Hedge Funds Under Fire:

A Flow-Impact Perspective on Fund Returns*

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Abstract

This paper demonstrates that fund flow significantly impacts fund return. We introduce a model of flow impact, and show that while inflows generate a smart-money effect, the outflow effect is predominantly determined by flow impact. A "smarter-money" strategy, such that concentrates in high-flow-impact funds fairs significantly better than a strategy which concentrates in low-flow-impact funds and earns up to 7% annually over 1994–2008, after controlling for various hedge-fund risk factors. The effect is strongly apparent among Long/Short Equity funds but there is no significant relation with share restrictions. The persistence of fund flow causes the returns to smarter money strategies to persist for over six months. The paper suggests that flow itself creates an impact which translates into returns and makes money appear "smarter" in hindsight.

JEL classification: G12; G14

Keywords: Hedge funds; Fund flows; Smart money; Asset pricing; Flow impact

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Introduction

Much of the finance literature about hedge funds has focused on understanding the risk-return relation. Unlike asset-pricing models developed for equities or fixed-income securities, the risk attribution for hedge funds is more complex because they may trade a variety of assets and typically apply sophisticated financial instruments, often times illiquid. For example, many hedge funds implement dynamic trading strategies which could lead to time-varying risk exposures. Fung and Hsieh (2001, 2004) and Agarwal and Naik (2004) find that option-based factors can be used to control for dynamic risk exposure, whereas Sadka (2009) shows exposure to aggregate liquidity variations can explain cross-sectional differences in hedge-fund returns. The performance analysis of hedge funds therefore typically considers linear multi-factor models that capture exposures to a range of equity, bond, and commodity indices as well as option-based trading strategies.

This paper focuses on flow as a possible determinant of hedge-fund performance. The capital flow into and out of funds has received much attention in the mutual-fund literature. The main puzzle is the fact that investors tend to chase mutual-fund performance (see Chevalier and Ellison (1997) and Sirri and Tufano (1998)), even though fund managers do not seem able to consistently provide abnormal returns to their investors. Other research documents significant persistence in mutual-fund rankings based on risk-adjusted performance (see, e.g., Grinblatt and Titman (1992), Goetzmann and Ibbotson (1994), and Brown and Goetzmann (1995)). Recently, Coval and Stafford (2007) show that flows into and out of mutual funds may induce significant price pressure on stocks they hold. Lou (2009) further argues that the persistency in mutual-fund flow could generate mutual-fund return predictability. In the context of hedge funds, Fung, Hsieh, Naik, and Ramadorai (2008) shows that hedge-fund flow is quite persistent and it responds to past return and past flow as investors chase performance, while Ding, Getmansky, Liang, and Wermers (2007) document a smart-money effect insofar as fund flows predict future hedge-fund performance, albeit the effect is reduced among funds with share restrictions.

Inspired by the market microstructure theory and the liquidity literature (see Kyle, 1985; Admati and Pfleiderer, 1988), this paper begins with the introduction of a flow-impact model, demonstrating that flow significantly impacts contemporaneous fund returns. This positive correlation suggests that the flow of capital from investors to a fund is eventually, at least in part, translated into buy and sell orders of individual securities by the fund manager, which in turn induce price

pressure reflected in the valuation of the fund. Our empirical specification is related to the Glosten and Harris (1988) model, which separates the different components of price impact, as well as to the reversal measure used in Pástor and Stambaugh (2003). In contrast to these studies, we can only estimate the total flow impact due to sample-size limitations, and instead of measuring market impact caused by transactions of individual securities, we can only measure the impact of flow at the fund level. In the cross-section of hedge funds, we find that flow impact is high in funds with relatively high share restriction, which suggests that flow impact is related to fund illiquidity.

The contribution of the paper is showing that while inflows generate a smart-money effect, the outflow effect is predominantly determined by flow impact. A "smarter-money" strategy, such that concentrates in high-flow-impact funds fairs significantly better than a strategy which concentrates in low-flow-impact funds and earns about 7% annually over 1994–2008, after controlling for hedge-fund risk factors. We study a variety of investment styles and find that the effect is strongly apparent among Long/Short Equity funds but there is no significant relation with share restrictions. The persistence of fund flow causes the returns to smarter money strategies to persist for over six months. The paper suggests that flow itself creates an impact which translates into returns and makes money appear "smarter" in hindsight.

Our reasoning for the contribution of fund flow to the persistence in fund return is similar in spirit to the argument in Lou (2009). One crucial difference, however, is that we recognize that funds significantly vary in their return-flow relation (i.e. flow impact) cross-sectionally, and we show this variation affects the cross-section of hedge-fund expected returns. Moreover, we uncover an asymmetric smart-money effect in hedge funds: Inflows are typically followed by fund outperformance with little relation to flow impact, yet the fund underperformance following outflows is completely determined by flow impact. In lame language, the evidence suggests "it is easy coming in, but you need to be smarter getting out." We also decompose fund flow into expected and unexpected components, and show that most of the impact on performance is due to the expected component, while the unexpected component has little impact on performance (though the impact of the latter is higher for outflows). As for the long-run performance, there is a significant positive difference between the long-run return of inflow-minus-outflow funds of high-versus-low flow impact (i.e. difference of difference), once again illustrating the importance of understanding flow impact.

We perform several robustness tests. First, we show that our results are unaffected by our definition of fund flow. Second, we demonstrate that the model of flow impact is unaffected by the

inclusion of lag flow, as most of the return-flow relation at the fund level is due to contemporaneous, not lag, flow. Third, to alleviate concerns of endogeniety, we conduct a two-step endogeneity test (see Hausman (1978)) and show the results are unchanged.

Despite the significant returns for double-sorted portfolios of hedge funds, active investment strategies designed to benefit from this phenomenon are unlikely to yield significant profits due to a variety of reasons, such as hedge-fund liquidity terms, the inability to short hedge funds and the fact that most hedge funds report returns and assets under management with some lag. Yet, the persistent long-run performance of some strategies depicted in the paper may merit a closer look in terms of practical investment opportunities. Moreover, the strategies seem to outperform in relatively liquid investment styles such as Long/Short Equity funds, and funds with relative short redemption notice periods (of up to 30 days).

This study has several important implications. First, the evidence about the impact of capital flow on return suggests the need to take into account flow impact in return evaluation. To assess management skill, one should not only control for aggregate risk factors (as in Fung and Hsieh (2001, 2004)) but also adjust the returns for the impact of flow. Fund volatility and Sharpe ratio may be better understood in light of the return-smoothing effect generated by fund flow. Second, in the context of portfolio allocation, using the flow-impact measure introduced here, investors may construct portfolios less sensitive to systematic redemption shocks. Third, over the past decade, the asset-management industry has experienced a tremendous growth of hedge-fund assets, peaking at 1.93 trillion dollars at the end of June 2008. Yet, the turmoil in the financial markets during 2008 has caused poor performance for many hedge funds, typically accompanied with considerable redemptions. The industry is estimated to have shrunk by 524 billion dollars to about 1.407 trillion dollars by the end of 2008, among which 183 billion dollars are estimated to be net withdrawals.[1] This further emphasizes the importance of understanding the effect of flow impact on outflow. Finally, the flow-impact measure could also provide an insight for the likelihood that a fund would meet its liquidity obligations. Despite our finding that in the cross-section, high-flow-impact funds are typically associated with long lockup and redemption notice periods, the outlier funds, those with high-flow impact and low share restriction, are likely to be funds that commit to more liquidity than they can supply. This liquidity imbalance seems a potentially interesting path for future research.

[1] See HFR Global Hedge Fund Industry Report, Year-End 2008.

The rest of this paper is organized as follows. Section 1 describes the data used for this study and the measure of fund flow. Section 2 introduces an estimation model of flow impact and discusses the estimation results in the cross-section of funds. Section 3 introduces smart money and its interaction with flow impact, while Sections 4 and 5 provide evidence on long-run performance and discuss several robustness tests, respectively. Section 6 concludes.

1 Data and Flow Measure

The hedge-fund data used for this study is the Lipper-TASS dataset. The data includes information about monthly hedge-fund returns, assets under management (AUM), as well as information about share restriction such as lockup and redemption notice periods. The data includes both "live" and "dead" funds. Table 1 describes some summary statistics including the number of funds in the data-set per year, as well as return and flow statistics. The data includes 966 hedge funds at the beginning of the sample (1994), increases to over 5,600 in 2006 before declining to 4,709 by 2008. Overall, the sample period includes 7,280 different funds. The funds in the sample are members of 12 hedge fund investment styles including Convertibles, Short Bias, Emerging Markets, Equity Neutral, Event Driven, Funds of Funds, Global Macro, Long/Short Equity, Managed Futures, Multi-strategy, and Others.

Mutual-fund and hedge-fund flows are extensively discussed in the literature. The main puzzle is the fact that investors tend to chase mutual-fund performance (see Chevalier and Ellison (1997), Sirri and Tufano (1998), and Berk and Green (2004)), even though fund managers do not seem able to consistently provide abnormal returns for their investors. In the context of hedge funds, Fung, Hsieh, Naik, and Ramadorai (2008) show that outperforming funds significant draw inflows, while Ding, Getmansky, Liang, and Wermers (2007) document a smart-money effect insofar as fund flows predict future hedge-fund performance, albeit the effect is reduced among funds with share restrictions. In sum, most of the flow literature tries to explain investor behavior, capital formation, smart-money effects, and convexity/concavity of flow.

To the best of our knowledge, this paper presents the first attempt to measure the contemporaneous impact of investor flow on hedge-fund return. We estimate investment flow by applying the conventional flow calculation (see, e.g., Sirri and Tufano (1998), Fung, Hsieh, Naik, and Ramadorai (2008)). In contrast to existing literature, which deals with flow at low frequencies, such

as quarterly, semi-annual, and annual, this paper analyzes flow using monthly intervals, which are typically the shortest available in most hedge-fund datasets. The monthly frequency enables us to potentially capture price effects that are transitory at lower frequencies.

We use the following formula to estimate fund flow

$$F_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1} \times (1 + R_{i,t})}{AUM_{i,t-1}}, \tag{1}$$

where $AUM_{i,t}$ represents the value of the assets under management of fund i at month t and $R_{i,t}$ is the fund's return. There are some occurrences in the data for which $AUM_{i,t}$=$AUM_{i,t-1}$. Such observations may result from stale reporting; we do not consider them reliable because of the unlikelihood that a fund's return in a given month would exactly be offset by its flow. Therefore, we only include flow observations calculated from two consecutive AUM observations that are not identical. Overall, our sample includes 392,300 monthly flow observations among which 356,229 are considered reliable (91% of flow points).

2 Estimation of Fund-Flow Impact

2.1 A Model of Fund-Flow Impact

To estimate the impact of fund flow on fund return, we estimate the following regression model, per fund, using the available fund observations over the sample period:

$$R_{i,t} = \alpha_i + \beta_{HF,i} R_{HF,t} + \beta_{F,i} F_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where $R_{i,t}$ is the return in excess of treasury bills of fund i during month t, α_i is the intercept term, $R_{HF,t}$ is the average monthly excess return over treasury bills of the hedge fund industry, $F_{i,t}$ is the fund flow, and $\varepsilon_{i,t}$ is the error term. The average hedge fund industry return controls for systematic risk. The contemporaneous flow captures the impact of flow on return.[2]

Drawing from market microstructure theory and the liquidity literature, we expect the flow coefficient to be positive. This is because the flow of capital from investors to a fund must eventually, at least in part, be translated into buy and sell orders of individual securities by the fund manager.

[2] Note that flow is defined above as the change in the value of the stock of assets under management, "cleaned" of the monthly fund return. This cleaning, aside from forming a correct measure of the fund's flow, eliminates also a mechanical reverse causality of the fund's flow on its return.

The buy and sell orders may induce price pressure, which will be reflected in the valuation of the fund. The microstructure literature includes various models of market impact, separating its permanent and transitory components. A permanent change in the stock price is typically associated with a change in its perceived intrinsic value (i.e., informational effect) and is dependent on both the amount of informed trading and the amount of noise trading (see Kyle, 1985; Admati and Pfleiderer, 1988). In contrast, a transitory price change corresponds to market making costs, such as the costs associated with inventory maintenance, order processing, or search (i.e., the noninformational effect). Our empirical specification is related to the Glosten and Harris (1988) model, which separates the different components of price impact, as well as to the reversal measure used in Pástor and Stambaugh (2003). In contrast to these studies, we can only estimate the total flow impact due to sample-size limitations. Our approach is also different insofar as the literature focuses on market impact caused by transactions of individual securities, while this paper measures the impact of flow at the fund level.

In contrast to mutual funds, hedge funds may respond to flow by altering the leverage ratio of the fund. For example, the hedge fund manager may decide to utilize lending facilities set up with the prime brokers and use borrowed capital to pay back investors without actually liquidating assets.[3] Since a fund's return exposure to systematic risk is proportional to the fund's leverage, an interaction term of hedge-fund index return and fund flow can measure a manager's change in leverage as a response to capital flow. However, unreported results show that adding such an interaction term to the estimation of Equation (2) does not have a significant impact.

Table 2 reports the estimation results of the model in Equation (2). After removing funds with less than 24 monthly returns and less than 12 reliable investment-flow observations, the hedge fund data-set includes 7,820 funds for the period January 1994 through December 2008. The table shows that average fund beta to the hedge fund industry is 1.02. The hypothesis that the average equity beta to the hedge fund industry equals zero is comfortably rejected with a t-statistic of 70.24. The flow coefficient is positive and significant with an average of 0.002 and a t-statistic of 3.5. The positive flow impact is consistent with the market microstructure literature which documents a positive impact of order flow on security prices. The average R^2 of this model is 0.33.

[3] See Ozik and Sadka (2009) for a detailed discussion of the response of hedge-fund managers to investment flow.

2.2 The Cross-Section of Flow Impact

The previous section introduces the distribution of the regression estimates of Equation (2). Although the sample of hedge funds shows that, on average, these funds exhibit significant regression coefficients, there is still significant cross-sectional variation. Table 3 provides a cross-sectional analysis of the regression estimates as a function of fund characteristics, which reveals several interesting management behaviors, as discussed below. The characteristics included for the regressions are: AUM, assets under management, is the amount of capital a fund manages in US dollars. AUM is measured two different ways: AUM_1 is the first AUM available for a fund at or after January 1994. AUM_2 is the mean of all AUMs available for a fund between January 2004 and December 2008. $RedNotice$, redemption notice period, is the number of days prior to withdrawing capital from a fund that an investor has to notify the hedge-fund manager; $Lockup$ is the number of days following an investment in which investors are not allowed to withdraw their capital.

2.2.1 Hedge-Fund Industry Exposure

Large hedge funds tend to have lower exposure to the hedge fund asset class compared to smaller funds, whereas funds which restrict investors' liquidity by imposing longer lockup periods or longer redemption notification periods tend to have higher exposure to the hedge funds asset class. As seen in Panel A of Table 3, $Log(AUM_1)$, and $Log(AUM_2)$ exhibit significantly negative coefficients on hedge fund average returns with both t-statistics at -2.5. The variables capturing the liquidity level committed by the fund managers to investors, namely $Redemption\ Notice\ Period$, and $Lockup$, have a significantly positive effect on a fund's exposure to the hedge fund asset class, with t-statistics of 2.80, and 6.55, respectively.

There are a couple of potential explanations for these finding. First, large hedge-fund-firms may have more resources, such as more analysts, better-trained traders, and better access to information, compared with their smaller counterparts. Consequently, large hedge are able to generate original trading ideas, whereas the smaller hedge-funds may have to compensate for their resource disadvantage by increasing fund exposure to common trading ideas. Second, hedge fund investors expect their funds to generate absolute positive returns independently of market conditions. They are often disappointed when funds perform poorly in down markets. Anecdotally, during the second half of 2008, equity markets in general and the hedge funds industry experienced negative returns

which were followed by very large redemptions from the hedge fund asset class . Nevertheless, managers who are likely aware of market premium and wish to benefit from it over time. must trade-off it off with the short-term threat of disappointed investors defecting from poor performing funds in falling markets. Our results may shed some additional light on this dilemma, suggesting that fund managers are more comfortable increasing their exposure to the hedge-fund asset class as long as the threat of immediate redemptions is mitigated in the presence of restrictive redemption terms, such as long notice periods, and long lockups.

2.2.2 Flow-Impact Coefficient

Panel B of Table 3 shows that flow-impact coefficients are significantly higher for illiquid funds, with t-statistics of 3.76 and 3.29 for $RedemptionNotification$ and $Lockup$ respectively. Large hedge funds exhibit significantly lower flow-impact with a t-statistic of -5.54 and -2.05 for $Log(AUM_1)$, and $Log(AUM_2)$. These results suggest that, to the extent that the flow-impact coefficient reflects the illiquidity of a fund's assets, hedge-fund managers choose the contractual liquidity terms of their funds (e.g., lockup period and redemption notification) consistently with the illiquidity risk of their funds' balance sheet, allowing funds holding illiquid assets to appropriately manage large redemptions. These results are consistent with Ding, Getmansky, Liang, and Wermers (2007) who find that the illiquidity proxy proposed by Getmansky, Lo, and Makarov (2004) is highly correlated with explicit share restrictions. However, we infer a fund's illiquidity from the market impact of investment flow on return rather than deducing it from the fund's return autocorrelation.

The lower flow impact among large funds is somewhat more puzzling. Intuitively, one would expect larger funds to have higher flow-impact due to the larger size of the trading positions. However, the findings seem to suggest that large firms benefit from scale and are able to reduce their trading "footprint". There are a few possible explanations for the latter. First, large firms may have access to more resources. For example, they may execute flow order more efficiently by employing better trained traders, having more counter-parties to trade with, and by relying on effective computer-based execution systems, which smaller firms may find more challenging to afford. Second, large hedge funds may also be part of a larger firm which manages multiple funds and could potentially balance supply and demand for securities within the firm, eliminating the need to pass orders directly through public markets. Third, the large scale of these funds may dictate investing in larger firms which are typically more liquid.

3 Smart Money and Flow Impact

In this section we demonstrate the role of flow impact for understanding the smart money effect. We use both portfolio sorts and cross-sectional regressions, and show the results are robust to fund share restriction and investment style. We report both excess returns and Fung-Hsieh alphas.[4]

3.1 Portfolio Sorts

We begin the analysis by demonstrating the existence of smart money in our sample of hedge funds. Following the literature (e.g. Fung, Hsieh, Naik, and Ramadorai (2008)), we sort hedge-funds into three equal-size portfolios based on their prior three-month flow (calculated as the arithmetic sum over the prior three months). We rebalance portfolios monthly and hold them for one month. The results are reported in Table 4. Consistent with a smart-money effect, portfolio returns increase with prior flow. The portfolio return spread of the high-minus-low flow earns 21 basis point per month (2.53% annually) with a t-statistic of 2.82.

For completeness, we also form portfolios based on historical flow-impact. Each month flow-impact is calculated per firm via Equation (2) using prior 60-month observations (we only use firms with at least 24 prior valid monthly observations). Similar to the flow portfolios, we form three equal-size portfolios based on rolling 60-month flow impact; portfolios are rebalanced monthly and held for one month (the first holding month is January 1999). Table 4 shows that the flow-impact portfolio return spread earns a negative average return of 12 basis points per month (t-statistic of -2.35), even though the relation of flow impact and future return is not monotonic.

To demonstrate the interaction of flow impact and the smart-money effect, we form portfolios of hedge funds based on 3-by-3 dependent sorts on prior three-month flow and prior 60-month flow impact. Table 5 reports the results: Panels A and C use portfolios sorted first by flow and then by flow impact, while Panels B and D use the opposite sorts. Since the cross-sectional correlation of flow and flow impact is close to zero, the results of the two sorts are quite similar.

The results of Panel A show that the smart-money effect, the average return to high-minus-low flow (F3–F1), is positive in each flow-impact group, yet the effect increases with flow impact. The smart-money effect is 40 basis points per month (t-statistic of 4.00) for the high-flow-impact funds

[4]We thank David Hsieh for providing the risk factors on his web site: http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls.

(B3F3–B3F1), while it is insignificant for the low-flow-impact funds (B1F3–B1F1). The difference-of-differences (DOD) return ((B3F3–B3F1)–(B1F3–B1F1)) is also significant (28 basis points per month; t-statistic of 2.13). Notice that the return difference of high-minus-low flow impact (B3–B1) is significantly negative for low-flow funds (31 basis points per month; t-statistic of -3.20) and insignificant for high-flow funds. This suggests that the "smarter-money" effect, i.e. the smart money among high-flow-impact funds, is asymmetric as it is mainly due to outflows, not inflows. The conclusions remain the same for the results of the opposite portfolio sorts in Panel B, and both portfolio sort returns are robust to the Fung-Hsieh factors.

The monthly and annual time series of returns to "smarter money" (B3F3–B3F1) and high-minus-low flow impact for low flow (B3F1–B1F1) are plotted in Figure 1. The annual time series show that the former is positive and the latter is negative for most of the years included in the sample. Interestingly, the years 2007 and 2008 do not seem to particularly affect the performance of these strategies, suggesting they are invariant to market-wide movements.

3.2 Liquidity Provision

Since this paper studies the impact of flow on fund returns, not only is it natural to compare a fund's flow impact to its level of illiquidity, as viewed by investors (as in Table 3), but it is also important to analyze the double-sorted portfolios of Table 5 for different share-restriction groups. We report the results for the portfolios sorted first by flow and then by flow impact—the opposite portfolio sort generates quite similar results and therefore, for brevity, we do not report here the results of this portfolio sort. Also, since the main conclusions are reached from the four corner portfolios (high and low, flow and flow impact), we focus on the differences between these portfolios as well as the DOD portfolio.

Table 6 reports the results. We follow the share-restriction classification scheme of Aragon (2007). A comparison of lockup versus no-lockup funds in Panel A reveals that for both subsets of funds, the smarter-money strategy (B3F3-B3F1) is significantly positive (33 basis points per month for no-lockup funds and 59 basis points for lockup funds) and the low-flow strategy significantly underperforms for high-flow-impact funds (-19 basis points per month for no-lockup funds and -71 basis points for lockup funds). Panel B shows similar results when funds a compared by their redemption notice period. Overall, looking across different liquidity provision groups, there does not exist a clear pattern. It seems that the flow strategies perform stronger in relatively more

illiquid funds, yet this relation is relatively weak.

From a theoretically point of view, it is not clear what to expect en-ante. On the one hand, if funds with low share restrictions are considered more liquid insofar as the ability of investors to redeem capital, then these type of funds would perhaps exhibit stronger return responses to flow demands (especially outflows). For example, as a response to outflow demand, a fund with a 30-day redemption notice period may need to disperse assets more quickly than a fund with a longer notice period, and this demand for immediacy may cause further price depreciation. (This also suggests a difference in the long-run performance of the flow strategies across different funds. We discuss this in a section below, yet we do not find significant difference between long-run performance across different funds according to their liquidity). On the other hand, in anticipation of such events, liquid funds may hold more liquid securities than do less liquid funds. Our findings do not find a significant return premium or discount when comparing the flow strategies across funds with different liquidity provisions.

3.3 Investment Style

We perform the double sorts based on flow and flow impact separately for each of the dozen investment styles. The results are reported in Table 7. Similar to the liquidity provision analysis in the previous section, we only focus on the differences of the four extreme portfolios and the DOD portfolio.

The investment style analysis reveals that styles may differ in their flow portfolio performance. The smarter-money effect (B3F3–B3F1) is positive in nine styles, three of which are statistically significant. Naturally, power issues may affect our results, as most investment styles include a few hundred funds with sufficient available information to form the portfolios. The most significant effect is exhibited among Long/Short Equity funds.

3.4 Cross-Sectional Regressions

The findings thus far are based on 3-by-3 portfolio sorts. There are two issues that are not fully addressed using the portfolio approach. First, it is likely that the top flow portfolio (F1) and the bottom flow portfolio (F3) represent inflow versus outflow funds, respectively, it is a function of the monthly distribution of flow over time. To better handle the issue of inflows versus outflows, we need

to separate out positive versus negative flow funds. Second, depending on the flow distribution, opening the cross-section of firms using three flow groups alone and using equal weights may not adequately reflect the cross-sectional relation of fund flow and future return. To address these issues, in this section we use the cross-sectional regressions methodology (e.g. Fama and MacBeth (1973)), and show our conclusions are unaffected by choice of methodology.

We run cross-sectional regressions of returns (excess of risk-free rate) at time t on past three-month flow, past 60-month rolling flow-impact, and the interaction of the two. In addition, we define a dummy variable that is assigned a value of 1 if the past three-month flow is negative and zero otherwise, and use its interaction with past flow and the interaction of flow and flow impact. Given significant outliers in the distribution of flow and flow impact, we winsorize these variables monthly at the 5% on both tails of the distribution. Furthermore, to gauge better understanding of the economic magnitudes of the coefficient estimates, we use standardized regressions, i.e. each independent variable is scaled by its cross-sectional standard deviation monthly. Table 8, Panel A, reports the coefficient estimates and their respective Fama-MacBeth t-statistics.

First noticeable is that across all model specifications, past flow has a positive and statistically significant coefficient, which is consistent with a smart-money effect in the hedge-fund space. However, when adding a dummy for negative flow, Model 2 shows that the smart-money effect is cancelled out for outflows, suggesting that smart-money exists only for inflows, not outflows. Consistent with the univariate portfolios in Table 4, the flow-impact coefficient is significantly negative, about -0.08%, even after including past flow, the dummy for negative past flow, and the interaction of flow and flow impact (Models 3–7). The interaction of flow and flow impact does not seem to have significant coefficient when added in Models 6–7. Yet, when the interaction of flow and flow-impact is also interacted with the outflows dummy in Model 8, the latter is significant (0.34%) and the flow-impact coefficient becomes insignificant. This result implies that flow impact is important only through its interaction with outflows, which is also consistent with the results reported in Table 5. Table 8, Panels B and C, repeat the analysis of Panel A, with the exception that instead of using fund returns in excess of the risk-free rate, we use the fund return in excess of its investment style average or liquidity provision group average. The results are quite similar to those reported in Panel A.

To summarize, the cross-sectional regression analysis shows that (a) the smart-money effect is present for inflows, regardless of flow impact, and (b) although outflows do not display a smart-

money effect, their interaction with flow impact predicts performance ("smarter money"). Overall, these results provide further support for the portfolio analysis in Table 5.

4 Long-Run Performance

We postulate that one explanation for the abnormal performance of the flow strategies is that fund flow affects fund valuation via price pressure. It is therefore natural to study the long-run performance of the flow strategies. High-flow-impact funds are expected to have a longer lasting effect on prices. Figures 2 and 3 plot the performance of the flow strategies over the 24 months post formation. We focus on the four extreme portfolios in Figure 2 (B1F1, B3F1, B1F3, and B3F3) as well as the portfolio spreads in Figure 3 (smarter money and DOD). The results are also tabulated in Table 9.

The long-run returns in Figure 2 are measured in excess of the hedge-fund industry average. The figure shows that the high-flow-impact strategies exhibit performance persistence that begins to reverse after nine months. This hold for both high and low past flow funds. In contrast, the low-flow-impact funds either exhibit a quicker reversal (after four months; for high flow) or non at all (for low flow). These results are further emphasized in the long-run performance of the smarter money plotted in Figure 3. The long-run of the DOD strategy persists for about 18 months, which suggests that the differences between the long-run performance of the flow strategies are quite persistent.

Additional insight is offered in Figure 4. This figure plots the differences between flow strategies of lockup versus no-lockup funds. We conclude that the spread between high-flow-impact and low-flow-impact is higher for lockup funds.

5 Additional Tests

The previous sections introduce the main results of the paper as they relate to smart money and flow impact. In what follows, we provide additional analysis and discussion to highlight the significance of the results.

5.1 Expected and Unexpected Flow

As hedge fund managers may anticipate flows and position their portfolios to accommodate them, it is interesting to the effects of expected and unanticipated flows. In the spirit of Fung, Hsieh, Naik, and Ramadorai (2008), we estimate the expected flow of a fund in a given month using the following regression model

$$F_{i,t} = \alpha_i + \beta_{LR,i}\Sigma_{\tau=t-3}^{t-1}R_{i,\tau} + \beta_{LF,i}\Sigma_{\tau=t-3}^{t-1}F_{i,\tau} + \varepsilon_{i,t}, \tag{3}$$

where $F_{i,t}$ is fund's i flow during month t, α_i is the intercept term, $\Sigma_{\tau=t-3}^{t-1}R_{i,\tau}$ is the arithmetic sum of the first three monthly lagged excess return preceding t, $\Sigma_{\tau=t-3}^{t-1}F_{i,\tau}$ is the arithmetic sum of the first three lagged monthly reliably reported flows preceding t, and $\varepsilon_{i,t}$ is the error term. For the analysis, we use the same 60-month historical rolling window that is used to estimate the flow impact.

Table 10 reports the results. Similar to Section 1, the funds are sorted by flow and flow-impact. However, in this section, three different signals of flow are applied and compared. Panel A reports the statistics of portfolio spreads using actual monthly flow, Panel B reports statistics when flow is replaced by expected flow estimated in Equation (4), and Panel C uses unexpected flow which is calculated as the difference between the actual monthly flow and the expected flow.

This section focuses on the impact of flows on portfolio returns at the time the flows occur. Therefore, differently from the previous sections, in addition to reporting the average returns in the months following portfolio formation, Table 10 also reports statistics for portfolio-formation months. The smarter money strategy (B3F3–B3F1) generates about 1% per month with a t-statistic of 10. As the flow is quite persistent, the average returns of the same spread in the following two months are also positive and significant. The average returns of the smarter money strategy also generates positive returns when sorted on expected flow. Panel B shows that this spread earns 0.54% and 0.30% at the formation month and the following month, respectively. Moreover, this spread continues to generate positive average returns during the following six months. In contrast, the smarter money strategy sorted by unexpected flows does not generate significant positive returns at all. We conclude that "smarter money" strategy works well with expected flow but much less so with unexpected flow. The outflow spreads (B3F1–B1F1) exhibit significant negative returns on all flow signals (actual, expected, and unexpected).

5.2 Lag-Flow Impact

The majority of the funds in the sample (about 77%) allow investors to subscribe on a monthly basis. About 8% deal intra-month and about 7% deal at frequencies lower than monthly——typically quarterly, semiannually, or annually. Managers who receive flow orders (either redemptions or subscriptions) have to appraise fund's assets at the day the flows "hit" the fund. Especially in low-frequency funds and in funds with long redemption-notice periods, it is safe to assume that the managers are aware of flows before they actually receive them——typically at the end of the reporting period (end of month, quarter, or year). The managers then can execute these flow-related orders before, at, or after the end of the reporting period. Managers who are more concerned by relative performance vis-à-vis peers may prefer to execute at the end of the reporting period——sometimes just before the close. [5] Others, could choose a different execution time.

If the manager chooses to fulfill flow-related orders at or before the end of the reporting period, the flow-impact would affect the monthly return of the same month. Alternatively, if the the executing occurs after the end of the reporting period (and possibly even on a later date), the flow-impact would affect the return of the following month.

We verify that flow mainly affects contemporaneous returns by adding the lagged flow to the model estimated in Equation (2) and reported in Table 2. The results reported in Table 11 show that lagged flow does not significantly impact current return, while contemporaneous flow remains significant. Relative to the basic flow-impact model in Table 2, adding lag flow increases the average R^2 only by 1.9% (from 33% to 34.9%).

5.3 Measure of Flow

Hedge fund managers do not directly disclose the capital amount and the time it enters and exists their funds. Therefore, one is left to estimate the flow using the fund reported returns and AUMs. Although Equation (1) provides a plausible estimation method, it also implicitly assumes that flows occur at the end of the month. There is a possibility, however, that capital flow occurs at different times during the month. Moreover, if flow is estimated with Equation (1) but actually occurs at the beginning of the month, the estimation of flow impact by Equation (2) could be biased. The

[5] See Brown, Ozik, and Scholz (2007) for a discussion of flow handling with respect to relative performance measures.

purpose of this subsection is to repeat the portfolio sort analysis using an alternative measure of flow, which assumes that all monthly flows occur at the beginning of the month. Under this assumption, the monthly flow is estimated as

$$AF_{i,t} = \frac{AUM_{i,t}}{AUM_{i,t-1} \times (1 + R_{i,t})} - 1. \tag{4}$$

Similar to Table 5, Table 12 reports the statistics of the portfolios and spread returns double sorted on quarterly flows and flow impact coefficients. In contrast, both flow and, in turn, flow impact are estimated using the alternative measure of flow (flow impact coefficients are estimated using Equation (2)). The results are similar to the results presented in Table 5, suggesting that the findings are robust to the measure of flow.

5.4 Endogeneity

This paper borrows the price-impact concept from market microstructure literature and applies it to hedge funds. However, individual securities and funds are structurally different in some aspects. In the case of securities, causality is easy to identify—— individual buy and sell orders induce price impact. However, this paper uses monthly fund data and causality is somewhat more difficult to establish. As discussed above, a fund manager may respond to capital flow on any day (not just the end of the reporting period). Likewise, funds that allow investors to subscribe and redeem frequently may experience several flow occurrences within the same month (about 8% of funds deal more frequently than monthly).

For these reasons, one may suspect reverse causality between contemporaneous flow and fund return. We use lag flow and lag return as instrumental variables and perform a two-step endogeneity test (see Hausman (1978)). We perform a chi-square test at 0.95 confidence, and we reject endogeneity in 6,743, or 96.6% of the funds.

6 Conclusion

This paper shows that flow significantly affecs fund returns. While inflows generate a smart-money effect, the outflow effect is predominantly determined by flow impact. A "smarter-money" strategy, such that concentrates in high-flow-impact funds fairs significantly better than a strategy which concentrates in low-flow-impact funds and earns up to 7% annually over 1994–2008, after

controlling for hedge-fund risk factors. We study a variety of investment styles and find that the effect is strongly apparent among Long/Short Equity funds but there is no significant relation with share restrictions. The persistence of fund flow causes the returns to smarter money strategies to persist for over six months. The paper suggests that flow itself creates an impact which translates into returns and makes money appear "smarter" in hindsight.

This study has several important implications. First, the evidence about the impact of capital flow on return suggests the need to take into account flow impact in return evaluation. To assess management skill, one should not only control for aggregate risk factors (as in Fung and Hsieh (2001, 2004)) but also adjust the returns for the impact of flow. Fund volatility and Sharpe ratio may be better understood in light of the return generated by fund flow. Second, in the context of portfolio allocation, using the flow-impact measure introduced here, investors may construct portfolios less sensitive to systematic redemption shocks. Finally, the flow-impact measure could also provide an insight for the likelihood that a fund would meet its liquidity obligations. Despite our finding that in the cross-section, high-flow-impact funds are typically associated with long lockup and redemption notice periods, the outlier funds, those with high-flow impact and low share restriction, are likely to be funds that commit to more liquidity than they can supply. This liquidity imbalance seems a potentially interesting path for future research.

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Table 1
Summary Statistics

The table reports the summary statistics of the Lipper-TASS hedge-fund dataset for the period of January 1994 to December 2008. Number of Funds counts the existing funds at the beginning of January and the funds which started reporting before the end of the respective year. Mean, standard deviation, 1st quartile, median, and 3rd quartiles are the 12-month means of the monthly cross-sectional statistics.

Year	Number of	Monthly Return (%)					Monthly Flow (%)				
	Funds	Mean	Std Dev	25%	Median	75%	Mean	Std Dev	25%	Median	75%
1994	966	0.04	4.83	-1.92	0.05	1.80	0.48	25.10	-1.05	0.03	2.60
1995	1218	1.37	5.53	-0.45	1.05	2.82	1.14	39.53	-1.55	0.00	1.15
1996	1519	1.42	5.10	-0.43	1.20	2.98	2.60	47.06	-1.41	0.01	2.52
1997	1774	1.41	5.18	-0.55	1.28	3.22	4.50	38.33	-0.66	0.17	4.23
1998	2044	0.39	6.61	-1.80	0.47	2.71	3.62	49.89	-1.54	0.06	2.64
1999	2321	2.02	6.06	-0.35	1.42	3.74	3.67	48.82	-1.85	0.01	2.31
2000	2600	0.89	6.35	-1.34	0.81	2.87	4.02	37.85	-1.14	0.04	2.87
2001	3034	0.52	4.76	-0.85	0.54	1.87	2.65	19.70	-0.62	0.10	3.29
2002	3496	0.25	3.93	-0.90	0.26	1.35	1.95	16.58	-0.72	0.09	2.96
2003	4021	1.32	6.57	0.06	0.86	2.05	5.09	38.07	-0.54	0.29	4.11
2004	4727	0.68	3.73	-0.24	0.54	1.42	4.49	24.82	-0.39	0.44	4.42
2005	5327	0.73	2.81	-0.26	0.56	1.55	1.33	17.28	-1.08	0.09	2.66
2006	5642	0.91	2.72	-0.07	0.75	1.71	2.35	22.79	-0.76	0.15	2.75
2007	5222	0.83	3.01	-0.27	0.67	1.72	1.13	10.64	-0.93	0.12	2.43
2008	4709	-1.63	5.53	-3.21	-1.32	0.49	-1.86	9.01	-3.54	-0.31	0.80

Table 2
Flow-Impact Model

This table reports cross-sectional summary statistics of fund-level time-series regressions. The regressions are of the form $R_{i,t} = \alpha_i + \beta_{HF,i}R_{HF,t} + \beta_{F,i}F_{i,t} + \varepsilon_{i,t}$, where $R_{i,t}$ is fund's i monthly return in excess of the three-month treasury bills in month t, $R_{HF,t}$ is the excess return of the hedge fund industry, $F_{i,t}$ is the monthly flow of fund i in month t, and $\varepsilon_{i,t}$ is the error term. The sample includes 7,280 hedge funds with at least 24 valid monthly observations of return and flow over the period January 1994 through December 2008.

	Mean	*t*-statistic of mean	Standard deviation	Percentiles		
				25%	50%	75%
α_i	0.000	-1.910	0.008	-0.004	0.000	0.004
T-stat (α_i)	0.102		1.786	-1.113	0.020	1.210
$\beta_{HF,i}$	1.020	70.244	1.001	0.340	0.806	1.420
T-stat ($\beta_{HF,i}$)	5.103		4.548	1.709	4.222	7.707
$\beta_{F,i}$	0.002	3.496	0.047	-0.009	0.001	0.014
T-stat ($\beta_{F,i}$)	0.130		1.132	-0.576	0.113	0.853
R^2	0.330		0.249	0.103	0.293	0.520

Table 3
Determinants of the Flow-Impact Estimates

This table reports results of cross-sectional regressions. The dependent variables are fund loadings $\beta_{HF,i}$, and $\beta_{F,i}$ estimated over the full sample using fund-level regressions of the following form: $R_{i,t} = \alpha_i + \beta_{HF,i}R_{HF,t} + \beta_{F,i}F_{i,t} + \varepsilon_{i,t}$, where $R_{i,t}$ is fund's i monthly return excess of the three-month treasury bills in month t, $R_{HF,t}$ is the average excess return of the hedge fund industry in month t, $F_{i,t}$ is the monthly flow of fund i in month t, and $\varepsilon_{i,t}$ is the error term. AUM_1 is the first asset under managment reported by a fund at or after Junuary 1994. AUM_2 is the average asset under management reported by a fund between January 1994 and December 2008. Red Notice is the Redemption Notice measured in days and Lockup is fund lockup period measured in days. The *t*-statistics are reported in square brackets. The sample includes 7,280 hedge funds with at least 24 valid monthly observations of return and flow over the period January 1994 through December 2008.

Panel A: Hedge Fund Industry Average

Intercept	1.215	1.256	0.939	0.942	1.261
	[13.14]	[11.39]	[55.79]	[76.33]	[11.47]
Log(AUM 1)	-0.014				
	[-2.52]				
Log(AUM 2)		-0.016			-0.019
		[-2.52]			[-2.93]
Red Notice			0.001		0.000
			[2.80]		[0.67]
Lockup				0.012	0.012
				[6.55]	[6.02]
N	6149	6868	7134	7134	6868
R^2	0.001	0.001	0.001	0.006	0.007

Panel B: Flow Impact

Intercept	0.037	0.015	-0.006	-0.003	0.015
	[5.21]	[1.80]	[-4.38]	[-3.49]	[1.86]
Log(AUM 1)	-0.002				
	[-5.54]				
Log(AUM 2)		-0.001			-0.001
		[-2.05]			[-2.61]
Red Notice			0.000		0.000
			[3.76]		[3.24]
Lockup				0.000	0.000
				[3.29]	[2.25]
N	6134	6859	7134	7134	6859
R^2	0.005	0.001	0.002	0.002	0.004

Table 4
Portfolios Separately Sorted by Flow and Flow Impact

Every month hedge funds are sorted by quarterly flow in the first case and by flow-impact in the second. Quarterly flow is the sum of the prior three-monthly flow observations and flow-impact is estimated using rolling windows of prior 60-month observations with at least 24 valid monthly observations of return and flow. Portfolios are sorted into equally weighted terciles, rebalanced monthly, and are denoted by Fi, and Bj indicating the *i* th quarterly flow tercile and the j- th flow-impact tercile (1 is low and 3 is high). The table reports raw portfolio excess returns over three-month treasury bills and risk-adjusted returns (alphas), calculated as the intercepts of regressions of portfolio excess returns on the excess return on the seven factors of Fung and Hsieh (2001). The sample includes hedge funds over the period January 1999 through December 2008.

	Flow (F)			Flow impact (B)	
Portfolio	Return	Fung-Hsieh Alpha	Portfolio	Return	Fung-Hsieh Alpha
F1	0.22%	0.31%	B1	0.43%	0.45%
	[1.33]	[3.21]		[2.24]	[3.91]
F2	0.28%	0.32%	B2	0.22%	0.27%
	[1.57]	[3.19]		[1.73]	[3.56]
F3	0.43%	0.44%	B3	0.30%	0.35%
	[2.60]	[3.96]		[1.61]	[3.27]
F3 – F1	0.21%	0.13%	B3 -B1	-0.12%	-0.10%
	[2.82]	[1.95]		[-2.35]	[-1.89]

Table 5
Portfolios Sorted by Flow Impact and Flow

Every month hedge funds are double sorted by flow impact and quarterly flow (3-by-3). Quarterly flow is obtained by aggregating the prior sum of three-monthly fund flows and flow-impact is estimated using rolling windows of prior 60-month observations with at least 24 valid observations of montly return and flow. Portfolios are equally weighted, rebalanced monthly, and are denoted B_iF_j, indicating the *i* th flow-impact tercile and the *j* th flow tercile (1 is low and 3 is high). Panels A, and C report the statistics of portfolios sorted first on flow impact and then on quarterly flow, while Panels B, and D report the opposite dependent sort. The table includes raw portfolio excess returns over the three-month treasury bills and risk-adjusted returns (alphas), are calculated as the intercepts of regressions of portfolio excess returns on the excess return on the seven factors of Fung and Hsieh (2001). The sample includes hedge funds over the period January 1999 through December 2008.

Portfolios sorted by flow and flow impact					Portfolios sorted by flow impact and flow				
Excess returns									
Panel A					Panel B				
Flow (F)	Flow impact (B)				Flow (F)	Flow impact (B)			
	B1	B2	B3	B3 – B1		B1	B2	B3	B3 – B1
F1	0.41%	0.18%	0.11%	-0.31%	F1	0.39%	0.18%	0.10%	-0.28%
	[2.01]	[1.45]	[0.55]	[-3.20]		[1.94]	[1.39]	[0.53]	[-2.98]
F2	0.31%	0.17%	0.29%	-0.01%	F2	0.31%	0.22%	0.30%	0.00%
	[1.57]	[1.25]	[1.45]	[-0.20]		[1.55]	[1.56]	[1.50]	[-0.02]
F3	0.53%	0.30%	0.50%	-0.03%	F3	0.53%	0.28%	0.49%	-0.04%
	[2.61]	[2.45]	[2.57]	[-0.33]		[2.60]	[2.28]	[2.59]	[-0.47]
F3 - F1	0.12%	0.11%	0.40%	0.28%	F3 - F1	0.14%	0.11%	0.39%	0.24%
	[0.94]	[1.93]	[4.00]	[2.13]		[1.12]	[1.86]	[3.90]	[1.89]
Fung-Hsieh alphas									
Panel C					Panel D				
Flow (F)	Flow impact (B)				Flow (F)	Flow impact (B)			
	B1	B2	B3	B3 – B1		B1	B2	B3	B3 – B1
F1	0.47%	0.27%	0.21%	-0.26%	F1	0.45%	0.27%	0.20%	-0.25%
	[3.39]	[3.29]	[2.05]	[-2.61]		[3.31]	[3.36]	[1.97]	[-2.51]
F2	0.33%	0.24%	0.36%	0.03%	F2	0.32%	0.27%	0.37%	0.04%
	[2.88]	[2.97]	[3.00]	[0.51]		[2.86]	[3.36]	[2.90]	[0.61]
F3	0.53%	0.32%	0.48%	-0.05%	F3	0.52%	0.31%	0.48%	-0.04%
	[3.72]	[3.81]	[3.66]	[-0.53]		[3.61]	[3.69]	[3.77]	[-0.45]
F3 – F1	0.06%	0.05%	0.27%	0.21%	F3 – F1	0.07%	0.05%	0.28%	0.21%
	[0.47]	[0.96]	[3.07]	[1.54]		[0.56]	[0.88]	[3.22]	[1.53]

Table 6
Portfolios Sorted by Flow Impact and Quarterly Flow: Share Restriction

Every month hedge funds are double sorted by flow impact and quarterly flow (3-by-3). Quarterly flow is obtained by aggregating the prior sum of three-monthly fund flows and flow-impact is estimated using rolling windows of prior 60-month observations with at least 24 valid observations of montly return and flow. Portfolios are equally weighted, rebalanced monthly, and are denoted BiFj, indicating the ith flow-impact tercile and the jth flow tercile (1 is low and 3 is high). Panels A reports statisitcs of no-lockup and lockup funds while Panel B reports statisitcs by redemption notice groups. The table includes raw portfolio excess returns over the three-month treasury bills and risk-adjusted returns (alphas), are calculated as the intercepts of regressions of portfolio excess returns on the excess return on the seven factors of Fung and Hsieh (2001). The sample includes hedge funds over the period January 1999 through December 2008.

Share Restriction	Return					Fung-Hsieh Alpha				
	B1F3 – B1F1	B3F3 – B3F1	B3F1 – B1F1	B3F3 – B1F3	(B3F3 – B3F1) – – (B1F3 – B1F1)	B1F3 – B1F1	B3F3 – B3F1	B3F1 – B1F1	B3F3 – B1F3	(B3F3 – B3F1) – – (B1F3 – B1F1)
Panel A. Lockup Period										
0	0.13%	0.33%	-0.19%	0.01%	0.20%	0.06%	0.20%	-0.14%	-0.01%	0.13%
[N=5,711]	[1.45]	[3.38]	[-2.33]	[0.12]	[1.99]	[0.74]	[2.34]	[-1.70]	[-0.13]	[1.28]
1	0.08%	0.59%	-0.71%	-0.20%	0.51%	0.06%	0.49%	-0.63%	-0.19%	0.43%
[N=1,569]	[0.26]	[3.58]	[-2.88]	[-0.80]	[1.47]	[0.17]	[3.03]	[-2.44]	[-0.74]	[1.18]
Panel B. Redemption Notice Period (days)										
0	0.42%	-0.18%	0.19%	-0.41%	-0.60%	0.31%	-0.24%	0.20%	-0.34%	-0.55%
[N=1,454]	[1.27]	[-0.74]	[0.63]	[-1.61]	[-1.54]	[0.90]	[-0.99]	[0.65]	[-1.41]	[-1.35]
(0,30]	0.15%	0.49%	-0.44%	-0.10%	0.34%	0.11%	0.39%	-0.36%	-0.09%	0.27%
[N=3,156]	[0.85]	[4.20]	[-3.19]	[-0.72]	[1.76]	[0.60]	[3.65]	[-2.56]	[-0.64]	[1.34]
(30,60]	0.09%	0.40%	-0.23%	0.08%	0.31%	0.04%	0.22%	-0.18%	2.79E-05	0.18%
[N=1,790]	[0.68]	[2.48]	[-1.57]	[0.81]	[1.70]	[0.33]	[1.44]	[-1.23]	[0.03]	[1.01]
(60,90]	-0.06%	0.23%	-0.20%	0.09%	0.29%	-0.12%	0.21%	-0.26%	0.06%	0.33%
[N=721]	[-0.31]	[0.89]	[-0.83]	[0.62]	[0.93]	[-0.63]	[0.89]	[-1.10]	[0.43]	[1.04]
(90, 365]	0.22%	0.57%	-0.52%	-0.17%	0.35%	0.30%	0.47%	-0.50%	-0.33%	0.17%
[N=159]	[0.79]	[2.28]	[-2.47]	[-0.53]	[0.94]	[1.03]	[1.83]	[-2.22]	[-1.03]	[0.44]

Table 7
Portfolios Sorted by Flow Impact and Quarterly Flow: Investment Style

Every month hedge funds are double sorted by flow impact and quarterly flow (3-by-3). Quarterly flow is obtained by aggregating the prior sum of three-monthly fund flows and flow-impact is estimated using rolling windows of prior 60-month observations with at least 24 valid observations of montly return and flow. Portfolios are equally weighted, rebalanced monthly, and are denoted BiFj, indicating the ith flow-impact tercile and the jth flow tercile (1 is low and 3 is high). The table reports statistics by investment style. The table includes raw portfolio excess returns over the three-month treasury bills and risk-adjusted returns (alphas), are calculated as the intercepts of regressions of portfolio excess returns on the excess return on the seven factors of Fung and Hsieh (2001). The sample includes hedge funds over the period January 1999 through December 2008.

Investment Style	Return					Fung-Hsieh Alpha				
	B1F3 – B1F1	B3F3 – B3F1	B3F1 – B1F1	B3F3 – B1F3	(B3F3 – B3F1) – – (B1F3 – B1F1)	B1F3 – B1F1	B3F3 – B3F1	B3F1 – B1F1	B3F3 – B1F3	(B3F3 – B3F1) – – (B1F3 – B1F1)
Convertibles	0.07%	-0.05%	0.08%	-0.04%	-0.12%	0.15%	0.42%	0.22%	0.49%	0.27%
[N=189]	[0.38]	[-0.14]	[0.47]	[-0.12]	[-0.35]	[0.75]	[1.23]	[1.32]	[1.48]	[0.81]
Short Bias	0.26%	0.52%	-0.42%	0.20%	0.42%	0.16%	0.34%	-0.37%	0.16%	0.35%
[N=38]	[0.33]	[0.88]	[-0.56]	[0.35]	[0.48]	[0.18]	[0.55]	[-0.42]	[0.27]	[0.35]
Emerging Markets	-0.14%	0.20%	-0.14%	0.20%	0.34%	-0.08%	0.40%	-0.25%	0.24%	0.48%
[N=374]	[-0.49]	[0.69]	[-0.53]	[0.71]	[0.83]	[-0.28]	[1.40]	[-0.90]	[0.82]	[1.18]
Equity Neutral	0.28%	-0.03%	0.11%	-0.20%	-0.31%	-0.08%	0.40%	-0.25%	0.24%	0.48%
[N=372]	[1.82]	[-0.19]	[0.67]	[-1.10]	[-1.48]	[-0.28]	[1.40]	[-0.90]	[0.82]	[1.18]
Event Driven	0.19%	0.41%	-0.29%	-0.08%	0.22%	0.10%	0.25%	-0.31%	-0.17%	0.14%
[N=518]	[1.50]	[2.31]	[-1.94]	[-0.63]	[1.05]	[0.84]	[1.42]	[-2.05]	[-1.42]	[0.69]
Fixed Income	0.24%	0.47%	-0.15%	0.08%	0.23%	0.20%	0.28%	-0.25%	-0.18%	0.07%
[N=278]	[1.50]	[2.77]	[-0.73]	[0.49]	[1.02]	[1.21]	[1.74]	[-1.17]	[-1.22]	[0.31]
Fund-of-Funds	0.23%	0.10%	0.04%	-0.10%	-0.13%	0.16%	-0.03%	0.09%	-0.10%	-0.19%
[N=2,071]	[1.89]	[1.02]	[0.39]	[-1.28]	[-1.20]	[1.24]	[-0.36]	[0.92]	[-1.52]	[-1.72]
Global Macro	0.69%	0.48%	0.08%	-0.13%	-0.21%	0.71%	0.13%	0.56%	-0.02%	-0.58%
[N=314]	[2.38]	[1.32]	[0.29]	[-0.43]	[-0.49]	[2.51]	[0.36]	[2.44]	[-0.06]	[-1.35]
Long/Short Equity	0.13%	0.58%	-0.37%	0.08%	0.45%	0.06%	0.44%	-0.28%	0.10%	0.38%
[N=2,078]	[0.81]	[3.41]	[-2.35]	[0.76]	[2.22]	[0.45]	[2.76]	[-1.89]	[0.89]	[1.92]
Managed Futures	0.16%	0.13%	-0.94%	-0.97%	-0.03%	0.19%	0.09%	-0.78%	-0.87%	-0.10%
[N=581]	[0.16]	[0.68]	[-1.25]	[-1.45]	[-0.03]	[0.18]	[0.49]	[-0.97]	[-1.22]	[-0.09]
Multi-strategy	-0.05%	0.29%	-0.32%	0.03%	0.34%	-0.04%	0.25%	-0.20%	0.09%	0.29%
[N=487]	[-0.22]	[1.91]	[-1.31]	[0.19]	[1.22]	[-0.18]	[1.55]	[-0.84]	[0.61]	[1.00]
Other	-0.76%	-0.36%	-0.38%	0.02%	0.40%	-0.82%	-0.60%	-0.10%	0.12%	0.23%
[N=20]	[-2.67]	[-1.40]	[-1.33]	[0.07]	[1.05]	[-2.75]	[-2.55]	[-0.37]	[0.39]	[0.59]

Table 8
Cross-Sectional Regressions

We run cross-sectional regressions of returns at time t on past three-month flow (*Flow*), past 60-month rolling flow-impact (*FlowImpact*) and the interaction of the two. In addition, we define a dummy variable (D) that is assigned a value of 1 if the past three-month flow is negative and zero otherwise, and use its interaction with past flow and the interaction of flow and flow impact. The independent variables are winsorized monthly at the 5% level on both tails of the distribution. We use standardized regressions, such that each independent variable is scaled by its cross-sectional standard deviation monthly. Panel A uses returns excess of risk-free rate; Panel B uses returns excess of investment style group average; and Panel C uses returns excess of share restriction group aveage. Fama and MacBeth (1973) t-statistics are reported in square brackets. The sample includes hedge funds over the period January 1999 through December 2008.

Panel A. Returns Exces of Risk-Free Rate

	Flow	D × Flow	FlowImpact	Flow × FlowImpact	D × Flow × FlowImpact
Model 1	0.07%				
	[2.04]				
Model 2	0.16%	-0.16%			
	[2.55]	[-1.82]			
Model 3			-0.08%		
			[-2.23]		
Model 4	0.07%		-0.08%		
	[2.01]		[-2.22]		
Model 5	0.15%	-0.15%	-0.07%		
	[2.50]	[-1.77]	[-2.20]		
Model 6	0.08%		-0.06%	0.00%	
	[2.33]		[-1.85]	[-0.06]	
Model 7	0.16%	-0.14%	-0.06%	0.00%	
	[2.60]	[-1.68]	[-1.83]	[-0.07]	
Model 8	0.15%	-0.13%	0.03%	-0.17%	0.34%
	[2.50]	[-1.65]	[0.87]	[-1.49]	[2.11]

Panel B. Returns Exces of Investment Style Average

	Flow	D × Flow	FlowImpact	Flow × FlowImpact	D × Flow × FlowImpact
Model 1	0.06%				
	[2.12]				
Model 2	0.13%	-0.12%			
	[2.46]	[-1.60]			
Model 3			-0.07%		
			[-2.27]		
Model 4	0.06%		-0.07%		
	[2.08]		[-2.27]		
Model 5	0.12%	-0.11%	-0.07%		
	[2.39]	[-1.53]	[-2.26]		
Model 6	0.07%		-0.06%	-0.01%	
	[2.43]		[-1.87]	[-0.21]	
Model 7	0.13%	-0.10%	-0.06%	-0.01%	
	[2.52]	[-1.44]	[-1.86]	[-0.21]	
Model 8	0.12%	-0.10%	0.04%	-0.18%	0.35%
	[2.42]	[-1.40]	[1.00]	[-1.60]	[2.16]

Panel C. Returns Exces of Share Restriction Average

	Flow	D × Flow	FlowImpact	Flow × FlowImpact	D × Flow × FlowImpact
Model 1	0.07%				
	[1.99]				
Model 2	0.16%	-0.17%			
	[2.60]	[-1.97]			
Model 3			-0.08%		
			[-2.40]		
Model 4	0.07%		-0.08%		
	[1.95]		[-2.40]		
Model 5	0.15%	-0.16%	-0.08%		
	[2.54]	[-1.91]	[-2.38]		
Model 6	0.08%		-0.07%	-0.01%	
	[2.27]		[-2.02]	[-0.08]	
Model 7	0.16%	-0.15%	-0.07%	-0.01%	
	[2.64]	[-1.83]	[-2.00]	[-0.09]	
Model 8	0.15%	-0.14%	0.03%	-0.17%	0.34%
	[2.55]	[-1.81]	[0.76]	[-1.50]	[2.11]

Table 9
Long-Run Performance of Spread Portfolios

Every month hedge funds are double sorted by flow impact and quarterly flow (3-by-3). Quarterly flow is obtained by aggregating the prior sum of three-monthly fund flows and flow-impact is estimated using rolling windows of prior 60-month observations with at least 24 valid observations of montly return and flow. Portfolios are equally weighted, rebalanced monthly, and are denoted BiFj, indicating the ith flow-impact tercile and the jth flow tercile (1 is low and 3 is high). The table reports statistics up to 24 month post portfolio formation. Panel A reports raw portfolio returns in excess of three month treasury bills and risk-adjusted returns. Panel B reports FH alphas, calculated as the intercepts of regressions of portfolio excess returns on the seven factors of Fung and Hsieh (2001). The sample includes 7,280 hedge funds with 24 valid monthly observations of return and flow from January 1999 through December 2008.

Panel A: Return

	B3F3 – B3F1			B3F1 – B1F1			(B3F3 – B3F1) – (B1F3 – B1F1)		
	Return	T-statistic	Cumulative	Return	T-statistic	Cumulative	Return	T-statistic	Cumulative
t+1	0.40%	[4.00]	0.40%	-0.31%	[-3.20]	-0.31%	0.28%	[2.13]	0.28%
t+2	0.25%	[2.87]	0.65%	-0.29%	[-2.68]	-0.60%	0.38%	[2.81]	0.65%
t+3	0.19%	[2.05]	0.84%	-0.16%	[-1.52]	-0.76%	0.21%	[1.60]	0.87%
t+4	0.18%	[2.17]	1.01%	-0.10%	[-1.14]	-0.86%	0.15%	[1.25]	1.01%
t+5	0.14%	[1.60]	1.16%	-0.17%	[-1.65]	-1.04%	0.24%	[1.98]	1.25%
t+6	0.13%	[1.46]	1.29%	-0.16%	[-1.46]	-1.20%	0.28%	[2.22]	1.53%
t+7	0.13%	[1.33]	1.41%	-0.11%	[-1.04]	-1.30%	0.22%	[1.68]	1.75%
t+8	0.06%	[0.67]	1.47%	-0.20%	[-1.68]	-1.50%	0.36%	[2.72]	2.11%
t+9	0.04%	[0.39]	1.51%	-0.14%	[-1.33]	-1.63%	0.25%	[1.85]	2.36%
t+10	-0.12%	[-1.17]	1.40%	-0.10%	[-0.83]	-1.73%	0.26%	[1.83]	2.61%
t+11	-0.09%	[-0.82]	1.31%	-0.16%	[-1.32]	-1.90%	0.28%	[1.87]	2.90%
t+12	-0.04%	[-0.48]	1.27%	-0.15%	[-1.36]	-2.05%	0.27%	[2.17]	3.17%
t+13	-0.03%	[-0.32]	1.24%	-0.08%	[-0.75]	-2.12%	0.19%	[1.44]	3.36%
t+14	-0.01%	[-0.11]	1.23%	-0.04%	[-0.41]	-2.16%	0.17%	[1.45]	3.53%
t+15	-0.04%	[-0.33]	1.19%	-0.10%	[-0.95]	-2.27%	0.17%	[1.17]	3.70%
t+16	-0.02%	[-0.22]	1.17%	-0.18%	[-1.58]	-2.45%	0.36%	[2.78]	4.06%
t+17	-0.09%	[-0.86]	1.08%	-0.17%	[-1.49]	-2.62%	0.35%	[2.53]	4.41%
t+18	-0.04%	[-0.42]	1.05%	0.01%	[0.18]	-2.60%	0.18%	[1.64]	4.59%
t+19	-0.08%	[-0.91]	0.96%	0.02%	[0.20]	-2.58%	0.09%	[0.77]	4.68%
t+20	-0.12%	[-1.28]	0.84%	0.04%	[0.47]	-2.54%	-0.01%	[-0.06]	4.67%
t+21	-0.12%	[-1.22]	0.72%	0.12%	[1.07]	-2.42%	-0.07%	[-0.48]	4.61%
t+22	-0.07%	[-0.65]	0.65%	0.07%	[0.62]	-2.35%	0.03%	[0.17]	4.63%
t+23	-0.06%	[-0.66]	0.59%	0.03%	[0.28]	-2.32%	0.02%	[0.17]	4.66%
t+24	0.02%	[0.21]	0.61%	-0.06%	[-0.60]	-2.38%	0.10%	[0.81]	4.76%

Panel B: Fung-Hsieh alpha

	B3F3 – B3F1			B3F1 – B1F1			(B3F3 – B3F1) – (B1F3 – B1F1)		
	Return	T-statistic	Cumulative	Return	T-statistic	Cumulative	Return	T-statistic	Cumulative
t+1	0.27%	[3.07]	0.27%	-0.26%	[-2.61]	-0.26%	0.21%	[1.54]	0.21%
t+2	0.17%	[2.01]	0.45%	-0.27%	[-2.33]	-0.53%	0.34%	[2.43]	0.55%
t+3	0.11%	[1.17]	0.55%	-0.09%	[-0.85]	-0.62%	0.13%	[0.93]	0.68%
t+4	0.13%	[1.49]	0.68%	-0.08%	[-0.86]	-0.70%	0.12%	[0.95]	0.80%
t+5	0.11%	[1.17]	0.79%	-0.17%	[-1.50]	-0.87%	0.21%	[1.62]	1.01%
t+6	0.11%	[1.25]	0.90%	-0.16%	[-1.36]	-1.02%	0.28%	[2.10]	1.29%
t+7	0.11%	[1.18]	1.01%	-0.09%	[-0.84]	-1.12%	0.21%	[1.49]	1.50%
t+8	0.08%	[0.79]	1.09%	-0.18%	[-1.50]	-1.30%	0.35%	[2.48]	1.84%
t+9	0.04%	[0.36]	1.13%	-0.13%	[-1.21]	-1.43%	0.24%	[1.69]	2.09%
t+10	-0.07%	[-0.68]	1.06%	-0.11%	[-0.87]	-1.54%	0.28%	[1.86]	2.36%
t+11	-0.05%	[-0.48]	1.01%	-0.12%	[-0.94]	-1.66%	0.21%	[1.37]	2.57%
t+12	-0.03%	[-0.37]	0.98%	-0.08%	[-0.72]	-1.74%	0.19%	[1.49]	2.76%
t+13	-0.04%	[-0.47]	0.93%	0.04%	[0.39]	-1.70%	0.06%	[0.47]	2.82%
t+14	-0.03%	[-0.25]	0.91%	0.02%	[0.25]	-1.68%	0.09%	[0.75]	2.91%
t+15	-0.05%	[-0.47]	0.86%	-0.01%	[-0.12]	-1.69%	0.09%	[0.65]	3.00%
t+16	0.03%	[0.37]	0.90%	-0.11%	[-0.92]	-1.80%	0.32%	[2.40]	3.33%
t+17	0.01%	[0.10]	0.91%	-0.13%	[-1.04]	-1.92%	0.35%	[2.38]	3.67%
t+18	0.05%	[0.58]	0.95%	0.04%	[0.52]	-1.88%	0.20%	[1.76]	3.87%
t+19	0.00%	[-0.01]	0.95%	0.07%	[0.69]	-1.81%	0.07%	[0.61]	3.94%
t+20	-0.05%	[-0.52]	0.90%	0.11%	[1.16]	-1.70%	-0.04%	[-0.31]	3.91%
t+21	-0.05%	[-0.47]	0.86%	0.18%	[1.63]	-1.52%	-0.10%	[-0.74]	3.80%
t+22	0.03%	[0.30]	0.89%	0.15%	[1.29]	-1.37%	-0.01%	[-0.08]	3.79%
t+23	0.00%	[-0.03]	0.89%	0.12%	[1.11]	-1.24%	-0.04%	[-0.33]	3.75%
t+24	0.08%	[0.80]	0.96%	0.03%	[0.30]	-1.21%	0.05%	[0.41]	3.80%

Table 10
Long-Run Performance of Spread Portfolios: Expected versus Unexpected Flow

Every month hedge funds are double sorted by flow impact and flow (3-by-3). Flow-impact is estimated using rolling windows of prior 60-month observations with at least 24 valid observations of montly return and flow. Flow is obtained using three different signlas: actual, expected and unexpected flow. Panel A reports the results where flow is the actual monthly flow, Panel B when it is the expected flow estimated using rolling windows of prior 60-month observations with at least 24 valid monthly observations of return and flow while Panel C reports the results with unanticipated flow (the difference between actual and expected flow). Portfolios are equally weighted, rebalanced monthly, and are denoted BiFj, indicating the ith flow-impact tercile and the jth flow tercile (1 is low and 3 is high). The table reports statistics up to 12 months post portfolio formation. The sample includes 7,280 hedge funds from January 1999 through December 2008.

Panel A: Actual Monthly Flow

	B3F3 – B3F1			B3F1 – B1F1			(B3F3 – B1F3) – (B3F3 – B1F3)		
	Return	T-statistic	Cumulative	Return	T-statistic	Cumulative	Return	T-statistic	Cumulative
t	0.98%	[10.08]	0.98%	-0.50%	[-4.37]	-0.50%	0.89%	[6.88]	0.89%
t+1	0.41%	[4.11]	1.39%	-0.11%	[-1.58]	-0.61%	0.01%	[0.08]	0.90%
t+2	0.27%	[3.10]	1.66%	-0.32%	[-2.72]	-0.93%	0.26%	[2.20]	1.16%
t+3	0.14%	[1.39]	1.80%	-0.22%	[-1.80]	-1.14%	0.16%	[1.18]	1.33%
t+4	0.17%	[2.16]	1.97%	-0.13%	[-1.18]	-1.27%	0.17%	[1.28]	1.50%
t+5	0.04%	[0.43]	2.01%	-0.08%	[-0.74]	-1.36%	-0.05%	[-0.34]	1.45%
t+6	0.06%	[0.87]	2.07%	-0.04%	[-0.43]	-1.39%	0.07%	[0.56]	1.52%
t+7	0.19%	[2.07]	2.26%	-0.20%	[-1.77]	-1.60%	0.31%	[2.07]	1.83%
t+8	0.05%	[0.68]	2.32%	-0.16%	[-1.54]	-1.76%	0.22%	[1.75]	2.05%
t+9	-0.03%	[-0.33]	2.29%	-0.01%	[-0.16]	-1.77%	0.05%	[0.48]	2.10%
t+10	-0.07%	[-0.68]	2.22%	-0.04%	[-0.40]	-1.81%	0.19%	[1.73]	2.29%
t+11	0.03%	[0.32]	2.25%	-0.11%	[-1.01]	-1.93%	0.18%	[1.36]	2.47%
t+12	-0.01%	[-0.08]	2.24%	-0.09%	[-0.92]	-2.01%	0.25%	[1.94]	2.72%

Panel B: Expected Flow

	B3F3 – B3F1			B3F1 – B1F1			(B3F3 – B1F3) – (B3F3 – B1F3)		
	Return	T-statistic	Cumulative	Return	T-statistic	Cumulative	Return	T-statistic	Cumulative
t	0.54%	[4.79]	0.54%	-0.34%	[-2.98]	-0.34%	0.43%	[3.27]	0.43%
t+1	0.30%	[2.57]	0.83%	-0.19%	[-2.03]	-0.53%	0.21%	[1.64]	0.64%
t+2	0.19%	[1.93]	1.02%	-0.18%	[-1.91]	-0.70%	0.08%	[0.59]	0.72%
t+3	0.14%	[1.66]	1.16%	-0.24%	[-2.15]	-0.95%	0.22%	[1.67]	0.93%
t+4	0.17%	[1.91]	1.33%	-0.07%	[-0.72]	-1.02%	0.11%	[0.91]	1.05%
t+5	0.17%	[1.86]	1.50%	-0.19%	[-1.70]	-1.21%	0.21%	[1.60]	1.26%
t+6	0.20%	[2.09]	1.70%	-0.07%	[-0.66]	-1.28%	0.10%	[0.74]	1.36%
t+7	0.05%	[0.53]	1.76%	0.04%	[0.39]	-1.24%	-0.03%	[-0.27]	1.32%
t+8	-0.07%	[-0.66]	1.68%	0.09%	[0.83]	-1.15%	-0.21%	[-1.47]	1.12%
t+9	-0.06%	[-0.61]	1.62%	0.08%	[0.75]	-1.07%	-0.07%	[-0.56]	1.04%
t+10	-0.07%	[-0.69]	1.55%	-0.02%	[-0.19]	-1.09%	0.03%	[0.19]	1.07%
t+11	-0.03%	[-0.28]	1.52%	-0.14%	[-1.35]	-1.23%	0.13%	[0.95]	1.20%
t+12	0.06%	[0.61]	1.58%	-0.06%	[-0.74]	-1.30%	0.13%	[1.08]	1.32%

Panel C: Unexpected Flow

	B3F3 – B3F1			B3F1 – B1F1			(B3F3 – B1F3) – (B3F3 – B1F3)		
	Return	T-statistic	Cumulative	Return	T-statistic	Cumulative	Return	T-statistic	Cumulative
t	0.11%	[1.26]	0.11%	-0.40%	[-3.40]	-0.40%	0.51%	[3.78]	0.51%
t+1	0.05%	[0.81]	0.16%	-0.08%	[-1.17]	-0.48%	-0.19%	[-1.57]	0.32%
t+2	0.08%	[0.96]	0.24%	-0.21%	[-2.14]	-0.69%	0.10%	[0.82]	0.42%
t+3	-0.06%	[-0.78]	0.17%	-0.05%	[-0.58]	-0.74%	-0.21%	[-1.67]	0.21%
t+4	-0.06%	[-0.83]	0.12%	-0.02%	[-0.25]	-0.76%	-0.13%	[-1.11]	0.08%
t+5	-0.14%	[-1.74]	-0.03%	0.03%	[0.34]	-0.72%	-0.19%	[-1.40]	-0.11%
t+6	-0.11%	[-1.39]	-0.14%	0.09%	[0.99]	-0.64%	-0.13%	[-1.03]	-0.24%
t+7	0.06%	[0.80]	-0.08%	-0.08%	[-0.96]	-0.72%	0.10%	[0.86]	-0.14%
t+8	0.05%	[0.59]	-0.02%	-0.12%	[-1.21]	-0.84%	0.25%	[2.06]	0.11%
t+9	-0.01%	[-0.07]	-0.03%	0.05%	[0.72]	-0.79%	-0.09%	[-0.69]	0.03%
t+10	-0.04%	[-0.50]	-0.07%	0.00%	[-0.01]	-0.79%	-0.03%	[-0.25]	-0.01%
t+11	0.05%	[0.51]	-0.02%	-0.08%	[-0.80]	-0.87%	0.02%	[0.12]	0.01%
t+12	-0.05%	[-0.69]	-0.08%	0.03%	[0.40]	-0.83%	-0.04%	[-0.34]	-0.03%

Table 11
Controlling for Lag Flow

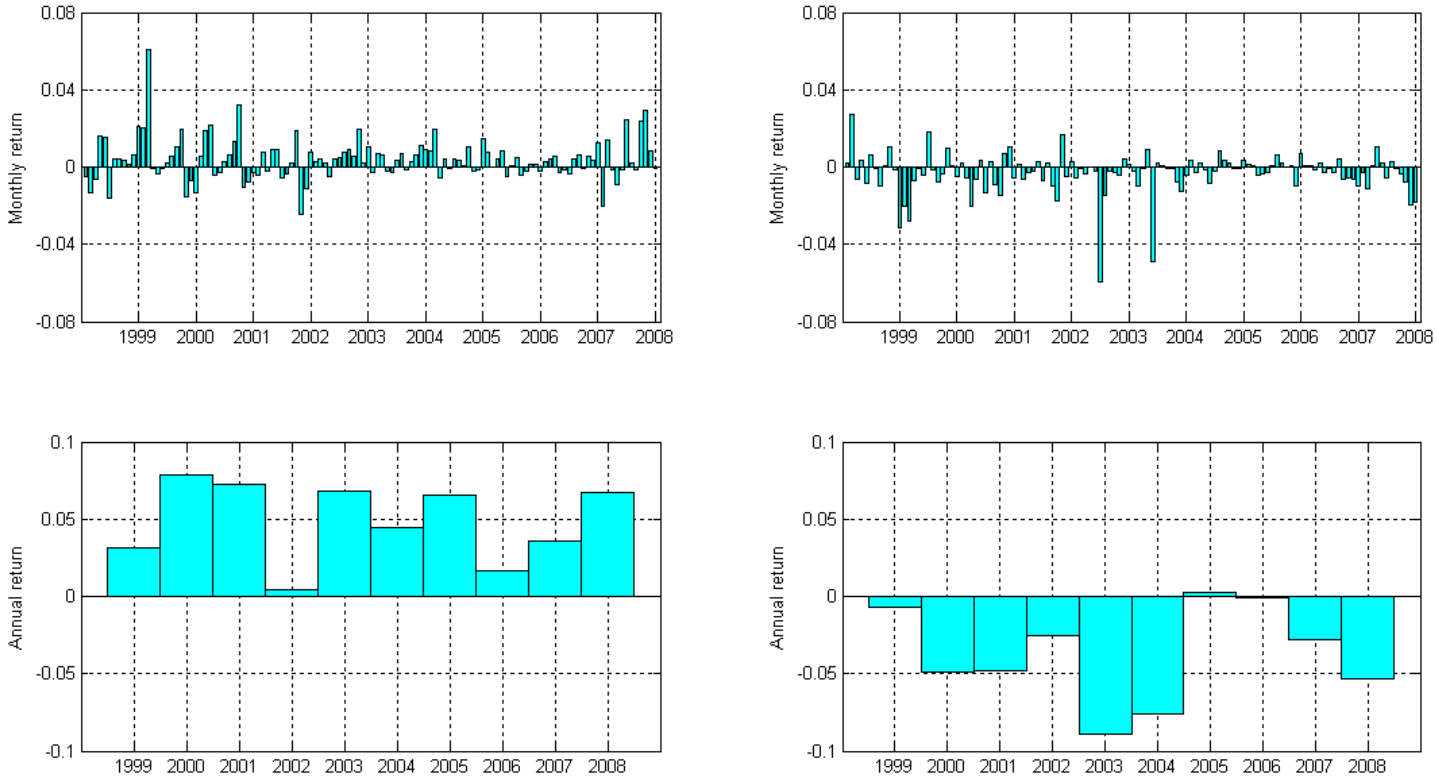
This table reports cross-sectional summary statistics of fund-level time-series regressions. The regressions are of the form $R_{i,t} = \alpha_i + \beta_{HF,i}R_{HF,t} + \beta_{F,i}F_{i,t} + \beta_{FL,i}F_{i,t-1} + \varepsilon_{i,t}$, where $R_{i,t}$ is fund's i monthly return excess of three-month treasury bills in month t, $R_{HF,t}$ is the excess return of the hedge fund industry, $F_{i,t}$ is the monthly flow of fund i in month t, and $\varepsilon_{i,t}$ is the error term. The sample includes 7,280 hedge funds with at least 24 valid monthly observations of return and flow between January 1994 and December 2008.

	Mean	*t*-statistic of mean	Standard deviation	Percentiles		
				25%	50%	75%
α_i	0.000	-2.129	0.008	-0.004	0.000	0.004
T-stat (α_i)	0.078		1.753	-1.110	0.023	1.172
$\beta_{HF,i}$	1.022	68.487	1.003	0.339	0.815	1.426
T-stat ($\beta_{HF,i}$)	5.043		4.511	1.706	4.170	7.569
$\beta_{F,i}$	0.002	2.617	0.058	-0.012	0.001	0.016
T-stat ($\beta_{Fi,t}$)	0.114		1.096	-0.589	0.108	0.827
$\beta_{FL,i}$	0.000	-0.422	0.060	-0.014	0.000	0.015
T-stat ($\beta_{FL,i}$)	0.034		1.033	-0.661	0.025	0.696
R^2	0.349		0.246	0.130	0.309	0.538

Table 12
Portfolios Sorted by Alternative Mesures of Flow and Flow Impact

Every month hedge funds are double sorted by flow impact and quarterly flow (3-by-3). Flows are caluclated assuming flows are received at the beginning of the month. Quarterly flow is obtained by aggregating the prior sum of three-monthly fund flows and flow-impact is estimated using rolling windows of prior 60-month observations with at least 24 valid observations of montly return and flow. Portfolios are equally weighted, rebalanced monthly, and are denoted B_iF_j, indicating the *i* th flow-impact tercile and the *j* th flow tercile (1 is low and 3 is high). Panels A, and C report the statistics of portfolios sorted first on flow impact and then on quarterly flow, while Panels B, and D report the opposite dependent sort. The table includes raw portfolio excess returns over the three-month treasury bills and risk-adjusted returns (alphas), are calculated as the intercepts of regressions of portfolio excess returns on the excess return on the seven factors of Fung and Hsieh (2001). The sample includes hedge funds over the period January 1999 through December 2008.

Portfolios sorted by flow and flow impact					Portfolios sorted by flow impact and flow				
Excess returns									
Panel A					Panel B				
Flow (F)	Flow impact (B)				Flow (F)	Flow impact (B)			
	B1	B2	B3	B3 – B1		B1	B2	B3	B3 – B1
F1	0.43%	0.18%	0.11%	-0.32%	F1	0.35%	0.17%	0.11%	-0.24%
	[2.10]	[1.44]	[0.59]	[-3.24]		[1.80]	[1.32]	[0.56]	[-2.81]
F2	0.31%	0.17%	0.26%	-0.06%	F2	0.32%	0.22%	0.31%	-0.02%
	[1.60]	[1.21]	[1.30]	[-0.80]		[1.63]	[1.55]	[1.52]	[-0.22]
F3	0.55%	0.29%	0.50%	-0.04%	F3	0.56%	0.28%	0.49%	-0.07%
	[2.65]	[2.38]	[2.59]	[-0.47]		[2.69]	[2.25]	[2.62]	[-0.73]
F3 - F1	0.12%	0.10%	0.39%	0.27%	F3 - F1	0.21%	0.11%	0.38%	0.17%
	[0.92]	[1.72]	[4.05]	[2.10]		[1.73]	[1.91]	[3.71]	[1.31]
Fung-Hsieh alphas									
Panel C					Panel D				
Flow (F)	Flow impact (B)				Flow (F)	Flow impact (B)			
	B1	B2	B3	B3 – B1		B1	B2	B3	B3 – B1
F1	0.48%	0.26%	0.23%	-0.26%	F1	0.41%	0.27%	0.22%	-0.19%
	[3.55]	[3.11]	[2.22]	[-2.56]		[3.32]	[3.37]	[2.14]	[-2.31]
F2	0.33%	0.23%	0.33%	-0.01%	F2	0.33%	0.25%	0.35%	0.02%
	[2.93]	[2.94]	[2.70]	[-0.09]		[2.89]	[3.16]	[2.77]	[0.29]
F3	0.54%	0.30%	0.49%	-0.04%	F3	0.56%	0.31%	0.49%	-0.07%
	[3.74]	[3.61]	[3.82]	[-0.45]		[3.72]	[3.73]	[3.90]	[-0.69]
F3 – F1	0.06%	0.05%	0.27%	0.21%	F3 – F1	0.15%	0.05%	0.27%	0.12%
	[0.44]	[0.79]	[3.15]	[1.56]		[1.17]	[0.90]	[3.03]	[0.95]



Panel A: Return difference (B3F3 – B3F1)

Panel B: Return difference (B3F1– B1F1)

Figure 1. The time series of flow/flow-impact portfolio return spreads. Every month hedge funds are double sorted by prior three-month flow and flow impact (3-by-3). Flow impact is estimated using prior 60-month rolling windows. Portfolios are equally weighted, rebalanced monthly, and are denoted B_iF_j, indicating the i^{th} flow-impact quartile and the j^{th} expected-flow quartile (1 is low and 3 is high). The flow impact of a fund is the flow coefficient in the regression of fund return on the hedge-fund average and fund flow. The years denote year-ends. The sample includes the universe of hedge funds on TASS for the period 1994–2008 (the first portfolio return observation is January 1999).

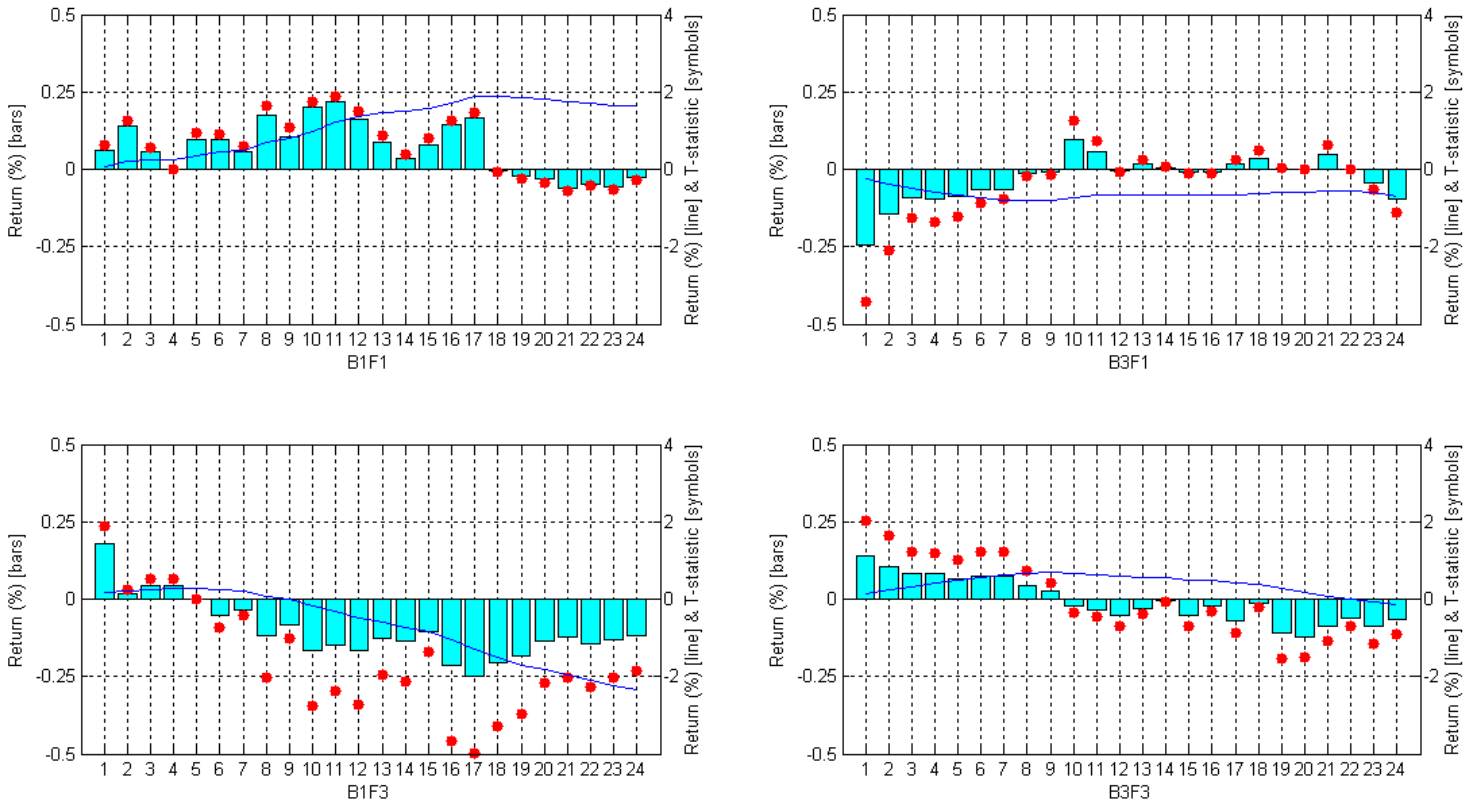
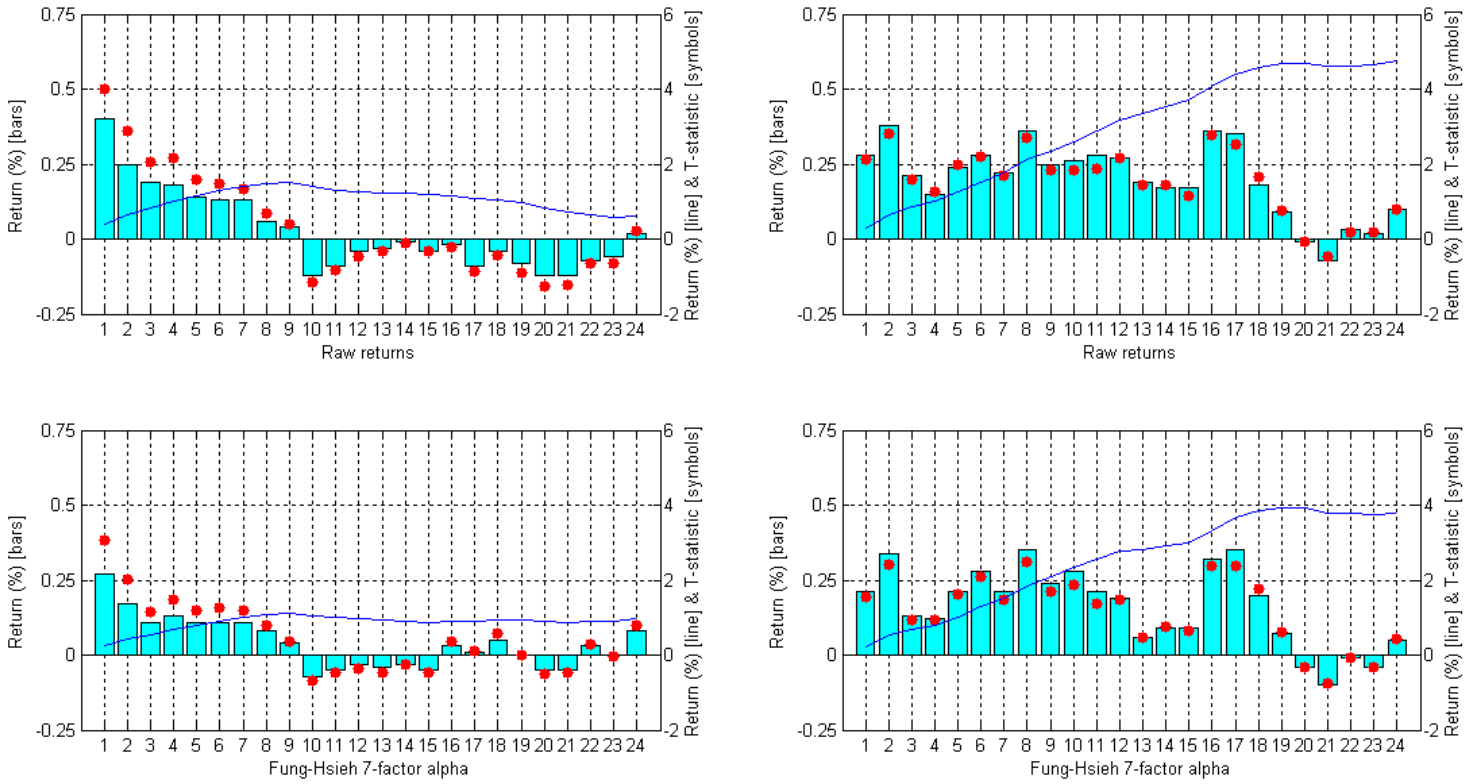


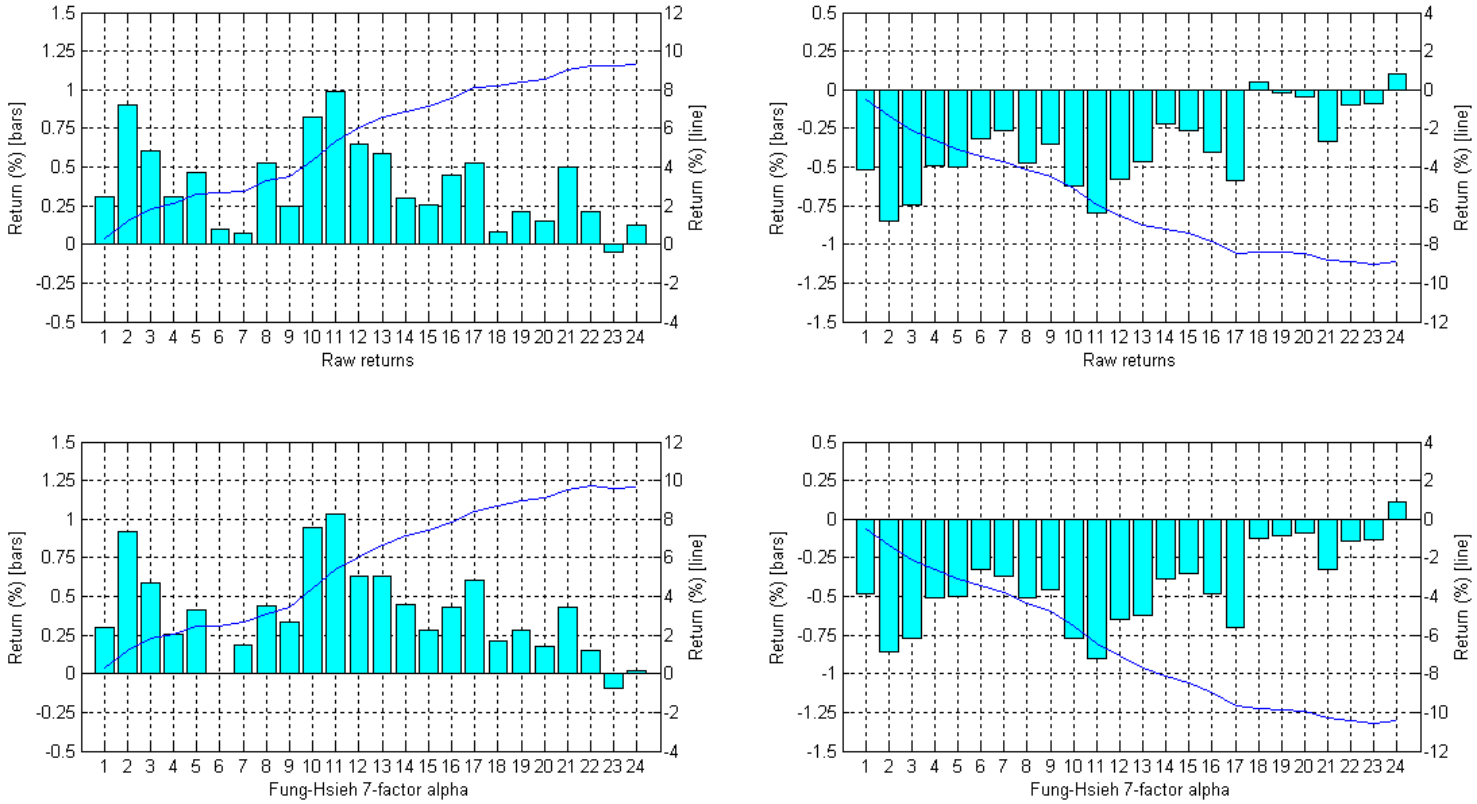
Figure 2. Long-run performance of portfolio return spreads. Every month hedge funds are double sorted by prior three-month flow and flow impact (3-by-3). Flow impact is estimated using prior 60-month rolling windows. Portfolios are equally weighted, rebalanced monthly, and are denoted B_iF_j, indicating the i^{th} flow-impact quartile and the j^{th} expected-flow quartile (1 is low and 3 is high). The flow impact of a fund is the flow coefficient in the regression of fund return on the hedge-fund average and fund flow. The figures plot the performance of the portfolio returns in excess of the hedge-fund industry average during the first 24 months post-formation (bars), their *t*-statistic (symbols), and the cumulative return (lines). The figures include both raw portfolio returns and risk-adjusted returns (alphas), calculated as the intercepts of regressions of portfolio returns on the seven factors of Fung and Hsieh (2001). The sample includes the universe of hedge funds on TASS for the period 1994–2008 (the first portfolio return observation is January 1999).



Panel A: Return difference
(B3F3 – B3F1)

Panel B: Return difference-of-differences
(B3F3 – B3F1) – (B1F3 – B1F1)

Figure 3. Long-run performance of portfolio return spreads. Every month hedge funds are double sorted by prior three-month flow and flow impact (3-by-3). Flow impact is estimated using prior 60-month rolling windows. Portfolios are equally weighted, rebalanced monthly, and are denoted B_iF_j, indicating the i^{th} flow-impact quartile and the j^{th} expected-flow quartile (1 is low and 3 is high). The flow impact of a fund is the flow coefficient in the regression of fund return on the hedge-fund average and fund flow. The figures plot the performance of the portfolio return spreads during the first 24 months post-formation (bars), their *t*-statistic (symbols), and the cumulative return (lines). The figures include both raw portfolio returns and risk-adjusted returns (alphas), calculated as the intercepts of regressions of portfolio returns on the seven factors of Fung and Hsieh (2001). The sample includes the universe of hedge funds on TASS for the period 1994–2008 (the first portfolio return observation is January 1999).



Panel A: Lockup minus NoLockup funds
(B3F3 – B3F1) – (B1F3 – B1F1)

Panel B: Lockup minus NoLockup funds
(B3F1 – B1F1)

Figure 4. Long-run performance of portfolio return spreads of Lockup and NoLockup funds. Every month hedge funds are double sorted by prior three-month flow and flow impact (3-by-3). Flow impact is estimated using prior 60-month rolling windows. Portfolios are equally weighted, rebalanced monthly, and are denoted B_iF_j, indicating the i^{th} flow-impact quartile and the j^{th} expected-flow quartile (1 is low and 3 is high). The flow impact of a fund is the flow coefficient in the regression of fund return on the hedge-fund average and fund flow. The figures plot the performance of the portfolio return spreads during the first 24 months post-formation (bars), their *t*-statistic (symbols), and the cumulative return (lines). The figures include both raw portfolio returns and risk-adjusted returns (alphas), calculated as the intercepts of regressions of portfolio returns on the seven factors of Fung and Hsieh (2001). The sample includes the universe of hedge funds on TASS for the period 1994–2008 (the first portfolio return observation is January 1999).