DISCUSSION PAPER SERIES

DP11156

WHO TRADES AGAINST MISPRICING

Mariassunta Giannetti and Bige Kahraman

FINANCIAL ECONOMICS

ISSN 0265-8003

WHO TRADES AGAINST MISPRICING?

Mariassunta Giannetti and Bige Kahraman

Discussion Paper 11156
Published 03 March 2016
Submitted 03 March 2016

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

WHO TRADES AGAINST MISPRICING?

Abstract

We provide evidence that open-end structures undermine asset managers' incentives to attack long-term mispricing. First, we compare open-end funds with closed-end funds. Closed-end funds purchase more underpriced stocks than open-end funds, especially if the stocks involve high arbitrage risk. We then show that hedge funds with high share restrictions, having a lower degree of open-ending, also trade against long-term mispricing to a larger extent than other hedge funds. Our analysis suggests that open-end organizational structures are an impediment to arbitrage.

JEL Classification: G12, G23

Keywords: Limits to Arbitrage, Flow performance Sensitivity, Capital Structure, Market Efficiency

Mariassunta Giannetti - mariassunta.giannetti@hhs.se
Stockholm School of Economics and CEPR

Bige Kahraman - bige.kahraman@sbs.ox.ac.uk
Saïd Business School, University of Oxford

Acknowledgements
We would like to thank Stefan Nagel (the editor), three anonymous referees, Yakov Amihud, Andrew Ang, Suleyman Basak, Martin Cherkes, Nick Barberis, Darwin Choi, Josh Coval, Sudipto Dasgupta, Francesco Franzoni, Greg Duffee, William Goetzmann, Gur Huberman, Charles Jones, Shimon Kogan, Xuewen Liu, Alberto Plazzi, Jeff Pontiff, Tarun Ramadorai, Ronnie Sadka, Neng Weng, Avi Wohl and seminar participants at the NBER Market Microstructure Meeting, the University of British Columbia Summer Conference in Finance, the European Finance Association, the Financial Intermediation Research Society, the Workshop on Financial Intermediation and Risk at the Barcelona GSE Summer Forum, the 6th Annual Hedge Fund Conference in Paris, the Paul Woolley Center for Capital Market Dysfunctionality Conference, the Humboldt University/ESMT Conference on Asset Management, the 2014 Jerusalem Finance Conference, the 3rd Luxembourg Asset Management Summit, HKUST, the Swiss Finance Institute at the University of Lugano, the Shanghai Advanced Institute of Finance at Jiaotong University, the Singapore Management University, the Duisenberg School of Finance, the Stockholm School of Economics, and Humboldt University for helpful comments. We thank Vikas Agarwal, Wei Jiang, Yuehua Tang, and Baozhong Yang for sharing their hedge funds data and Andreas Johansson, Mats Levander and Viktor Thell for research assistance. Giannetti acknowledges financial support from the Jan Wallander and Tom Hedelius Foundation and the Bank of Sweden Tercentenary Foundation. All errors are our own.

Who Trades Against Mispricing?*

Mariassunta Giannetti
Stockholm School of Economics, CEPR, and ECGI

Bige Kahraman
Saïd Business School, University of Oxford

February 2016

Abstract

We provide evidence that open-end structures undermine asset managers' incentives to attack long-term mispricing. First, we compare open-end funds with closed-end funds. Closed-end funds purchase more underpriced stocks than open-end funds, especially if the stocks involve high arbitrage risk. We then show that hedge funds with high share restrictions, having a lower degree of open-ending, also trade against long-term mispricing to a larger extent than other hedge funds. Our analysis suggests that open-end organizational structures are an impediment to arbitrage.

Keywords: Limits to Arbitrage, Flow performance Sensitivity, Capital Structure, Market Efficiency
JEL Classification: G12, G23

---

* We would like to thank Stefan Nagel (the editor), three anonymous referees, Yakov Amihud, Andrew Ang, Suleyman Basak, Martin Cherkes, Nick Barberis, Darwin Choi, Josh Coval, Sudipto Dasgupta, Francesco Franzoni, Greg Duffee, William Goetzmann, Gur Huberman, Charles Jones, Shimon Kogan, Xuewen Liu, Alberto Plazzi, Jeff Pontiff, Tarun Ramadorai, Ronnie Sadka, Neng Weng, Avi Wohl and seminar participants at the NBER Market Microstructure Meeting, the University of British Columbia Summer Conference in Finance, the European Finance Association, the Financial Intermediation Research Society, the Workshop on Financial Intermediation and Risk at the Barcelona GSE Summer Forum, the 6th Annual Hedge Fund Conference in Paris, the Paul Woolley Center for Capital Market Dysfunctionality Conference, the Humboldt University/ESMT Conference on Asset Management, the 2014 Jerusalem Finance Conference, the 3rd Luxembourg Asset Management Summit, HKUST, the Swiss Finance Institute at the University of Lugano, the Shanghai Advanced Institute of Finance at Jiaotong University, the Singapore Management University, the Duisenberg School of Finance, the Stockholm School of Economics, and Humboldt University for helpful comments. We thank Vikas Agarwal, Wei Jiang, Yuehua Tang, and Baozhong Yang for sharing their hedge funds data and Andreas Johansson, Mats Levander and Viktor Thell for research assistance. Giannetti acknowledges financial support from the Jan Wallander and Tom Hedelius Foundation and the Bank of Sweden Tercentenary Foundation. All errors are our own.

Author contact information: Mariassunta Giannetti, Stockholm School of Economics, Drottninggatan 89, 113 60 Stockholm, Sweden, mariassunta.giannetti@hhs.se. Bige Kahraman, Said Business School, Park End Street, Oxford OX1 1HP, UK, bige.kahraman@sbs.ox.ac.uk.

Do open-end organizational structures prevail because they are the most efficient, as argued by Fama and Jensen (1983)? Or, as Stein's (2005) model shows, the degree of open-ending in the market can be socially excessive because open-end organizational structures discourage asset managers from trading against mispricing? This paper aims to contribute to this debate by providing evidence that open-end structures indeed weaken managerial incentives to trade against mispricing.

The seminal paper of Shleifer and Vishny (1997) describes the mechanism through which open-end structures can be a serious impediment to exploiting profitable trading opportunities. Asset managers invest other people's money. Fund investors typically lack the specialized knowledge to evaluate an asset manager's strategy and may simply evaluate the manager on the basis of his recent past performance. If the long-term mispricing that a fund manager is exploiting fails to converge in the short run, investors may decide that the manager is incompetent and refuse to provide him with more capital, and even withdraw some of it. To avoid encountering such bad scenarios in the future, asset managers may neglect mispricing for which convergence to fundamentals is unlikely to be either smooth or rapid. Only asset managers whose flows are less sensitive performance may thus be willing to trade against long-term mispricing.

To test this hypothesis, we begin by contrasting the trading behavior of open- and closed-end funds. Open- and closed-end funds are subject to similar regulations, but differently from open-end funds, closed-end funds' assets under management do not depend on performance-driven investor flows. If investor flows undermine managers' incentives as described by Shleifer and Vishny (1997), we expect closed-end funds to be more inclined to trade against long-term mispricing. Next, we exploit that hedge funds often impose share restrictions constraining withdrawals. Share

restrictions decrease the funds' flow performance sensitivity (Hombert and Thesmar, 2014). We thus expect hedge funds with high share restrictions to be more inclined to trade against long-term mispricing than hedge funds with low share restrictions. Finding that any differences between closed- and open-end funds are reproduced between hedge funds with high and low share restrictions would provide an independent validation of our hypothesis.

For our tests, it is important to identify types of mispricing for which arbitrage is risky and can be expected to be profitable only in the long run. Forced sales of distressed funds can give rise to fire sales events that cause a dramatic drop in stock prices. Fire sales have been shown to bring about long-lasting mispricing of financial assets, persisting for up to two years (Coval and Stafford, 2007; Duffie, 2010). Uncertainty on the timing of convergence can significantly reduce the short-term returns from investing in fire sale stocks making this type of mispricing particularly suitable for our tests.

As additional evidence, we use mispricing that arises when noise traders' irrational enthusiasm for stock characteristics shifts or when investors misinterpret what they perceive to be private information about systematic economic factors. A common prediction of behavioral models is that noise traders' demand induces positive comovement among stocks with similar characteristics (Daniel, Hirshleifer, and Subrahmanyam, 2001; Barberis and Shleifer, 2003). This type of mispricing suits our conceptual framework as the timing of convergence to fundamental value is uncertain due to the unpredictable nature of shifts in noise traders' demand.

We find that closed-end funds are more inclined to buy undervalued stocks than open-end funds. The difference in the net purchases of closed- and open-end funds in fire sale stocks is about half of the standard deviation of all trades, indicating

that the effects are not only statistically, but also economically significant. Differences in trading behavior are even more pronounced for stocks with high arbitrage risk (such as smaller stocks and stocks with highly volatile returns), as predicted by Shleifer and Vishny (1997). Similarly, hedge funds with higher share restrictions have more investments in undervalued stocks compared to other hedge funds.

Not only are our findings robust across different classes of asset managers, but they also survive a battery of robustness checks that aim to rule out that certain fund characteristics, correlated with the fund's organizational structure (such as the fund's style or the fund manager's ability), drive our findings. For instance, fund managers that comanage open- and closed-end funds trade more against mispricing in their closed-end funds, suggesting that our results are not driven by differences in managerial ability. In addition, open-end funds appear less likely to purchase fire sale stocks even when we control for various measures of the funds' financial slack, confirming the hypothesis that the incentives arising from funds' organizational structures matter.

Finally, the cross-sectional variation of the effects supports the mechanisms on which our interpretation of the findings relies upon. Fund characteristics that we show to be associated with a lower sensitivity of flows to performance (such as a longer managerial tenure or more institutional investment in the fund) increase the funds' propensity to purchase undervalued stocks. Taken jointly, our tests highlight that organizational structures lowering the sensitivity of flows to performance strengthen asset managers' incentives to trade against mispricing.

Our paper is related to a growing literature that explores asset managers' trading strategies. Existing literature provides mixed evidence on the extent to which

financial institutions trade against mispricing. For instance, Edelen, Ince and Kadlec (2013), Greenwood and Nagel (2011), Mitchell, Pedersen, and Pulvino (2007) and Brunneimeir and Nagel (2004) find that institutional investors, including hedge funds, trade in a way that accentuates mispricing. Akbas, Armstrong, Sorescu, Subrahmanyam (2014), Cao, Chen, Goetzmann, and Lian (2013), Kokkonen and Suominen (2014), however, show that hedge funds tend to correct mispricing. By considering differences between institutions, we show that open-end organizational structures act as an impediment to long-term risky arbitrage and contribute to the debate between Fama and Jensen (1983) and Stein (2005) on the efficient organization of the asset management industry. Our results imply that since open-end organizational structures are prevalent, institutional investors appear not to trade against mispricing, if taken as a group. Exploiting the heterogeneity in share restrictions among hedge funds, we also identify the characteristics of hedge funds that are more inclined to attack mispricing.

Another strand of literature explores the effects of the liability structure on the funds' performance and investments in illiquid assets. Aragon (2007) and Agarwal, Daniel, and Naik (2009) find that hedge funds with high redemption restrictions have higher returns, presumably because they are able to invest in illiquid assets and obtain an illiquidity premium. Cherkes, Sagi, and Stanton (2008) show that closed-end funds' returns are more exposed to illiquid assets. Instead of focusing on the funds' tendency to invest in illiquid assets, we highlight the effect of funds' organizational structures and share restrictions on trading in mispriced securities. We show that this effect is independent from the illiquidity of the assets stressed in previous literature.

The remainder of this paper is organized as follows. Section 1 provides background information and describes the data sources. Section 2 describes how

different funds' features relate to the funds' flow performance sensitivity. Sections 3 and 4 describe how funds with different organizational structures trade against mispricing. Section 5 concludes.

1. Institutional Background and Data Sources

Most investment vehicles, including open-end mutual funds and (most) hedge funds, have an open-end structure. As a consequence, funds' assets under management depend on the funds' past performance not only because they are funded with redeemable claims, which expose them to withdrawal risk, but also because weaker performance tends to translate in less new investments. Closed-end funds and, to a lower extent, hedge funds with share restrictions are notable exceptions. Below we discuss their institutional features and the data sources used in the empirical analysis.

1.1. Closed-end and Open-end Funds

Closed-end funds are professionally managed investment companies that typically sell a fixed number of shares at one time (in an initial public offering), after which the shares trade on a secondary market. The vast majority of closed-end funds does not accept new investments.[1] Closed-end funds also have no obligation to redeem investors' shares.

By contrast, open-end funds' assets under management depend on investors' decisions to invest or redeem. Closed-end funds are otherwise similar to open-end funds and are also subject to similar regulations. Both closed- and open-end funds are regulated primarily under the same sections of the Investment Company Act of 1940,

[1] A minority of closed-end funds is continuously offered (about 4 % in our dataset). These funds are excluded from our sample.

and subject to SEC registration and the Securities Act of 1933 and the Securities Exchange Act of 1934. Differently from open-end funds, closed-end funds are allowed to borrow (see Almazan, Brown, Carlson, Chapman, 2004), but in practice only a few closed-end funds use leverage (Dimson, 2002). Also, closed-end funds are allowed to invest in asset classes that cannot be liquidated in less than one week.

We obtain data on the entire universe of US closed-end funds from Lipper Inc., distributed by Thomson Reuters, and from Morningstar Direct. Lipper and Morningstar have similar coverage. If a fund appears in both Lipper and Morningstar, we use data from Lipper. In this way, we construct a survivorship bias free dataset that provides information on quarterly asset holdings and a variety of other fund characteristics, such as monthly returns, total net assets under management (TNA), annual fees, and allocation schemes. We complement this data with S&P Capital IQ, which provides information on closed-end funds' liabilities (if any).

We obtain the correspondent information on characteristics and quarterly stockholdings for open-end mutual funds from the CRSP Survivorship Bias Free Mutual Fund Database and the Thomson Reuters Mutual Fund Holdings database, respectively. We further obtain information on some open-end funds' characteristics, such as managerial ownership and governance, from Morningstar Direct. During our sample period, many mutual funds have multiple share classes. Since each share class of a fund has claims to the same portfolio holdings, we aggregate all the observations at the fund level. As is common in the literature, for qualitative fund attributes, such as objectives and year when the fund was first offered, we use the attributes of the oldest share class; for the total net assets under management, we sum the net assets of all share classes, and take the TNA-weighted average for the rest of the quantitative attributes (e.g., returns, expenses). We exclude index funds by removing funds that

are identified by CRSP or Morningstar as index funds and by screening funds' names and eliminating any fund whose name contains the word "index". We also exclude open-end funds with extreme flows (as discussed in Subsection 3.1) from all the analyses.

Finally, we obtain information on stock characteristics and prices from COMPUSTAT and CRSP, respectively.

Our tests rely on two samples. The first sample allows us to focus on quarterly changes in funds' stockholdings. This sample goes from January 2004 to December 2014 because data on closed-end funds' holdings are not widely available for earlier periods. For consistency with previous literature, we eliminate the holdings of open- and closed-end funds with TNA less than 1 million or that report less than 10 stock holdings.

The second sample does not require holdings data, but only funds' monthly returns, which are available for both closed- and open-end funds starting from January 1990. To focus on a more homogeneous set of funds, we include only funds specialized in domestic equity in this sample. As a result, this sample includes a total of 406 US based closed-end funds.

[Insert Table 1 here]

Panel A of Table 1 summarizes the funds' main characteristics. Since closed-end funds tend to be smaller than open-end funds, we exclude open-end funds in the top TNA quintile from all analyses.[2] Consequently, as shown in Table 1, the average size of the open-end funds in our sample is similar to that of the closed-end funds. Open- and closed-end funds also charge similar annual fees; closed-end funds have

[2] All results we present hereafter are qualitatively invariant if we include the top quintile of open-end funds in the analysis. We present these results in Table A.3 of the Internet Appendix.

higher style-adjusted performance (also more positively skewed). On average, closed-end funds have a leverage of 6.8 %.

Table 1 also compares the main characteristics of the stocks held by closed- and open-end funds. A number of important patterns immediately emerge. First, we confirm the conjecture that closed-end funds hold more illiquid stocks (e.g., Cherkes, Sagi and Stanton (2008)); to our knowledge, our paper is the first to provide direct evidence on closed-end funds' preference for illiquid assets using holdings data. Moreover, closed-end funds appear more contrarian compared to open-end funds as they invest more in value stocks and engage less in momentum trading.

1.2. Hedge Funds

To evaluate the relevance of open-end structures for a broader class of asset managers, we also explore the effects of share restrictions on hedge fund managers' trading. Hedge funds are subject to much more flexible regulation than open- and closed-end funds, which allows them to use leverage more aggressively and take short positions. They also have fee structures that provide them with steep incentives. For all these reasons, hedge funds are closer to the ideal of "rational arbitrageurs" than any other class of investors (Brunnermeier and Nagel, 2004).

Hedge funds are organized on an open-end basis. However, at their inception, hedge funds can impose share restrictions that limit investors' ability to redeem by requiring advance notification or by restricting redemptions to predetermined periods (Aragon, 2007; Agarwal, Daniel and Naik, 2009). Also, some hedge funds have lock up periods that impose a minimum investment time on new investors. Because of the share restrictions, hedge funds' degree of open-endness varies. Hedge funds may thus

provide an independent test for the relevance of open-end structures on asset managers' propensity to trade against mispricing.

We obtain information on hedge funds' characteristics including returns, assets under management and share restrictions from Lipper Tass, CISDIM/Morningstar, and Hedge Fund Research. As Agarwal, Fos and Jiang (2013) describe, these three commercial datasets provide information on largely different subsets of hedge funds. We exclude any funds that appear in more than one dataset.

The hedge fund datasets do not provide information on the hedge funds' stock holdings, which is essential for some of our tests. We obtain hedge funds' stockholdings from Thomson Financial 13F. Since Thomson Financial 13F and the hedge funds' databases provide no common identifiers that allow us to match the hedge funds to their management companies, we obtain the match between hedge funds' commercial databases and 13F quarterly ownership from Agarwal, Jiang, Tang and Yang (2013) and Agarwal, Fos and Jiang (2013). The match includes only management companies that are relatively "pure-play" hedge funds, and does not include full-service banks whose investment arms engage in hedge fund business. We focus on the post-1994 period to mitigate potential survivorship bias, as most of the databases start reporting information on "defunct" funds only after 1994.

As mentioned above, share restrictions consist of redemption notice period, payout period and lock up period. The lock up period represents the minimum number of days an investor must commit the capital. At the end of the lock up period, an investor who wishes to withdraw her capital needs to give advance notice (redemption notice period) and then may have to wait some additional time to receive the money because the hedge fund allows her to redeem only at fixed dates (payout period). Panel A of Table 2 summarizes the duration of each type of share restrictions. We

approximate the payout period assuming that fund investors have uniformly distributed liquidity shocks. Thus, on average, an investor will have to wait 45 days before being able to redeem her capital if the hedge fund has a quarterly (90 days) payout period.

[Insert Table 2 here]

Following Agarwal, Daniel, and Naik (2009), we measure share restrictions by adding up the number of days of the lock up period, the advance notice period, and the redemption period.[3] There is large variation in the extent of share restrictions: the combined number of days associated with share restrictions is 60 days for the bottom quartile and over 300 days for the upper quartile.

Panel B and C of Table 2 describe differences in the stockholdings and other fund characteristics of hedge funds with share restrictions above and below the median. Overall, there appear to be no big differences in most variables. However, as we test in the next section, hedge funds with higher share restrictions seem to have lower flow performance sensitivity.

2. Organizational Structures and Flow Performance Sensitivity

Our maintained hypothesis is that a lower degree of open-endness decreases an asset manager's propensity to attack long-term risky mispricing because it decreases the fund's flow performance sensitivity. In this section, we show that the organizational structure is indeed associated with the funds' flow performance sensitivity.

A large literature documents that open-end funds' flows are sensitive to past performance (see, for instance, Chevalier and Ellison (1997), Sirri and Tufano (1998),

[3] Tables A.6 and A.8 of the Internet Appendix show that our results still hold if we do not consider the lock up period, which matters only for new investors, in the definition of share restrictions.

Huang, Wei, and Yan (2007), Spiegel and Zhang (2013)). As is customary, the flows of open-end fund i in month t are computed from the fund's monthly returns (R) and total net assets under management (TNA): $flow_{i,t} = [TNA_{i,t} - TNA_{i,t-1} \times (1 + R_{i,t})]/TNA_{i,t-1}$. Figure 1 shows that the flows experienced by open-end funds vary greatly for different level of performance. For instance, funds in the bottom decile of performance experience monthly flows equivalent to -1.3% of their assets under management. By contrast, funds in the top decile of performance experiences monthly inflows equivalent to 2.1% of the assets under management.

We compute each open-end fund's flow performance sensitivity by regressing the fund's monthly flows on its average performance in the past 12 months using a rolling regression window of 24 months. Open-end funds have a mean flow performance sensitivity of 23%.

Existing literature (e.g., Chevalier and Ellison, 1997; Huang, Wei, and Yan, 2007) suggests that the sensitivity of flows to past performance varies across open-end funds. For instance, asset managers with long tenures have a lower sensitivity of flows to performance because investors are less likely to update their beliefs about more senior managers (Choi, Kahraman and Mukherjee, 2015). James and Karceski (2006) and Chen, Goldstein and Jiang (2010) also document a lower sensitivity of flows to performance in funds with a larger fraction of shares held by institutional investors, which have the specialized knowledge to evaluate fund managers' strategies.

In what follows, we show that open-end funds with these characteristics (more senior managers or more institutional investors) indeed have a lower sensitivity of

flows to performance and exploit this finding to provide evidence that the flow performance sensitivity can explain the role of organizational structure.

As we explain in Subsection 1.1, open-end funds create and redeem their shares on demand. This leads to investor flows. Closed-end funds, on the other hand, have a fixed number of shares traded on a stock exchange and do not create or redeem shares on demand like open-end funds. However, they occasionally issue and repurchase shares as any other listed company, leading to some change in their total net assets, which may be viewed as flows.[4] Given that the timing of share issues and repurchases is under complete managerial control, any relationship between performance and asset under management arising from the change in shares outstanding is not expected to weaken managerial incentives to trade against mispricing to the same extent as investor flows do in open-end funds. Nevertheless, for sake of completeness, we compute the sensitivity of flows to performance also for the closed-end funds.

As share issuance and repurchases are rather rare, the "manager-driven" flows of closed-end funds are much smaller than the "investor-driven" flows of open-end funds and have a median of zero. Similarly, the flow performance sensitivity of closed-end funds appears also small with a median of 0.18% and an average that is less than 1/10th of that of open-end funds (1.5% versus 23%).

Column 1 of Table 3 documents that the flow performance sensitivity of open-end funds is also statistically and significantly larger than that of closed-end funds. Column 2 shows how this difference varies across open-end funds with different

[4] We identify that only 13% (4.4%) of the closed-end fund observations are associated with share issues (repurchases). The amount raised from new equity issues is on average 3% of total net assets, and closed-end funds use about 2.2% of their assets for repurchasing shares when they do so. As shown in Table A.2 of the Internet Appendix, controlling for the change in closed-end funds' shares outstanding does not affect our findings.

characteristics.[5] Consistent with existing literature, open-end funds with more senior managers and open-end funds with more institutional investors have a lower sensitivity of flows to performance.[6] Panel B of Figure 1 shows that this is the case for funds in each decile of performance.

Similar to open-end funds, hedge funds' assets under management are known to have a positive flow performance sensitivity (Goetzmann, Ingersoll, and Ross, 2003 and Agarwal, Daniel, and Naik, 2004). We compute the flow performance sensitivity for hedge funds as we do for open- and closed-end funds. Consistent with Hombert and Thesmar (2014), column 3 shows that the sensitivity of flows to performance decreases with hedge funds' share restrictions.

This evidence allows us to formulate predictions on the characteristics of the managers that we expect to be less inclined to trade against mispricing. Not only do we expect open-end funds to purchase less undervalued stocks than closed-end funds, but we expect any differences to be particularly pronounced for funds run by managers with shorter managerial tenure and a lower proportion of institutional investors. Finally, we expect hedge funds with higher share restrictions to be also more inclined to trade against mispricing than hedge funds with lower share restrictions.

Since the sensitivity of flows to performance is likely to be estimated with noise, in what follows we not only show that funds with a lower sensitivity of flow to performance are more inclined to trade against mispricing, but we also directly relate funds' characteristics that affect the sensitivity of flows to performance (such as the organizational structure) to the funds' tendency to trade against mispricing.

[5] Since these fund characteristics are only available for open-end funds, we are unable to include the direct effect. This is the case for a few other variables also in Tables 7, 8 and 9 where we explore cross-sectional differences across funds.

[6] In Table A.1 of the Internet Appendix, we show that these findings are robust to controlling for funds' financial slack.

3. Organizational Structures and Trading in Fire Sale Stocks

3.1. Methodology

Our objective is to test whether funds with closed-end or less open-ended structures take more aggressive positions against mispricing. We identify mispriced stocks following Coval and Stafford (2007), who show that distressed funds experiencing large outflows create negative price pressure on the stocks they hold. As Coval and Stafford (2007), we identify stocks subject to sale pressure because of extreme outflows using the following measure:

$$Pressure_{s,t} = \frac{\sum_i max(0, \Delta Hold_{i,s,t}) | flow_{i,t} > P90 - \sum_i max(0, -\Delta Hold_{i,s,t}) | flow_{i,t} < P10}{Avg\ Volume_{s,t-12:t-6}}.$$

The pressure experienced by stock *s* in quarter *t* is the difference between flow-induced purchases and flow-induced sales during the quarter, divided by the stock's average trading volume during prior quarters.[7] Flow-induced sales are reductions in shares by mutual funds experiencing severe outflows – that is, quarterly flows below the 10th percentile.

In each quarter, stocks with *Pressure* below the 10th percentile are considered to experience fire sales. Our final sample includes 12,024 fire sale stocks during the period 2004-2014. By construction, these events are not clustered over time. The minimum and maximum number of fire sale stocks across quarters are, respectively, 291 and 423, and the standard deviation is 37.89.

[7] Following Coval and Stafford (2007), we require a minimum of ten mutual fund owners before we calculate the *Pressure* variable.

Stocks subject to fire sales experience large price drops, which typically revert over a horizon of about 24 months.[8] These reversals distinguish forced trading from other potentially information-motivated trading (Coval and Stafford, 2007; Khan, Kogan and Serafeim, 2012) because any discretionary selling pressure (caused by sales of mutual funds without extreme outflows) is expected to be associated with permanent price drops.

Due to the large price reversals, investors who trade against distressed mutual funds can earn substantial returns for providing liquidity. In our sample, the annualized Sharpe ratio from investing in fire sale stocks over a period of 24 months is 1.95.[9] However, the timing of the reversals is highly uncertain. In the spirit of Della Vigna and Pollet (2008), we use a measure of speed of convergence, which is defined as the cumulative abnormal returns earned by investing in all fire sale stocks in a given quarter in the first 12 months period, divided by the cumulative abnormal returns earned investing in the same stocks over a 24 months horizon. The bottom quartile of this ratio is 0.099, while for the top quartile is 0.649, indicating significant variation in the speed of convergence. Consistent with this, the Sharpe ratios from investing in a portfolio of fire sale stocks show substantial variation depending on investors' holding periods. While the annualized Sharpe ratio from investing in fire sale stocks over a period of 24 months is 1.95, the annualized Sharpe ratio is considerably lower at short horizons (e.g., the Sharpe ratio is 0.05 for holding periods of three months, and 0.76 for holding periods of nine months).

[8] Figure A.1 in the Internet Appendix shows price drops and reversals for the fire sale stocks in our sample. The fire sale quarter (that is, the quarter when the stock's *Pressure* is in the bottom decile) is the quarter in which fire sale stocks' valuations bottom out. As Coval and Stafford (2007) show, fire sale stocks begin experiencing selling pressure and some price decline in the quarters preceding the fire sale because mutual funds' flows are correlated over time.

[9] To obtain abnormal returns, each period, we calculate the equal-weighted returns from buying the portfolio of fire sale stocks and selling all stocks held by mutual funds (as in Coval and Stafford (2007). Portfolios are rebalanced quarterly to drop all stocks that reach the end of their event period and add all stocks that have recently been involved in a fire sale. We consider the Sharpe ratios of this strategy implemented for different holding periods.

The considerable uncertainty on the timing of return reversals may lead to short-term underperformance, and thus discourage asset managers with high sensitivity of flows to past performance from purchasing fire sale stocks. A simple observation on the aggregate sales and purchases of asset managers provides some support for our hypothesis. For instance, closed-end funds on average purchase 3.75% of the forced sales, while (non-distressed) open-end funds not only do not buy but contribute to the selling pressure by selling an additional 1.86% of the forced sales. Approximately 13% of the fire sales are not purchased by the remaining non-distressed 13F funds, suggesting that individual investors also provide liquidity.

In the following subsections, we test whether organizational structures with high flow performance sensitivity weaken asset managers' willingness to trade against mispricing. We start our analysis by comparing the changes in the positions of open- and closed-end funds in stocks experiencing fire sales. For each fire sale event, we exclude all funds with extreme inflows or outflows (flows above the top decile or below the bottom decile), that is, the funds that are considered in the definition of the variable *Pressure*. Thus, any differences between closed- and open-end funds cannot be driven by distressed open-end funds with extreme outflows.

If the structure of a fund's liabilities affects manager's willingness to trade against mispricing, we expect significant differences in trading stocks that experience fire sales or purchases. We also investigate how this trading behavior varies with stock and fund characteristics. These cross-sectional tests allow us to further link the theory to our empirical analysis and shed light on the mechanism behind the main results.

3.2. Closed-end and Open-end Funds' Trading in Fire Sale Stocks

3.2.1 Baseline Results

Table 4 provides preliminary support for the importance of organizational structure. While closed- and open-end funds appear to have similar propensities to trade when we consider their entire portfolio, stark differences between the two groups of asset managers emerge when we consider their trading in fire sale stocks. We observe that closed-end funds purchase fire sale stocks during the quarter following the fire sale:[10] 65% of closed-end funds' trades in fire sale stocks consist of purchases. On the other hand, 58% of open-end funds' trades in fire sale stocks are sales, and only a small fraction (17%) are purchases. This behavior does not appear to depend on the funds' access to funding (Panel B).

[Insert Table 4 here]

To evaluate the significance of the differences in trading behavior between closed- and open-end funds in a more systematic way, we estimate the following model for all fire sale stocks:

$$\Delta shares(t+k)_{i,s,t} = \alpha + \beta_1 Closed_i + \beta_2 X_{s,t} + \beta_3 X_{i,t} + \beta_4 X_t + \varepsilon_{i,s,t},$$

where k ranges from -2 to +3, that is, it starts two quarters before the fire sale and ends three quarters after. The dependent variable captures the quarterly changes in shares held by fund i in stock s between quarter t and quarter t-1, divided by the total number of shares outstanding of stock s. Our sample only includes observations of stock s and fund i if fund i held shares of s at t or t-1. The main variable of interest is the dummy $Closed_i$, which is equal to one if fund i is a closed-end fund.[11] The matrices $X_{s,t}$ and $X_{i,t}$ represent time-varying controls for stock and fund

[10] As we show below, this is the quarter in which differences in trading between closed- and open-end funds emerge.

[11] In some tests, to make the tables easier to read, we used the dummy *Open* (defined as *1-Closed)*.

characteristics, respectively. Stock characteristics include market capitalization (*Size*); idiosyncratic volatility, calculated over the past two years (*VOL*); a proxy for illiquidity, computed following Amihud (2002) (*ILLIQ*); book to market value (*BM*); and cumulative abnormal returns in the past 6 months (*MOM*). We also control for fund size, measured by the natural logarithm of the fund's TNA (*log TNA*) and include quarter fixed effects to capture aggregate market-wide effects. We cluster standard errors at the fund level to take into account that a fund's trades may be correlated.

[Insert Table 5 here]

Table 5 shows that there is no statistical difference in the purchases of open- and closed-end funds up to quarter *t*, that is, the quarter when prices bottom out. However, we find that closed-end funds buy significantly more than open-end funds in the quarter following the fire sale, *t+1*. The effect is not only statistically, but also economically significant. To have a more immediate interpretation of the coefficients, we standardize the dependent variable $\Delta shares(t+k)_{i,s,t}$ using the standard deviation of all trades of open- and closed-end funds (including trades in non fire sale stocks). Thus, the coefficient of the dummy *Closed* in column 4 of Table 4 implies that in the quarter following the fire sale, the net purchases of a typical closed-end fund are almost half of a standard deviation larger than for open-end funds.

Importantly, we observe no statistical difference in the behavior of closed- and open-end funds in the two following quarters. These findings suggest that the differences in trading behavior between open- and closed-end funds are driven by the fire sale events and the consequent price drops as opposed to differences in unobserved firm characteristics. If the latter were the case, we would have observed

differences in trading also in the quarters preceding the fire sale or when prices have started to converge to their fundamental values in quarters *t+2* and *t+3*.

Overall, the evidence in Table 5 suggests that closed-end funds take more aggressive positions against mispricing than open-end funds and that their trades may contribute to the price reversals we observe. However, closed-end funds' capital is likely to be too small to correct the mispricing.[12]

3.2.2 The Role of Stock Characteristics

To better understand the mechanism behind the observed differences in trading of fire sale stocks between closed- and open-end funds, we explore the extent to which the differences vary with stock characteristics. Since differences in trading emerge in the quarter following the fire sale, we focus the empirical analysis on quarter *t+1*.

If closed-end structures help to overcome limits to arbitrage, we would expect differences between closed- and open-end funds to be more pronounced for stocks with higher arbitrage risk (Shleifer and Vishny, 1997). Small stocks tend to attract individual investors, whose trades can lead to unpredictable short-term fluctuations in share prices. This makes these stocks unattractive for open-end fund managers as they increase the risk of short-term fund underperformance. Similarly, stocks with higher idiosyncratic volatility are considered to involve high arbitrage risk (e.g., Pontiff, 2006). Therefore, we expect open-end funds to be particularly reluctant to trade against mispricing in stocks that are smaller or have higher idiosyncratic volatility.

[12] We also show that the differences in trading are not driven by the fact that closed-end funds simply buy any stocks that have fallen in value. Excluding fire sale stocks, we sort all stocks based on their average monthly return in a given quarter and select the ones with returns below the 10th percentile. As shown in Table A.4 of the Internet Appendix, we do not see any differences in the trading of closed- and open-end funds in these stocks.

This is precisely what we find in columns 1 and 2 of Table 6. These results provide strong support for our hypothesis.

[Insert Table 6 here]

Previous literature highlights the propensity of closed-end funds to invest in illiquid assets. Our finding that the trading behavior of closed-end funds differs from the trading of open-end funds only in the quarter following the fire sale already indicates that it is unlikely that closed-end funds trade these stocks to a larger extent simply because they are more illiquid. We confirm this interpretation in column 3 where we show that closed-end funds' trading in fire sale stocks is unrelated to the stocks' liquidity, measured using the price impact ratio of Amihud (2002). Other firm characteristics, such as the book-to-market ratio or the firm's cumulative return over the previous six months, are also unrelated to the trades of closed-end funds in the quarter following a fire sale. Thus, differences in trading behavior do not appear to be driven by differences in investment styles.

3.2.3 The Role of the Flow performance Sensitivity

In this section, we provide further evidence on the mechanisms behind our baseline results. As predicted by Shleifer and Vishny (1997), we expect open-end funds with higher flow performance sensitivity to be particularly reluctant to purchase fire sale stocks compared to other open-end funds. In column 1 of Table 7, we show that not only open-end mutual funds trade more against mispricing as captured by the dummy *Open*, but open-end funds with a higher flow performance sensitivity to so to an even larger extent. This confirms that managers' incentives are important.

[Insert Table 7 here]

We also examine the role of fund characteristics, which we have shown to be associated with the funds' flow performance sensitivity. As we show in Table 3, open-end fund managers with longer tenures and more sophisticated investors, such as institutional investors, have a lower sensitivity of flows to performance. Therefore, these funds should have stronger incentives to trade against mispricing. This is precisely what we find. Column 2 shows that open-end fund managers purchase more fire sale stocks as their tenure increases, and column 3 documents that the propensity to purchase fire sale stocks increases with institutional ownership.

Columns 4 and 5 conduct additional tests to examine whether the fund characteristics indeed affect the results through the flow performance sensitivity channel. In column 4, we include all three characteristics, that is, the dummy variable *Open*, managerial tenure and institutional ownership. In column 5, we include the fund's flow performance sensitivity estimated from these three characteristics. Thus, in column 5, we only use the variation in these three characteristics that is related to flow performance sensitivity. A comparison of column 4 and 5 indicates that these two empirical specifications explain a similar amount of variation in the data, which reinforces our interpretation that the effects we document are due to differences in the sensitivity of flows to performance.[13]

3.2.4 Controlling for Financial Slack

One concern with our results might be that even though we exclude open-end funds that experienced extreme outflows, the sample may still include some open-end funds that have relatively large outflows and are financially constrained. Table 8 presents a number of tests to assess this possibility as well as to control for the effect

[13] We thank the Editor for this suggestion.

of the funds' financial slack. First, we repeat our analysis excluding open-end funds with past flows in the bottom quartile of our sample (of non-distressed funds) and include past flows as a control variable. Columns 1 and 2 show that open-end funds with large outflows do not drive our findings.

[Insert Table 8 here]

We also consider that financial constraints can arise from funds' pre-existing positions in stocks that become subject to fire sales. Fire sales lead to a large drop in stock prices thus causing losses for the funds holding the stocks. If distressed open-end funds have a greater portfolio overlap with other (non-distressed) open-end funds than with closed-end funds, then non-distressed open-end funds are more likely to incur losses because of their pre-existing positions in fire sale stocks. We construct a fund level measure of exposure to fire sale stocks, *Prior Exposure*, which is the fund's portfolio weight in fire sale stocks prior to the shock. In column 3, we introduce this variable as a control. As expected, *Prior Exposure* negatively affects funds' propensity to purchase fire sale stocks, however, the effect of the organizational structure remains unaffected suggesting that this negative spillover does not drive our findings.

We also consider that some closed-end funds use leverage. This may increase these funds' ability to fund purchases of fire sale stocks, but could also expose them to rollover risk (Tang, 2012). As shown in Table 1, and consistent with Cherkes, Sagi, and Stanton (2008) and Dimson (2002), leverage is low for equity closed-end funds (about 6.8 % on average). Therefore, we do not expect closed-end funds' leverage to play an important role in our findings. Nevertheless, in column 4, we construct a proxy for the closed-end funds' leverage using Capital IQ, and include it in the regression. We find no evidence that debt financing affects our findings.

In the rest of Table 8, we control for other measures of the funds' financial structure that could vary between open- and closed-end funds. Funds tend to fund their purchases with the sales of existing positions.[14] Funds with a more illiquid portfolio may be unable to mobilize assets to finance purchases of fire sale stocks. To assess this possibility, we control for the average illiquidity of the stocks in each fund's portfolio. In column 5, we measure stock illiquidity using the price impact measure of Amihud (2002). In column 6, we consider the average book to market ratio of stocks in the funds' portfolios as stocks with high book to market ratios require a long investment horizon and therefore are unlikely to provide immediacy. Finally, in column 7, we include the proportion of the fund's TNA held as cash. All these robustness checks leave our results unaffected, suggesting that differences in financial slack are not driving our findings.

This conclusion is also supported by evidence showing that the differences in trading between open- and closed-end funds emerge during both good and bad market times. In Table A.5 in the Internet Appendix, we measure market conditions using, in turn, aggregate (open-end) fund flows, the VIX index capturing aggregate market uncertainty, and a dummy variable capturing the recent financial crisis (which we set equal to one from the third quarter of 2008 to the end of 2009 or, alternatively, from the third quarter of 2007 to the end of 2009). The effects we document do not appear to vary with market conditions.

3.2.5 Additional Robustness Checks

[14] In each quarter, open-end funds and closed-end funds on average sell stocks that are worth 31% and 25% of their fund TNA, respectively. A typical open-end funds has a cash stock of 2.9%, and capital flows make up about 1.2% of total net assets. Closed-end funds on average appear to hold negative cash largely driven by the fact that a few of them use leverage.

Table 9 reports the results from additional robustness checks. One possible concern is that the differences in trading behavior between closed- and open-end funds may be related to differences in ability. In column 1 of Table 9, we control for managerial ability using a manager's past performance (calculated prior to the fire sale quarter). Our findings on the effect of organizational structure remain unaffected.

Moreover, we repeat our analysis in a subsample of open- and closed-end funds that are comanaged by the same manager. This allows us to control for manager specific characteristics, such as ability. Column 2 of Table 9 shows that these managers purchase more fire sale stocks in their closed-end funds than in their open-end funds. The coefficient is somewhat smaller than in the benchmark estimates in column 4 of Table 5, reflecting that these managers have longer tenures than the average manager in the sample and a lower sensitivity of flows to past performance in their open-end funds.

[Insert Table 9 here]

Consistent with this result, we also document that differences in trading between open- and closed-end funds are unrelated to the closed-end fund discount. Ross (2002) and Berk and Stanton (2012) argue that a closed-end fund discount emerges when the fees charged by the fund are not compensated by the fund manager's ability to generate returns. If our results were driven by the closed-end fund managers' superior ability to identify fire sales, we should observe that less able fund managers with higher discounts trade against mispricing to a lower extent; however, this is not the case (column 3).

This result is relevant also for another reason. Even if closed-end fund managers' flows are not sensitive to performance, their willingness to trade against mispricing could be affected by the managerial labor market. The incentives provided

by the managerial labor market in turn could make the differences in capital structure we explore less relevant. For instance, an increase in the closed-end funds' discount may lead activist investors to launch campaigns to open the funds (Bradley, Brav, Goldstein and Jiang, 2010). A higher fund discount could also increase the probability of managerial turnover (Wu, Wemers and Zechner, 2013). Thus, the managers of closed-end funds with high discounts may have greater focus on short-term performance. The result in column 3, however, indicates that the fund's discount is unrelated to the trading activity of closed-end funds.

In column 4, we consider that the non-distressed open-end mutual funds may be specialized in different sectors from the distressed ones. This would imply that these funds do not purchase fire sale stocks because they are constrained to invest in different sectors. To account for these differences in fund style, we construct a proxy for the similarity of each fund's stock portfolio with the open-end funds that are distressed at quarter *t*. In the spirit of Wahal and Wang (2011), we measure fund similarity using the share of the equity portfolio of each find *i* that is common with the equity portfolio of a distressed fund at time *t*. We average this measure for all open-end funds that are distressed at time *t*. This measure, which we label *Portfolio Overlap*, is similar to *Prior Exposure*, but takes into account also the distressed open-end funds' holdings that are not subject to fire sales. The effect of organizational structure appears unaffected when we control for *Portfolio Overlap*, which has a negative and significant coefficient, suggesting that the negative stock to common holdings, captured by the *Prior Exposure*, prevails.

Finally, it does not appear that our results are driven by differences in managerial compensation and funds' governance. Managers with different compensation levels may have different risk taking incentives and this may determine

the differences in trading strategy we observe. As is common in the literature (see, for instance, Kacperczyk and Schnabl, 2013), we proxy for compensation using annual fees. In Table 1, annual fees appear similar for closed- and open-end funds and are therefore unlikely to lead to different trading behavior. Nevertheless, in column 5 of Table 9, we evaluate this possibility and show that annual fees do not have any impact on our findings.

Similarly, in columns 6 and 7, we explore the role of managerial ownership and the quality of boards using data from Morningstar. Morningstar reports open-end fund managers' investments in their funds (in $), and also assigns open-end funds ratings depending on the quality of their boards (Gil-Bazo and Ruiz-Verdu, 2009). We control for the level of managerial ownership and construct a dummy that takes value equal to one if a fund's board has top quality rating. Our findings appear robust to the inclusion of these controls.

Overall, these tests provide strong support that closed-end funds are more inclined to purchase fire sale stocks than open-end funds. The funds' cross-sectional differences and the robustness of the results to a wide set of controls further suggest that the mechanism driving the effects is related to the differences in flow performance sensitivities between closed- and open-end funds.

3.3 Hedge Funds' Trading in Fire Sale Stocks

To provide an independent test of the degree of open-endness on funds' propensity to purchase fire sale stocks, we turn to hedge funds. Such an independent test may be particularly valuable to further evaluate the generality of our findings, not only because hedge funds are subject to much more flexible regulation than open- and

closed-end funds, but also because hedge funds' flows are less likely to be correlated with the flows of distressed mutual funds.

As we have shown in Section 2, hedge funds that impose higher share restrictions on their investors in the form of longer lock up, redemption and payout periods have a lower sensitivity of flows to performance. According to Shleifer and Vishny (1997), we should therefore observe that hedge funds with higher share restrictions are more inclined to purchase fire sale stocks.

We identify a total of 1,157 management companies that can be considered pure-play hedge funds and that trade around fire sales. Table 10 shows that while hedge funds with high share restrictions have a slightly smaller propensity to sell and purchase stocks in general, they are more likely to purchase fire sale stocks than hedge funds with low share restrictions (57% vs. 39%, respectively) in the quarter of the fire sale.[15]

[Insert Table 10 here]

This conclusion is borne out by the multivariate analysis in Table 11, which shows that a one-standard-deviation increase in share restrictions, equivalent to 190 days, increases the net purchases of a hedge fund by 1.4 standard deviations in the quarter of the fire sale (quarter *t*) in comparison to other hedge funds. No differences in trading related to the intensity of share restrictions emerge in other quarters.[16]

[Insert Table 11 here]

[15] As we show below, this is the quarter in which differences between hedge funds with high and low share restrictions emerge.

[16] Results are similar if we include further controls for hedge fund characteristics (Table A.6 of the Internet Appendix). In these tests, we control for managerial compensation (measured by annual fees, incentive fee and high-water marks), size of a typical investor (proxied by minimum investment requirements) and funds' use of leverage. We also show that our results hold if we exclude the lock up period, which is relevant only for new investors, from the definition of *Restrictions* (Tables A.6 and A.8)

Furthermore, the cross-sectional effects are fully consistent with our earlier findings on closed-end funds: Hedge funds with high share restrictions buy fire sale stocks of small firms and of firms with high idiosyncratic volatility to a larger extent than other hedge funds. As noted before, these are precisely the stocks that are riskier to arbitrage in the short-term. This evidence supports the hypothesis that the degree of open-ending affects asset managers' willingness to trade against mispricing.

A few interesting differences emerge from our earlier findings on closed-end funds. First, we observe that hedge funds respond to fire sales more readily than closed-end funds. While closed-end funds' purchases occur in the quarter following the fire sale *(t+1)*, hedge funds with high share restrictions purchase more in the fire sale quarter *(t)*. This is consistent with the view that hedge funds attract more sophisticated asset managers who may be able to identify mispricing more readily than other institutional investors.

Second, to make a comparison with the closed- and open-end funds tests, in Table A.7 of the Internet Appendix, we use a dummy capturing share restrictions above the sample median, instead of the continuous measure of share restrictions. The difference in trading behavior between closed- and open-end funds is economically larger than the differences between hedge funds (estimates are 0.41 vs 0.27). This is consistent with the fact that the closed-end fund structure insulates managers from performance-sensitive flows to a larger extent than share restrictions above the median. In addition, all hedge funds, including hedge funds with low share restrictions, increase their investments in fire sale stocks (whereas open-end funds typically liquidate their shares in these stocks). This may also contribute to attenuate differences between hedge funds.

4. Organizational Structures and Exposure to Aggregate Mispricing

4.1. Methodology

We have so far shown differences in trading between funds in fire sale stocks. In this section, we explore whether similar differences exist for a different type of mispricing. In particular, we focus on more aggregate forms of mispricing, which are driven by investor sentiment and not by some open-end funds' distress. This allows us to assess the generality of our findings.

According to behavioral models (e.g., Daniel, Hirshleifer, and Subrahmanyam, 2001; Barberis and Shleifer, 2003), mispricing arises when noise traders' irrational enthusiasm for stock characteristics shifts or when investors misinterpret what they perceive to be private information about systematic economic factors. A common prediction of these theories is that noise traders' demand induces positive comovement among stocks with similar characteristics. For instance, the stocks of small companies are systematically undervalued, when noise traders' demand is particularly low (Baker and Wurgler, 2004; Lemmon and Portniaguina, 2006). This type of mispricing suits our conceptual framework as the timing of convergence to fundamental value is uncertain due to the unpredictable nature of shifts in noise traders' demand.

We test whether closed-end funds invest more than open-end funds in stocks that are likely to be undervalued when noise traders' demand is low compared to other times. Since this test exploits shifts in noise traders' demand, it necessitates a relatively longer sample period to capture a number of these shifts. To achieve this, instead of using the holdings data, we regress fund returns on the returns of mispriced stocks' factor portfolios and infer the funds' exposure from the portfolio loadings. This methodology has been used in several studies, including Sharpe (1992), Brown,

Goetzmann, and Park (2000), and Brunnermeier and Nagel (2004), and requires only fund returns, which are available both for closed- and open-end funds starting from 1990.

As shown by Brunnermeier and Nagel (2004), each fund's return can be written as the weighted average of the returns on a few asset classes plus some idiosyncratic return. Given the focus of our analysis, we consider a portfolio of undervalued stocks and the market return. The return of fund *i* during month *t* ($R_{i,t}$) can thus be written as:

$$R_{i,t} = (b - g)R_{m,t} + gR_{s,t} + \epsilon_{i,t},$$

where $R_{s,t}$ is the monthly return of a portfolio of undervalued stocks (*s*) and $R_{m,t}$ is the market monthly return. Here *b* is the weight of the fund on the market portfolio, which is around one for a fund that tracks the market portfolio and zero for a market neutral fund; *g* is the exposure to the portfolio of undervalued stocks. A larger *g/b* therefore implies that the fund's holdings are more tilted towards undervalued stocks.

We expect closed-end funds to be more exposed than open-end funds to stocks with characteristics associated with undervaluation in periods of low noise traders' demand compared to other periods. To capture this, we estimate the following equation in which we allow exposures to factor portfolios to differ between open- and closed-end funds:

$$R_{i,t} = \left(b - g_{Open}\right)R_{m,t} + \left(b - g_{Closed}\right)Closed_{\,i} \times R_{m,t} + g_{Open}\, R_{s,t} + g_{Closed}\, Closed_{\,i} \times Neg\ Sent_t \times R_{s,t} + \mathbf{\Gamma X} + \varepsilon_{i,t},$$

where *Neg Sent*$_t$ is a dummy that takes value equal to 1 when noise traders' demand is low as captured by different market sentiment indexes, which we introduce below;

$Closed_i$ is a dummy identifying closed-end funds; and **X** is a matrix of controls that includes the lower-order interaction terms, including the dummy closed. We allow the exposure of closed- and open-end funds to the market portfolio to vary. We expect that $g_{Closed} > 0$ if closed-end funds are more inclined to purchase undervalued stocks during periods of low noise traders' demand than open-end funds. Since closed- and open-end funds may have different investment styles, we consider only funds specialized in domestic equity.

4.2. Closed-end and Open-end Funds' Exposure to Aggregate Mispricing

To operationalize the above framework, we need to identify the stock characteristics that are associated with undervaluation when noise traders' demand is low. We follow Baker and Wurgler (2006) and Lemmon and Portniaguina (2006).[17] Baker and Wurgler (2006) find that when noise traders' demand, captured by their beginning-of-period measure of market sentiment, is low, young, highly volatile, small, unprofitable, distressed, high R&D, and non-dividend paying stocks earn particularly high abnormal returns in subsequent periods and can therefore be considered undervalued. For instance, following periods of negative sentiment, the abnormal monthly returns average 2.37% for stocks in the bottom decile of size, while stocks in the top decile only earn about 0.92%.

[Insert Table 12 here]

Table 12 relates funds' monthly returns to the monthly returns of portfolios of stocks that are underpriced during periods of negative sentiment (defined using the indicator of sentiment orthogonalized to macro-economic conditions of Baker and

[17] We do not consider other anomalies, for instance, the ones studied by Stambaugh, Yu and Yuan (2012), because profits from these anomalies typically arise on the short leg of the strategy. Open- and closed-end mutual funds are restricted from shorting. Also, not all anomalies involve long-term mispricing.

Wurgler (2006)).[18] It is evident that during periods of negative sentiment closed-end funds are more exposed to portfolios of underpriced stocks. The differences are not only statistically but also economically significant. For instance, column 1 shows that closed-end funds typically overweigh small stocks compared to open-end funds (the coefficient of *Portfolio* x *Closed* is positive). However, the rate at which closed-end funds overweigh small stocks increases from approximately 7% in periods of positive sentiment to 17% in periods of negative sentiment. The extent to which closed-end funds overweigh other portfolios of underpriced stocks during periods of negative sentiment is similar.

[Insert Table 13 here]

In Table 13, we present the results from a number of robustness checks. For expositional purposes, we only present the results for small stocks. In column 1, we allow closed- and open-end funds to differ in their exposure to liquidity risk. Our results, if anything, become stronger once we control for different exposure to the Pastor and Stambaugh's (2003) liquidity factor. In column 2, we allow for differences in exposure to the momentum factor. Consistent with Table 1, open-end funds hold portfolios that are more heavily invested in momentum stocks; yet including this control has no bearing for our results. In column 3, we also allow the exposure to the market portfolio to vary in periods of high and low sentiment, but we find no statistically significant differences. Overall, it seems unlikely that open- and closed-end funds' exposure to different factors can explain our findings.

One might also be concerned that the sentiment index is the first principal component of six sentiment proxies including the closed-end fund discount. This is

[18] Baker and Wurgler (2006) define sentiment as the first principal component of six different proxies orthogonalized to several macro variables. The sentiment proxies include trading volume as measured by NYSE turnover, the dividend premium, the average closed-end fund discount, the number and first-day returns on IPOs, and the equity share in new issues. This index is widely used in the literature (e.g., Stambaugh, Yu and Yuan, 2012) and captures historical accounts of bubbles and crashes.

unlikely to play an important role in our analysis because closed-end funds' trading behavior in fire sale stocks appears to be unrelated to the funds' discount in Table 9. Nevertheless, to show that our results are unrelated to the dynamics of the closed-end fund discount, we compute an alternative measure of sentiment, which is defined as the first principal component of all proxies in Baker and Wurgler (2006) except the discount. We repeat our analysis using the alternative index. Our results in column 4 are unaffected.

Our results also do not depend on the specific proxy for market sentiment we use. Lemmon and Portniaguina (2006) use a measure of sentiment based on consumer surveys of the Michigan Survey Research Center and provide evidence that small stocks are undervalued in periods with low consumer confidence. Column 5 shows that closed-end funds appear more exposed to undervalued small stocks also when we capture low noise traders' demand using the survey-based index of market sentiment.

Finally, Hirshleifer and Jiang (2010) argue that external financing activities can also be used to identify systematic mispricing arising from noise traders' demand. The patterns in firms' long-run returns suggest that firms issue equity (or risky debt) when they are overvalued, and buy back equity (or retire risky debt) when they are undervalued. Stocks' sensitivities to common movements in this source of mispricing predict the cross-section of asset returns. Since external financing activities are associated with long-term mispricing, the Hirshleifer and Jiang's (2010) factor allows us to perform a test of our hypothesis without relying on any proxies of market sentiment.

Column 6 shows that our earlier conclusions continue to be fully supported: Closed-end funds are significantly more exposed than open-end funds to a portfolio long in stocks that comove with firms that repurchase (and are thus revealed to be

undervalued) and short in stocks that comove with firms that issue equity or risky debt (and are thus revealed to be overvalued).

4.3. Hedge Funds' Exposure to Aggregate Mispricing

We also test whether hedge funds with high share restrictions hold portfolios that are more exposed to undervalued stocks during periods of negative sentiment. Since we explore funds' exposures to different portfolios of US equities, we focus on 3,400 hedge funds that are specialized in US equity.[19]

[Insert Table 14 here]

The estimates in Table 14 are in line with our earlier findings. Hedge funds with high share restrictions overweigh sentiment-prone stocks in times of negative sentiment, that is, when they are undervalued. For instance, in periods of negative sentiment, hedge funds with one-standard-deviation higher share restrictions overweigh small stocks by about 3.4% (column 1). We observe the same pattern for other sentiment-prone stocks (columns 2 to 9).

[Insert Table 15 here]

Table 15 presents a number of robustness checks. The estimates in column 1 show that results are unaffected if we allow hedge funds to differ in their exposure to liquidity risk (Sadka, 2010). In the same vein, our results remain robust if we allow hedge funds with different intensity of share restrictions to have differential exposure to the momentum factor (columns 2). Thus, consistently with our earlier evidence, a

[19] In particular, we select hedge funds with the following styles: long/short equity and multi-strategy hedge funds from Lipper Tass; equity hedge funds, excluding the ones specialized on a particular sector from HFR; and long/short equity, equity market neutral long-only equity hedge funds from CISDM.

high sensitivity of flows to performance increases fund managers' focus on short-term returns.

Results are equally invariant if we allow the exposure to the market portfolio to vary in periods of high and low sentiment (column 3), control for the Fung and Hsieh (2004) factor exposures (column 4), compute sentiment excluding the closed-end fund discount (column 5), or use a measure of sentiment based on consumer surveys of the Michigan Survey Research Center (column 6). Finally, hedge funds with high share restrictions appear to have higher exposure to undervalued stocks also when we use Hirshleifer and Jiang (2010) factor, without relying on proxies for market sentiment (column 7).

5. Conclusions

This paper provides evidence that open-end structures weaken managerial incentives to trade against mispricing, as conjectured by Shleifer and Vishny (1997). More specifically, we show that asset managers with lower sensitivity of flows to performance (e.g., closed-end funds and hedge funds with high share restrictions) are more likely to buy stocks that are underpriced due to fire sales or negative sentiment shocks.

To this extent, our paper contributes to the debate on the organization of the asset management industry. Open- and closed-end fund structures involve costs and benefits. Fama and Jensen (1983) argue that open-ending might be an optimal response to agency problems. If a fund is set up on a closed-end basis, dispersed investors have no recourse in the face of managerial misbehavior and may see their entire investment slowly eaten away. However, Stein (2005) challenges this view and

shows that because of competition, too many asset managers may choose an open-end structure and too little capital may be available for long-term arbitrage.

This paper provides empirical evidence on the benefit of closed-end fund structures (and share restrictions) on asset managers' propensity to trade against mispricing. While our analysis is silent about the potential agency costs of closed-end fund structures, Wu, Wermers and Zechner (2013) suggest that managerial career concerns may provide a disciplining mechanism alternative to fund flows and thus help resolving potential agency problems in closed-end funds. Further assessing the costs and benefits of closed- and open-end organizational structures is an exciting area for future research.

Our findings may suggest a new interpretation for the closed-end discount, which could rationalize why funds with a higher discount have higher subsequent returns (Pontiff, 1995). This relation could arise from our finding that closed-end structures increase funds' propensity to hold stocks that are unpopular among retail investors. Solomon, Soltes and Sosyura (2013) argue that the demand for open-end funds that hold popular stocks is high even if holdings of popular stocks are unrelated to future fund performance. Higher demand translates in inflows for open-end funds, but it can only affect the share price and generates a premium (or a discount when demand is low) in funds with closed-end structures because shares are not redeemable. Changes in investor demand driven by fund managers' holdings of unpopular stocks may thus generate a discount. We leave this question to future research.

References

Agarwal, V. and N. Y. Naik, 2004, Risks and portfolio decisions involving hedge funds, *Review of Financial Studies* 17: 63-98.

Agarwal, V., N. D. Daniel, and N. Y. Naik, 2009, Role of managerial incentives and discretion in hedge fund performance. *Journal of Finance* 64: 2221–2256.

Agarwal, V., V. Fos, and W. Jiang, 2013, Inferring Reporting-Related Biases in Hedge Fund Databases from Hedge Fund Equity Holdings. *Management Science* 59: 1271–1289.

Agarwal, V., W. Jiang, Y. Tang, and B. Yang, 2013, Uncovering hedge fund skill from the portfolio holdings they hide. *Journal of Finance* 68: 739–783.

Almazan, A., K. C. Brown, M. Carlson, and D. A. Chapman, 2004, Why constrain your mutual fund manager? *Journal of Financial Economics* 73: 289–321.

Akbas, F., W. J. Armstrong, S. Sorescu, and A. Subrahmanyam, 2014, Smart Money, Dumb Money, and Equity Return Anomalies. *Journal of Financial Economics*, forthcoming.

Amihud, Y., 2002, Illiquidity and Stock Returns: Cross-section and Time-series Effects. *Journal of Financial Markets* 5:31–56.

Aragon, G. O., 2007, Share restrictions and asset pricing: Evidence from the hedge fund industry. *Journal of Financial Economics* 83:33–58.

Baker, M. and J. Wurgler, 2006, Investor Sentiment and the Cross-Section of Stock Returns. *Journal of Finance* 61:1645–1680.

Baker, M. and J. Wurgler, 2007, Investor sentiment in the stock market. *Journal of Economic Perspectives* 21:129-151.

Barberis, N. and A Shleifer, 2003, Style Investing. *Journal of Financial Economics* 68 (2): 161–99.

Berk, J. B. and R. Stanton, 2007, Managerial Ability, Compensation, and the Closed End Fund Discount. *Journal of Finance*, 62: 529–556.

Bradley, M., A. Brav, I. Goldstein, and W. Jiang, 2010, Activist arbitrage: a study of open-ending attempts of closed-end funds. *Journal of Financial Economics* 95: 1–19.

Brunnermeier, M. and S. Nagel, 2004, Hedge funds and the technology bubble. *Journal of Finance* 59, 2013–2040.

Brown, Steven J. and W. N. Goetzmann, 2003, Hedge funds with style, *Journal of Portfolio Management* 29:101–112.

Cao, C., Y. Chen, W. N. Goetzmann, and B. Liang, 2012, The Role of Hedge Funds in the Security Price Formation Process, Working Paper, Yale University.

Chen, Q., Goldstein, I. and Jiang, W., 2010. Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics*, *97*(2), pp.239-262.

Cherkes, M., J. Sagi, J., and R. Stanton, 2008, A Liquidity-Based Theory of Closed-End Funds. *Review of Financial Studies* 22: 257–297.

Choi, D., B. Kahraman, A. Mukherjee, 2015. Learning About Mutual Fund Managers. *Forthcoming, Journal of Finance*

Coval, J., and E. Stafford, 2007, Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics* 86: 479–12.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 2001, Overconfidence, Arbitrage, and Equilibrium Asset Pricing. *Journal of Finance* 56: 921-965.

DellaVigna, S. and J.M. Pollet, 2009, Investor inattention and Friday earnings announcements. *The Journal of Finance*, *64*(2), 709-749.

Dimson, E. and C. Minio Kozerski, 2002, Closed□End Funds: A Survey. *Financial Markets, Institutions & Instruments 8*, 1–41.

Edelen, R M, O Ince, and G B Kadlec, 2013, Institutional Investors and Stock Return Anomalies. *Journal of Financial Economics*, forthcoming.

Fung, W., and D.A. Hsieh, 2004, Hedge fund benchmarks: A risk-based approach, *Financial Analysts Journal* 60: 60-80.

Gil-Bazo, J. and P. Ruiz-Vendu, 2009, The Relation between Price and Performance in the Mutual Fund Industry, *Journal of Finance* 64: 2153-2183.

Goetzmann, W. N., J. E. Ingersoll, and S. A. Ross, 2003, High-water marks and hedge fund management contracts, *Journal of Finance* 43: 1685-1717.

Greenwood, Robin, and Stefan Nagel, 2009, Inexperienced investors and bubbles, *Journal of Financial Economics* 93: 239–258.

Hirshleifer, D., and D. Jiang, 2010, A Financing-Based Misvaluation Factor and the Cross-Section of Expected Returns. *Review of Financial Studies* 23: 3401–3436.

Hombert, Johan, and David Thesmar., 2014. Overcoming limits of arbitrage: Theory and evidence. *Journal of Financial Economics* 111.1: 26-44.

Huang, J., Wei, K. D., and Yan, H., 2007. Participation costs and the sensitivity of fund flows to past performance. *The Journal of Finance*, *62*(3), 1273-1311.

James, Christopher, and Jason Karceski., 2006. Investor monitoring and differences in mutual fund performance. *Journal of Banking & Finance* 30. 10: 2787-2808.

Kacperczyk, M., and Schnabl, P., 2013, How Safe Are Money Market Funds?. *Quarterly Journal of Economics*, *128*(3), 1073-1122.

Khan, M., L. Kogan, and G. Serafeim, 2012, Mutual Fund Trading Pressure: Firm-Level Stock Price Impact and Timing of SEOs. *Journal of Finance* 67: 1371–1395.

Lemmon, M, and E Portniaguina, 2006, Consumer Confidence and Asset Prices: Some Empirical Evidence. *Review of Financial Studies* 19: 1499–1529.

Mitchell, M., L. H. Pedersen, and T. Pulvino, 2007, Slow Moving Capital. *American Economic Review* 97:215–220.

Pastor, L., and R. F. Stambaugh, 2003, Liquidity risk and expected stock returns. *Journal of Political Economy* 111:642–85.

Pontiff, J., 1995, Closed-end fund premia and returns implications for financial market equilibrium. *Journal of Financial Economics* 37: 341–370.

Pontiff, J., 2006, Costly Arbitrage and the Myth of Idiosyncratic Risk. *Journal of Accounting and Economics* 42: 35–52.

Ross, S. A., 2002, A neoclassical look at behavioral finance; closed-end funds, Princeton Lectures in Finance III.

Sadka, R. 2010, Liquidity risk and the cross-section of hedge-fund returns. *Journal of Financial Economics* 98, 54–71.

Sharpe, William F., 1992, Asset allocation: Management style and performance measurement, *Journal of Portfolio Management*, Winter, 7–19.

Shleifer, A, and R.W. Vishny, 1997, The Limits of Arbitrage. *Journal of Finance* 52: 35-55.

Solomon, D. H., E. F. Soltes , and D. Sosyura, 2013, Winners in the spotlight: Media coverage of fund holdings as a driver of flows. *Journal of Financial Economics*, forthcoming.

Stambaugh, R. F., J. Yu and Y. Yuan, 2012, The short of it: Investor sentiment and anomalies. *Journal of Financial Economics* 104: 288–302.

Stein, J. C., 2005, Why are most funds open-end? Competition and the limits to arbitrage. *Quarterly Journal of Economics* 120:247–72.

Wahal, S. and A. Y. Wang, 2011, Competition among mutual funds. *Journal of Financial Economics* 99, 40–59.

Wu, Y., R. Wermers, and J. Zechner, 2013, Managerial Rents vs. Shareholder Value in Delegated Portfolio Management: The Case of Closed-End Funds. Working Paper, University of Maryland.

Appendix
Variable Definitions

Fund-level Characteristics

Closed	A dummy variable that is equal to one for closed-end funds
Open	A dummy variable that is equal to one for open-end funds
Share Restrictions	Sum of the days of the lock up period, redemption notice period and payout period, divided by 100; for hedge funds without lock up period, redemption notice period and payout period, this variable is set to zero
High Restrictions	A dummy variable that is equal to one if the hedge fund has share restrictions above sample median
Lock up period	Minimum time an investor has to wait for a withdrawal after her initial investment
Redemption notice period	Advance notice an investor has to give to the fund before being able to withdraw
Payout period	Time that the fund takes to return the capital after the notice period is over
Log TNA	Natural logarithm of TNA as of quarter-end
Flow	Monthly change in TNA less the total returns over the month, divided by TNA in the previous month; winsorized at 2.5%
FPS	A fund's flow performance sensitivity, estimated regressing the fund's monthly net flows on its past 12 month average monthly returns using a 24 month rolling window; winsorized at 2.5%
Past Perf	The fund's 12 month style-adjusted cumulative return; for closed-end funds, it is computed as the NAV appreciation. For each group of funds (open- or closed-), we identify the main investment styles and calculate a fund's return in excess of the average return of funds with the same style. The closed-end funds' styles are from Lipper and Morningstar; we use the investment objective code (IOC) to identify the styles of open-end funds
Discount	Average closed-end fund discount, (NAV-share price)/NAV in the past 12 months; winsorized at 1%
Annual Fees	The fund's annual expense ratio
Leverage	Closed-end funds' total debt divided by total assets, obtained from Capital IQ, available at annual frequency and populated for the entire year
Past Flows	Average monthly fund flows in the past 12 months, as a proportion of TNA at the beginning of the period
Tenure	Natural logarithm of an open-end fund manager's tenure (in years)
Cash	Funds' cash holdings divided by fund TNA
Prior Exposure	Total portfolio weight of fire sale stocks in a fund's portfolio 6 months prior to the fire sale event
Portfolio Overlap	Average of the proportion of a fund portfolio that is common with distressed mutual funds 6 months prior to the fire sale event

Institutional	Fund assets held by institutional investors divided by the fund's TNA; available only for open-end funds
Man Ownership	Managers' direct investments in their fund, in dollars (reported in thousands); available only for open-end funds. *High man ownership* is equal to one for managers with ownership in the top quartile
Board quality	Morningstar's board quality grade (which can be A, B, C or D), available only for open-end funds. *High board quality* is equal to one for open-end funds with the top grade
Fund BM	Average book to market ratio of a fund's portfolio
Fund ILLIQ	Average ILLIQ of a fund's portfolio
Incentive Fee	Annual incentive fees charged by hedge funds
High-water mark	A dummy variable that is equal to one if a hedge fund imposes a high watermark
Min Inv	Minimum investment required by a hedge fund (in thousand $)
Leveraged	A dummy variable that is equal to 1 if a hedge fund uses leverage

Stock-level Characteristics

VOL	Standard deviation of idiosyncratic monthly returns, calculated over a 2-year window (in %). Idiosyncratic monthly returns are the residuals in a regression of a stock's monthly return on the three Fama and French (1993) factors
ILLIQ	A proxy for illiquidity, computed following Amihud (2002), as the average ratio of the absolute value of daily returns to the stock daily volume in a given quarter; winsorized at 1%
Size	Market capitalization at the quarter end (in millions)
BM	Ratio of the latest book value from annual statements to the latest market value in a given quarter
MOM	Cumulative monthly returns in the past six months
$\Delta shares(t)_{i,s,t}$	The change in number of shares held by fund *i* in stock *s* between the end of quarter *t* and *t-1* as a fraction of stock *i*'s total shares outstanding at the end of quarter *t-1*, scaled by its standard deviation (in %). It varies across firms, funds, and quarters.

Characteristics-Based Portfolios

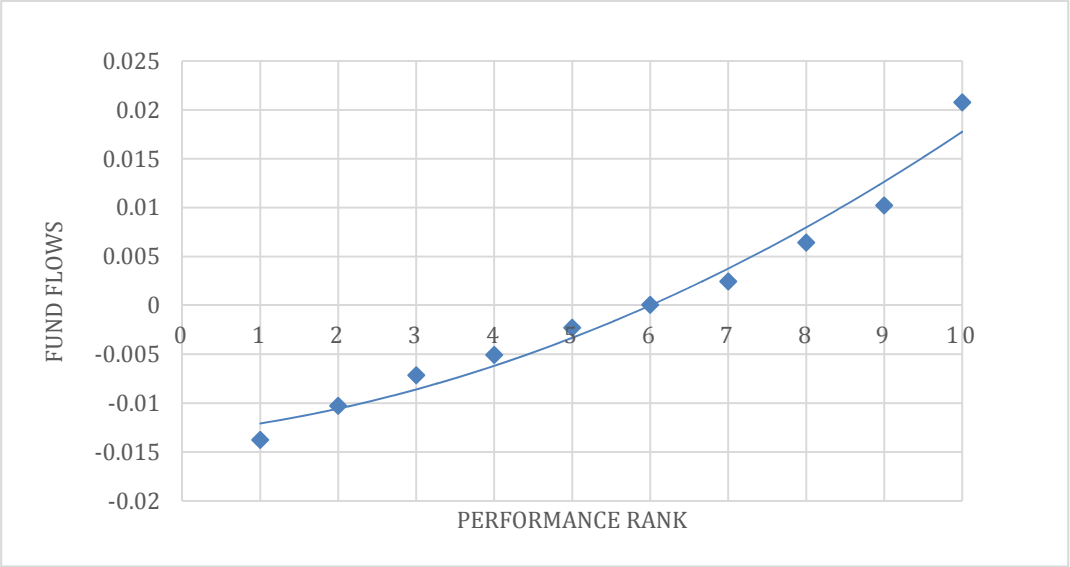
Market Equity	Price times shares outstanding as of June of year *t*
Small	A dummy variable that is equal to one if market equity is in the bottom decile defined based on NYSE breakpoints
Age	Number of years since the firm's first appearance on CRSP, measured to the nearest month in June of year *t*
Young	A dummy variable that is equal to one if the firm's age is in the bottom decile defined based on NYSE breakpoints
Vol	Standard deviation of monthly returns over the 12 months

	ending in June of year *t*
High Vol	A dummy variable that is equal to one if Vol is in the top decile, defined based on NYSE breakpoints
ROE	E+/BE, where E+ is income before extraordinary items (Item 18) plus income statement deferred taxes (Item 50) minus preferred dividends (Item 19) when it is positive and BE is the Book Equity; both E+ and BE are measured at the fiscal year-end of calendar year *t – 1*
BE	Book value of equity at the fiscal year-end of calendar year *t – 1*
Nonprofitable	A dummy variable that is equal to one if E<=0, where E is income before extraordinary items (Item 18) plus income statement deferred taxes (Item 50) minus preferred dividends (Item 19)
BM	Book value of equity at the fiscal year-end of calendar year *t – 1*, divided by market equity
Low BM	A dummy variable that is equal to one if BM is in the bottom decile defined based on NYSE breakpoints
D/BE	Dividends per share at the ex date (Item 26) times Compustat shares outstanding (Item 25), divided by book equity at the fiscal year-end of calendar year *t – 1*
Nonpayer	A dummy variable that is equal to one if the company does not pay out dividends
RD	Research and development expenditures (Item 46) over total assets at the fiscal year-end of calendar year *t – 1*
High R&D	A dummy variable that is equal to one if RD is in the top decile defined based on NYSE breakpoints
External Finance	Change in assets (Item 6) minus the change in retained earnings (Item 36), divided by total assets at the fiscal year-end of calendar year *t – 1*
High External Finance	A dummy variable that is equal to one if External Finance is in the top decile defined based on NYSE breakpoints
Sales Growth	The change in net sales (Item 12), divided by prior-year net sales at the fiscal year-end of calendar year *t – 1*
Low Sales	A dummy variable that is equal to one if Sales Growth is in the bottom decile, defined based on NYSE breakpoints

Figure 1
The Effect of Performance on Open-end Fund Flows

This figure presents average fund flows for funds in different deciles of performance. In Panel B, the high (low)-sensitivity funds are funds with institutional ownership below (above) the median and whose managers have tenure below (above) the median.

Panel A



Panel B

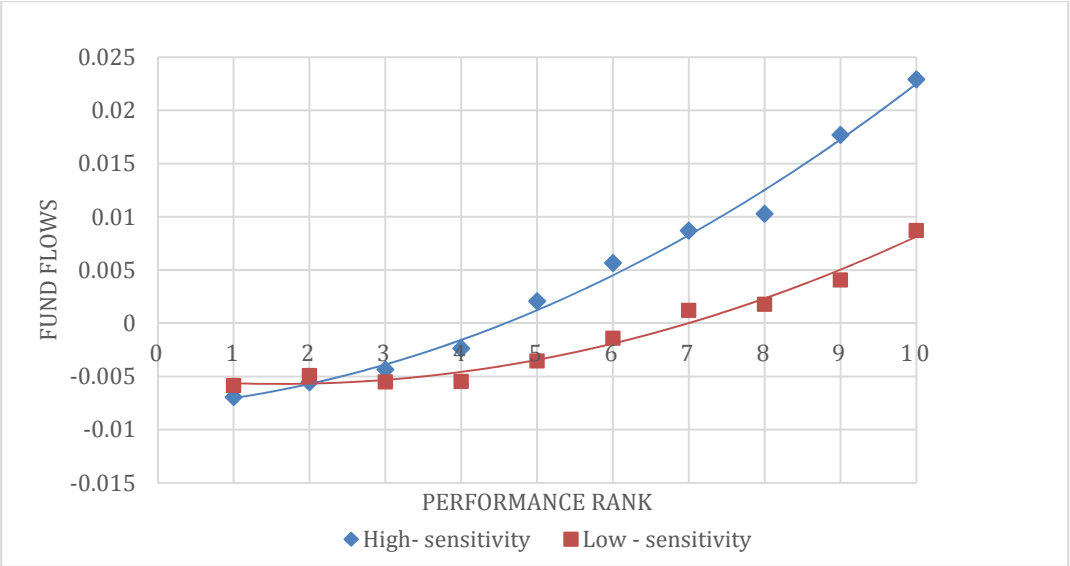


Table 1
Descriptive Statistics: Open-end versus Closed-end Funds

Panel A describes the main characteristics of the closed- and open-end funds in the holdings sample. The unit of observation is the fund-quarter. Panel B compares the characteristics of the stocks held by open- and closed-end funds. All variables are defined in the Appendix.

A. Holdings: Fund Characteristics

Fund	N	Variable	Mean	Median	Std Dev
Open	23,869	Log TNA	5.4958	5.7064	1.4155
		Fees	0.0132	0.0124	0.0051
		Past Perf	0.0002	-0.0038	0.0826
		Flows	0.0041	0.0018	0.0293
		FPS	0.2264	0.1315	0.7496
		Tenure	1.8653	1.9459	0.8457
		Cash	0.0285	0.0177	0.0373
		Institutional	0.2157	0.0077	0.3608
		Prior Exposure	6.5653	4.3265	8.2565
		Portfolio Overlap	15.5602	12.8094	13.3704
		Man ownership	298.86	187.50	3248.15
		High board quality	0.1159	0.0000	0.3201
Closed	6,437	Log TNA	5.7135	5.7048	1.1188
		Fees	0.0136	0.0125	0.0055
		Past Perf	0.0062	-0.0025	0.1593
		Discount	0.0540	0.0694	0.0891
		FPS	0.0149	0.0018	0.1211
		Leverage	0.0688	0.0000	0.1125
		Cash	-0.0621	0.0069	0.1817
		Prior Exposure	4.0158	2.3408	5.3073
		Portfolio Overlap	8.2559	5. 9470	7.1312

B. Holdings: Stock Characteristics

Fund	N	Variable	Mean	Median	Std Dev
Open	2,782,005	MOM	0.1170	0.0896	0.3886
		Size	8.3789	8.2480	1.8015
		VOL	7.8589	6.6958	4.8241
		ILLIQ	0.0464	0.0004	1.7075
		BM	0.7045	0.4384	4.7456
Closed	323,281	MOM	0.0706	0.0595	0.3046
		Size	8.9410	9.0650	1.8791
		VOL	6.8055	5.7231	4.1542
		ILLIQ	0.1568	0.0002	3.4882
		BM	1.0736	0.5108	5.8475

Table 2
Descriptive Statistics: Hedge Funds

Panel A provides the duration of different types of share restrictions for the hedge funds in the holdings sample (reported in days). Panel B describes the characteristics of the stocks held by hedge funds with share restrictions above and below the median in the holdings sample. Panel C describes differences in fund characteristics. All variables are defined in the Appendix.

Panel A: Share Restrictions

Variable	25th Pctl	Mean	Median	75th Pctl	Std Dev
Redemption notice period	30	43.8320	37.5	60	24.0942
Payout period	15	46.5878	30.4167	67.5	42.1577
Lock up period	0	120.5533	12.0000	194.0000	174.6018
Share restrictions	60	197.94	120	308.50	190.96

Panel B: Stock Characteristics

Restrictions	< Median			Median>		
Variable	Mean	Median	Std	Mean	Median	Std
MOM	0.1178	0.0657	0.4993	0.1081	0.0621	0.4966
Size	7.4885	7.4329	2.0117	7.5379	7.4707	2.0118
VOL	9.3278	7.9848	5.7436	9.7205	8.2860	5.9050
ILLIQ	0.3019	0.0014	4.3424	0.2844	0.0012	4.1760
BM	0.6939	0.4073	1.3503	0.6625	0.3926	1.2701

Panel C: Fund Characteristics

Restrictions	< Median			Median>		
Variable	Mean	Median	Std	Mean	Median	Std
Log TNA	15.1352	16.1257	3.6609	14.4820	14.2660	3.4527
FPS	0.3419	0.3015	0.4541	0.2615	0.2402	0.4307
Annual fees	0.0138	0.0125	0.0051	0.0137	0.0150	0.0042
Incentive fees	0.1796	0.2000	0.0533	0.1914	0.2000	0.0313
High-water marks	0.7832	1.0000	0.3386	0.8970	1.0000	0.2550
Leveraged	0.5802	0.6364	0.4372	0.6352	0.8000	0.4135
Min Inv	1,546,350	1,000,000	2,939,394	1,492,286	1,000,000	1,573,602

Table 3
Determinants of Funds' Flow Performance Sensitivity

The dependent variable is a fund's flow performance sensitivity, computed each month, from a rolling regression of monthly flows on performance over the past 12 months using a 24-month rolling regression. In columns 1 and 2, the sample includes monthly observations for all closed and open-end mutual funds in our sample. In column 3, the sample includes all hedge funds. We present ordinary least squares estimates with errors clustered at the fund level and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. All variables are defined in the Appendix.

Dependent Variable: FPS			
	(1)	(2)	(3)
	Closed- and Open-End Funds		Hedge Funds
Open	0.4404***	0.5061***	
	(0.013)	(0.044)	
Open x Tenure		-0.0203**	
		(0.010)	
Open x Institutional		-0.1789**	
		(0.085)	
Share restrictions			-0.0126**
			(0.005)
Observations	326,274	221,004	127,403
R-squared	0.039	0.057	0.131

Table 4
Trading Activities of Open-end and Closed-end Funds

This table presents the proportion of positions that are purchases, sales, or unchanged in closed- and open-end funds' entire portfolio and in the fraction of the portfolio that has been subject to a fire sale during the previous quarter. In Panel B, we define a dummy *financial slack* for closed- and open-end funds, respectively, that takes value equal to 1 if a fund-quarter observation is above the median for all proxies of financial slack (which include flows, cash, Amihud illiquidity factor of stockholdings, and average market to book value of stockholdings, prior exposure to fire sale stocks, and closed-end fund leverage). All variables are defined in the Appendix.

Panel A. Whole Sample

Fund	Activity	Entire Portfolio	Fire Sale Sample
Open	Purchase	0.3212	0.1722
	Sell	0.3408	0.5858
	Hold	0.3380	0.2420
Closed	Purchase	0.2779	0.6510
	Sell	0.2776	0.1032
	Hold	0.4444	0.2458

Panel B. The Role of Financial Slack

Fund	Financial Slack	Activity	Entire Portfolio	Fire Sales
Open	Low	Purchase	0.3152	0.1667
		Sell	0.3676	0.5978
		Hold	0.3172	0.2355
	High	Purchase	0.3448	0.1910
		Sell	0.2833	0.5480
		Hold	0.3719	0.2610
Closed	Low	Purchase	0.2543	0.6425
		Sell	0.2606	0.1053
		Hold	0.4851	0.2522
	High	Purchase	0.2874	0.6629
		Sell	0.2954	0.1030
		Hold	0.4172	0.2340

Table 5
Closed- and Open-end Funds' Trades in Fire Sale Stocks

We compare the change in holdings of closed- and open-end funds around fire sale events. Quarter *t* is the quarter of the fire sale, identified as in Coval and Stafford (2007). The dependent variable is a fund's change in quarterly holdings ($\Delta shares(t+k)_{i,s,t}$) in the quarters preceding, during or following the fire sale, as indicated on top of each column, divided by the firm's number of shares outstanding at the beginning of the quarter. We divide $\Delta shares(t+k)_{i,s,t}$ by the standard deviation of all $\Delta shares(t+k)_{i,s,t}$ (including non fire sale stocks) of closed- and open-end funds during the sample period. All remaining variables are defined in the Appendix. All equations include time fixed effects and a constant whose coefficients are not reported. We present ordinary least squares estimates with errors clustered at the fund level and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	(1) Δ Shares (t-2)	(2) Δ Shares (t-1)	(3) Δ Shares (t)	(4) Δ Shares (t+1)	(5) Δ Shares (t+2)	(6) Δ Shares (t+3)
Closed	0.0017	0.0270	0.0650	0.4140***	0.1804	0.2544
	(0.195)	(0.056)	(0.071)	(0.158)	(0.183)	(0.239)
Size	-0.2351***	-0.0812***	-0.0530***	0.3411***	0.3781***	0.3122***
	(0.029)	(0.010)	(0.017)	(0.054)	(0.049)	(0.049)
VOL	0.0310***	0.0097***	-0.0074	-0.0648***	-0.0422***	-0.0379***
	(0.009)	(0.003)	(0.005)	(0.018)	(0.012)	(0.014)
ILLIQ	-0.0105	-0.0077*	-0.0024	0.0711*	0.0072	0.0040
	(0.020)	(0.004)	(0.013)	(0.042)	(0.026)	(0.022)
BM	0.0010	-0.0079	-0.0523***	-0.0099	-0.0615	0.0098
	(0.011)	(0.012)	(0.011)	(0.026)	(0.073)	(0.012)
MOM	0.0362	-0.0530	0.4315***	0.4298	0.5027***	0.1069
	(0.167)	(0.074)	(0.116)	(0.291)	(0.191)	(0.207)
Log TNA	0.1894***	0.0736***	0.0275	-0.2379***	-0.2489***	-0.2254***
	(0.035)	(0.012)	(0.018)	(0.064)	(0.056)	(0.054)
N	104,662	136,334	175,439	128,504	94,779	78,435
R-squared	0.005	0.005	0.002	0.004	0.006	0.006

Table 6
Stock Characteristics and Closed- and Open-End Funds' Trades in Fire Sales

We compare the change in holdings of closed- and open-end funds in fire sale stocks with different characteristics. The dependent variable is a fund's change in quarterly holdings ($\Delta shares(t+1)_{i,s,t}$) in the quarter following the fire sale, identified as in Coval and Stafford (2007), divided by the firm's number of shares outstanding at the beginning of the quarter. We divide $\Delta shares(t+1)_{i,s,t}$ by the standard deviation of all $\Delta shares(t+1)_{i,s,t}$ of closed- and open-end funds (including non fire sale stocks) during the sample period. All remaining variables are defined in the Appendix. All equations include time fixed effects and a constant whose coefficients are not reported. We present ordinary least squares estimates with errors clustered at the fund level and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable: Δ Shares (t+1)					
	(1)	(2)	(3)	(4)	(5)
Closed	3.4252***	-0.4398	0.4244***	0.3937**	0.4380***
	(0.753)	(0.333)	(0.159)	(0.162)	(0.161)
Closed x Size	-0.3779***				
	(0.081)				
Closed x VOL		0.1191**			
		(0.054)			
Closed x ILLIQ			-0.1035		
			(0.077)		
Closed x BM				0.0243	
				(0.038)	
Closed x MOM					-0.3790
					(0.335)
Size	0.3720***	0.3132***	0.3417***	0.3408***	0.3413***
	(0.059)	(0.052)	(0.054)	(0.054)	(0.054)
VOL	-0.0635***	-0.1286***	-0.0647***	-0.0648***	-0.0648***
	(0.017)	(0.028)	(0.018)	(0.018)	(0.018)
ILLIQ	0.0657	0.0693	0.1134**	0.0711*	0.0711*
	(0.043)	(0.042)	(0.047)	(0.042)	(0.042)
BM	-0.0109	-0.0144	-0.0101	-0.0163	-0.0101
	(0.025)	(0.025)	(0.026)	(0.034)	(0.026)
MOM	0.4369	0.4119	0.4317	0.4286	0.4538
	(0.291)	(0.287)	(0.291)	(0.290)	(0.305)
Log TNA	-0.2382***	-0.2387***	-0.2378***	-0.2378***	-0.2379***
	(0.065)	(0.064)	(0.064)	(0.064)	(0.064)
Observations	128,504	128,504	128,504	128,504	128,504
R-squared	0.004	0.004	0.004	0.004	0.004

Table 7
Funds' Flow performance Sensitivity and Trades in Fire Sales

We compare the extent to which trading in fire sale stocks varies with fund characteristics. Quarter *t+1* is the quarter following the fire sale, identified as in Coval and Stafford (2007). The dependent variable is a fund's change in quarterly holdings ($\Delta shares(t+1)_{i,s,t}$) in the quarter following the fire sale, divided by the stock's total number of shares outstanding. We divide $\Delta shares(t+1)_{i,s,t}$ by the standard deviation of all $\Delta shares(t+1)_{i,s,t}$of closed- and open-end funds (including non fire sale stocks) during the sample period. All remaining variables are defined in the Appendix. All equations include controls for time fixed effects and a constant whose coefficients are not reported. We present ordinary least squares estimates with errors clustered at the fund level and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable: Δ Shares (t+1)					
	(1)	(2)	(3)	(4)	(5)
Open	-0.3958**	-0.9739***	-0.5251***	-1.1211***	
	(0.158)	(0.285)	(0.184)	(0.334)	
Open x FPS	-0.1775**				
	(0.082)				
Open x Tenure		0.2333**		0.2790**	
		(0.109)		(0.132)	
Open x Institutional			0.4711*	0.4014*	
			(0.252)	(0.212)	
$\widehat{FPS}$					-1.5323***
					(0.463)
Size	0.3402***	0.3428***	0.3688***	0.3685***	0.3630***
	(0.055)	(0.061)	(0.066)	(0.072)	(0.070)
VOL	-0.0678***	-0.0775***	-0.0590***	-0.0758***	-0.0763***
	(0.018)	(0.022)	(0.019)	(0.025)	(0.025)
ILLIQ	0.0714*	0.0753*	0.0708*	0.0748*	0.0748*
	(0.042)	(0.043)	(0.043)	(0.043)	(0.044)
BM	-0.0106	-0.0174	-0.0100	-0.0174	-0.0170
	(0.026)	(0.030)	(0.027)	(0.031)	(0.031)
MOM	0.4468	0.6313*	0.4511	0.7568*	0.7493*
	(0.299)	(0.364)	(0.331)	(0.415)	(0.414)
Log TNA	-0.2422***	-0.3405***	-0.2338***	-0.3490***	-0.3505***
	(0.067)	(0.075)	(0.076)	(0.090)	(0.090)
Observations	126,821	88,370	108,642	74,732	74,732
R-squared	0.004	0.005	0.004	0.005	0.005

Table 8
Controlling for Funds' Financial Slack

We compare the change in holdings of closed- and open-end funds around fire sale events controlling for the funds' financial slack. Quarter *t+1* is the quarter following the fire sale identified as in Coval and Stafford (2007). The dependent variable is a fund's change in quarterly holdings ($\Delta shares(t+1)_{i,s,t}$) in the quarter following the fire sale, divided by the stock's total number of shares outstanding; the measure is standardized using the deviation of all $\Delta shares(t+1)_{i,s,t}$ of closed- and open-end funds (including non fire sale stocks) during the sample period. All remaining variables are defined in the Appendix. All equations include controls for time fixed effects and a constant whose coefficients are not reported. In columns 1 and 2 we exclude open-end funds with flows in the bottom quartile (in our sample of non distressed funds). We present ordinary least squares estimates with errors clustered at the fund level and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable: Δ Shares (t+1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	*Excluding if flows < P25*						
Open	-0.3545**	-0.3644**					
	(0.159)	(0.160)					
Closed			0.5081***	0.4007**	0.3675**	0.3615**	0.5451***
			(0.157)	(0.174)	(0.161)	(0.166)	(0.148)
Open x Past Flows		0.2965					
		(0.476)					
Prior Exposure			-0.0202**				
			(0.010)				
Closed x Leverage				0.3209			
				(1.171)			
Fund ILLIQ					0.8720		
					(1.299)		
Fund BM						0.2261*	
						(0.131)	
Cash							1.7862*
							(0.921)
Size	0.3075***	0.3145***	0.3660***	0.3411***	0.3528***	0.3411***	0.3750***
	(0.061)	(0.063)	(0.065)	(0.054)	(0.057)	(0.054)	(0.059)
VOL	-0.0625***	-0.0629***	-0.0595***	-0.0648***	-0.0645***	-0.0644***	-0.0569***
	(0.021)	(0.021)	(0.019)	(0.018)	(0.017)	(0.018)	(0.018)
ILLIQ	0.0770	0.0772	0.1274***	0.0711*	0.0670	0.0706*	0.0720*
	(0.052)	(0.052)	(0.049)	(0.042)	(0.046)	(0.042)	(0.042)
BM	-0.0467*	-0.0475*	-0.0155	-0.0099	-0.0096	-0.0207	-0.0184
	(0.025)	(0.025)	(0.031)	(0.026)	(0.026)	(0.026)	(0.028)
MOM	0.3993	0.4063	0.4199	0.4296	0.4284	0.4307	0.4429
	(0.371)	(0.384)	(0.335)	(0.291)	(0.291)	(0.290)	(0.314)
Log TNA	-0.2206***	-0.2169***	-0.3218***	-0.2379***	-0.2460***	-0.2474***	-0.2766***
	(0.072)	(0.074)	(0.074)	(0.064)	(0.063)	(0.063)	(0.069)
Observations	98,578	96,589	105,129	128,504	128,483	128,483	108,611
R-squared	0.003	0.003	0.004	0.004	0.004	0.004	0.004

Table 9
Additional Robustness Tests

Quarter *t+1* is the quarter following the fire sale identified as in Coval and Stafford (2007). The dependent variable is a fund's change in quarterly holdings ($\Delta shares(t+1)_{i,s,t}$) in the quarter following the fire sale, divided by the stock's total number of shares outstanding. We divide $\Delta shares(t+1)_{i,s,t}$ by the standard deviation of all $\Delta shares(t+1)_{i,s,t}$ of closed- and open-end funds (including non fire sale stocks) during the sample period. All remaining variables are defined in the Appendix. All equations include controls for time fixed effects and a constant whose coefficients are not reported. In column 2, we restrict the sample to open- and closed-end funds that are comanaged by the same manager. We present ordinary least squares estimates with errors clustered at the fund level and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable: Δ Shares (t+1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample		*Comanagers*					
Closed	0.6717***	0.2792*	0.5090***	0.3722**	0.4967***		
	(0.168)	(0.149)	(0.152)	(0.157)	(0.147)		
Open						-0.3131**	-0.7421**
						(0.131)	(0.288)
Past Perf	-0.1088						
	(0.828)						
Closed x Discount			0.0876				
			(0.731)				
Portfolio Overlap				-0.0375***			
				(0.011)			
Expenses					-35.9000*		
					(20.457)		
Open x High Man Ownership						-0.3374**	
						(0.142)	
Open x High Board Quality							0.6584
							(0.739)
Size	0.3507***	0.0691	0.3456***	0.4499***	0.3423***	0.3828***	0.4212***
	(0.056)	(0.092)	(0.047)	(0.068)	(0.054)	(0.060)	(0.128)
VOL	-0.0620***	-0.0130	-0.0617**	-0.0639***	-0.0616***	-0.0611*	-0.1161***
	(0.018)	(0.022)	(0.026)	(0.019)	(0.018)	(0.033)	(0.042)
ILLIQ	0.0722*	0.0767***	0.0706*	0.1307***	0.1025***	0.0721*	0.0255
	(0.042)	(0.015)	(0.037)	(0.044)	(0.037)	(0.038)	(0.053)
BM	-0.0160	0.0065	-0.0142	-0.0018	-0.0116	-0.0168	0.0214
	(0.028)	(0.012)	(0.026)	(0.027)	(0.027)	(0.030)	(0.055)
MOM	0.4362	0.1509	0.4229	0.4022	0.4452	0.4550	1.0423*
	(0.297)	(0.251)	(0.403)	(0.320)	(0.291)	(0.544)	(0.553)
Log TNA	-0.2385***	0.0948	-0.2374***	-0.2908***	-0.2726***	-0.2201***	-0.2110
	(0.067)	(0.101)	(0.039)	(0.067)	(0.067)	(0.057)	(0.231)
Observations	124,836	11,077	127,508	113,305	127,192	92,252	34,748
R-squared	0.004	0.007	0.004	0.005	0.004	0.004	0.008

Table 10
The Trading Activities of Hedge Funds

This table presents the proportion of positions that are purchases, sales, or unchanged in the entire portfolio and in the portfolio of stocks that have been subject to fire sales during the quarter for high and low share restrictions hedge funds.

Share Restrictions	Activity	Entire Portfolio	Fire Sales
Low	Purchase	0.3229	0.3950
	Sell	0.3913	0.3737
	Hold	0.2858	0.2313
High	Purchase	0.2905	0.5774
	Sell	0.3571	0.2102
	Hold	0.3524	0.2123

Table 11
Hedge Funds' Trades in Fire Sale Stocks

We explore how the change in holdings of hedge funds varies around fire sale events. *Share Restrictions* is the sum of the number of days in the lock up, redemption notice and payout periods, divided by 100. Quarter *t* is the quarter of the fire sale identified as in Coval and Stafford (2007). The dependent variable is a fund's change in quarterly holdings ($\Delta shares(t+k)_{i,s,t}$) in the quarters preceding, during or following the fire sale, as indicated on top of each column, divided by the firm's number of share outstanding at the beginning of the quarter. We divide $\Delta shares(t+k)_{i,s,t}$ by the standard deviation of all $\Delta shares(t+k)_{i,s,t}$ of hedge funds (including non fire sale stocks) during the sample period. All remaining variables are defined in the Appendix. All equations include time fixed effects and a constant whose coefficients are not reported. We present ordinary least squares estimates with errors clustered at the fund level and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ Shares (t-2)	Δ Shares (t-1)	Δ Shares (t)	Δ Shares (t+1)	Δ Shares (t+2)	Δ Shares (t)	Δ Shares (t)
Share Restrictions	-0.0053	0.0167	0.0736**	0.0077	-0.0070	0.2283**	0.0137
	(0.011)	(0.012)	(0.032)	(0.034)	(0.009)	(0.097)	(0.025)
Share Restrictions x Size						-0.0211**	
						(0.010)	
Share Restrictions x Vol							0.0063**
							(0.003)
Size	0.0382***	-0.1196***	-0.2405***	0.1068**	0.0419**	-0.2055***	-0.2395***
	(0.014)	(0.007)	(0.018)	(0.049)	(0.016)	(0.026)	(0.018)
Vol	-0.0047***	0.0099***	0.0277***	-0.0398***	-0.0082***	0.0275***	0.0175**
	(0.001)	(0.002)	(0.004)	(0.007)	(0.001)	(0.004)	(0.007)
ILLIQ	0.0056***	-0.0150***	-0.0235***	0.0210**	0.0025	-0.0231***	-0.0235***
	(0.002)	(0.002)	(0.006)	(0.011)	(0.005)	(0.007)	(0.006)
BM	-0.0016	-0.0010	0.0010	0.0111	0.0009	0.0012	0.0010
	(0.003)	(0.002)	(0.005)	(0.010)	(0.002)	(0.005)	(0.005)
MOM	-0.0676**	0.0785	0.0249	-0.0350	-0.0369	0.0269	0.0267
	(0.027)	(0.055)	(0.049)	(0.163)	(0.028)	(0.049)	(0.049)
Log TNA	0.0056	0.0142	0.0354***	0.0274	0.0007	0.0365***	0.0354***
	(0.004)	(0.010)	(0.012)	(0.017)	(0.004)	(0.012)	(0.012)
Observations	44,560	52,564	70,868	68,704	51,996	70,868	70,868
R-squared	0.023	0.066	0.051	0.010	0.020	0.051	0.051

Table 12
Closed- and Open-end Funds' Exposure to Aggregate Mispricing

The dependent variable is the monthly return of fund *i*. On top of each column, we indicate the portfolio of potentially undervalued stocks we consider in that specification. Portfolios are formed once per year using market equity, age, and volatility at the end of June of year *t*, and accounting data at the fiscal year-end of calendar year *t – 1*. Portfolios are constructed based on NYSE decile breakpoints. Portfolio is the equally weighted monthly return of a given portfolio of stocks. Market is the value-weighted excess market return of all NYSE, AMEX, and NASDAQ stocks, which we obtain from Ken French's website. *Neg Sent* is a dummy variable that takes value equal to 1 during periods of negative sentiment, defined as in Baker and Wurgler (2007). All remaining variables, including the definition of firm characteristics used for the portfolio construction, are defined in the Appendix. We present ordinary least squares estimates with errors clustered at the fund and time levels and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Portfolio	Small	High Vol	Young	Low BM	High R&D	High External	Low Sales	Nonpayer	Nonprofitable
Portfolio x Neg Sent x Closed	0.0684***	0.0612***	0.1026***	0.0859***	0.0629**	0.0751***	0.0594**	0.0952***	0.0764***
	(0.016)	(0.020)	(0.031)	(0.032)	(0.025)	(0.022)	(0.023)	(0.027)	(0.021)
Portfolio x Closed	0.0465***	-0.0010	0.0022	-0.0497	-0.0278	0.0031	0.0199	0.0019	0.0128
	(0.012)	(0.018)	(0.024)	(0.031)	(0.021)	(0.019)	(0.022)	(0.026)	(0.018)
Portfolio x Neg Sent	0.0326	0.0200	0.0464	0.0867***	0.0351	0.0311	0.0088	0.0398	0.0315
	(0.037)	(0.025)	(0.040)	(0.033)	(0.024)	(0.025)	(0.031)	(0.040)	(0.028)
Portfolio	0.0546	0.0420*	0.0551	0.0702**	0.0521***	0.0408*	0.0644**	0.0786**	0.0438*
	(0.034)	(0.024)	(0.038)	(0.030)	(0.020)	(0.023)	(0.028)	(0.037)	(0.026)
Neg Sent	0.0026*	0.0027*	0.0029*	0.0029*	0.0028*	0.0030*	0.0023	0.0026*	0.0029*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Closed	-0.0076***	-0.0071***	-0.0073***	-0.0071***	-0.0070***	-0.0074***	-0.0073***	-0.0073***	-0.0075***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market	0.9721***	0.9926***	0.9478***	0.9362***	0.9376***	0.9486***	0.9516***	0.9476***	0.9482***
	(0.017)	(0.021)	(0.019)	(0.018)	(0.019)	(0.018)	(0.017)	(0.017)	(0.018)
Market x Closed	-0.2940***	-0.2722***	-0.3018***	-0.2756***	-0.2818***	-0.2998***	-0.3065***	-0.3005***	-0.3063***
	(0.026)	(0.029)	(0.025)	(0.024)	(0.023)	(0.025)	(0.026)	(0.025)	(0.025)
Constant	0.0018***	0.0022***	0.0023***	0.0025***	0.0018***	0.0021***	0.0020***	0.0018***	0.0021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	272,373	272,373	272,373	272,373	272,373	272,373	272,373	272,373	272,373
R-squared	0.568	0.567	0.567	0.568	0.567	0.567	0.568	0.570	0.568

Table 13
Closed- and Open-end Funds' Exposure to Aggregate Mispricing: Additional Robustness

The dependent variable is the monthly return of fund *i*. Small is the equally weighted monthly return of the portfolio of small stocks. The portfolio is formed once per year using market equity at the end of June of year *t* and constructed using NYSE decile breakpoints. Stocks with market capitalization below this breakpoint are considered small. Market is the value-weighted excess market return of all NYSE, AMEX, and NASDAQ stocks, which we obtain from Ken French's website. In columns 1 to 3, *Neg Sent* is a dummy variable that takes value equal to 1 during periods of negative sentiment, defined as in Baker and Wurgler (2007). In column 4, *Neg Sent* is a dummy variable that takes value equal to 1 during periods of negative sentiment, defined as the first principal component of trading volume as measured by NYSE turnover; the dividend premium; the number and first-day returns on IPOs; and the equity share in new issues. In column 5, negative sentiment is a dummy variable that takes value equal to 1 when the index of consumer sentiment compiled by the University of Michigan Survey Research Center is below the median. In column 6, UMO is the underpriced minus overpriced factor of Hirshleifer and Jiang (2010). Momentum is the return of the momentum portfolio from Ken French's website. All remaining variables are defined in the Appendix. We present ordinary least squares estimates with errors clustered at the fund and time levels and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
				Sentiment-No CEF Discount	Sentiment-Michigan	Hirshleifer-Jiang Factor
Small x Neg Sent x Closed	0.0767***	0.0525***	0.0481***	0.0610***	0.0597***	
	(0.017)	(0.013)	(0.014)	(0.020)	(0.019)	
Small x Closed	0.0426***	0.0394***	0.0410***	0.0446*	0.0540***	
	(0.009)	(0.015)	(0.015)	(0.027)	(0.014)	
UMO x Closed						0.1215***
						(0.025)
Small x Neg Sent	0.0320	0.0435***	0.0438***	-0.0408	0.0319	
	(0.037)	(0.005)	(0.005)	(0.039)	(0.034)	
Neg Sent	0.0026*	0.0026***	0.0026***	0.0001**	-0.0009	
	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)	
Small	0.0548	0.0565***	0.0563***	0.0848***	0.0585**	
	(0.034)	(0.006)	(0.006)	(0.021)	(0.028)	
UMO						0.0023
						(0.024)
Closed	-0.0080***	-0.0074***	-0.0080***	-0.0069***	-0.0078***	-0.0085***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Market	0.9722***	0.9802***	0.9822***	0.9542***	0.9634***	0.9655***
	(0.017)	(0.007)	(0.009)	(0.019)	(0.017)	(0.022)
Market x Closed	-0.2949***	-0.3120***	-0.3198***	-0.3452***	-0.2952***	-0.2428***
	(0.026)	(0.026)	(0.031)	(0.031)	(0.027)	(0.020)
PS LIQ	-0.0024	-0.0016	-0.0022		-0.0013	0.0007
	(0.017)	(0.002)	(0.002)		(0.017)	(0.018)
PS LIQ x Closed	0.0513***	0.0524***	0.0537***		0.0451***	0.0511***
	(0.018)	(0.010)	(0.009)		(0.017)	(0.015)
Mom		0.0273***	0.0271***			
		(0.005)	(0.004)			
Mom x Closed		-0.0578***	-0.0569***			
		(0.012)	(0.012)			
Market x Neg Sent			-0.0049			
			(0.006)			
Market x Neg Sent x Closed			0.0143			
			(0.022)			
Neg Sent x Closed			0.0012**			
			(0.001)			
Constant	0.0019***	0.0015***	0.0016***	0.0009	0.0027***	0.0030***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Observations	272,373	272,373	272,373	272,373	272,373	272,373
R-squared	0.568	0.569	0.569	0.532	0.568	0.562

Table 14
Hedge Funds' Exposure to Aggregate Mispricing

The dependent variable is the monthly return of hedge fund *i*. On top of each column we indicate the portfolio of potentially undervalued stocks we consider in that specification. Portfolios are formed once per year using market equity, age, and volatility at the end of June of year *t*, and accounting data at the fiscal year-end of calendar year *t – 1*. Portfolios are constructed based on NYSE decile breakpoints. Portfolio is the equally weighted monthly return of a given portfolio of stocks. Market is the value-weighted excess market return of all NYSE, AMEX, and NASDAQ stocks, which we obtain from Ken French's website. *Neg Sent* is a dummy variable that takes value equal to 1 during periods of negative sentiment, defined as in Baker and Wurgler (2007). All remaining variables, including the definition of firm characteristics used for the portfolio construction, are defined in the Appendix. We present ordinary least squares estimates with errors clustered at the fund and time levels and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Portfolio	(1) Small	(2) High Vol	(3) Young	(4) Low BM	(5) High R&D	(6) High External	(7) Low Sales	(8) Nonpayer	(9) Nonprofitable
Portfolio x Neg Sent x Share Restrictions	0.0179***	0.0102**	0.0124*	0.0154**	0.0113***	0.0114***	0.0152***	0.0179***	0.0120***
	(0.006)	(0.005)	(0.007)	(0.007)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)
Portfolio x Share Restrictions	-0.0048	-0.0050	-0.0046	-0.0109	-0.0073	-0.0061	-0.0061	-0.0063	-0.0057
	(0.007)	(0.005)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.007)	(0.005)
Portfolio x Neg Sent	-0.1222**	-0.0930***	-0.1101*	-0.1301**	-0.0815**	-0.0888**	-0.1001**	-0.1143*	-0.0906**
	(0.056)	(0.036)	(0.062)	(0.053)	(0.032)	(0.036)	(0.047)	(0.059)	(0.040)
Portfolio	0.2005***	0.1523***	0.1856***	0.2361***	0.1544***	0.1540***	0.1751***	0.2131***	0.1582***
	(0.052)	(0.034)	(0.059)	(0.046)	(0.027)	(0.031)	(0.044)	(0.053)	(0.036)
Neg Sent	0.0027**	0.0029**	0.0032**	0.0031*	0.0026*	0.0032**	0.0026**	0.0026*	0.0032**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share Restrictions	-0.0000	0.0001	0.0000	0.0001	0.0001	0.0001	0.0000	0.0000	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market	0.4344***	0.3835***	0.3993***	0.3835***	0.3877***	0.3926***	0.4005***	0.3971***	0.3913***
	(0.023)	(0.023)	(0.024)	(0.021)	(0.022)	(0.023)	(0.023)	(0.023)	(0.023)
Market x Share Restrictions	0.0097*	0.0096*	0.0092*	0.0111**	0.0109**	0.0099*	0.0092*	0.0088*	0.0096*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.0061***	0.0063***	0.0068***	0.0069***	0.0061***	0.0063***	0.0062***	0.0062***	0.0064***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	220,122	220,122	220,122	220,122	220,122	220,122	220,122	220,122	220,122
R-squared	0.155	0.155	0.151	0.157	0.156	0.156	0.155	0.156	0.155

Table 15
Hedge Funds' Exposure to Aggregate Mispricing: Additional Robustness

The dependent variable is the monthly return of hedge fund *i*. Small is the equally weighted monthly return of the portfolio of small stocks. The portfolio is formed once per year using market equity at the end of June of year *t* and constructed using NYSE decile breakpoints. Stocks with market capitalization below this breakpoint are considered small. Market is the value-weighted excess market return of all NYSE, AMEX, and NASDAQ stocks, which we obtain from Ken French's website. In columns 1 to 4, *Neg Sent* is a dummy variable that takes value equal to 1 during periods of negative sentiment, defined as in Baker and Wurgler (2007). In column 5, *Neg Sent* is a dummy variable that takes value equal to 1 during periods of negative sentiment, defined as the first principal component of trading volume as measured by NYSE turnover; the dividend premium; the number and first-day returns on IPOs; and the equity share in new issues. In column 6, *Neg Sent* is a dummy variable that takes value equal to 1 when the index of consumer sentiment compiled by the University of Michigan Survey Research Center is below the median. In column 7, UMO is the underpriced minus overpriced factor of Hirshleifer and Jiang (2010). Momentum is the return of the momentum portfolio from Ken French's website. Fung and Hsieh Factors are the 7 hedge fund factors in Fung and Hsieh (2004). All remaining variables are defined in the Appendix. We present ordinary least squares estimates with errors clustered at the fund and time levels and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5) Sentiment-No CEF Discount	(6) Sentiment-Michigan	(7) Hirshleifer-Jiang Factor
Small x Neg Sent x Restrictions	0.0180***	0.0157***	0.0209***	0.0191***	0.0112**	0.0104**	
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	
UMO x Restrictions							0.0077**
							(0.004)
Small x Restrictions	-0.0050	-0.0042	-0.0087	-0.0076	0.0009	0.0034	
	(0.007)	(0.006)	(0.007)	(0.007)	(0.005)	(0.004)	
Small x Neg Sent	-0.1224**	-0.0994**	-0.0952**	-0.0916**	-0.0924*	0.0140	
	(0.056)	(0.042)	(0.041)	(0.043)	(0.048)	(0.048)	
Small	0.1996***	0.2086***	0.2065***	0.1998***	0.1662***	0.1101***	
	(0.052)	(0.041)	(0.039)	(0.043)	(0.041)	(0.038)	
Neg Sent	0.0026*	0.0019*	0.0017	0.0004	0.0027**	-0.0039***	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
UMO							-0.0268
							(0.021)
Restrictions	-0.0000	-0.0000	0.0007	0.0005	-0.0000	-0.0000	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market	0.4328***	0.4675***	0.4881***	0.4840***	0.4328***	0.4210***	0.3501***
	(0.023)	(0.022)	(0.037)	(0.039)	(0.023)	(0.017)	(0.020)

Market x Restrictions	0.0096*	0.0084	0.0094	0.0095	0.0096*	0.0091***	0.0097**
	(0.005)	(0.006)	(0.007)	(0.007)	(0.005)	(0.002)	(0.004)
PS LIQ	0.0206	0.0107	0.0102	0.0136	0.0232	0.0230	0.0180
	(0.016)	(0.016)	(0.017)	(0.018)	(0.016)	(0.016)	(0.017)
PS LIQ x Restrictions	0.0031	0.0030	0.0045*	0.0039	0.0028	0.0029	0.0032*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MOM		0.0932***	0.0953***	0.0916***			
		(0.020)	(0.019)	(0.020)			
MOM x Restrictions		-0.0032	-0.0031	-0.0035			
		(0.003)	(0.003)	(0.003)			
Market x Neg sent			-0.0327	-0.0258			
			(0.037)	(0.038)			
Market x Neg sent x Restrictions			-0.0022	-0.0027			
			(0.005)	(0.005)			
Neg sent x Restrictions			-0.0009*	-0.0006			
			(0.001)	(0.000)			
Constant	0.0059***	0.0054***	0.0054***	0.0055*	0.0058***	0.0085***	0.0079***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
Observations	220,122	220,122	220,122	220,122	220,122	220,122	220,122
R-squared	0.156	0.162	0.163	0.163	0.155	0.155	0.171
HF Factors	No	No	No	Yes	No	No	No

Internet Appendix
(not for publication)

Figure A.1
Average Cumulative Abnormal Returns of Fire Sale Stocks

This figure presents the average cumulative abnormal returns of fire sale stocks, defined as in Coval and Stafford (2007). In each period, we form a portfolio of fire sale stocks and calculate the average monthly abnormal returns for these portfolios. Cumulative average abnormal returns are monthly returns in excess of the equal-weighted average return of all stocks held by mutual funds at the start of the month. We start cumulating the abnormal returns 12 months before the fire sale event. The fire sale quarter is *t=0*.

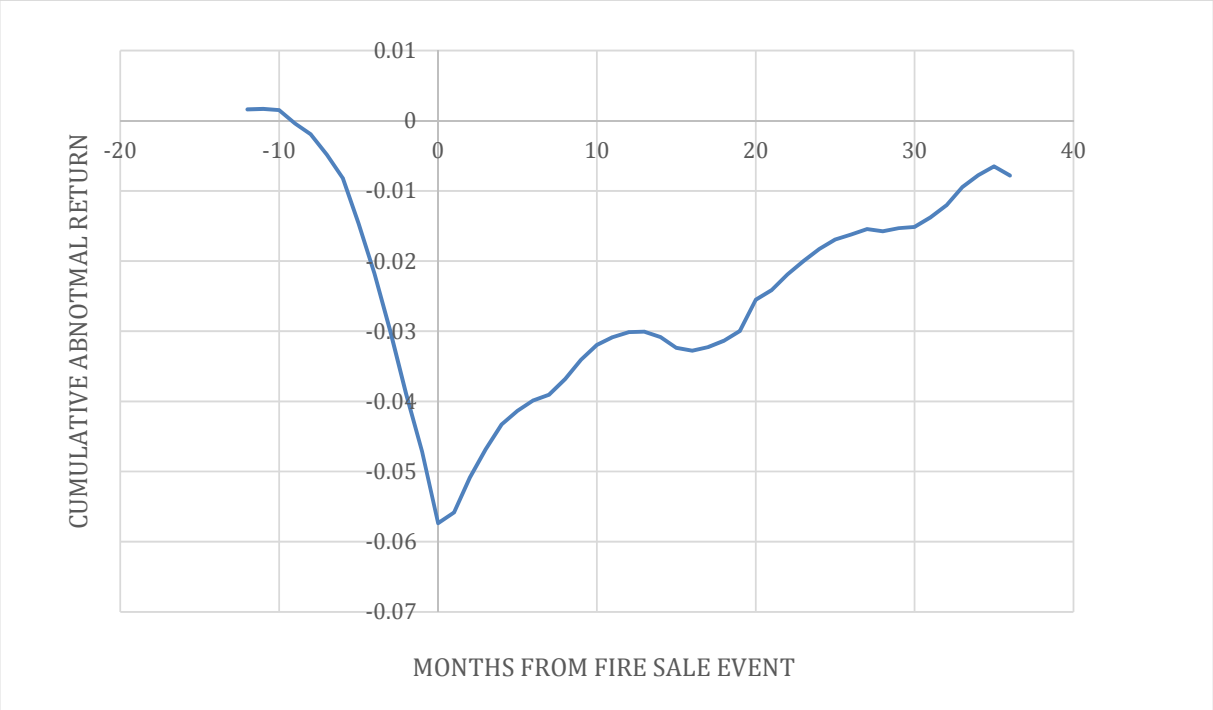


Table A.1
Flow performance Sensitivity and Financial Slack

The dependent variable is a fund's flow performance sensitivity, computed each month, from a rolling regression of monthly flows on performance over the past 12 months using a 24-month rolling regression. The sample includes monthly observations for all closed- and open-end mutual funds in our sample. We present ordinary least squares estimates with errors clustered at the fund level and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable: FPS	
	(1)
Open	0.4470***
	(0.076)
Open x Tenure	-0.0169**
	(0.008)
Open x Institutional	-0.1699**
	(0.083)
Past Flow	0.2669*
	(0.161)
Fund ILLIQ	0.1393
	(0.097)
Fund BM	-0.0908
	(0.087)
Prior Exposure	0.0001
	(0.001)
Cash	-0.0048*
	(0.003)
Constant	0.0212***
	(0.002)
Observations	146,854
R-squared	0.068

Table A.2
Controlling for Closed-End Funds' Change in Shares Outstanding

This table reproduces column (4) of Table 5 in the paper controlling for the closed-end funds' change in (split-adjusted) shares outstanding, divided by the firm's number of shares outstanding at the beginning of the quarter, *Δ Shrout*. The dependent variable is a fund's change in quarterly holdings in the quarter following the fire sale. All remaining variables are defined in the Appendix. All equations include time fixed effects and a constant whose coefficients are not reported. We present ordinary least squares estimates with errors clustered at the fund level and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	Δ Shares (t+1)
Closed	0.4847***
	(0.150)
Δ Shrout	10.5642
	(8.896)
ILLIQ	0.0710*
	(0.042)
MOM	0.4223
	(0.292)
Size	0.3426***
	(0.055)
VOL	-0.0639***
	(0.018)
BM	-0.0141
	(0.027)
Log TNA	-0.2389***
	(0.065)
Observations	127,590
R-squared	0.004

Table A.3
Including the Largest Open-End Funds

Panel A. Open- and Closed-end Funds' Trades in Fire Sale Stocks

This table reproduces the results of Table 5 in the paper, but includes also open-end funds in the top TNA quintile. We compare the change in holdings of closed- and open-end funds around fire sale events. Quarter *t* is the quarter of the fire sale, identified as in Coval and Stafford (2007). The dependent variable is a fund's change in quarterly holdings ($\Delta shares(t+k)_{i,s,t}$) in the quarters preceding, during or following the fire sale, as indicated on top of each column, divided by the firm's number of shares outstanding at the beginning of the quarter. We divide $\Delta shares(t+k)_{i,s,t}$ by the standard deviation of all $\Delta shares(t+k)_{i,s,t}$ (including non fire sale stocks) of closed- and open-end funds during the sample period. All remaining variables are defined in the Appendix. All equations include time fixed effects and a constant whose coefficients are not reported. We present ordinary least squares estimates with errors clustered at the fund level and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Shares (t-2)	Δ Shares (t-1)	Δ Shares (t)	Δ Shares (t+1)	Δ Shares (t+2)	Δ Shares (t+3)
Closed	0.1773	0.0588	0.0772	0.4060**	0.0590	0.2332
	(0.158)	(0.048)	(0.074)	(0.161)	(0.195)	(0.248)
Size	0.0227	-0.0334***	-0.0869***	0.3577***	0.3558***	0.3107***
	(0.098)	(0.009)	(0.014)	(0.087)	(0.057)	(0.057)
VOL	0.0439**	0.0026	-0.0161***	-0.0526***	-0.0493***	-0.0745***
	(0.022)	(0.002)	(0.004)	(0.018)	(0.011)	(0.021)
ILLIQ	-0.0082	-0.0064**	-0.0050	0.0491***	0.0174**	0.0221
	(0.006)	(0.003)	(0.006)	(0.012)	(0.008)	(0.014)
BM	-0.0095	-0.0139	-0.0785***	-0.1364	0.1271*	-0.0452
	(0.014)	(0.009)	(0.011)	(0.104)	(0.075)	(0.035)
MOM	0.0428	0.0842	0.4824***	0.9436***	0.9411***	0.6620**
	(0.144)	(0.053)	(0.106)	(0.244)	(0.175)	(0.299)
Log TNA	-0.0054	0.0196	-0.0026	-0.4350***	-0.4163***	-0.5459***
	(0.050)	(0.016)	(0.014)	(0.060)	(0.064)	(0.076)
Observations	363,683	450,412	557,255	432,023	338,086	289,062
R-squared	0.000	0.001	0.001	0.001	0.004	0.003

Panel B. Closed- and Open-end Funds' Exposure to Aggregate Mispricing

This table reproduces the results of Table 12 in the paper, but includes also open-end funds in the top TNA quintile. The dependent variable is the monthly return of fund *i*. On top of each column we indicate the portfolio of potentially undervalued stocks we consider in that specification. Portfolios are formed once per year using market equity, age, and volatility at the end of June of year *t*, and accounting data at the fiscal year-end of calendar year *t – 1*. Portfolios are constructed based on NYSE decile breakpoints. Portfolio is the equally weighted monthly return of a given portfolio of stocks. Market is the value-weighted excess market return of all NYSE, AMEX, and NASDAQ stocks, which we obtain from Ken French's website. *Neg Sent* is a dummy variable that takes value equal to 1 during periods of negative sentiment, defined as in Baker and Wurgler (2007). All remaining variables, including the definition of firm characteristics used for the portfolio construction, are defined in the Appendix. We present ordinary least squares estimates with errors clustered at the fund and time levels and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Portfolio	Small	High Vol	Young	Low BM	High RD	High Ext	Low Sales	Nonpayer	Nonprofitable
Portfolio x Neg Sent x Closed	0.0683***	0.0746***	0.1118***	0.1124***	0.0750***	0.0832***	0.0679***	0.1024***	0.0857***
	(0.005)	(0.017)	(0.024)	(0.023)	(0.019)	(0.018)	(0.017)	(0.019)	(0.016)
Portfolio x Closed	0.0475***	-0.0055	-0.0016	-0.0508*	-0.0284	-0.0021	0.0187	0.0038	0.0073
	(0.008)	(0.019)	(0.021)	(0.027)	(0.019)	(0.018)	(0.020)	(0.022)	(0.017)
Portfolio x Neg Sent	0.0250	0.0037	0.0329	0.0571**	0.0174	0.0192	-0.0049	0.0254	0.0184
	(0.033)	(0.022)	(0.034)	(0.029)	(0.021)	(0.022)	(0.027)	(0.034)	(0.025)
Portfolio	0.0571**	0.0484**	0.0595*	0.0710***	0.0538***	0.0465**	0.0679***	0.0795**	0.0499**
	(0.028)	(0.020)	(0.031)	(0.025)	(0.016)	(0.020)	(0.024)	(0.032)	(0.022)
Neg Sent	0.0010	0.0011	0.0014	0.0014	0.0011	0.0014	0.0007	0.0010	0.0013
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Closed	-0.0075***	-0.0072***	-0.0071***	-0.0070***	-0.0070***	-0.0073***	-0.0072***	-0.0073***	-0.0074***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market	0.8911***	0.8621***	0.8671***	0.8589***	0.8601***	0.8669***	0.8711***	0.8669***	0.8663***
	(0.016)	(0.019)	(0.018)	(0.018)	(0.019)	(0.018)	(0.017)	(0.016)	(0.018)
Market x Closed	-0.2161***	-0.2237***	-0.2238***	-0.2011***	-0.2072***	-0.2210***	-0.2291***	-0.2231***	-0.2272***
	(0.019)	(0.013)	(0.016)	(0.014)	(0.011)	(0.016)	(0.018)	(0.017)	(0.016)
Constant	0.0019***	0.0022***	0.0023***	0.0025***	0.0020***	0.0021***	0.0021***	0.0019***	0.0021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	725,851	725,851	725,851	725,851	725,851	725,851	725,851	725,851	725,851
R-squared	0.561	0.561	0.561	0.562	0.561	0.562	0.562	0.563	0.562

Table A.4
Do Closed-End Funds Just Buy Any Stocks with Low Previous Returns?

We compare the change in holdings of closed- and open-end funds in stocks that have fallen in value. Excluding fire sale stocks, we sort all stocks based on their average monthly return in a given quarter and select the ones with returns below the 10th percentile. Quarter *t* is the quarter when stock price is in the bottom decile. The dependent variable is a fund's change in quarterly holdings $\Delta shares(t+k)_{i,s,t}$ divided by the firm's number of shares outstanding at the beginning of the quarter. We divide $\Delta shares(t+k)_{f,i,s}$ by the standard deviation of all $\Delta shares(t+k)_{i,s,t}$ of closed- and open-end funds (including non fire sale stocks) during the sample period. All remaining variables are defined in the Appendix. All equations include time fixed effects and a constant whose coefficients are not reported. We present ordinary least squares estimates with errors clustered at the fund level and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	(1) Δ Shares (t-2)	(2) Δ Shares (t-1)	(3) Δ Shares (t)	(4) Δ Shares (t+1)	(5) Δ Shares (t+2)	(6) Δ Shares (t+3)
Closed	-0.0736	-0.0471	-0.0120	0.0346	-0.0109	0.0239
	(0.871)	(0.029)	(0.415)	(0.090)	(0.007)	(0.017)
Size	-2.9057**	-0.0577***	-0.2375*	0.1400***	0.0056*	0.0257***
	(1.224)	(0.008)	(0.124)	(0.045)	(0.003)	(0.009)
VOL	-0.0158	0.0160***	0.0633*	0.0028	0.0001	-0.0029
	(0.114)	(0.002)	(0.037)	(0.013)	(0.002)	(0.003)
ILLIQ	-0.1408	-0.0023	-0.0728	0.0122**	-0.0029	0.0018
	(0.101)	(0.004)	(0.066)	(0.006)	(0.003)	(0.001)
BM	-0.0140	-0.0019	0.0858**	-0.0126**	0.0008	0.0006
	(0.064)	(0.001)	(0.039)	(0.006)	(0.001)	(0.001)
MOM	-4.6937	0.0013	1.4111***	-0.3130	-0.0265**	0.0709
	(4.690)	(0.031)	(0.515)	(0.388)	(0.012)	(0.100)
Log TNA	2.4553	0.0642***	0.1641	-0.3265*	-0.0009	0.0558
	(1.603)	(0.009)	(0.166)	(0.194)	(0.003)	(0.099)
Observations	150,413	194,076	247,600	183,172	129,846	107,191
R-squared	0.001	0.004	0.001	0.000	0.001	0.001

Table A.5
Closed- and Open-end Funds' Trades in Fire Sale Stocks under Different Market Conditions

We compare the change in holdings of closed- and open-end funds around fire sale events and examine how the effects of the closed-end fund structure vary across different market conditions, captured by the following proxies: *AggFlow* measuring the aggregate flows in open-end funds, defined as the sum of all the open-end fund flows, divided by the aggregate open-end fund assets at the beginning of the quarter; the *VIX* index, capturing aggregate market uncertainty; the *Crisis 1* dummy that takes value equal to 1 from the third quarter of 2007 to the fourth quarter of 2009; and the *Crisis 2* dummy that takes value equal to 1 from the third quarter of 2008 to the fourth quarter of 2009. Quarter t is the quarter of the fire sale identified as in Coval and Stafford (2007). The dependent variable is a fund's change in quarterly holdings ($\Delta shares(t+1)_{i,s,t}$) in the quarter following the fire sale, divided by the firm's number of shares outstanding at the beginning of the quarter. We divide $\Delta shares(t+1)_{i,s,t}$ by the standard deviation of all $\Delta shares(t+1)_{f,i,s}$ of closed- and open-end funds (including non fire sale stocks) during the sample period. All remaining variables are defined in the Appendix. All equations include time fixed effects and a constant whose coefficients are not reported. We present ordinary least squares estimates with errors clustered at the fund level and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable: Δ Shares (t+1)	(1)	(2)	(3)	(4)
Closed	0.4263***	0.8520***	0.5786***	0.6199***
	(0.161)	(0.309)	(0.162)	(0.169)
Closed x Aggflow	0.6776			
	(0.545)			
Aggflow	-1.0494***			
	(0.213)			
Closedx VIX		-0.0132		
		(0.011)		
VIX		0.0126**		
		(0.005)		
Closed x Crisis1			0.0796	
			(0.236)	
Crisis1			0.1395	
			(0.129)	
Closed x Crisis2				-0.1234
				(0.331)
Crisis2				0.1241
				(0.166)
Log TNA	-0.2217***	-0.2012***	-0.2040***	-0.2037***
	(0.062)	(0.061)	(0.061)	(0.062)
Size	0.3577***	0.3385***	0.3396***	0.3370***
	(0.055)	(0.054)	(0.054)	(0.054)
VOL	-0.0599***	-0.0627***	-0.0603***	-0.0611***
	(0.017)	(0.017)	(0.017)	(0.017)
ILLIQ	0.0721*	0.0720*	0.0720*	0.0720*
	(0.042)	(0.042)	(0.042)	(0.042)
BM	0.0006	0.0013	0.0033	0.0027
	(0.025)	(0.025)	(0.025)	(0.025)
MOM	0.2995	0.2608	0.2685	0.2532
	(0.255)	(0.251)	(0.255)	(0.254)
Observations	127,715	128,504	128,504	128,504
R-squared	0.003	0.003	0.003	0.003

Table A.6
Hedge Funds' Trades in Fire Sale Stocks: Robustness Checks

This table reports the results of robustness checks we conduct for the hedge funds analysis. *Share Restrictions* is the sum of the number of days in the lock up, redemption notice and payout periods, divided by 100. *Alternative Share Restrictions* is defined as *Share Restrictions*, but excluding the lock up period. In column 1, we repeat the analysis defining share restrictions excluding the lock up period. Columns 2 to 4 include controls in the specification presented in column 3 of Table 11. We explore hedge fund trading around fire sale events. Quarter *t* is the quarter of the fire sale identified as in Coval and Stafford (2007). The dependent variable is a fund's change in quarterly holdings ($\Delta shares(t)_{i,s,t}$) in the quarter of the fire sale, divided by the firm's number of share outstanding at the beginning of the quarter. We divide $\Delta shares(t)_{i,s,t}$ by the standard deviation of all $\Delta shares(t)_{i,s,t}$ of hedge funds (including non fire sale stocks) during the sample period. All remaining variables are defined in the Appendix. All equations include time fixed effects and a constant whose coefficients are not reported. We present ordinary least squares estimates with errors clustered at the fund level and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable: Δ Shares (t)				
	(1)	(2)	(3)	(4)
Alternative Share Restrictions	0.3081***			
	(0.090)			
Share Restrictions		0.0751**	0.0743**	0.0730**
		(0.035)	(0.033)	(0.032)
Size	-0.2408***	-0.2557***	-0.2512***	-0.2489***
	(0.019)	(0.021)	(0.021)	(0.021)
Vol	0.0275***	0.0299***	0.0306***	0.0309***
	(0.004)	(0.005)	(0.005)	(0.005)
ILLIQ	-0.0238***	-0.0259***	-0.0263***	-0.0266***
	(0.006)	(0.006)	(0.007)	(0.006)
BM	0.0010	-0.0009	-0.0005	-0.0004
	(0.005)	(0.006)	(0.006)	(0.006)
MOM	0.0286	0.0252	0.0239	0.0286
	(0.048)	(0.053)	(0.054)	(0.054)
Log TNA	0.0400***	0.0483***	0.0431***	0.0415***
	(0.012)	(0.015)	(0.013)	(0.012)
Annual Fees		16.5364		
		(11.419)		
Incentive fee		-0.2844		
		(1.506)		
High-water Mark		0.2972		
		(0.182)		
Min Inv			-0.0000	
			(0.000)	
Leveraged				0.0980
				(0.146)
Observations	70,868	58,502	58,297	58,681
R-squared	0.052	0.058	0.057	0.057

Table A.7
Hedge Funds' Trades in Fire Sale Stocks: Using a Discrete Measure of Share Restrictions

We explore how the change in holdings of hedge funds varies around fire sale events. *High Restrictions* is a dummy variable that is equal to 1 if the fund has share restrictions above sample median; share restrictions is the sum of the number of days in the lock up, redemption notice and payout periods, divided by 100. Quarter *t* is the quarter of the fire sale identified as in Coval and Stafford (2007). The dependent variable is a fund's change in quarterly holdings ($\Delta shares(t+k)_{i,s,t}$) in the quarters preceding, during or following the fire sale, as indicated on top of each column, divided by the firm's number of share outstanding at the beginning of the quarter. We divide $\Delta shares(t+k)_{i,s,t}$ by the standard deviation of all $\Delta shares(t+k)_{i,s,t}$ of hedge funds (including non fire sale stocks) during the sample period. All remaining variables are defined in the Appendix. All equations include time fixed effects and a constant whose coefficients are not reported. We present ordinary least squares estimates with errors clustered at the fund level and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	(1) Δ Shares (t-2)	(2) Δ Shares (t-1)	(3) Δ Shares (t)	(4) Δ Shares (t+1)	(5) Δ Shares (t+2)	(6) Δ Shares (t)	(7) Δ Shares (t)
High Restrictions	0.0492	0.1283	0.2789***	-0.1494	-0.5001	0.9316***	-0.0421
	(0.048)	(0.078)	(0.099)	(0.116)	(0.390)	(0.329)	(0.091)
High Restrictions x Size						-0.0898***	
						(0.034)	
High Restrictions x Vol							0.0336***
							(0.010)
Size	-0.1056***	-0.1801***	-0.2426***	0.1083**	0.3316***	-0.1856***	-0.2404***
	(0.007)	(0.011)	(0.018)	(0.048)	(0.126)	(0.027)	(0.018)
Vol	0.0098***	0.0142***	0.0272***	-0.0390***	-0.0368***	0.0269***	0.0063
	(0.002)	(0.002)	(0.004)	(0.007)	(0.012)	(0.004)	(0.006)
ILLIQ	-0.0099**	-0.0191***	-0.0234***	0.0203*	-0.0069	-0.0221***	-0.0234***
	(0.005)	(0.004)	(0.006)	(0.011)	(0.029)	(0.007)	(0.006)
BM	0.0047*	-0.0033	0.0011	0.0111	-0.0218	0.0012	0.0012
	(0.003)	(0.004)	(0.005)	(0.010)	(0.017)	(0.005)	(0.005)
MOM	0.0147	0.1158	0.0273	-0.0411	1.4854**	0.0268	0.0258
	(0.046)	(0.095)	(0.049)	(0.162)	(0.645)	(0.048)	(0.048)
Log TNA	0.0091	0.0190	0.0327***	0.0226	-0.0219	0.0345***	0.0324***
	(0.007)	(0.012)	(0.013)	(0.015)	(0.045)	(0.013)	(0.012)
Observations	45,463	52,564	70,868	68,704	51,996	70,868	70,868
R-squared	0.060	0.058	0.051	0.010	0.004	0.052	0.053

Table A.8

Hedge Funds' Exposure to Aggregate Mispricing: Using an Alternative Measure of Share Restrictions

This table reproduces Table 12 in the paper, but share restrictions are defined excluding the lock up period (*Alt Restrictions*). The dependent variable is the monthly return of hedge fund *i*. On top of each column we indicate the portfolio of potentially undervalued stocks we consider in that specification. Portfolios are formed once per year using market equity, age, and volatility at the end of June of year *t*, and accounting data at the fiscal year-end of calendar year *t – 1*. Portfolios are constructed based on NYSE decile breakpoints. Portfolio is the equally weighted monthly return of a given portfolio of stocks. Market is the value-weighted excess market return of all NYSE, AMEX, and NASDAQ stocks, which we obtain from Ken French's website. *Neg Sent* is a dummy variable that takes value equal to 1 during periods of negative sentiment, defined as in Baker and Wurgler (2007). All remaining variables, including the definition of firm characteristics used for the portfolio construction, are defined in the Appendix. We present ordinary least squares estimates with errors clustered at the fund and time levels and corrected for heteroskedasticity. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Portfolio	(1) Small	(2) High Vol	(3) Young	(4) Low BM	(5) High R&D	(6) High External	(7) Low Sales	(8) Nonpayer	(9) Nonprofitable
Portfolio x Neg Sent x Alt Restrictions	0.0649**	0.0362*	0.0366*	0.0546*	0.0446***	0.0415**	0.0540**	0.0613**	0.0415**
	(0.028)	(0.019)	(0.020)	(0.028)	(0.016)	(0.019)	(0.023)	(0.029)	(0.021)
Portfolio x Alt Restrictions	-0.0056	-0.0117	0.0004	-0.0361	-0.0257	-0.0161	-0.0119	-0.0095	-0.0117
	(0.028)	(0.020)	(0.030)	(0.027)	(0.017)	(0.019)	(0.023)	(0.029)	(0.021)
Portfolio x Neg Sent	-0.1436**	-0.1041**	-0.1177*	-0.1465**	-0.0974***	-0.1020**	-0.1172**	-0.1323*	-0.1029**
	(0.064)	(0.041)	(0.070)	(0.060)	(0.036)	(0.041)	(0.055)	(0.068)	(0.046)
Portfolio	0.1966***	0.1528***	0.1771***	0.2460***	0.1621***	0.1562***	0.1740***	0.2097***	0.1576***
	(0.061)	(0.039)	(0.068)	(0.053)	(0.031)	(0.037)	(0.052)	(0.064)	(0.042)
Neg Sent	0.0027**	0.0029**	0.0033**	0.0031*	0.0026*	0.0033**	0.0026**	0.0026*	0.0032**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Restrictions	0.0004	0.0007	0.0006	0.0008*	0.0008*	0.0007	0.0006	0.0005	0.0007
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market	0.4309***	0.3822***	0.3990***	0.3776***	0.3828***	0.3905***	0.3998***	0.3966***	0.3903***
	(0.028)	(0.028)	(0.029)	(0.026)	(0.026)	(0.027)	(0.028)	(0.028)	(0.028)
Market x Alt Restrictions	0.0248	0.0219	0.0197	0.0303	0.0289	0.0234	0.0203	0.0190	0.0213
	(0.021)	(0.021)	(0.020)	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Constant	0.0058***	0.0059***	0.0064***	0.0064***	0.0056***	0.0059***	0.0058***	0.0058***	0.0059***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	221,382	221,382	221,382	221,382	221,382	221,382	221,382	221,382	221,382
R-squared	0.155	0.155	0.151	0.157	0.156	0.156	0.155	0.156	0.155