Flows, Price Pressure, and Hedge Fund Returns*

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Abstract

We study how capital flows affect hedge fund returns. The contemporaneous relation is positive: funds with high flows outperform funds with low flows during the month of the flows. This immediate reaction, combined with feedback trading, gives rise to a cycle: flows exert price pressure, this effect on returns induces more flows, and these flows cause further price pressure. The cycle is so strong that it takes almost two years before a full return reversal is witnessed. This flow-return cycle also contributes to the observed persistence in hedge fund performance. The impact of flows on returns also has implications for performance evaluation: roughly one third of the estimated hedge fund alphas are due to flows.

JEL Classification: G12, G14, G23

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1 Introduction

Over the past two decades, hedge funds have experienced large inflows of capital. On the other hand, academic literature shows that fund flows result in an uninformed demand shift, which may affect asset prices. In this paper, we study the effect that capital flows have on hedge fund returns. Our results are consistent with a mechanism where funds respond to flows by scaling their portfolios up or down, rather than diversifying. These trades have a contemporaneous price impact on the funds' underlying assets, leading to an effect on fund-level returns. Reversal of the initial flow-induced price pressure is delayed by the price impact exerted by further performance-chasing flows. Such a mechanism and our results are in line with the ideas and results presented by Lou (2011) in the mutual fund context.

The existing literature on uninformed demand shocks has mainly focused on studying equity benchmark index redefinitions (Shleifer, 1986, Harris and Gurel, 1986, Greenwood, 2005) and the flow-driven trading of mutual funds in US equities (Coval and Stafford, 2007, Frazzini and Lamont, 2008, Chen, Hanson, Hong, and Stein, 2009, Greenwood and Thesmar, 2011, Khan, Kogan, and Serafeim, 2011, and Lou, 2011). In particular, the latter studies look at capital flows in and out of mutual funds, and investigate the price impacts of the flows on the stocks held by the funds. Compared to these studies, the use of hedge fund data allows us to examine the flow-related phenomena with a much broader set of underlying assets and investment strategies. The fact that our results are consistently present across different types of hedge funds shows that flow-induced price pressure is not limited to equities only.[1] Also, the sequential nature of flows and returns, where monthly flows are submitted before learning the concurrent return–something that does not hold for mutual funds–allows us to quantify the contemporaneous effect that flows have on fund-level returns and hedge fund performance attribution.

Our paper contains four key results. First, hedge fund returns exhibit statistically and economically significant flow-induced price pressure: funds that receive high inflows outperform funds experiencing large outflows during the month of the flows. Second, when the returns are traced over the subsequent months, reversal of the initial price impact occurs relatively slowly: a full reversal takes around 18 months on average. Third, flow-induced price pressure contributes to the observed persistence in hedge fund returns. Fourth, and maybe most interestingly from a practitioner's point of view, flows have implications for performance attribution, as estimated hedge fund alphas fall by around 30% when controlling for flow impacts. These results contribute to the existing literature on flow-induced price pressure as well as the hedge fund literature. Next, we review the related literature and how our results link to and extend this body of research.

Our first result is that capital flows have a contemporaneous effect on hedge fund returns: funds with large inflows outperform funds with large outflows during the month of the flows. This effect is present in calendar time portfolios sorted on flows, in fund-level time series regressions, as well as in cross-sectional regressions. When we sort hedge funds into five flow portfolios,

[1] One of our robustness checks shows that our results also hold for the subsample of hedge funds that includes only funds that do not report an equity focus.

the high flow funds outperform low flow funds by 0.54% per month. This indicates that hedge fund flows are sizeable enough in relation to the liquidity of the underlying assets that flows have a significant price impact. We argue that the contemporaneous causality runs from flows to returns. First, this is the usual assumption in the literature.[2] Second, Edelen and Warner (2001) study daily aggregate mutual fund flows and, using intraday stock index data, establish that the positive contemporaneous relation between flows and returns arises because flows cause returns. Third, and most importantly, hedge funds are particularly well suited for this choice of causality, as lengthy notification periods, infrequent trading, and delays in return reporting all but guarantee that investors are required to submit their subscriptions and redemptions before learning about the contemporaneous returns.[3]

The liquidity of hedge funds' underlying assets varies considerably, so the contemporaneous effect of flows on returns may also differ from one fund to another. We measure the sensitivity of fund returns to capital flows in a structural vector autoregressive (SVAR) model that allows for a contemporaneous effect of flows on returns. On average, the coefficient of contemporaneous flows in the return equation is positive and statistically significant, further supporting our portfolio sort results. We also employ the SVAR model to arrive at monthly estimates of the funds' *ex ante* flow sensitivity of returns. We then sort funds according to both flow sensitivity and flows, and find that the strength of the flow impact is significantly increasing in flow sensitivity. This finding is consistent with flows exerting price pressure on the underlying assets, and with our measure of flow sensitivity being a proxy for the liquidity of the underlying assets.

Our result of a positive contemporaneous relation between flows and returns is consistent with hedge funds responding to flows by scaling their positions in existing holdings rather than diversifying. Although this has not been studied in the context of hedge funds, mutual funds are known to respond to flows by scaling their holdings up or down rather initiating new positions (see Khan, Kogan, and Serafeim, 2011, Lou, 2011, Pollet and Wilson, 2008, and Coval and Stafford, 2007). Therefore, price impacts occur at the level of individual holdings, but this price pressure also affects fund-level returns.[4]

In a related paper, Coval and Stafford (2007) document a positive contemporaneous relation between large mutual fund flows and returns on the stocks held by funds experiencing the large flows. Lou (2011) determines the amount of mutual fund stock trading that is due to flows, and constructs a measure of mutual fund flow-induced price pressure (FIPP) for individual stocks.

[2]See e.g. Jinjarak, Wongswan, and Zheng (2011), Ozik and Sadka (2010), Froot, O'Connell, and Seasholes (2001), and Hasbrouck (1991). With the exception of Ozik and Sadka (2010), these papers estimate SVAR models for various markets that incorporate a contemporaneous effect from flows to returns. Ozik and Sadka (2010) run a regression of hedge fund returns on contemporaneous flow and average hedge fund returns.

[3]Robustness checks confirm our choice of causality, as our results hold also when sorting on expected flow, and when considering only those hedge funds that allow subscriptions and redemptions once a month, or less frequently and have a notification period of one month or longer.

[4]Chordia, Roll, and Subrahmanyam (2002) show that when price pressure stems from order imbalances, the effects can be detected even at an aggregate market level. Note that we are not able to analyze the effects on the level of the underlying assets as such data is only available for the US equity holdings of hedge funds. On the other hand, by focusing on fund-level returns, we are able to conduct our analyses at a monthly frequency: even in the case of mutual funds, holdings data are available at a quarterly frequency at best.

He finds that high FIPP stocks outperform low FIPP stocks in the portfolio formation quarter. This finding is in line with our evidence of a positive contemporaneous flow effect on returns at the hedge fund level. Edelen and Warner (2001) also document a positive relation between aggregate daily mutual fund flow and market returns. For hedge funds, Ozik and Sadka (2010) calculate a fund-level flow sensitivity measure similar to ours and also find it to be positive on average. However, they do not pursue the topic of flow impact further, as their focus is on the existence of smart money among hedge fund investors.[5]

Second, we trace the cumulative outperformance of the initial high flow hedge funds over the low flow funds to examine the long term impact of the flows. The cumulative outperformance remains relatively flat for the first eight months following the flow, after which it starts to slowly revert. A full reversal of the initial price impact takes a total of around 20 months. Such a surprisingly slow onset of reversal is consistent with the ideas and findings of Lou (2011). He finds that the stock-level mutual fund flow-induced price impact does not start to revert until the second year after the initial flow. He also concludes that it can take up to three years for full reversal to occur. Lou (2011) offers a flow-based explanation for the delayed onset of reversal: good performance due to the positive price impact of the initial inflow attracts further inflows, which again exert additional price pressure, leading to continued good performance, further inflows, and so on. Such a flow-return cycle can be strong enough to override reversal in the medium term.[6,7] Note that such a delay in the onset of the reversal is not present in, for example, Coval and Stafford (2007) and Khan, Kogan, and Serafeim (2011). The former focuses on very large inflows and outflows, and the latter on very large inflows only. Compared to our setup, and that in Lou (2011), these extreme flows are likely to cause a larger initial price impact. Thus the flow-return cycle is not able to sustain the flow-induced misvaluation and the stock-level price impact starts reverting immediately.

Our hedge fund-level long-term results support the existence of a flow-return cycle in three ways. One, on average, the initial high flow funds continue to receive significantly larger flows than the initial low flow funds for at least the following nine months. Two, the reversal starts much sooner for the subset of funds that–for one reason or another–do not experience a continuation of large flows. This shows that if the flow part of the cycle breaks down, the whole flow-return cycle falls apart. Three, the flow-return cycle is more pronounced for funds with more flow-sensitive returns, further indicating that the subsequent flows do play a role in postponing the reversal.

[5]The Ozik and Sadka (2010) measure of flow sensitivity is the coefficient of flows in a regression of fund returns on contemporaneous flow and average hedge fund returns. We prefer the SVAR framework for estimating the flow sensitivity as it controls for the joint dynamics of flows and returns, including lagged effects.

[6]The flow-return cycle builds on the existence of strong performance chasing by fund investors. Evidence of performance chasing in mutual funds is provided by e.g. Sirri and Tufano (1998) and Chevalier and Ellison (1997). For hedge funds, feedback trading has been found by e.g. Ding, Getmansky, Liang, and Wermers (2009), Fung, Hsieh, Naik, and Ramadorai (2008), Getmansky (2005), Agarwal, Daniel, and Naik (2004), and Goetzmann, Ingersoll, and Ross (2003). Our findings yield strong support for performance chasing in the hedge fund context.

[7]If trades convey new information, there should be no reversal. However, flows are assumed to represent uninformed, non-fundamental demand, and our results support this assumption.

Our result of a positive contemporaneous relation between flows and hedge fund returns could also be consistent with the smart money hypothesis. This hypothesis assumes that investors are able to identify have-alpha funds, which results in a positive relation between flows and returns. However, our long-term results of no continuation in the outperformance of high flow funds are against the existence of smart money. Existing literature provides inconclusive evidence of smart money in the mutual fund industry. Gruber (1996) and Zheng (1999) show that smart money does exist, but conversely, Sapp and Tiwari (2004) argue that the observed smart money effect for mutual funds is, in fact, due to stock return momentum. Frazzini and Lamont (2008) find that limited short-term smart money quickly reverts, resulting in long-term dumb money. The evidence in support of smart hedge fund money is even more scarce. Ozik and Sadka (2010) find some evidence of short-term smart money, but only in the subset of funds with flow-sensitive returns. Fung, Hsieh, Naik, and Ramadorai (2008) and Agarwal, Daniel, and Naik (2004) show that flows lead to lower future alphas. Ding, Getmansky, Liang, and Wermers (2009) provide evidence that the existence of smart money can depend on the amount of share restrictions hedge funds employ. Finally, using a data set of buy and sell indications in a secondary market for hedge funds–where transactions have no flow effects on the funds–Ramadorai (2011) discovers that buy indications have no predictive ability for hedge fund performance, and sell indications have only minor predictive ability.

Our third result is that the flow-return cycle contributes significantly to the observed performance persistence in hedge funds. To mention just a few, Jagannathan, Malakhov, and Novikov (2010), Kosowski, Naik, and Teo (2007), and Agarwal and Naik (2000) document persistence in hedge fund performance. In theory, our finding of a positive contemporaneous relation between flows and returns could be caused by a combination of performance-chasing flows and some type of fundamental momentum in hedge fund returns. If both returns and flows depended on past returns, we could observe a relation between the two even in the absence of a causal link. We show that this is not the case, as both past returns and contemporaneous flows have a significant positive impact on hedge fund returns. We also construct two investment strategies–one for the flow impact and the other for momentum–and compare their returns. Both of these strategies deliver positive and very significant Fung and Hsieh (2004) alphas. When the flow impact is controlled for, the momentum alpha disappears. However, even in the presence of the momentum returns, the flow impact alpha remains positive and significant. We therefore conclude that the two effects coexist and, if anything, flow impact is a driver of performance persistence rather than the other way around. These findings are connected to those in Lou (2011), who finds that mutual fund flow-based return predictability can fully account for the persistence in mutual fund performance, and partially account for stock price momentum. As hedge funds invest broadly across asset classes and geographical regions, our results may also help in explaining why Asness, Moskowitz, and Pedersen (2009) find momentum virtually everywhere, within and across markets.

Finally, our fourth set of results deals with the implications of flow impact for hedge fund performance attribution. If the price impact exerted by flows is not perfectly correlated with the employed risk factors, a part of what is interpreted to be pure manager skill may be driven by flows. This concern is also raised by Lou (2011), Khan, Kogan, and Serafeim (2011), and Coval and Stafford (2007). Further, both Khan, Kogan, and Serafeim (2011) and Coval and Stafford (2007) discuss the consequences of flow impacts on fund managers' compensation. To our knowledge, we are the first to quantify the flow effect on estimated alphas. In practice, we augment the Fung and Hsieh (2004) seven-factor model with a flow impact factor. Our results reveal that the estimates of hedge fund alphas fall by around 30% when including the flow impact factor, further underscoring the importance of assessing flow impacts when measuring the sources of hedge fund returns.

In addition to the aforementioned papers, ours is also closely related to three recent papers that examine hedge fund flows and returns from different angles. All these papers–Ozik and Sadka (2010, 2011) and Teo (2011)–differ from our setup in the sense that they examine the relation between returns and lagged capital flows, whereas we study the contemporaneous effect. First, as briefly mentioned above, Ozik and Sadka (2010) study the smart money effect and find some evidence of short-term smart money, but this effect is present only for highly flow sensitive funds. They interpret this as evidence of some investors being able to forecast future flows, or being smart about money. In a related paper, Ozik and Sadka (2011) show that the short-term predictive power of flows may be a result of hedge fund insiders front-running large outsider flows. Namely, they show that flows positively affect future returns in funds with tight share restrictions and weak governance. Teo (2011) measures excessive liquidity risk of relatively liquid hedge funds by the effect of previous month's flows on returns.[8]

The rest of the paper is structured as follows. Section 2 introduces the data used in this study. Section 3 contains the analysis of the contemporaneous effect of flows on returns, and Section 4 presents the long-term impacts of flows. In Section 5 we disentangle flow impact and hedge fund return momentum, and in Section 6 we examine the implications of flow impact on hedge fund performance attribution. Section 7 contains a variety of robustness checks, and Section 8 concludes.

2 Data

Our monthly hedge fund return data comes from the Lipper TASS database. The sample period runs from January 1994 to December 2010. We limit the available data set in several ways. First, we exclude all funds of funds. Second, we require that a fund have at least 36 monthly observations available. Third, we only use data beginning in 1994 to mitigate issues relating to funds that are no longer alive: data on defunct funds is not available in the database prior to 1994. We also require that a fund have at least one million USD in assets under management (AUM), and the AUM figures must also be credible, or change from one month to the next.

[8] Teo (2011) defines funds with monthly or more frequent redemptions as liquid.

After these eliminations, we are left with a sample of 2,918 funds. The flow data utilized in this study is calculated with the data on returns and assets under management as follows:

$$f_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1}(1 + r_{i,t})}{AUM_{i,t-1}}$$

where $f_{i,t}$ is the percentage flow of capital to fund i in month t, $r_{i,t}$ is the return for fund i in month t, and $AUM_{i,t}$ denotes the assets under management of fund i at the end of month t.

Descriptive statistics on the returns, in USD and the funds' currency of denomination, and flows in our sample can be found in Table 1.

[Table 1 here]

We use returns in different currencies for different purposes. In our portfolio sorts, we use the USD returns. For funds denominated in other currencies, we convert the local currency returns using end-of-month exchange rates. In the fund-level vector autoregressive models, we use the local currency returns. Finally, in the fund-level performance attribution regressions, we again use the USD returns as the risk factors we employ are based on USD returns.

3 Contemporaneous flow impact

In this section we study the contemporaneous impact of capital flows on hedge fund returns. We analyze the effect by both sorting hedge funds into flow portfolios and by running cross-sectional regressions.

3.1 Flow-sorted portfolios

We begin by forming portfolios of hedge funds based on the contemporaneous net flows of capital into the funds. We argue that the contemporaneous direction of causality runs from flows to returns. First, this is the usual assumption in the literature (see e.g. Jinjarak, Wongswan, and Zheng, 2011, Ozik and Sadka, 2010, Froot, O'Connell, and Seasholes, 2001, and Hasbrouck, 1991). Second, Edelen and Warner (2001) study daily aggregate mutual fund flows and, using intraday stock index data, establish that the positive contemporaneous relation between flows and returns arises because flows cause returns. Third, and most importantly, hedge funds are particularly well suited for this choice of causality, as lengthy notification periods, infrequent trading, and delays in return reporting all but guarantee that investors are required to submit their investment decisions before learning about the contemporaneous returns.[9]

[9]Although the month t flows are likely to materialize at the end of the month, fund managers know the net flow well before the month end, thanks to lengthy notification periods. Hence, the managers can prepare the fund for the change in shareholders' equity by increasing or decreasing the portfolio already before the end of the month. Such buying of additional securities can naturally be financed against the future flows.

Table 2 presents the average excess returns and Fung and Hsieh (2004) seven-factor alphas for five monthly updated flow portfolios.[10,11]

[Table 2 here]

Flows have a positive and statistically significant effect on both excess and risk-adjusted returns. The high flow portfolio earns a significantly greater return and alpha than the low flow portfolio. The difference in excess returns is 0.53%, and the difference in alphas 0.54%, on a monthly basis. The finding of a positive relation between flows and returns may have a number of explanations. First, the relation can be a manifestation of smart money, where at least some investors are able to identify and allocate money to funds with superior performance. Second, the flow impact may be a result price pressure caused by the flows (due to imperfect liquidity of funds' underlying assets). These issues will be further addressed by analyzing long-term returns in Section 4. The results show no support for smart money, but are consistent with the price pressure hypothesis.

The positive contemporaneous relation between flows and returns also suggests that the positive total alpha of the hedge fund industry may be partially driven by the large flows into these funds over the past two decades. We investigate the role of flow impact for performance measurement in Section 6.

In Section 7, we provide a number of robustness checks for the key result of flows affecting contemporaneous returns positively. We find the result to be robust to backfilling, return smoothing, across fund types, and across time periods. In the robustness check section, we also show that the result is not driven by reverse causality, as the contemporaneous flow impact is also present in illiquid funds, and when sorting on expected flows.[12] In both of these cases, the contemporaneous return cannot affect the measure of flows.

Hedge funds differ considerably in the liquidity of the assets they hold. Hence, it is highly likely that the contemporaneous flow impact also differs from one fund to the next. It turns out to be useful to study how the flow impact varies in an *ex ante* measure of funds' flow sensitivity of returns. To measure this flow sensitivity, we employ a structural vector autoregressive (SVAR) framework for flows and returns. This model allows for a contemporaneous effect of flows on returns while jointly controlling for the lagged flows and returns. Appendix A provides a more detailed description of the SVAR framework, including average coefficient estimates. As is shown in Table A1, the average coefficient of contemporaneous flow in the return equation is positive

[10] The factors are three trend following factors (for bonds, currencies, and commodities; Fung and Hsieh (2001)), an equity market factor (S&P 500 index), a size factor (Russell 2000 index minus S&P 500 index), a bond market factor (Barclays Capital U.S. Government Index), and a credit spread factor (Barclays Capital U.S. Corporate Baa Index minus the Barclays Capital U.S. Corporate Aaa Index). Data for the trend following factors are available on David Hsieh's website at `http://faculty.fuqua.duke.edu/ dah7/DataLibrary/TF-FAC.xls`.

[11] These flow-sorted portfolios, naturally, are not investable, as we use forward looking data in their construction. Further, managing a long-short hedge fund portfolio on a monthly basis is, for all practical purposes, impossible due to share restrictions, time lags in return reporting, and the inability to short hedge funds. However, our goal is not to present a profitable investment strategy, but to study the effect flows have on contemporaneous returns.

[12] Illiquid funds are defined as those that allow for subscriptions and redemptions once a month, or less frequently, and have a notification period of one month or longer.

and statistically significant. This result provides fund-level time series support for our portfolio sort result of positive flow impact. For the purpose of portfolio sorts, we estimate the SVAR model for each fund each month using the previous five years of data, and use the coefficient of contemporaneous flows in the return equation as our measure of flow sensitivity. Hence, our month t estimate of flow sensitivity is based on data from month $t-60$ to month $t-1$. As negative values of flow sensitivity are not economically meaningful, we truncate the estimates by replacing negative values with zero.[13]

Next, we perform a double sort of funds based on *ex ante* flow sensitivities and contemporaneous flows. The result presented above–that flows have a positive effect on contemporaneous returns–should be stronger for funds with more flow sensitive returns. We first sort the funds into three categories based on *ex ante* flow sensitivity. The first category always contains those funds that have flow sensitivity estimates of zero or less (truncated to zero). The two other categories divide the funds with positive flow sensitivity estimates in half. As before, there are five flow categories.[14] Table 3 presents the returns and alphas of the resulting 15 portfolios.

[Table 3 here]

Flows have no effect on the returns of the hedge funds in the lowest flow sensitivity category. This result is not surprising, as the low flow sensitivity category contains the funds with no expected sensitivity to flows whatsoever. The impact of flows on contemporaneous returns increases monotonically in flow sensitivity, and is positive and very significant for highly flow sensitive funds. This finding fits well with the notion that flow sensitivity is a proxy for the liquidity of a fund's underlying assets. For the most flow sensitive funds–i.e. those most likely to hold illiquid assets–the difference in monthly alpha between high and low flow portfolios is 1.86%, which is highly significant both statistically and economically. Further, most of the significant alphas are clustered to the two highest flow categories.

Next, we turn our attention to the effect of flow sensitivity at different levels of flows (columns of Table 3). Low flow sensitivity funds significantly outperform high sensitivity funds in the two lowest flow categories. Conversely, high flow sensitivity funds outperform during higher levels of flow. In the middle flow category, where flows are close to zero, there is no difference in performance between funds with different flow sensitivities. Based on these results, it appears that our flow sensitivity measure captures the variation in flow impacts well.

Taken together, the above results confirm that capital flows have a significant effect on hedge fund returns. Further, this effect is particularly strong for funds with high *ex ante* flow sensitivity, i.e. the funds that presumably hold more illiquid assets. The flow effect is non-existent in the low flow sensitivity funds with presumably more liquid assets. This is consistent with the notion that price pressure is stronger during times of low liquidity and for assets with poor liquidity.

[13] Ozik and Sadka (2010) estimate flow sensitivity of returns in a univariate OLS framework. Our SVAR model can be seen as an extension of this, as it controls also for the joint dynamics of flows and returns.

[14] Note that we differ slightly from standard double sorts by sorting separately over flow sensitivity and flow. This results in the flow category breakpoints being equal across flow sensitivity categories. This way, the difference in flows between the high and low flow funds is of similar magnitude in each flow sensitivity category.

3.2 Cross-sectional regressions

In order to confirm that the results based on the portfolio sort methodology are robust to other fund characteristics that could also affect performance, we run monthly cross-sectional regressions of fund returns on flow, flow sensitivity, and the interaction between flow and flow sensitivity, and average the coefficient estimates in the spirit of Fama and MacBeth (1973). We also include fund size, fund age, and category dummies as controls. Each month, flow, size, and age are demeaned and standardized. Flow sensitivity is not demeaned, but it is standardized by dividing by its standard deviation. Hence, the coefficient of flow can be interpreted as the impact of flows for funds with *ex ante* zero flow sensitivity. The coefficient of the interaction between flow sensitivity and flow gives the increase in the effect of flow when flow sensitivity is increased by one standard deviation.

The time series averages of the coefficients of the cross-sectional regressions, including their Fama-MacBeth t-statistics, are reported in Table 4. Columns 1 and 2 present the results without controls, and columns 3 to 5 with controls. Figure 1 presents the coefficient of capital flows as a function of flow sensitivity.

[Table 4 and Figure 1 here]

Consistent with the evidence garnered from portfolio sorts, the effect of the contemporaneous flow is positive and statistically significant (column 1), even after controlling for fund characteristics and styles (column 3). The coefficient of flow sensitivity is positive and significant. The interaction between flow and flow sensitivity is also positive and significant (columns 2 and 4), further corroborating our hypothesis that capital flows into hedge funds can have a substantial effect on fund returns, and that this effect varies in the liquidity of the funds' assets. In the models that include the interaction term (columns 2 and 4), the coefficient of flow is equal to zero. As stated above, this gives the effect of flows on returns for funds that have *ex ante* flow insensitive returns. The zero unconditional coefficient of flow, together with the positive interaction coefficient, again provides empirical support for our SVAR-based measure of flow sensitivity: it appears to capture the cross-sectional variation in fund returns' response to flows.

For completeness, Figure 1 plots the total coefficient of flow as a function of flow sensitivity together with a 95% confidence interval. As is evident from the discussion above, the coefficient of flow for zero flow sensitivity funds is equal to zero. The coefficient of flow is increasing in flow sensitivity. The coefficient is statistically different from zero at levels of flow sensitivity of around 0.2 and higher.[15]

Finally, in column 5 we verify that our results are not driven by the well-known practice of return smoothing that introduces artificial positive autocorrelation in reported returns (for more on this topic, see e.g. Asness, Krail, and Liew, 2001, Getmansky, Lo, and Makarov, 2004, and Bollen and Pool, 2008). Such autocorrelation, together with performance-chasing flows,

[15] Note that the flow sensitivities are standardized every month by dividing by its standard deviation. Hence a flow sensitivity of 0.2 refers to a value that is equal to 0.2 times the monthly standard deviation.

may inflate the coefficients of the cross-sectional regressions. We employ the Getmansky, Lo, and Makarov (2004) methodology to unsmooth reported returns. They present a model where reported hedge fund returns are a moving average of the current and past true returns. When regressing unsmoothed returns on flow, flow sensitivity, their interaction, and controls (column 5), the results remain qualitatively and quantitatively unchanged from those presented in column 4 for reported returns. Therefore, our results are not sensitive to the return-smoothing behavior of hedge funds.

4 Long-term flow impact

In this section, we extend our analysis beyond the contemporaneous effect of flows. In other words, we turn our attention to how returns and flows develop after portfolio formation month. This long-term analysis will allow us to evaluate what lies behind the contemporaneous impact: smart money, price pressure, or some other explanation. If the smart money hypothesis holds, we would observe high flow funds outperforming low flow funds for some time following the flow. On the other hand, price pressure would manifest itself as follows. High flow funds would outperform low flow funds during the month of flows due to the initial price impact. In the medium or long term, however, as the prices revert, funds that initially experienced a positive flow impact would underperform those that experienced a negative flow impact.

To analyze the long term impact of flows, we form five portfolios based on month t flows and trace the returns from month $t-12$ to $t+24$. Figure 2 presents the differences in risk-adjusted returns for high flow and low flow funds for the 37 months surrounding the portfolio formation month. The differences are presented separately for all funds and the three flow sensitivity categories. Figure 3 depicts the cumulative outperformance of high flow funds over low flow funds following the initial price impact of flows, again separately for all funds and the three flow sensitivity categories.[16]

[Figures 2 and 3 here]

Looking first at the month-by-month results regarding all funds (top left panel of Figure 2), there is a striking difference in the returns before and after the formation month. Before the flow occurs, the high flow funds outperform the low flow funds by 0.6-1.1% per month. These differences are all statistically and economically significant, and corroborate the existence of return chasing (see e.g. Fung, Hsieh, Naik, and Ramadorai, 2008). Following the month t flow, the outperformance all but disappears. The statistically significant outperformance of high flow funds continues for only one month after the portfolio formation.[17]

[16]Figures 2 and 3 are based on the risk adjusted returns. As the loadings of the high minus low flow portfolio on the Fung and Hsieh (2004) risk factors are very low, figures based on raw returns would be very similar.

[17]Teo (2011), with a sample of hedge funds with monthly (or more frequent) redemptions, also finds that with a two-month gap between portfolio formation and alpha evaluation, there is no significant difference in the returns of a high-flow and low-flow portfolio. The alpha spread is significant with a one-month gap, however.

The fact that the outperformance of the high flow funds continues for only one month is, in our opinion, not enough to support the smart money hypothesis. This continued outperformance is likely to have a flow-based explanation. First, further flows may chase the positive returns caused by large month t flows, and in turn have a positive effect on month $t + 1$ returns. In fact, further analysis below will provide support for such a flow-return cycle. Second, Ozik and Sadka (2011) provide evidence that some investors may engage in flow front-running, or trading in advance of other investors anticipating the price impact caused by flows. Third, in illiquid markets, fund managers may invest a part of the money received in month t only in month $t+1$ to avoid excessive price impact. Lou (2011) also argues that flow-based return predictability can fully account for the smart money effect.

All flow sensitivity categories exhibit a similar strong pattern of return chasing: high month t flow funds significantly outperform low flow funds for the 12 months preceding t. As reported above in Table 3, the month t impact of flows is increasing in flow sensitivity and not statistically significant for the low sensitivity funds. Only high flow sensitivity funds experience a significant one-month persistence of the outperformance of high flow funds. Such outperformance is not present in the low and medium flow sensitivity categories. This finding supports our earlier presumption that the observed one-month outperformance has a flow-related explanation, and that smart money is an unlikely explanation for the positive contemporaneous flow-return relation.

Turning our attention to Figure 3, we see that the cumulative outperformance of the high flow funds increases slightly for the first eight months following the flow, after which it starts to revert (all funds, left panel). The initial flow impact fully reverts in 20 months. This pattern resonates with the results of Lou (2011), who reports a one-year delay before the onset of reversal. He interprets this finding through a flow-return cycle: funds receiving inflows scale up their holdings, creating price pressure in their underlying assets. As investors respond to past returns through feedback trading, the initial price impacts attract further flows, which, in turn, exert further price pressure on the assets held by the fund. This flow-return cycle is so strong that it overrides reversal in the medium term, delaying the eventual onset of a reversal.

It is not clear *a priori* how long it should take for reversal to occur after an initial price pressure-driven impact. Stock market literature suggests that reversals occur relatively rapidly. Harris and Gurel (1986) document complete reversals within two weeks of changes to the composition of the S&P 500 index, and Mitchell, Pulvino, and Stafford (2004) report reversals of all or at least half of initial price impacts within one month surrounding M&A announcements and closings. A medium-term view is provided by Greenwood (2005), who documents that full reversal in the Japanese stock market took ten to twenty weeks following a redefinition of the Nikkei 225 index. However, when flow-based demand shocks are the main driver behind price pressure, reversal may take much longer. In particular, Khan, Kogan, and Serafeim (2011), Lou (2011), Ozik and Sadka (2010), and Coval and Stafford (2007) document reverting trends in returns for periods ranging from 12 to 36 months following a flow shock. Our result is also reminiscent of the dumb money analysis of Frazzini and Lamont (2008), who show that cumulative raw returns to a high minus low strategy based on the past three months of their flow measure begin to drop clearly over a six to twelve month horizon.

There is a marked difference in the cumulative outperformance between the different flow sensitivity categories. Medium flow sensitivity funds display a pattern very similar to the all funds sample: slight widening of the cumulative performance gap for 8 months, followed by a gradual reversal. For the high flow sensitivity category the performance gap further widens over the first five months, after which it stays relatively flat for six more months before slowly reverting. In 24 months, the cumulative outperformance returns to the level of the initial flow impact, roughly 1.7%. The result regarding the highly flow-sensitive funds is similar to that in Ozik and Sadka (2010). For the low flow sensitivity funds–for which there is practically no initial flow impact–the cumulative relative performance of high minus low flow funds stays near zero for the first ten months, after which the high flow funds begin to underperform the low flow funds.

A number of important conclusions arise from these patterns in the data. First, the fact that the long-term effect of flows varies in the flow sensitivity of hedge fund returns provides further support for our assumption that further flows delay the reversal of the initial price impact. Stronger flow sensitivity results in larger initial widening of the cumulative performance gap and more delayed reversal. This is consistent with the flow-return cycle.

Second, the eventual long-term underperformance of the high flow funds relative to low flow funds even in the low flow sensitivity category confirms the existence of diseconomies of scale in the hedge fund industry: larger funds underperform smaller ones in the long run. Teo (2009), Fung, Hsieh, Naik, and Ramadorai (2008), and Agarwal, Daniel, and Naik (2004) also present evidence supporting diseconomies of scale in hedge funds. Third, the fact that the initial impact of flows takes on average 20 months to revert may have important implications for fund performance evaluation. If performance is evaluated–for whatever purpose–over a horizon shorter than what is required for the reversal, the effect of flows should perhaps be controlled for. In Section 6, we address this issue further by quantifying the implications of flow-induced price impacts on the measurement of hedge fund performance. We show that flow impacts account, on average, for roughly 30% of estimated hedge fund alphas.

To analyze the role of further flows in driving the long-term performance of the high minus low flow portfolio, we present two additional sets of results. First, we trace the difference in flows experienced by high and low month t funds after month t. Second, we reproduce the cumulative outperformance graph for a subset of funds where the aforementioned flow-return cycle is relatively weak. Figure 4 plots the quarterly difference in flows between the high and low month t flow funds for the two years–or eight quarters–following month t.[18]

[Figure 4 here]

The high month t flow funds continue to receive higher flows than the low month t flow funds

[18] We present the results aggregated over three-month periods as some funds only allow for redemptions and/or subscriptions on a quarterly basis. By aggregating the flows we ensure that there is always one calendar quarter end in each observation.

for the two years following month t. The difference is statistically significant for each of the eight quarters, though we argue that flow differences of less than about 5% per quarter are not likely to have an economically significant impact on the return difference. Comparing Figure 4 to Figure 3 suggests a link between the flow and performance gaps. The flow difference is quite large for the first three quarters following month t (between six and 12 percent per quarter). This horizon coincides with the widening of the cumulative performance gap. Thus, the further flows feed the flow-return cycle for around three quarters. Starting from the fourth quarter after month t, the flow difference between month t high and low flow funds is much smaller, and the cumulative outperformance of high flow funds begins to revert.

As the evidence so far points to a strong relation between the future flows and the performance gap between high and low month t flow funds, we perform one more analysis to separate the effect of flow from return reversal. As before, we sort funds according to their month t flows, and trace the return difference between high and low flow funds for the following 24 months. This time, however, we limit the study to funds that receive close-to-zero flows in the following months. For each month $t+k$ (where $k = 1, \ldots, 24$) we sort all funds into three groups according to month $t+k$ flow. From the medium group–which contains the funds with flows closest to zero–we draw the original, month t, high and low flow funds, and record their return difference.[19] This way we attempt to limit the effect of further flows driving returns as in the flow-return cycle discussed previously. Figure 5 presents the differences in risk-adjusted returns for high month t flow and low month t flow funds (left panel), and the cumulative outperformance of the high flow funds over the low flow funds (right panel) for the ensuing 24 months, taking into account only the funds receiving close-to-zero flows after month t.

[Figure 5 here]

This series of return differences–which should be relatively free of further price impact of flows–also displays the one-month continuation of the outperformance by high flow funds. After that, the low flow funds start outperforming the high flow funds consistently (except for the insignificant outperformance of high flow funds during month $t+5$). We interpret the results as follows. First, the widening of the performance gap in month $t+1$ is a result of fund managers investing part of the month t flows only in month $t+1$. Second, and more importantly, a return reversal seems to set in much faster in the absence of further flow-induced price impacts.

Based on all of our long-term results, we conclude that there is no evidence of smart money, and that the reversal of the initial price impact is slowed down by further flow-induced price impacts.

Our results of a positive contemporaneous effect of flows followed by eventual underperformance of initial high flow funds is consistent with a number of recent papers examining returns to strategies employed by hedge funds. Hedge fund flows are found to have a positive effect on the

[19] We sort into only three groups according to month $t+k$ flows to ensure that the medium group contains a sufficient number of period t high and low flow funds.

contemporaneous returns and/or a negative effect on future returns of e.g. value investing Kokkonen and Suominen (2011), stock market liquidity-related strategies (Jylhä, Rinne, and Suominen, 2011), and currency carry trades (Jylhä and Suominen, 2011). Wang and Zheng (2008) provide some evidence of the relation between aggregate-level hedge fund flows and returns.

Our empirical analysis underscores the importance of employing a horizon of sufficient length when interpreting the results. The first six to 12 months of figure 3 could lead us to a very different conclusion. During this period, the performance gap remains relatively stable, with no significant continuation or reversal.

First, the result of equal performance of the month t high and low flow funds is consistent with the seminal model of Berk and Green (2004), where fund flows rationally respond to performance, even though fund managers are unable to produce any excess returns on average. Such a situation arises due to competitive provision of capital, and decreasing returns to scale for managers in deploying their ability. Due to perfect competition, the marginal return on the last dollar invested is zero. Relaxing the assumption of perfectly elastic supply of capital would lead to a setup where funds earn positive risk-adjusted returns, but these returns are equal across funds. The initial outperformance of high flow funds would act to equate expected risk-adjusted returns across funds, with no widening or reversal of the performance gap in the future.

Second, the initial flow-induced price impact with flat future performance difference would be consistent with models of capital-constrained arbitrage, a mechanism that would work as follows. At any given time, hedge funds are not able to fully take advantage of all arbitrage opportunities due to capital constraints. However, upon receiving positive capital inflows, hedge funds invest more heavily in their arbitrage opportunities, leading to a price impact that exhausts the arbitrage (i.e. prices revert to fundamentals). Thus there is no performance difference between high and low flow funds in future periods. Key examples of models incorporating such a mechanism are Shleifer and Vishny (1997), who show that in the presence of noise traders, the price of a security does not necessarily equal its fundamental value, and Gromb and Vayanos (2002), who assert that in segmented markets, the prices of two identical securities can differ even without noise traders.

Third, Ozik and Sadka (2011) find that flows have a permanent effect on fund values, using a subset of funds with share restrictions. They explain this result with a difference in portfolio composition pre and post flow. Ozik and Sadka (2011) posit that price pressure takes place, but the permanent impact is a result of disproportionate trading in assets, due to which the price reversal is not evidenced in the post flow portfolio.

Although a medium-horizon inspection of the results presented in Figure 3 reveals a resemblance to the settings described above, the evidence presented in Figures 4 and 5 shows that further flows, and their impact on prices, play an important role in delaying the reversal of the initial price impact. Thus, we conclude that flow-induced price pressure is, on aggregate, present in hedge fund returns: the initial price impact does eventually revert, but it takes a relatively long time.

5 Relation to performance persistence

In this section, we study the relation between flow impact and performance persistence. The existence of the flow-return cycle presented above raises the question of whether flows have a role in the observed persistence in hedge fund performance. For example, Jagannathan, Malakhov, and Novikov (2010), Kosowski, Naik, and Teo (2007), and Agarwal and Naik (2000) find that hedge fund returns exhibit momentum: past winning funds tend to outperform past losing funds.

The link between the flow-return cycle and momentum is investigated in the context of mutual funds by Lou (2011), who finds that mutual fund flow-based return predictability can fully account for the persistence in mutual fund performance, and partially account for stock price momentum. In other related work, Vayanos and Woolley (2011) present a model for return momentum and reversals, where momentum arises from flows responding gradually to return shocks.

To disentangle flow impact and performance persistence, we present two sets of results: first, we extend the cross-sectional regressions of Table 4 to include the effect of past returns, and second, we study the returns to flow-based and past return-based trading strategies.

In Table 5, we augment the cross-sectional regression results presented in Table 4 of Section 3.2 by including the fund's return over the previous 12 months as an additional explanatory variable. Column 1 repeats column 4 of Table 4 for reference. Column 2 presents the results of regressing returns on past returns and controls.

[Table 5 here]

The coefficient of past returns is positive and statistically significant, confirming that there is momentum in hedge fund returns. Column 3 presents a broad model where returns are regressed on flow, flow sensitivity, their interaction, and past returns. All variables retain their significance, and the changes in the magnitude of coefficients from columns 1 and 2 are relatively small. Hence, we conclude that flow impact and performance persistence are, at least to some extent, separate phenomena.

One potential reason for the finding of performance persistence is the smoothing of reported hedge fund returns. Again, to check that are results are not driven by such smoothing, column 4 reproduces the results of column 3 but using the unsmoothed returns (Getmansky, Lo, and Makarov, 2004) as the dependent variable. The coefficients of flow, flow sensitivity, and the interaction are slightly lower, but retain their level of statistical significance. However, the coefficient of past returns drops from 0.062 to 0.026, and the associated t-statistic drops from 3.89 to 2.09. This result indicates that while both flow impact and momentum coexist also in unsmoothed returns, accounting for smoothing is important when assessing the momentum effect: a part of what appears to be performance persistence may be a reflection of return smoothing.

Our second approach to studying the relation between flow impact and performance persistence is an analysis of trading strategy returns. We form two strategies: one based on flows and the other based on past returns. Our flow strategy, HML_{flow}, holds a long position in the quintile of funds receiving the highest flows, and a short position in the funds receiving the lowest flows.[20] The momentum strategy holds a long (short) position in the quintile of funds with highest (lowest) returns over the preceding 12 months. Neither of these strategies is implementable in practice, but our goal is to study the relation between the two phenomena, not present profitable investment strategies. Table 6 presents the results of regressing returns to both strategies on the seven Fung and Hsieh (2004) risk factors and the return of the other strategy.

[Table 6 here]

Columns 1 and 3 of Table 6 show that both strategies have positive and highly significant risk-adjusted returns. The strategies' returns are correlated, and hence help to explain each other: the coefficient of momentum in the HML_{flow} regression and the coefficient of HML_{flow} in the momentum regression are both positive and statistically significant (columns 2 and 4). Comparing the intercepts of columns 2 and 4 reveals an interesting finding. Even in the presence of momentum, HML_{flow} has a positive and very significant alpha. However, in the presence of HML_{flow}, the alpha of the momentum strategy is not statistically distinguishable from zero. The last result suggests that there are no systematic momentum returns that are not captured by the flow impact.

As a summary of the findings in this section, we conclude that although performance persistence and flow impact are related phenomena, they seem to coexist. If anything, our results support the notion that flows are a driver behind momentum, rather than flow impact being a manifestation of momentum. Our results resonate with those of Coval and Stafford (2007), who find that a flow-based trading strategy offers returns beyond those of a simple momentum strategy. Lou (2011) also concludes that flow-induced price pressure and momentum are distinct phenomena. Our cross-sectional evidence is in line with this: past performance has an effect on returns beyond that of the flow impact.

6 Implications for performance attribution

Having now established that capital flows have a significant impact on hedge fund returns, it is also highly relevant to address the implications this has for hedge fund performance attribution. Coval and Stafford (2007) raise the issue of price pressure and subsequent reversals in the context of evaluating the performance of fund managers. They attest that a portion of performance can be attributed to price pressure, at least over periods of several quarters, and raise the issue of how to control for the price pressure effects in performance measurement. In a similar vein, Khan, Kogan, and Serafeim (2011) also note that persistent price pressure effects have implications for managerial performance evaluation, especially when considering how short-run returns should be rewarded.

[20]Note that this strategy is equal to the difference between the high and low flow funds in our initial flow-based portfolio sorts in Table 2.

To address these concerns, we quantify the impact of flows on alphas by constructing a flow impact factor to augment the Fung and Hsieh (2004) model of seven risk factors. Like above in Section 5, our flow impact factor, HML_{flow}, holds a long position in the quintile of funds receiving the highest flow and a short position in the funds receiving the lowest flow. We also condition the effect of flow impact on the monthly flow experienced by the fund, and estimate the following model for each fund in our sample:

$$r_{i,t} - r_t^f = (\alpha_i^u + \alpha_i^c f_{i,t}) + (\beta_i^u + \beta_i^c f_{i,t}) HML_{flow,t} + \gamma_i' FS_t + \varepsilon_{i,t}, \tag{1}$$

where $r_{i,t}$ is the return of fund i in month t, r_t^f is the risk free rate, $f_{i,t}$ is the net capital flow into fund i during month t, and FS_t is the vector of Fung and Hsieh (2004) factors. The α^u and β^u parameters measure the unconditional risk-adjusted return and exposure to the HML_{flow} factor, respectively. They can be interpreted as the alpha and exposure when flow equals zero. The conditional parameters, α^c and β^c, measure the effect of flows on risk-adjusted return and HML_{flow} exposure, respectively. Table 7 reports the average coefficients of the standard Fung and Hsieh (2004) model and our flow-impact augmented model estimated for the 2,918 hedge funds in our sample. Figure 6 presents the loading of HML_{flow} and the risk-adjusted return as functions of flow, based on the augmented model.

[Table 7 and Figure 6 here]

First, on average, the funds have a significant exposure to all Fung and Hsieh (2004) factors (column 1). The average alpha is equal to 0.55% per month, and is statistically very significant. On average, the standard model explains 34% of the time series variation in hedge fund returns.

The results of the augmented model reveal a number of interesting findings. First of all, the unconditional coefficient of HML_{flow} (β^u above) is positive and very significant. As the effect of HML_{flow} is conditional on flows, this coefficient represents the loading on HML_{flow} when flow is equal to zero. We interpret the positive coefficient in the following way. As hedge fund portfolios are not completely orthogonal, even funds that receive no flows enjoy the price impact of other funds' flows on their holdings.

Second, the coefficient of flows (α^c) is practically zero. This means that there is no significant impact of flows on risk-adjusted performance that is not captured by the conditional loading on HML_{flow}. Hence, HML_{flow} seems to do a relatively good job, on average, in capturing the impact of flows on the returns of individual hedge funds.

Third, the coefficient of the interaction between flow and HML_{flow} (β^c) is positive and significant. This implies that, quite expectedly, the average fund's loading on HML_{flow} depends on capital flows: the larger the flows, the larger the loading. The positive relation between the flow and the coefficient of HML_{flow} is also evident in the left panel of Figure 6.

Finally, and most interestingly, the estimate of alpha (α^u) is significantly lower for the augmented model than for the standard Fung and Hsieh (2004) model. The unconditional alpha of the augmented model is 0.39% per month, roughly 30 percent less than that of the standard model. The difference between the two alphas is statistically very significant (column 3). Again, the risk-adjusted return in the augmented model is conditional on flows. However, the coefficient of flow is virtually zero, and risk-adjusted return is close to the unconditional alpha (0.39%) and below the Fung and Hsieh (2004) alpha for all reasonable values of flow, as is evident in the right panel of Figure 6.

Note that we use forward looking information–i.e. the capital flows–to construct the flow impact factor. Hence, investors cannot replicate the returns to this factor. For this reason, the lower alpha of the augmented model should not be interpreted as hedge fund managers being less skilled than appears to be the case when using the Fung and Hsieh (2004) model. The fact that the average coefficient of HML_{flow} is positive indicates that, on average, hedge funds enjoy the positive flow impacts even during months when they do not receive flows themselves. As this impact cannot be replicated *ex ante*, it could be viewed as managerial skill. However, this skill is not idiosyncratic, but a common trait of hedge funds.

Overall, these results indicate that flows have a major impact on the estimates of risk-adjusted returns. Academics and practitioners should account for the impact when assessing the sources of hedge fund returns. A model such as our augmented framework may result in a very different picture of sources of returns than a standard model without flow impact–especially for funds with sizeable flows or high flow sensitivity.

7 Robustness checks

We perform several robustness checks on our result that high flow funds outperform low flow funds. The results of the various robustness checks are presented in Table 8. The table presents the differences in excess and risk-adjusted returns between high and low flow portfolios. For reference, the first row gives the results for the whole sample, as presented above in Table 2.

[Table 8 here]

7.1 Backfill bias

When hedge funds are included in a database such as TASS, they typically backfill their whole return history into the database. This gives rise to what is commonly referred to as backfill bias: funds with poor performance are less likely to be included in databases, and funds that are included are more likely to have a good track record. This bias could, in theory, affect our results. To check that this is not the case, we perform the flow sort adding the typical backfill bias correction: we only include funds in the analysis after the date they were added to the TASS database. In other words, we do not use the backfilled data at all. The second row of Table 8 confirms that our results are not driven by the backfill bias. In the backfill bias-free subsample, high flow funds outperform low flow funds by 0.42% in excess returns and by 0.46% in risk-adjusted returns.

7.2 Return smoothing

To test that our results are robust to return smoothing, we calculate the average unsmoothed returns of the five flow-sorted portfolios and compare the return difference between the high and low flow portfolios. In order to calculate unsmoothed returns, we again employ the Getmansky, Lo, and Makarov (2004) moving average framework. Row 3 of Table 8 shows the difference in unsmoothed returns, excess and risk-adjusted, for the high and low flow portfolios. The differences (0.39% and 0.40% for excess and risk-adjusted returns, respectively) are somewhat smaller than for reported returns (0.53% and 0.54%), but statistically very significant. This confirms that our key finding is robust to return smoothing. In Section 3.2 we already establish that the results of the cross-sectional regressions are also robust to using the Getmansky, Lo, and Makarov (2004) corrected returns.

7.3 Endogeneity of flows

A second concern may be that flows are endogenous to returns. Our underlying assumption is that infrequent subscriptions and redemptions, lengthy notification periods, and lags in return reporting result in hedge fund investors having to submit their subscriptions and redemptions prior to learning the contemporaneous return. Hence, we treat flow as being exogenous. To alleviate any concerns of endogeneity, we perform two alternative portfolio sorts that should be free of endogeneity issues.

First, we form portfolios based on expected flows rather than realized flows. Our monthly estimate of expected flow is based on a reduced-form VAR model using the past 60 months of data. Hence, our forecast of period t flows is independent of period t returns. The results of this portfolio sort are presented on the fourth row of Table 8. The results based on the expected flow portfolios are similar to those based on realized flow. Again, the return differences are slightly lower (0.34% for both excess and risk-adjusted returns), but statistically very significant. This re-confirms our finding that flows have a positive effect on contemporaneous returns and alphas.

Second, we form portfolios based on realized flows, but only for the sub-sample of hedge funds that are relatively illiquid from an investor's point of view: subscriptions and redemptions are allowed once a month or less frequently, and the notification period is one month or longer. For these funds, by construction, investors must submit their month t flows before learning anything about month t returns. The results are presented on the fifth row of Table 8. For these funds, the outperformance of high flow funds is even stronger than within the full sample: the high minus low differences in excess returns and alphas are 0.60% and 0.63% per month, respectively. Both figures are statistically very significant. This finding can be explained as follows: hedge funds that allow less frequent subscriptions and redemptions are able, if they so choose, to hold more illiquid assets compared to those funds that allow capital flows more frequently. The relative illiquidity of their holdings makes these funds more sensitive to capital flows.

Finally, we identify a completely different way to measure capital flows, based on inception of new fund classes. Many funds have numerous share classes, and there may be a plethora reasons for introducing a new share class into an existing fund. These reasons can be broadly divided into demand-driven and supply-driven reasons. An example of a supply-driven reason is the introduction of a euro-denominated share class to a fund that was previously only available in dollars. A demand-driven inception happens when there is sizeable demand for a new share class with e.g. different terms or domicile. We posit that new share classes that are introduced for demand-driven reasons are likely to start with larger initial capital. This new capital could then have a price impact on the investment strategy as a whole, also affecting the fund's pre-existing share classes. Identifying such demand-driven fund class inceptions provides an alternative setting for testing for flow impact in hedge fund returns.

Identifying the reasons for fund inception is not trivial, as no background information regarding the inceptions is provided in the TASS database. We assume that fund class inceptions that are denominated in the same currency as a pre-existing class are more likely to be demand-driven. We identify a total of 1,132 such fund inceptions with at least 24 months of data available on the pre-existing class prior to the event.[21] We then perform an event study with these events, and compare the returns of the pre-existing funds to the average hedge fund performance during the event month. On average, the pre-existing funds outperform the hedge fund average by 0.31% during the event month. This outperformance is statistically significant with an associated t-statistic equal to 3.05. This result, again, provides further support to our notion that capital flows affect hedge fund returns contemporaneously.[22]

7.4 Different types of funds

To show that the flow effect is not driven by some specific group of funds, we repeat the flow sorting for various subsets of hedge funds. First, on rows 6—9 of Table 8, we sort funds according to their flows within the four broad hedge fund strategies as defined by Agarwal, Daniel, and Naik (2009).[23] A statistically significant positive flow impact is present in three of the four categories. Only in the relative value category the high flow funds do not outperform low flow funds.

As earlier literature has studied flow-induced price pressure in the context of (mainly US) equities, it is interesting to confirm that flow impact is also present in non-equity hedge funds. On the tenth and eleventh row of Table 8, we present the flow impact separately for funds that report they are primarily focused on equities, and funds that do not have a primary equity focus. Though larger for equity funds, the flow effect is statistically and economically significant also for

[21] We require the minimum of 24 prior months of data on the pre-existing fund class to estimate the variance of abnormal returns.

[22] To alleviate any concerns of endogeneity–i.e. new fund classes being launched during months of high strategy return–we repeat the event study for those 414 events that happen on the first day of the month. For these events, the outperformance is equal to 0.66% (t-statistic 3.90). Hence, the result seems not to be driven by endogeneity.

[23] The broad strategies are Directional traders (TASS categories dedicated short bias, emerging markets, and global macro), Relative value (convertible arbitrage, equity market neutral, and fixed income arbitrage), Security selection (long/short equity hedge), and Multiprocess (event driven and multi-strategy).

non-equity funds. This finding is important, as it shows that other asset classes beside equities also exhibit flow-induced price pressure.

On rows 12 and 13 of Table 8, we present the flow impact for leveraged and non-leveraged funds separately. Flow impact is positive and statistically significant in both of these categories. Rows 14 and 15 show that the flow impact is present also regardless of the funds' use of derivatives. Overall, these results suggest that the flow impact is consistently present in various kinds of hedge funds, and that our key results are not driven by some specific groups of funds.

7.5 Different time periods

Finally, we check that the flow impact is consistently present in different time periods. We split the sample period in three equally long sub-periods (five years and eight months each) and present the flow impact for each subperiod on rows 16—18 of Table 8. The flow impact is positive in all three sub-periods, and very significant in the first two. In the last sub-period (May 2005 to December 2010) the alpha of the high minus low flow portfolio is positive (0.26%) but significant only at a 10% level (associated t-statistic equal to 1.94). The low alpha and weak significance are driven by the poor returns to the HML_{flow} strategy in the spring of 2009. Excluding the recent financial crisis period from the last sub-period increases the alpha and makes it statistically significant.

It has been suggested that hedge funds exhibit anomalous December returns (Agarwal, Daniel, and Naik, 2011) and engage in price manipulation at quarter-ends (Ben-David, Franzoni, Landier, and Moussawi, 2011). Hence our last robustness check consists of checking that the flow impact is not driven by returns around year ends or quarter ends. On row 19 of Table 8 we exclude all the Decembers from the sample, on row 20 all Decembers and Januaries, and on row 21 all Marches, Junes, Septembers, and Decembers. The magnitude and significance of the flow impact is not materially affected by these exclusions: high flow funds still significantly outperform low flow funds.

Overall, we conclude from our robustness checks that the impact of flows on hedge fund returns is robust to alternative definitions of flows and returns. Further, the flow impact is a pervasive phenomenon that is not related to any specific fund types or periods of time.

8 Conclusions

In this paper, we study how capital flows affect hedge fund returns. This study is motivated by two observations. First, hedge funds have received large inflows of capital over the past two decades. Second, earlier literature has established that fund flows constitute an uninformed demand shift which may easily affect asset prices. We provide a comprehensive analysis of the asset pricing effects of hedge fund flows.

We present four key results regarding the flow-return dynamics. First, flows have a statistically and economically significant positive effect on contemporaneous returns. When we sort hedge funds in five portfolios based on their contemporaneous flow, high flow funds outperform low flow funds by 0.54% per month. In addition to calendar time portfolios, this effect is significantly present also in monthly cross-sectional regressions and fund-level time series regressions.

Second, the initial flow-induced price impact does revert, but it takes a substantial amount of time: reversal begins, on average, eight months after the flow, and the full price impact takes 20 months to revert. We provide evidence that the delay in the onset of reversal stems from a flow-return cycle. The initial flow exerts price pressure in the fund's underlying assets and has a positive impact on fund returns. Further flows respond to past returns, and the fund receives additional flows, which cause a further price impact, high returns, continued high flows, and so on. Such a cycle is strong enough to override reversal in the medium term. This mechanism and our results are consistent with and extend those presented in the mutual fund context by Lou (2011).

Third, the flow-return cycle contributes to observed persistence in hedge fund performance. As past winners tend to receive higher flows than past losers, the continued good performance of past winners is partially driven by the flow-induced price pressure.

Fourth, we quantify the effect of flows on performance attribution on the level of individual funds. We augment the standard Fung and Hsieh (2004) hedge fund risk factor model with a flow impact factor. We find that the average unconditional alpha falls by roughly 30% when the flow impact is controlled for.

Our results extend the existing literature on fund flow driven price impacts. The existing literature has mainly focused on the US equity holdings of mutual funds. Using hedge fund data, we show that the flow-based phenomena are present also in a wider variety of underlying assets and investment strategies. We also contribute to the hedge fund literature by providing new evidence of hedge funds' impact on their underlying markets and the sources and dynamics of hedge fund returns.

In addition to academics, our results bear relevance for hedge fund practitioners as well. All our key results have implications for fund managers, hedge fund investors, as well as regulators. Probably most interestingly from a practitioners' point of view, we show that the fund-level estimates of hedge fund alphas are significantly affected by flows. Hence, the flow impact should be controlled for when attributing fund performance to managerial skill and factor exposures. This should be highly relevant in at least the contexts of fund selection, fund monitoring, and fund manager compensation.

Appendix A: Measuring flow sensitivity of hedge fund returns

In order to obtain a fund-specific measure of flow sensitivity of returns, we employ a structural vector autoregressive (SVAR) model for flows and returns for each fund separately. Our measure of flow sensitivity is the coefficient of contemporaneous flow in the return equation. We choose to work with a SVAR model as it matches previously reported flow-return patterns well. By including the joint dynamics of flows and returns in the estimation, we are able to control for feedback trading (Fung, Hsieh, Naik, and Ramadorai, 2008), herding (Nofsinger and Sias, 1999), return autocorrelation (Getmansky, Lo, and Makarov, 2004), as well as reversal of potential flow induced price pressure. A simple regression of contemporaneous returns on contemporaneous flows (such as in Ozik and Sadka, 2010) may suffer from omitted variable biases due to exclusion of lagged returns and flows.

We start with reduced-form VAR model with lag length $p = 3$. In the interest of simplicity, we choose the same lag length for each fund and both equations in the VAR. Our general reduced-form VAR is given in Equation 2.

$$\begin{bmatrix} f_t \\ r_t \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \sum_{j=1}^{p} \begin{bmatrix} \Phi_{j,11} & \Phi_{j,12} \\ \Phi_{j,21} & \Phi_{j,22} \end{bmatrix} \begin{bmatrix} f_{t-j} \\ r_{t-j} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}, \tag{2}$$

where r_t is the return in month t, f_t is the net capital flow in month t, and $t = 1, \ldots, T$. The reduced-form system can be written compactly as

$$\boldsymbol{y_t} = \boldsymbol{c} + \boldsymbol{\Phi_1 y_{t-1}} + \cdots + \boldsymbol{\Phi_p y_{t-p}} + \boldsymbol{u_t}, \tag{3}$$

where $\boldsymbol{y_t} = (f_t, r_t)'$, $\boldsymbol{c} = (c_1, c_2)'$, $\boldsymbol{u} = (u_{1t}, u_{2t})'$, and $\boldsymbol{\Phi_1}, \ldots, \boldsymbol{\Phi_p}$ are (2×2) coefficient matrices.

As we are interested in the contemporaneous effect of flows on returns, we proceed with a structural VAR model. The SVAR allows one of the variables to have a contemporaneous effect on the other. We choose to treat flows as depending only on the lagged variables, but having a contemporaneous effect on returns. First, this is the form that allows us to fully examine the impact of flows on returns. Second, we argue that time lags in hedge funds' return reporting, infrequent trading, and lengthy notification periods result in investors submitting their period t flows before learning the period t return.

We now add the contemporaneous flow term to the return equation as follows

$$r_t = c_2^* + A_0 f_t + \sum_{j=1}^{p} \phi_{j,21}^* r_{t-j} + \sum_{j=1}^{p} \phi_{j,22}^* f_{t-j} + \varepsilon_{2t}. \tag{4}$$

In practice, we estimate the matrix $\boldsymbol{A}$ such that

$$\boldsymbol{A} = \begin{bmatrix} 1 & 0 \\ A_0 & 1 \end{bmatrix}$$

and

$$\boldsymbol{A y_t} = \boldsymbol{c^*} + \boldsymbol{\Phi_1^* y_{t-1}} + \cdots + \boldsymbol{\Phi_p^* y_{t-p}} + \boldsymbol{\varepsilon_t}, \tag{5}$$

where $\boldsymbol{c^*} = \boldsymbol{Ac}$, $\boldsymbol{\Phi_j^*} = \boldsymbol{A\Phi_j}$, and $\boldsymbol{\varepsilon_t} = \boldsymbol{Au_t}$. Also, the covariance matrix of $\boldsymbol{\varepsilon_t}$, $\boldsymbol{\Sigma_\varepsilon} = \boldsymbol{A\Sigma_u A'}$ will be diagonal when $\boldsymbol{A}$ is defined as above. In the bivariate case, identification of the structural system requires that one of the possible two contemporaneous terms–in our case, the impact of return on flow–be restricted to zero.

Table A1: **Average VAR coefficients.**

	RVAR: flow	RVAR: return	SVAR: return
Flow (t)			**0.015**
			(3.72)
Flow ($t-1$)	**0.086**	-0.004	**-0.005**
	(23.89)	(-1.67)	(-1.98)
Flow ($t-2$)	**0.055**	-0.003	-0.003
	(17.50)	(-0.96)	(-1.15)
Flow ($t-3$)	**0.108**	-0.004	**-0.005**
	(36.40)	(-1.57)	(-2.03)
Return ($t-1$)	**0.259**	**0.156**	**0.157**
	(2.26)	(38.97)	(38.69)
Return ($t-2$)	**0.382**	**-0.019**	**-0.021**
	(4.36)	(-5.90)	(-6.47)
Return ($t-3$)	**0.248**	**0.014**	**0.015**
	(3.43)	(4.66)	(4.85)
Constant	0.104	**0.695**	**0.672**
	(0.88)	(45.30)	(44.56)

In Table A1, we present the average coefficients of the reduced-form and structural VAR models estimated for all funds using full data. Note that for the flows, the SVAR equation is equal to the reduced-form equation and is hence not repeated in the table. Our key coefficient of interest, namely the coefficient of contemporaneous flow in the SVAR return equation, is on average positive and statistically significant. This results supports the existence of flow-induced price pressure.

In the portfolio sorts and cross-sectional regressions we use the SVAR model to obtain monthly *ex ante* estimates of flow sensitivity. Our estimate of month t flow sensitivity is the coefficient of contemporaneous flow in the SVAR return equation estimated on data from month $t-60$ to $t-1$.[24] This way the month t flows and returns do not affect the month t estimate of flow sensitivity. As negative values of flow sensitivity are not economically meaningful, we truncate the estimates by replacing all negative values with a zero. Table A2 presents the results of sorting

[24]We require a minimum of 36 monthly observations within the 60 month window to perform the estimation.

hedge funds monthly according to their estimated flow sensitivity. The first category contains all those observations where the flow sensitivity is equal to zero. The two other categories split the positive flow sensitivity observations in half. There is no difference in performance between the high and low flow sensitivity funds, indicating that flow sensitivity as such is not a priced risk factor in hedge fund returns. The measure of flow sensitivity, however, turns out to be very useful in double sorts, cross-sectional regressions, and long term analyses.

Table A2: **Flow sensitivity sorted portfolios**

	Lo	Med	Hi	Hi-Lo
Excess return	**0.51**	**0.46**	**0.59**	0.09
	(3.14)	(3.27)	(2.53)	(0.96)
Alpha	**0.33**	**0.28**	**0.34**	0.02
	(3.03)	(3.24)	(2.73)	(0.30)

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Table 1: **Descriptive statistics.** This table gives the descriptive statistics of the key variables used in this study: hedge fund return in USD, hedge fund return in the fund's reporting currency, and net capital flow into the fund. All data is on a monthly frequency. The sample has 2,918 hedge funds and 229,494 fund-month observations. The sample period is 1/1994 through 12/2010.

	Return (USD)	Return (Local)	Net capital flow
Mean	0.92	0.90	1.42
Standard deviation	5.38	5.27	10.77
25th percentile	-0.98	-0.88	-0.81
Median	0.82	0.79	0.05
75th percentile	2.74	2.58	2.32
Skewness	0.63	0.69	2.34
Excess kurtosis	15.75	16.86	17.74

Table 2: **Capital flow and hedge fund returns.** This table presents the returns, excess and risk-adjusted, for five hedge fund portfolios sorted based on contemporaneous capital flow. Capital flow is the realized flow into the funds during the portfolio formation month. All portfolios are updated monthly. t-statistics are given in parentheses, and values in boldface are significant at the five-percent level. The sample has 204 monthly return observations. The sample period is 1/1994 through 12/2010.

	Lo	2	3	4	Hi	Hi-Lo
Excess return	**0.48**	0.08	0.32	**0.72**	**1.01**	**0.53**
	(2.72)	(0.40)	(1.60)	(3.76)	(5.61)	(4.54)
Alpha	**0.29**	-0.15	0.11	**0.53**	**0.83**	**0.54**
	(2.44)	(-1.29)	(0.99)	(4.52)	(6.01)	(5.50)

Table 3: **Flow sensitivity, realized flow, and hedge fund returns.** This table presents the returns, excess (Panel A) and risk-adjusted (Panel B), for 15 hedge fund portfolios sorted based on flow sensitivity and capital flow. Flow sensitivity is measured as the coefficient of contemporaneous flows in the return equation of a structural VAR model using the previous 60 months (from $t-60$ to $t-1$) of data. Capital flow is the realized flow into the funds during the portfolio formation month. All portfolios are updated monthly. t-statistics are given in parentheses, and values in boldface are significant at the five-percent level. The sample has 204 monthly return observations. The sample period is 1/1994 through 12/2010.

Panel A: Excess return		**Flow**					
		Lo	2	3	4	Hi	Hi-Lo
Flow Sensitivity	Lo	**0.77**	0.21	0.31	**0.58**	**0.63**	-0.14
		(4.62)	(1.23)	(1.48)	(3.30)	(4.05)	(-1.26)
	Med	0.20	0.13	0.27	**0.72**	**0.95**	**0.76**
		(1.31)	(0.79)	(1.73)	(4.49)	(6.09)	(5.03)
	Hi	0.18	-0.20	0.40	**0.91**	**1.86**	**1.67**
		(0.71)	(-0.73)	(1.54)	(3.56)	(6.05)	(6.09)
	Hi-Lo	**-0.58**	**-0.42**	0.10	**0.33**	**1.23**	**1.81**
		(-3.61)	(-2.97)	(0.64)	(2.98)	(5.21)	(6.49)

Panel B: Alpha		**Flow**					
		Lo	2	3	4	Hi	Hi-Lo
Flow Sensitivity	Lo	**0.61**	0.00	0.11	**0.40**	**0.46**	-0.15
		(4.66)	(0.03)	(0.82)	(3.52)	(3.77)	(-1.39)
	Med	0.00	-0.08	0.11	**0.60**	**0.80**	**0.80**
		(0.00)	(-0.62)	(1.01)	(5.07)	(4.65)	(5.21)
	Hi	-0.08	**-0.48**	0.15	**0.66**	**1.63**	**1.71**
		(-0.49)	(-2.74)	(0.95)	(4.50)	(5.80)	(6.05)
	Hi-Lo	**-0.69**	**-0.48**	0.04	**0.26**	**1.17**	**1.86**
		(-4.61)	(-3.43)	(0.34)	(2.99)	(5.36)	(6.73)

Table 4: **Cross-sectional regressions.** This table presents the Fama-MacBeth averages of monthly cross-sectional coefficients from regressions of hedge fund returns on capital flow, flow sensitivity, the interaction of flow and flow sensitivity, and controls (fund size (log), fund age, and fund style). Capital flow is the contemporaneous flow into a fund during month t. Flow sensitivity is measured as the coefficient of contemporaneous flows in the return equation of a structural VAR model using the previous 60 months (from $t-60$ to $t-1$) of data. Fama-MacBeth t-statistics are given in parentheses. Values in boldface are significant at the five-percent level. The sample has 2,918 funds and 204 monthly cross-sectional regressions (1/1994-12/2010).

	Reported returns				Unsmoothed returns
	(1)	(2)	(3)	(4)	(5)
Flow	**0.019**	0.000	**0.015**	0.000	-0.006
	(3.33)	(-0.05)	(3.07)	(-0.05)	(-1.34)
Flow sensitivity		**0.017**		**0.020**	**0.016**
		(2.03)		(2.70)	(2.49)
Flow × Flow sensitivity		**0.060**		**0.051**	**0.043**
		(5.68)		(4.54)	(3.71)
Fund characteristics	No	No	Yes	Yes	Yes
Style dummies	No	No	Yes	Yes	Yes
Adjusted R^2	0.005	0.026	0.171	0.186	0.137

Table 5: **Cross-sectional regressions with past return.** This table presents the Fama-MacBeth averages of monthly cross-sectional coefficients from regressions of hedge fund returns on capital flow, flow sensitivity, the interaction of flow and flow sensitivity, past return, and controls (fund size (log), fund age, and fund style). Capital flow is the contemporaneous flow into a fund during month t. Flow sensitivity is measured as the coefficient of contemporaneous flows in the return equation of a structural VAR model using the previous 60 months (from $t-60$ to $t-1$) of data. Past return is the fund's realized return over the past 12 months (from $t-13$ to $t-1$). Fama-MacBeth t-statistics are given in parentheses. Values in boldface are significant at the five-percent level. The sample has 2,918 funds and 204 monthly cross-sectional regressions (1/1994-12/2010).

	Reported returns			Unsmoothed returns
	(1)	(2)	(3)	(4)
Flow	0.000		-0.006	-0.008
	(-0.05)		(-1.42)	(-1.89)
Flow sensitivity	**0.020**		**0.016**	**0.013**
	(2.70)		(2.44)	(2.17)
Flow × Flow sensitivity	**0.051**		**0.044**	**0.037**
	(4.54)		(3.75)	(3.24)
Past return		**0.066**	**0.062**	**0.026**
		(4.10)	(3.89)	(2.09)
Fund characteristics	Yes	Yes	Yes	Yes
Style dummies	Yes	Yes	Yes	Yes
Adjusted R^2	0.186	0.208	0.224	0.166

Table 6: **Flow impact and performance persistence.** This table presents the results of regressing returns to a flow impact strategy on the Fung and Hsieh (2004) factors and the returns to a past return strategy, and the results of regressing returns to a past return strategy on the Fung and Hsieh (2004) factors and the returns to a flow impact strategy. HML_{flow} is the return to a strategy that holds a long (short) position in the quintile of hedge funds with the highest (lowest) contemporaneous net capital flow. Momentum is the return to a strategy that holds a long (short) position in the quintile of hedge funds with the highest (lowest) past return, measured over the previous 12 months (from $t-13$ to $t-1$). Both strategies are updated monthly. t-statistics are given in parentheses, and values in boldface are significant at the five-percent level. The sample has 204 monthly return observations. The sample period is 1/1994 through 12/2010.

	HML_{flow}		Momentum	
Intercept	**0.005**	**0.004**	**0.008**	0.002
	(5.50)	(4.60)	(3.55)	(0.51)
Bond trend	-0.009	-0.002	**-0.038**	-0.027
	(-1.26)	(-0.36)	(-2.09)	(-1.60)
Currency trend	0.004	0.003	0.002	-0.003
	(0.75)	(0.70)	(0.24)	(-0.34)
Commodity trend	0.005	-0.005	**0.058**	**0.052**
	(0.80)	(-0.88)	(2.37)	(2.56)
Equity	**-0.070**	-0.045	-0.155	-0.067
	(-3.09)	(-1.82)	(-1.02)	(-0.49)
Size	**0.101**	0.059	0.258	0.132
	(2.43)	(1.84)	(1.89)	(1.40)
Bond	0.031	-0.018	0.301	0.262
	(0.40)	(-0.23)	(1.23)	(1.45)
Credit	-0.088	0.074	**-0.990**	**-0.880**
	(-0.68)	(0.55)	(-5.16)	(-4.11)
Momentum		**0.163**		
		(5.03)		
HML_{flow}				**1.252**
				(4.48)
Adjusted R^2	0.108	0.287	0.210	0.369

Table 7: **Flow impact and performance attribution.** This table presents the average coefficients of regressing monthly hedge fund returns on the Fung and Hsieh (2004) factors and a flow impact factor (HML_{flow}), contemporaneous net capital flow, and the interaction of HML_{flow} and capital flow. HML_{flow} is the return to a strategy that holds a long (short) position in the quintile of hedge funds with the highest (lowest) contemporaneous net capital flow. The first column presents the standard Fung and Hsieh (2004) results, whereas the second column presents results of a model augmented with the flow impact. The third column gives the difference in the coefficients. Average coefficients with their t-statistics (in parentheses) are presented. Values in boldface are significant at the five-percent level. The sample has 2,918 hedge funds. The sample period is 1/1994 through 12/2010

	(1)	(2)	(2)-(1)
Intercept	**0.548**	**0.389**	**-0.159**
	(35.83)	(23.95)	(-15.02)
Bond trend	**0.003**	**0.005**	**0.002**
	(3.10)	(5.08)	(6.85)
Currency trend	**0.005**	**0.003**	**-0.002**
	(5.82)	(2.98)	(-7.69)
Commodity trend	**0.014**	**0.014**	0.000
	(12.31)	(12.77)	(0.03)
Equity	**0.317**	**0.325**	**0.008**
	(37.02)	(37.91)	(4.61)
Size	**0.102**	**0.079**	**-0.023**
	(15.17)	(12.73)	(-10.53)
Bond	**0.106**	**0.086**	**-0.020**
	(7.66)	(6.21)	(-4.87)
Credit	**0.340**	**0.364**	**0.024**
	(13.04)	(13.11)	(3.01)
HML_{flow}		**0.171**	
		(9.89)	
Flow		0.004	
		(1.51)	
Flow $\times$ HML_{flow}		**0.018**	
		(8.23)	
Adjusted R^2	0.344	0.404	0.060

Table 8: **Robustness checks.** This table presents the difference in returns, excess and risk-adjusted, between hedge funds with high (top quintile) contemporaneous capital flow and low (bottom quintile) flow for various sub-samples of the data. Capital flow is the realized flow into the funds during the portfolio formation month. All portfolios are updated monthly. t-statistics are given in parentheses, and values in boldface are significant at the five-percent level. When not stated otherwise, the sub-samples have 204 monthly return observations with sample period from 1/1994 to 12/2010. See Section 7 for further details about the various sub-samples and their construction.

	Excess Return	t-stat	Alpha	t-stat	
(1)	Full sample	**0.53**	(4.54)	**0.54**	(5.5)
(2)	No backfill	**0.42**	(2.94)	**0.46**	(3.25)
(3)	Unsmoothed returns	**0.39**	(3.35)	**0.4**	(3.24)
(4)	Expected flow	**0.34**	(4.19)	**0.34**	(3.83)
(5)	Illiquid funds	**0.6**	(4.28)	**0.63**	(4.13)
(6)	Directional traders	**0.52**	(2.08)	**0.61**	(2.3)
(7)	Relative value	-0.17	(-1.39)	-0.19	(-1.45)
(8)	Security selection	**1.12**	(5.57)	**1.15**	(6.73)
(9)	Multiprocess	**0.33**	(3.2)	**0.38**	(3.34)
(10)	No equity focus	**0.42**	(3.27)	**0.37**	(3.02)
(11)	Equity focus	**0.66**	(5.17)	**0.72**	(5.85)
(12)	Non-leveraged	**0.71**	(5.42)	**0.73**	(4.92)
(13)	Leveraged	**0.43**	(2.94)	**0.45**	(3.51)
(14)	No derivatives	**0.63**	(4.7)	**0.65**	(4.22)
(15)	Derivatives	**0.36**	(2.66)	**0.36**	(2.25)
(16)	1/94-8/99	**0.62**	(3.46)	**0.78**	(3.99)
(17)	9/99-4/2005	**0.74**	(3.32)	**0.57**	(3.14)
(18)	5/2005-12/2010	0.24	(1.46)	0.24	(1.94)
(19)	No December	**0.51**	(4.38)	**0.53**	(4.41)
(20)	No December, January	**0.52**	(4.3)	**0.54**	(4.53)
(21)	No end-of-quarter	**0.49**	(3.59)	**0.54**	(3.97)

Figure 1: **Coefficient of flow as function of flow sensitivity.** This graph gives the average coefficient of capital flows as a function of flow sensitivity in a regression of hedge fund returns on flows, flow sensitivity, their interaction, and controls (fund size, age, and style dummies). The graph is based on column 4 of Table 4. Capital flow is the contemporaneous flow into a fund during month t. Flow sensitivity is measured as the coefficient of contemporaneous flows in the return equation of a structural VAR model using the previous 60 months (from $t-60$ to $t-1$) of data. The gray area gives the 95% confidence interval. The sample has 2,918 funds and 204 monthly cross-sectional regressions (1/1994-12/2010).

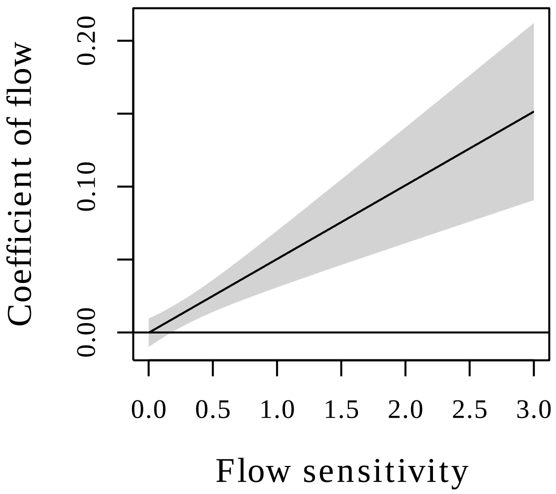

Figure 2: **Monthly return difference.** This figure presents the month-by-month difference in risk-adjusted returns between portfolios of hedge funds with high and low period t flows. The results are presented for all funds (top left panel), low flow sensitivity funds (top right panel), medium flow sensitivity funds (bottom left panel), and high flow sensitivity funds (bottom right panel) separately. Flow sensitivity is measured as the coefficient of contemporaneous flows in the return equation of a structural VAR model using the previous 60 months (from $t-60$ to $t-1$) of data. Capital flow is the realized flow into the funds during month t. Gray bars represent significance at the five-percent level. The sample has 204 monthly return observations. The sample period is 1/1994 through 12/2010.

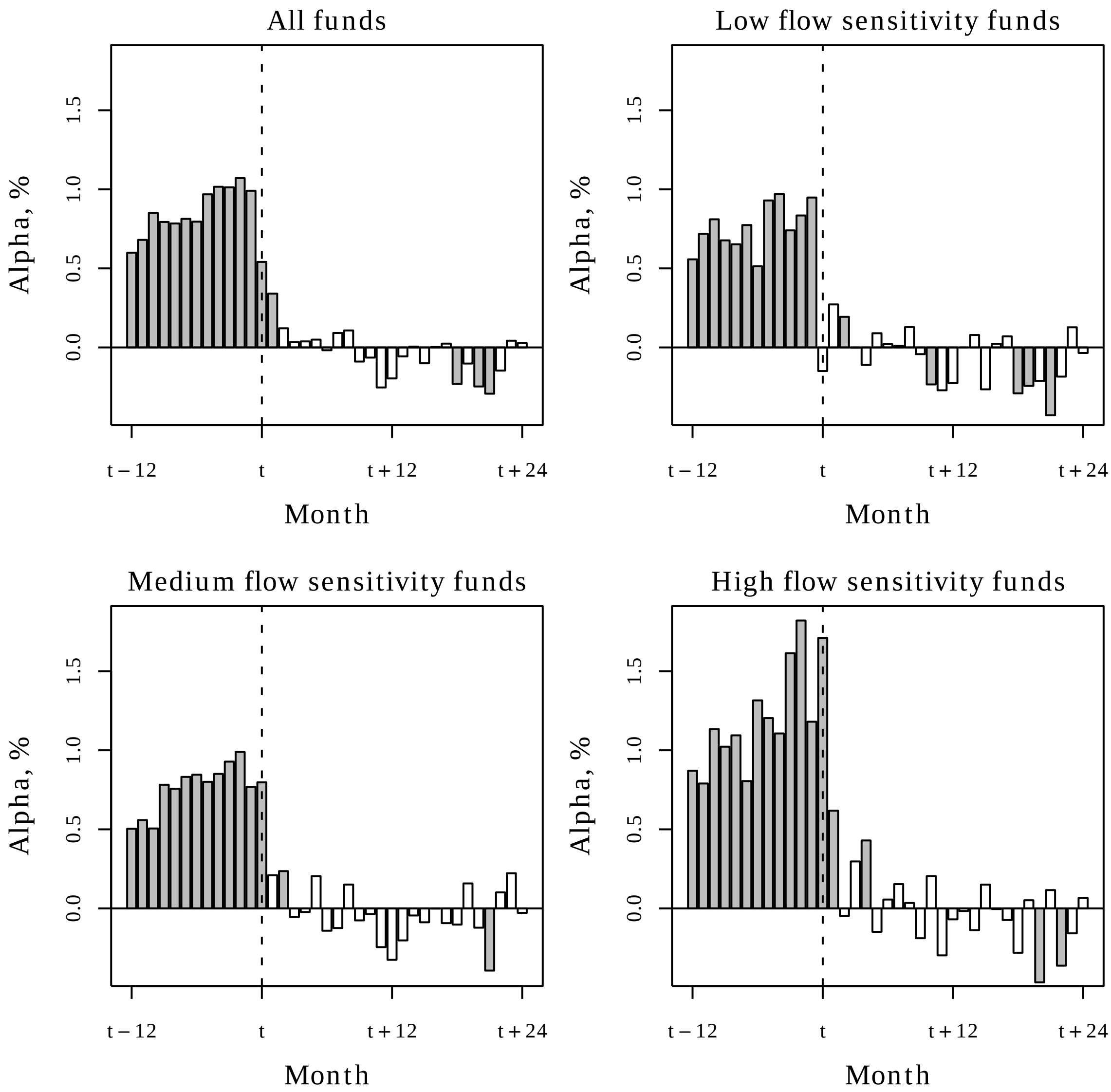

Figure 3: **Cumulative return difference.** This figure presents the monthly cumulative difference in risk-adjusted returns between portfolios of hedge funds with high and low period t flows. The results are presented for all funds (left panel) and the three flow sensitivity categories separately (right panel). Flow sensitivity is measured as the coefficient of contemporaneous flows in the return equation of a structural VAR model using the previous 60 months (from $t-60$ to $t-1$) of data. Capital flow is the realized flow into the funds during month t. The sample has 204 monthly return observations. The sample period is 1/1994 through 12/2010.

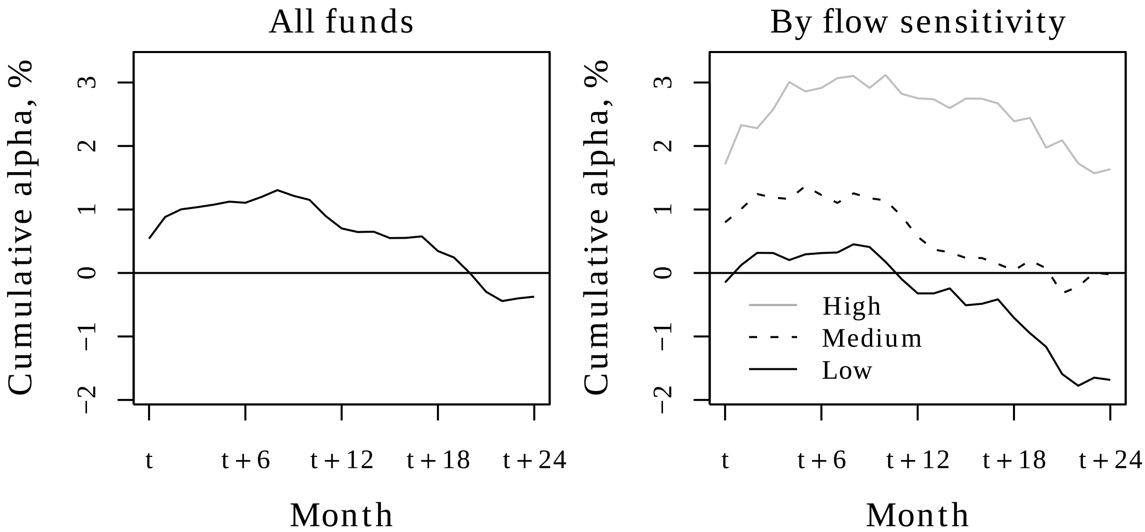

Figure 4: **Flow difference.** This figure presents the average quarterly difference in net capital flows between portfolios of hedge funds with high and low period t flows. Gray bars represent significance at the five-percent level. The sample has 204 three-month flow observations. The sample period is 1/1994 through 12/2010.

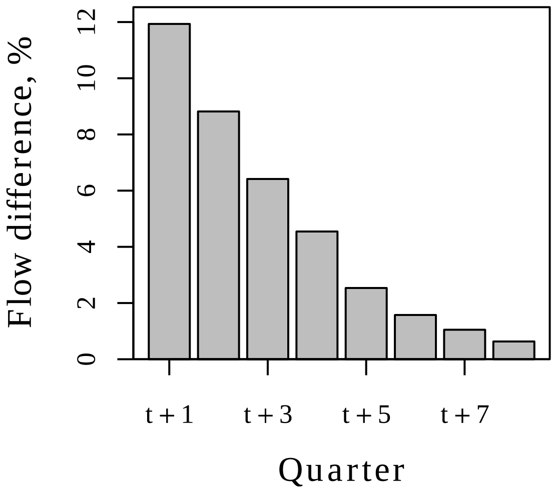

Figure 5: **Return difference in absence of further flows.** This figure presents the difference in risk-adjusted returns between portfolios of hedge funds with high and low period t flows and close-to-zero month $t+k$ $(k=1,\ldots,24)$ flows. The subset of funds is selected separately for each month from the original group of high and low flow funds. The left panel presents the month-by-month difference in risk-adjusted return, and the right column gives the cumulative return difference. Gray bars represent significance at the five-percent level. The sample has 204 monthly return observations. The sample period is 1/1994 through 12/2010.

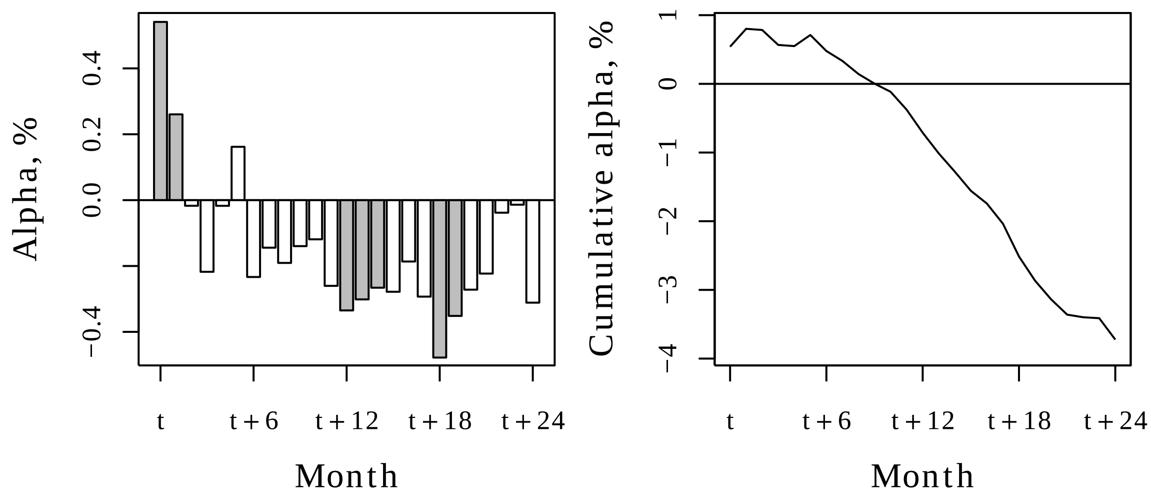

Figure 6: **Coefficient of flow factor and alpha as function of flow.** This graph gives the average coefficient of the flow impact factor (HML_{flow}) and the intercept as functions of capital flow in a regression of monthly hedge fund returns on the Fung and Hsieh (2004) factors, HML_{flow}, capital flow, and an interaction between flow and HML_{flow}. The graph is based on column 2 of Table 7. The gray areas give the 95% confidence intervals. The sample has 2,918 funds and the sample period is from 1/1994 to 12/2010.