	0.0061	0.0020	0.0204	0.0062	0.0034	0.0183
Excess net return	0.0042	0.0047	0.0063	0.0042	0.0044	0.0060

This table compares average fund characteristics for two samples of actively managed US domestic equity funds during the period 1998–2013 by year. Panel A shows the relevant variables for 2585 funds with entries in both the N-SAR filings and the CRSP mutual fund database. Panel B shows the relevant variables for 3529 funds available in the CRSP mutual fund database. All variables are taken from the CRSP mutual fund database

by using derivatives for flow management purposes. Investors are therefore better off investing in funds with flow management ability.

Consequently, policy makers, such as the SEC, should consider our results when regulating the use of derivatives for mutual funds. Prohibiting funds from using derivatives may lead to lower performance as funds would not be allowed to employ flow risk management strategies. Furthermore, our findings imply that researchers and investors need to take into account how successful funds are in managing flow risk when assessing fund performance in general, or the flow-performance relation and the smart money effect in particular.

Acknowledgments We are grateful for helpful comments and suggestions by an anonymous referee, Ralf Elsas, Jon Fulkerson, Scott Gibson, Paul Koch, Christian Koziol, Thomas Maehlmann, Michael McKenzie, Blake Phillips, David Rakowski, Stefan Ruenzi, Christian Schlag, Hendrik Scholz, Sara Shirley, Timothy Simin, Erik Theissen, and participants at 2013 German Finance Association doctoral seminar at the University of Wuppertal, 2014 HypoVereinsbank-UniCredit Group doctoral seminar at the University of Mannheim, 2014 International Finance and Banking Society Conference, 2014 Northern Finance Association Conference, 2014 Southern Finance Annual Meeting, 2015 Midwest Finance Annual Meeting, and 2015 Financial Management Association European Conference. We acknowledge financial support by the Research Center Global Business Management of the University of Augsburg. All remaining errors are our own.

Appendix: N-SAR-CRSP matching and data screening

To obtain our data set we download 106,357 individual N-SAR-filings in text format from the SEC's EDGAR online database for the period 1998–2013. We parse the individual text filings into a consistent table format using regular expressions under Linux. In addition, we extract ticker symbols from the header sections of the filings.

In the next step, we merge the N-SAR filings with the CRSP mutual fund database. Unfortunately, there is no common identifier in both CRSP and N-SAR. Even worse, in N-SAR there is no consistent fund identifier over time. Although the general instructions of the SEC urge registrants to use consistent information, the company identification key (CIK) and series numbers change over time for a substantial number of funds. Consequently, we have to match N-SAR with CRSP by using their fund names for each reporting date. For entries where ticker information is available in both CRSP and N-SAR filings, we additionally use the ticker symbols to match the funds. To improve our matching accuracy we clean fund names in CRSP and N-SAR by hand, e.g., we delete special characters such as "," and ":" and write abbreviations in a consistent manner (e.g., "Small Cap" for "Small CP" or "Small Capitalization"). Furthermore, as fund name entries in N-SAR are often erroneous we correct them manually. We conduct the actual matching of fund names with Winkler's (1990) Jaro-Winkler string distance metric as implemented in the SimMetrics open source library. In tests with our database, we have found the Jaro-Winkler algorithm to be superior to other string matching techniques in the SimMetrics library regarding speed and matching accuracy.

Since algorithmic matching techniques partly deliver false positive matches, we manually check all matches for plausibility and clean the merged sample from false positives as in Chen et al. (2013). We discard funds with discrepancies of more than 10 % for net assets reported in N-SAR and CRSP for more than 25 % of the time from our sample. Following Christoffersen et al. (2013) we remove fund months if in- or outflows in month t are larger than 100 % of the TNA from CRSP in month $t - 1$, or absolute net flows are larger than 50 % of the TNA from CRSP in month $t - 1$. We further drop all fund months in the top 1.5 % of difference between net flows from N-SAR and implied net flows from CRSP.

Table 12 displays cross-sectional means of fund characteristics for both the merged N-SAR-CRSP sample and the complete actively managed domestic equity fund universe from CRSP. Funds in our sample have higher TNA and they are somewhat older. Evans et al. (2015) find similar results are for their matched sample. Overall, there are no substantial differences between both data sets. Consequently, we conclude that our sample is representative for the universe of all actively managed U.S. domestic equity funds.

References

Acharya V, Pedersen LH (2005) Asset pricing with liquidity risk. J Financ Econ 77:375–410

Agarwal V, Gay GD, Ling L (2014) Window dressing in mutual funds. Rev Financ Stud 27:3133–3170

Alexander GJ, Cici G, Gibson S (2007) Does motivation matter when assessing trade performance? An analysis of mutual funds. Rev Financ Stud 20:125–150

Almazan A, Brown KC, Carlson M, Chapman DA (2004) Why constrain your mutual fund manager? J Financ Econ 73:289–321

Angrist JD, Imbens GW (1995) Two-stage least squares estimation of average causal effects in models with variable treatment intensity. J Am Stat Assoc 90:431–442

Bae KH, Yi J (2008) The impact of the short–short rule repeal on the timing ability of mutual funds. J Bus Financ Acc 35:969–997

Berk JB, Green RC (2004) Mutual fund flows and performance in rational markets. J Polit Econ 112:1269–1295

Cao C, Ghysels E, Hatheway F (2011) Derivatives do affect mutual fund returns: evidence from the financial crisis of 1998. J Futures Mark 31:629–658

Carhart MM (1997) On persistence in mutual fund performance. J Financ 52:57–82

Cashman GD, Deli DN, Nardari F, Villupuram S (2012) Investors do respond to poor mutual fund performance: evidence from inflows and outflows. Financ Rev 47:719–739

Cashman GD, Deli DN, Nardari F, Villupuram S (2014) Investor behavior in the mutual fund industry: evidence from gross flows. J Econ Financ 38:541–567

Chen Q, Goldstein I, Jiang W (2010) Payoff complementarities and financial fragility: evidence from mutual fund outflows. J Financ Econ 97(2):239–262

Chen H, Desai H, Krishnamurthy S (2013) A first look at mutual funds that use short sales. J Financ Quant Anal 48:761–787
Chevalier J, Ellison G (1997) Risk taking by mutual funds as a response to incentives. J Polit Econ 105:1167–1200
Chordia T (1996) The structure of mutual fund charges. J Financ Econ 41:3–39
Christoffersen SEK, Evans R, Musto DK (2013) What do consumers' fund flows maximize? Evidence from their brokers' incentives. J Financ 68:201–235
Cici G, Palacios LF (2015) On the use of options by mutual funds: do they know what they are doing? J Bank Financ 50:157–168
Clifford CP, Fulkerson JA, Jordan BD, Waldman S (2013) Risk and fund flows. SSRN working paper. http://ssrn.com/abstract=1752362. Accessed 16 June 2013
Clifford CP, Fulkerson JA, Hong X, Jordan BD (2014) Investment restrictions and fund performance. SSRN working paper. http://ssrn.com/abstract=2485518. Accessed 10 December 2014
Coval J, Stafford E (2007) Asset fire sales (and purchases) in equity markets. J Financ Econ 86:479–512
Cremers M, Petajisto A, Zitzewitz E (2013) Should benchmark indices have alpha? Revisiting performance evaluation. Crit Financ Rev 2:1–48
Del Guercio D, Tkac PA (2002) The determinants of the flow of funds of managed portfolios: mutual funds vs. pension funds. J Financ Quant Anal 37:523–557
Deli DN, Varma R (2002) Contracting in the investment management industry: evidence from mutual funds. J Financ Econ 63:79–98
DeLisle RJ, Lee B, Mauck N (2015) The dynamic relation between options trading, short selling, and aggregate stock returns. Rev Quant Financ Account (forthcoming)
Dubofsky DA (2010) Mutual fund portfolio trading and investor flow. J Bank Financ 34:802–812
Edelen RM (1999) Investor flows and the assessed performance of open-end mutual funds. J Financ Econ 53:439–466
Edelen RM, Evans R, Kadlec GB (2012) Disclosure and agency conflict: evidence from mutual fund commission bundling. J Financ Econ 103:308–326
Evans R, Ferreira MA, Porras Prado M (2015) Fund performance and equity lending: why lend what you can sell? http://ssrn.com/abstract=2101604 Accessed 23 April 2015
Fama EF, French KR (1993) Common risk factors in the returns on stocks and bonds. J Financ Econ 33:3–56
Fama EF, MacBeth JD (1973) Risk, return, and equilibrium: empirical tests. J Polit Econ 81:607–636
Ferson WE, Schadt RW (1996) Measuring fund strategy and performance in changing economic conditions. J Financ 51:425–461
Frino A, Lepone A, Wong B (2009) Derivative use, fund flows and investment manager performance. J Bank Financ 33:925–933
Fulkerson JA, Jordan BD, Riley TB (2013) Return chasing in bond funds. J Fix Income 22:90–103
Greene JT, Hodges CW, Rakowski DA (2007) Daily mutual fund flows and redemption policies. J Bank Financ 31:3822–3842
Gruber MJ (1996) Another puzzle: the growth in actively managed mutual funds. J Financ 51:783–810
Huang J, Wei KD, Yan H (2007) Participation costs and the sensitivity of fund flows to past performance. J Financ 62:1273–1311
ICI (2014) Investment Company Factbook 2014. A Review of Trends and Activity in the U.S. Investment Company Industry 54
Ippolito RA (1992) Consumer reaction to measures of poor quality: evidence from the mutual fund industry. J Law Econ 35:45–70
Ivkovic Z, Weisbenner S (2009) Individual investor mutual fund flows. J Financ Econ 92:223–237
Jensen MC (1968) The performance of mutual funds in the period 1945–1964. J Financ 23:389–416
Keswani A, Stolin D (2008) Which money is smart? Mutual fund buys and sells of individual and institutional investors. J Financ 63:85–118
Kuhnen CM (2009) Business networks, corporate governance, and contracting in the mutual fund industry. J Financ 64:2185–2220
Li CA, Ma HC (2010) The performance and cash flows of newly raised funds. Rev Pac Basin Financ Mark Polic 13:539–557
Loon Y (2011) Model uncertainty, performance persistence and flows. Rev Quant Financ Acc 36:153–205
Lou D (2012) A flow-based explanation for return predictability. Rev Financ Stud 25:3457–3489
Lynch-Koski J, Pontiff J (1999) How are derivatives used? Evidence from the mutual fund industry. J Financ 54:791–816
Maher JJ, Brown RM, Kumar R (2008) Firm valuation, abnormal earnings, and mutual funds flow. Rev Quant Financ Acc 31:167–189
O'Neal ES (2004) Purchase and redemption patterns of US equity mutual funds. Financ Manag 33:63–90

Pástor L, Stambaugh RF (2003) Liquidity risk and expected stock returns. J Polit Econ 111:642–685
Qian M (2011) Stale prices and the performance evaluation of mutual funds. J Financ Quant Anal 46:369–394
Rakowski D (2010) Fund flow volatility and performance. J Financ Quant Anal 45:223–237
Rakowski D, Wang X (2009) The dynamics of short-term mutual fund flows and returns: a time-series and cross-sectional investigation. J Bank Financ 33:2102–2109
Reuter J (2006) Are IPO allocations for sale? Evidence from mutual funds. J Financ 61:2289–2324
Rohleder M, Scholz H, Wilkens M (2011) Survivorship bias and mutual fund performance: relevance, significance, and methodical differences. Rev Financ 15:441–474
Sapp T, Tiwari A (2004) Does stock return momentum explain the "smart money" effect? J Financ 59:2605–2622
Shrider DG (2009) Running from a bear: how poor stock market performance affects the determinants of mutual fund flows. J Bus Financ Acc 36:987–1006
Sirri ER, Tufano P (1998) Costly search and mutual fund flows. J Financ 53:1589–1622
Wang C-J (2015) Instrumental variables approach to correct for endogeneity in finance. In: Lee C-F, Lee JC (eds) Handbook of financial economics and statistics. Springer, New York, pp 2578–2600
Warner JB, Wu JS (2011) Why do mutual fund advisory contracts change? Performance, growth, and spillover effects. J Financ 66:271–306
White H (1980) A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica 48:817–838
Winkler WE (1990) String comparator metrics and enhanced decision rules in the Fellegi-Sunter model of record linkage. Proceedings of the Section on Survey Research, 354–359
Zheng L (1999) Is money smart? A study of mutual fund investors' fund selection ability. J Financ 54:901–933