CFR-Working Paper NO. 07-09

Do hedge funds manage their reported returns?

V. Agarwal • N. D. Daniel • N. Y. Naik

centre for financial research
Look deeper

Do hedge funds manage their reported returns?

Vikas Agarwal
Georgia State University and CFR

Naveen D. Daniel
Drexel University

and

Narayan Y. Naik
London Business School

September 15, 2009

Vikas Agarwal is from Georgia State University, Robinson College of Business, 35, Broad Street, Suite 1221, Atlanta GA 30303, USA. e-mail: vagarwal@gsu.edu. Tel: +1-404-413-7326. Fax: +1-404-413-7312. Vikas Agarwal is also a Research Fellow at the Centre for Financial Research (CFR), University of Cologne. Naveen Daniel is from Drexel University, Drexel University, LeBow College of Business, 101 N 33rd St., Room 212, Philadelphia, PA 19104, USA. email: nav@drexel.edu. Tel: +1-215-895-5858. Fax: +1-215-895-2955. Narayan Y. Naik is from London Business School, Sussex Place, Regent's Park, London NW1 4SA, United Kingdom: e-mail: nnaik@london.edu Tel: +44-20-7000-8223 Fax: +44-20-7000-8201. We thank Nick Bollen, Joseph Chen (WFA discussant), Stephan Dieckmann, Julian Franks, Gerald Gay, Jason Greene, Jayant Kale, Ron Kaniel, Omesh Kini, Iwan Meier, Lalitha Naveen, Igor Osobov, Henri Servaes, Clemens Sialm, Chester Spatt, Jeremy Stein, Melvyn Teo, Hongjun Yan, and seminar participants at the Conference on Conflicts of Interest in Financial Markets at Vanderbilt University, 2007 Institutional Investors Conference at the University of Texas, Austin, 9th Annual Financial Econometrics Conference on Hedge Funds and Associated Risks at the University of Waterloo, Arizona State University, Drexel University, Georgia State University, HEC Montreal, IAE Sorbonne, London Business School, Rotterdam School of Management, Texas Tech University, University of Delaware, and 2007 Western Finance Association meetings for many helpful comments and constructive suggestions. We especially thank Stefan Nagel for helping us with the holdings data on hedge funds. We are grateful for funding from BSI Gamma Foundation and support from the BNP Paribas Hedge Fund Centre. A significant part of this work was carried out when Vikas Agarwal was visiting the Centre as the BNP Paribas Research Fellow. This research was supported, in part, by a research grant from the Robinson College of Business, Georgia State University. We are grateful to Josh Rosenberg of Hedge Fund Research Inc., Chicago, TASS Investment Research Ltd., London and Zurich Capital Markets, Switzerland for providing us with the data on hedge funds and hedge fund indexes. We thank Bill Fung and David Hsieh for generously providing us the data on hedge fund factors. We are thankful to Burak Ciceksever for excellent research assistance.

Do hedge funds manage their reported returns?

Abstract

For funds with greater incentives and greater opportunities to inflate returns, we find that (i) returns during December are significantly higher than those during the rest of the year even after controlling for risk in both time-series and the cross-section; (ii) this *December spike* is greater than that for funds with lower incentives and opportunities to inflate returns. These results suggest that hedge funds manage their returns upwards in an opportunistic fashion in order to earn higher fees. Finally, we provide strong evidence that funds inflate December returns by under-reporting returns earlier in the year but only weak evidence that funds borrow from January returns in the following year.

Do hedge funds manage their reported returns?

Hedge funds are compensated by incentive fees based on annual performance exceeding prespecified thresholds, which in turn are determined by the hurdle rate and high-water mark provisions. Additionally, better annual performance results in more investor inflows into the fund. Hence, there exist strong incentives for managers to improve performance as the year comes to a close.[1] Using a comprehensive database of hedge funds, we, for the first time, show that hedge funds inflate their reported returns in an opportunistic fashion in order to earn higher fees. This "returns management" phenomenon in hedge funds resembles the well-known "earnings management" phenomenon in corporations.

Since the incentive to inflate returns is highest in December, we first estimate what we term as the "December residual-spike." This is the return in December less the average return from January to November after controlling for risk both in the time-series (examples: factor premiums, factor loadings) and in the cross-section (example: managerial incentives). Consistent with returns management, we find that the magnitude of the December spike is systematically related to the benefits and costs associated with returns management.

We focus on two types of incentives faced by hedge fund managers. First one relates to the promise of rewards for good performance. Second one relates to the threat of penalties in the form of capital withdrawal by investors following poor performance. These incentives motivate funds to report better performance.

To capture the first set of incentives that reward good performance, we recognize that the performance-based compensation contract provides asymmetric call-option-like payoff. We

[1] Incentive fees are paid if year-end net asset value (NAV) exceeds the threshold NAV. With a hurdle rate provision, the manager does not get paid any incentive fee if the fund returns are below the specified hurdle rate, which is usually a cash return like the London Interbank Offered Rate (LIBOR). Thus, the threshold NAV equals year-beginning NAV × (1 + LIBOR). With a high-water mark provision, the manager earns incentive fees only on new profits, i.e., after recovering past losses, if any. Thus, the threshold NAV equals the highest year-end NAV of prior years.

proxy these incentives by the moneyness and delta (pay-performance sensitivity) of the incentive-fee call option as of November-end. Additionally, incentives arise from the flow-performance sensitivity, as investors direct more money into hedge funds that perform better relative to their peer group (see, e.g., Agarwal, Daniel, and Naik (2004)). We proxy these incentives by the performance rank for each fund based on January–November returns relative to its peer group.

To capture the second set of incentives related to penalties for poor performance, we first consider lockup and restriction periods, which determine the severity of threat of capital withdrawals.[2] Shorter lockup and restriction periods imply that investors could withdraw their capital quickly in response to poor performance. Therefore, they act as a disciplining mechanism, which can lead to managers paying excessive attention to short-term performance, thereby providing incentives for returns management. Furthermore, given the flow-performance relation, larger funds that charge higher percentage management fee stand to lose the most from capital withdrawals. We proxy such an incentive by the November-end dollar management fee (= Management Fee Rate × Assets as of November-end). Therefore, taken together, the second set of incentives includes lockup and restriction periods, and the November-end dollar management fee.

In addition to the two types of incentives, arguably funds must also have opportunities to manage returns. For example, funds with higher volatility may be able to hide returns management with greater ease, and therefore may display bigger December spike. Similarly, funds with higher exposure to liquidity risk can more easily influence the prices of securities

[2] Lockup period represents the minimum time the investor has to commit the capital. After the lockup period is over, an investor wishing to withdraw gives advance notice (notice period) and then waits additional time to receive the money (redemption period). Since notice and redemption periods are applied back to back, we combine these two periods, and for expositional convenience simply refer to it as the "restriction period."

they own to inflate the December returns. In light of this, we proxy the opportunities to manage returns by a fund's volatility and a fund's exposure to liquidity risk.

Consistent with returns management, we find that funds with higher incentives (in-the-money, higher delta, top 20% performers, shorter lockup periods, shorter restriction periods, higher $ management fees) and greater opportunities (higher volatility, lower liquidity) (i) exhibit a significantly positive December residual-spike of between 34bp to 70 bp. (ii) this residual-spike is greater than that for funds with lower-incentives and fewer opportunities. Our results are robust to controlling for omitted risk factor, time-varying factor loadings, and the possibility that managers might just work harder in December.

The evidence of returns management begs the following question: What are the mechanisms by which hedge funds manage their returns? We focus on two mechanisms. All else equal, investors direct more money into funds that report a greater fraction of monthly returns that are positive.[3] This provides incentives for the manager to engage in intra-year smoothing of returns so as to maximize the present value of fees. Specifically, the first mechanism would involve funds underreporting positive returns realized during the early part of the year to create reserves which can be added to future returns if they happen to be negative ("saving for the rainy day"). Any unused reserves get added to the December returns when financial audit takes place at the end of the year. This can potentially give rise to a December spike.[4] The second mechanism relates to funds "borrowing" from their future performance to report higher returns in December in order to earn their incentive fees in the current year itself.[5] Funds can push up the

[3] Later, we provide evidence in support of this investor behavior.
[4] It is important to note that "saving for the rainy day" is associated with December spike only when the fund has had significant positive returns in the earlier part of the year to create reserves. If that is not the case, the manager would be tempted to inflate returns earlier in the year resulting in lower December returns. Our empirical tests later in the paper account for these reserves.
[5] In the context of earnings management in corporate firms, DeGeorge, Patel, and Zeckhauser (1999) document saving and borrowing behavior, which they refer to as "saving for a better tomorrow" and "borrowing for a better today". Bergstresser and Phillipon (2006) document inter-year smoothing of earnings by corporations.

security prices at December-end by last-minute buying. This is followed by price reversals in January, which effectively amounts to borrowing from January returns. We find strong evidence in support of savings hypothesis but only weak evidence in favor of borrowing hypothesis.

Our findings contribute to the literature that explores the effect of managerial incentives for earnings management (Healy, 1985; Bergstresser and Phillipon, 2006; Burns and Kedia, 2006). We are the first to show a similar effect in hedge funds. Our findings have important implications for hedge fund regulators and investors. Recently, the Securities and Exchange Commission (SEC) has been especially concerned about issues related to accurate valuation of securities in hedge fund portfolios.[6] Return management behavior in hedge funds is important from the point of view of investor welfare, too. If some hedge funds inflate returns in December, investors cashing out at year-end benefit at the cost of those entering and remaining in those funds. Further, if funds save for the rainy day by underreporting in the earlier part of the year, investors cashing out earlier may lose to other investors. Hence, investors entering and leaving the fund at different points in time may get systematically rewarded or penalized as a result of returns management by hedge funds. Our findings can help regulators and investors spend their limited resources to pay particular attention to funds with higher incentives and greater opportunities to manage returns.

The remainder of the paper is organized as follows. Section II shows how our investigation contributes to the existing literature. Section III presents testable hypotheses. Section IV describes the data and construction of variables. Section V demonstrates how we estimate the December spike. Section VI provides evidence relating to the tests of our key hypotheses while Section VII discusses the robustness of our results to several alternative

[6] In roundtable discussions held at the SEC office in 2003, one of the panel discussions exclusively focused on issues associated with *valuation*, allocation, use of commissions, and personal trading. See http://www.sec.gov/spotlight/hedgefunds/hedgeagenda.htm for more details.

interpretations. Section VIII sheds light on the modus operandi of returns management. Section IX offers concluding remarks.

II. Related Literature

Our study contributes to the literature on earnings management and executive compensation by documenting returns management in hedge funds and its relation to economic incentives and opportunities available to the manager to engage in such an activity.

There exists a large literature on earnings management in corporations.[7] It shows that firms manage earnings toward specific earnings thresholds (see, e.g., Burgstahler and Dichev (1997), DeGeorge, Patel, and Zeckhauser (1999), and Daniel, Denis, and Naveen (2008)). In particular, it shows that firms, *inter alia,* manage earnings to avoid reporting losses, avoid earnings decline, or meet dividend thresholds. In case of hedge funds, the threshold to earn incentive fees is the strike price of the option-like incentive fee contract, and the returns necessary to meet that threshold represents the moneyness of the option. Our investigation shows that the magnitude of December spike in hedge funds is larger for funds with in-the-money and near-the-money options relative to those with out-of-the-money options. This is similar to the results of Efendi, Srivastava, and Swanson (2007), who document that the likelihood of misstating financial statements to boost stock prices increases when the CEO owns a sizable holding of in-the-money options.

The present study also adds to the executive compensation literature examining the relation between earnings management and incentives from compensation.[8] Healy (1985) and Gaver, Gaver, and Austin (1995) relate managers' accrual policies with incentives arising from

---

[7] See Healy and Wahlen (1999), Dechow and Skinner (2000), Fields, Lys, and Vincent (2001), and Stolowy and Breton (2004) for surveys on this literature.

[8] See Murphy (1999) and Core, Guay, and Larcker (2003) for surveys of the literature on executive compensation.

their bonus contracts. Goldman and Sleazak (2006) provide theoretical underpinnings for why stock-based compensation can induce earnings management. Although stock-based compensation motivates the managers to exert more effort, it can also tempt them to exaggerate their performance. Burns and Kedia (2006) find that the delta of CEO's option portfolio is positively related to the propensity of misreporting. We contribute to this strand of literature by establishing a link between incentives and returns management in a different setting. Specifically, we show that hedge funds with higher delta of their call-option-like incentive fee contracts exhibit a larger December spike.

While documenting the December spike and returns management in hedge funds, we control for well-documented year-end effects in mutual fund returns. For example, Carhart et al. (2002) show that mutual funds trade strategically in the securities they hold to inflate their year-end portfolio prices. To the extent that hedge funds hold the same securities as mutual funds, their returns can also get passively inflated in December. However, unlike mutual funds, hedge funds have explicit incentives at year-ends from their asymmetric performance-linked incentive fee contracts. Hence, hedge funds may be tempted to actively inflate their year-end returns in order to earn their incentive fees. Our finding that the magnitude of spike at year-end relative to that at quarter-ends is substantially higher for hedge funds compared to mutual funds is consistent with this conjecture. Our results therefore highlight the differences between mutual funds and hedge funds, and the important role of incentives in year-end effects.

Chandar and Bricker (2002) study earnings management in closed-end mutual funds through discretion in valuation of restricted securities. Discretion of this sort in financial reporting is likely to be higher for hedge funds that invest in relatively illiquid securities. When we examine the relation between liquidity and returns management, we find that hedge funds with greater exposure to illiquidity exhibit higher December spike.

Finally, our paper complements the literature on return smoothing by hedge funds. Getmansky, Lo, and Makarov (2004) show positive autocorrelations in monthly returns and attribute it to hedge funds' exposure to illiquidity and potential smoothing of returns. Bollen and Krepely (2007) demonstrate that it is difficult to detect intentional smoothing of returns by looking at autocorrelations. In this paper, we uncover one of the effects of return smoothing on hedge fund return distribution. We argue that hedge funds can intentionally smooth returns during the earlier part of the year by underreporting their positive returns (saving for the rainy day). This, in turn, can potentially result in December spike when the underreported returns get added back at year-end when financial performance is audited.

III. Hypotheses Development

Like shareholders of corporate firms, hedge fund investors also face an agency problem. Hedge funds try to mitigate the agency problem by offering hedge fund managers performance-linked compensation (incentive fees), often subject to the hurdle rate and high-water mark provisions. The incentive fee resembles a call option on the net asset value (NAV), making it similar to the option-based compensation of top executives in corporations. Although such a compensation scheme motivates the manager to exert effort and improve fund performance, it can also tempt the manager to inflate returns to earn greater incentive fees.

In addition to the explicit incentives embedded in the compensation contracts, fund managers also face implicit incentives to improve their yearly performance. It is well-known that capital flows into hedge funds are positively related to prior annual performance (see e.g., Agarwal, Daniel, and Naik (2004)). Greater assets under management would also yield higher compensation arising from asset-based management fees. Thus, hedge funds face both explicit as well as implicit incentives to inflate returns.

Typically, incentive fees are paid once a year based on annual performance. As the year draws to a close, the manager is better able to judge whether the fund's performance will be sufficiently greater in the remaining periods such that the year-end NAV will be greater than the threshold NAV. This suggests that if the manager is close to the threshold NAV or above it, he is likely to engage in returns management to benefit from additional incentive fees. Such returns management is more likely to get reflected in December, the last month of the year. Thus, after controlling for several fund characteristics that have been shown to affect returns, we expect December returns should be higher than the average returns during the other 11 months. We term this the "*December return-spike*." Additionally, we also control for the possibility that fund returns in December could be high because factor premiums could be high in December during our sample period and funds could actively increase their risk exposures in December to improve year-end performance. We term the difference in return between December and the rest of the year after including such additional controls as the "*December residual-spike*." Of course, this December spike (be it return-spike or residual-spike) will be observed only for the subsample of funds who have the incentives and the opportunities to manage returns, and not for the overall sample. This yields our first hypothesis.

Hypothesis 1: For funds with higher incentives and greater opportunities to manage returns, December return-spike and residual-spike should be positive.

We expect the December spike to be related systematically to the costs and benefits of returns management. We develop these hypotheses here. As discussed in Section II, we know from the earnings management literature that incentives can arise from thresholds in case of corporations. We also know that incentives arise from the pay-for-performance sensitivity (delta) of the executive compensation contract. Drawing from these insights, we use the distance from the threshold (moneyness) and delta of the call-option-like incentive fee contract to proxy for the explicit incentives faced by hedge funds. For example, if by November-end, the call option of a fund is deep out of the money, inflating returns in December might not help to earn any incentive fee for the year. Hence, one would expect the in-the-money and near-the-money funds to exhibit greater December spike compared to the out-of-the-money funds. Further, we also expect funds with greater pay-performance sensitivity (or higher delta) to exhibit greater December spike because managers of such funds stand to gain more from returns management. In addition to the explicit incentives induced by the incentive fee contract, the response of investors' capital flows to prior performance provides implicit incentives to engage in returns management. We therefore expect that funds with superior relative performance should have higher incentives to inflate year-end returns.

Both the explicit and implicit incentives discussed above motivate the fund to inflate year-end performance due to the promise of increased compensation. However, there exist other contractual features such as lockup and restriction periods that exacerbate the penalties for poor performance, and hence provide incentives to manage returns. For example, funds with shorter lockup and restriction periods can experience rapid capital outflows subsequent to poor performance. This can result in excessive attention being paid to short-term performance, thus providing incentives for returns management. Furthermore, larger funds that charge higher percentage management fee stand to lose the most from capital withdrawals. Thus, we expect funds with high dollar management fee at November-end, computed as the product of percentage management fee and the size of the fund at that time, to have greater incentives to inflate December returns.

In addition to the incentives to inflate returns, funds must also have the *opportunities* to engage in this behavior. Arguably, hedge funds with more volatile trading strategies have greater opportunities to inflate returns, because it may be more difficult for investors to detect such an activity in more volatile funds. Furthermore, hedge funds that trade in relatively illiquid securities have better opportunities to influence the prices of securities they own, sometimes for the purpose of inflating returns.[9] These arguments provide us with our second hypothesis:

Hypothesis 2: All else equal, funds that have higher incentives (higher moneyness, higher delta, higher relative performance, lower lockup and restriction periods, and higher dollar management fee) should exhibit greater December spikes. Further, funds with greater opportunities (higher volatility and lower liquidity) should also exhibit greater December spikes.

If we find evidence in support of Hypotheses 1 and 2, we could then say that hedge funds engage in returns management. It would then be natural to explore the mechanisms they employ to manage their returns. It is conceivable that hedge funds "*save for the rainy day*" and create reserves by underreporting positive returns earlier in the year and use them during bad months to avoid reporting losses. In the case of hedge funds, the tendency to create reserves could be driven by investors' preference for funds with fewer loss-making months. While saving for the rainy day does not lead to higher reported annual returns and hence higher incentive fees in the current year, it could lead to higher fees in the future. In Appendix B, we provide empirical evidence that, all else equal, higher the number of months within a calendar year in which the fund reports positive returns, greater is the capital that investors put into the fund. The resulting increase in assets under management will lead to higher fees in the future, and hence funds have an incentive to engage in such behavior. In case some reserves remain unutilized by the end of the year, the manager is forced to include them in December due to auditing reasons, thus leading to

[9] Recently, declining valuations of securities backed by subprime mortgages have fueled the debate on accurate valuation of illiquid securities. Pulliam, Smith, and Siconolfi (2007) discuss this issue in their *Wall Street Journal* article and how this can provide incentives to "inflate marks." Their article also mentions the three levels of precision set by the Financial Accounting Standards Board (FASB) ranging from the most precise method of "marking to market", followed by "marking to matrix", to the least precise method of "marking to model" to value securities.

the December spike. This leads us to our third hypothesis.

Hypothesis 3 (Savings Hypothesis): All else equal, December returns should be higher when reserves leading up to December are higher.

It is well-documented that mutual funds push up the prices of securities they hold at December-end by creating a short-term price pressure through purchases during the last few minutes of trading on the last day of the year (see e.g., Carhart et al. (2002), Bernhardt and Davies (2005)). This is followed by price reversals in January, which effectively amounts to *borrowing* from January returns. It is plausible that hedge funds borrow from January returns in a similar fashion.[10] By doing so, funds can earn their incentive fees earlier. This provides us with our fourth hypothesis.

Hypothesis 4 (Borrowing Hypothesis): All else equal, higher hedge fund returns in December should be followed by lower returns in January of the following year.

We expect hypotheses 3 and 4 to hold for the subsamples of funds with high incentives and opportunities, and not necessarily for the overall sample. Having developed our hypotheses, we next describe the data and key variables that we use to test these four hypotheses.

IV. Data and Variable Construction

IV.A. Data Description

In this paper, we construct a comprehensive hedge fund database that is a union of five large databases, namely, Center for International Securities and Derivative Markets (CISDM), Hedge Fund Research (HFR), Morgan Stanley Capital International (MSCI), Tremont Advisory Shareholder Services (TASS) (now Lipper), and Eureka. The databases report net-of-fee monthly

[10] Another way that the hedge fund manager could borrow from future returns is by selling deep out-of-the-money put options on the index and delta-hedging them in December. Selling the puts generates income up front, while the cost of replication through dynamically delta-hedging is incurred over a period that can extend beyond December. However, this argument assumes that the computation of NAV does not account simultaneously for both the short position in the option and the delta-hedge component.

returns, assets under management, and fund characteristics, such as hurdle rate and high-water mark provisions, lockup, notice, and redemption periods, incentive fee rate, management fee rate, inception date, and fund strategy.[11] This enables us to resolve occasional discrepancies among different databases as well as to create a sample that is more representative of the hedge fund industry. Our sample period extends from January 1994 to December 2006. We focus on post-1994 period to mitigate potential survivorship bias, as most of the databases start reporting information on "defunct" funds only after 1994.[12] After merging the four databases, we find that there are 11,305 hedge funds: 6,976 remained live as of December, 2006 while 4,329 became defunct during our sample period. In Figure 1, we report the overlap among the five databases with a Venn diagram. It highlights the fact that there are a large number of hedge funds that are unique to each of the four databases. 70.4% of the funds come from just one of the five databases and less than 1% of the sample belongs to all five databases. Merging them, therefore, helps to capture a more representative sample of the hedge fund universe. As in Agarwal, Daniel, and Naik (2009), we classify funds into four broad strategies: Directional, Relative Value, Security Selection, and Multi-Process Traders.

IV.B. Measures of Performance

We consider two performance measures for our study. Our first measure is gross return of fund *i* in month *m*, $\text{Returns}_{i,m}$, where *m* runs from January 1994 to December 2006. We compute the gross-of-fee returns from net-of-fee returns following the methodology of Agarwal, Daniel, and Naik (2009). The reason for using gross-of-fees returns instead of net-of-fee returns is to mitigate any problems created by the path dependency in the computation of incentive fees,

[11] The database provides information on contractual features as of the last date for which the fund's data is available. Following previous researchers, we assume that these contract features hold throughout the life of the fund. Discussions with industry experts suggest that this is a reasonable assumption, as it is easier for a manager to start a new fund with different contract terms instead of going through the legal complications of changing existing contracts with numerous investors.

[12] As in Fung and Hsieh (2000), defunct funds include those that are liquidated, merged/restructured, and funds that stopped reporting returns to the database vendors but may have continued operations.

which can induce smoothing in net-of-fee monthly returns (see Getmansky, Lo and Makarov (2004)). Gross returns do not suffer from this problem. In the rest of the paper, for brevity, we simply refer to gross returns as returns. For robustness, we repeat our analysis using net-of-fee returns and obtain similar inferences (we report these results in Section VII).

To test for December spike, we need to control for the systematic risks of hedge funds. Hence we employ a second measure, $Residual_{i,m}$, which is the residual return of fund *i* during month *m*. For this purpose, we estimate fund-level time-series regressions of excess returns on the seven factors of Fung and Hsieh (2004).[13] This is in the spirit of Bollen and Krepely (2007), who estimate the predicted returns from Fung and Hsieh's (2004) seven-factor model and define it as the nondiscretionary component of hedge fund returns. Thus, the residuals can be thought of as the discretionary component of returns over which the manager may be able to exercise influence. The motivation behind this measure is analogous to that for the discretionary accruals in earnings management literature, which are defined as the residuals from a regression of accruals on explanatory variables (such as change in sales etc.) that are predicted to be related to accruals (see for example, Jones (1991) and Ball and Shivakumar (2006)).

In Table I, we report the summary statistics of the performance measures. We find that the mean monthly gross fund returns are 1.15%. As expected, the average monthly residuals are virtually zero.

IV.C. Measures of Risk Exposures

As hedge fund returns are available only on a monthly basis, it is difficult to use a time-series approach to estimate the month-to-month risk exposures using a multifactor model. Therefore, we use a cross-sectional approach to determine the variation in risk exposures over time. In particular, each month, we compute $CS\ Volatility_m$, the cross-sectional dispersion in

[13] Our results are robust to computing residuals using a nine-factor model by augmenting the Fung and Hsieh (2004) seven-factor model with book-to-market and momentum factors. We also report these results in Section VII.

returns of N hedge funds during month m, as $\sqrt{\sum_{i=1}^{N}(r_{i,m}-\overline{r}_m)^2}$ where $r_{i,m}$ is the return of fund i in month m, and $\overline{r}_m$ is the cross-sectional average of fund returns in month m.[14] If funds increase their risk exposures, then CS Volatility$_m$ will increase. Hence, we use CS Volatility$_m$ to proxy for the risk exposures. From Table I, we observe that the mean (median) cross-sectional volatility of funds' monthly returns is 7.81% (6.43%). As an alternative to cross-sectional volatility, in Section VII, we allow funds to vary their risk exposures to market factor on a monthly basis. Our results reported later with this control are qualitatively similar.

IV.D. Measures of Incentives to Manage Returns

Goetzmann, Ingersoll, and Ross (2003) point out that the incentive fee contract in hedge funds provides the manager with a call option and theoretically model the value of this option. When a hedge fund receives capital flows at different points in time, the incentive fee contract resembles a *portfolio* of call options, where each option is related to the capital inflow at a given point in time and has its own strike price (dictated by the NAV at the time of entry and whether the fund has hurdle rate and high-water mark provisions). Following the insights of Goetzmann, Ingersoll, and Ross (2003), we empirically estimate the moneyness and delta of this portfolio of call options using the methodology of Agarwal, Daniel, and Naik (2009).

Our first measure of returns management incentives is related to the moneyness of the call option portfolio. To construct this, we keep track of the capital flows into each fund and the corresponding NAV (the spot price S). We then compute the exercise price (X) of each option (reset at the beginning of each year) depending on hurdle rate and high-water mark provisions.

[14] Cross-sectional dispersion has been studied in different contexts in the extant literature. For example, Solnik and Roulet (2000) use dispersion in country index returns to improve estimates of correlation between country markets, Silva, Sapra, and Thorley (2001) relate dispersion in security returns to dispersion in fund performance, while Campbell, Lettau, Malkiel, and Xu (2001) discuss the relation between dispersion and stock volatility at the index and individual security levels .

Finally, we compute the moneyness of each option as the difference in the spot price and exercise price, divided by the exercise price, (i.e., $(S - X)/X$). This implies that the moneyness of the portfolio of call options would then be equal to the weighted-average moneyness of different options granted by investors' capital inflows at different points in time.

Our *Hypothesis 2* states that funds that are in the money and near the money are more likely to engage in returns management compared to funds that are out of the money. For this purpose, we categorize funds into three groups based on the moneyness at the end of November. We first compute the mean (μ) and standard deviation (σ) of a fund's returns using the entire data in our sample. We provide an example to illustrate our classification algorithm. Suppose a fund has μ and σ of 1% and 5%. This fund is deemed to be *near the money* if its moneyness lies between –6% $[-(\mu + \sigma)]$ and +4% $[-(\mu - \sigma)]$. Following this example further, if the fund's moneyness is greater than +4%, we define it to be *in the money,* and if the fund's moneyness is less than –6%, we define it to be *out of the money*. It is important to note that the use of μ and σ for categorizing funds based on moneyness does not depend on the normality of fund return distribution. In fact, during our sample period, we find, on average, 32% of the funds are near the money, 43% are in the money, and remaining 25% are out of the money, suggesting that the return distribution is far from normal. Furthermore, in Section VI, we use alternative procedures to classify funds based on their moneyness and demonstrate that our results are robust to different classification criteria.

Our second measure of returns management incentives is the delta of the portfolio of call options endowed to the fund by the incentive fee contract. The delta of each of the call options depends on the current NAV (S), the threshold NAV that must be reached before the manager can claim an incentive fee (X), and other fund characteristics, such as the fund size and fund volatility. We follow Agarwal, Daniel, and Naik (2009) to compute the delta as of the end of each month, which equals the expected dollar change in the manager's compensation for a one-percent change in the fund's month-end NAV. From Table I, we find that the mean (median) delta equals $210,000 ($4,000).[15]

Our third measure of incentives is the fractional rank of the fund at November-end of each year. For this purpose, we follow Sirri and Tufano (1998) and assign a fractional rank between 0 and 1 (1 being the best) to each fund every year based on its January–November returns relative to other funds following the same strategy. We notice in Table I, as expected, the mean fractional rank as of November-end is 0.5.

As discussed before, moneyness, delta, and fractional rank capture incentives that reward good performance. Our next three measures of incentives belong to the group of incentives that penalizes poor performance. The first two of these returns management incentives are lockup period and restriction period. From Table I, we observe that the mean lockup period (restriction period) is 0.16 (0.28) year. Our last measure is the dollar management fee at the end of November. From Table I, we observe that the average fee is $2.34 million.

IV.E. Measures of Opportunities to Manage Returns

Our first measure of opportunities for returns management is fund volatility. From Table I, we observe that the mean (median) fund volatility is 4.20% (3.10%). Our second measure of opportunities is the liquidity of each fund, which we capture by its exposure to the liquidity risk factor of Pastor and Stambaugh (2003). For this purpose, we estimate fund-level time-series regression of excess returns on the seven factors of Fung and Hsieh (2004), augmented with the liquidity risk factor.[16] A higher beta on the liquidity risk factor implies that the fund has greater

[15] Coles, Daniel, and Naveen (2006) report the mean (median) delta of executive stock options for the top 1500 firms in S&P during 1992–2002 to be $600,000 ($206,000).

[16] We use value-weighted liquidity risk factor for our analysis. All our results are robust to the use of equally-weighted liquidity risk factor.

exposure to illiquidity and therefore is more illiquid.[17] From Table I, we observe that the mean (median) of the liquidity beta is 0.05 (0.01). The interquartile range of liquidity beta is 0.18 (i.e., 0.11 – (–0.07)) suggests that there is considerable cross-sectional variation in the liquidity risk exposure across different hedge funds.

IV.F. Measures of Reserves

To test our *Savings Hypothesis*, we construct a measure of reserves. We define $\text{Reserves}_{i,m-1}$ to be the cumulative return from January of each year up to month $m-1$ of the same year if positive, and to be zero otherwise. Since the reserves can *only* be used to spike December returns if they are actually available, we consider only the positive cumulative returns. From Table I, we observe that the mean (median) of the reserves variable is 8.11% (3.25%).

Having described the salient features of our data and our key variables, we now proceed with the tests of our hypotheses.

V. December Spike

Tests of our hypothesis requires us to first estimate the December spike in a multivariate setting that controls for risk in both the time-series and cross-sectional settings. Before conducting multivariate analysis, we provide in Table II, a univariate comparison of gross returns and residual returns of hedge funds in our sample for December and the monthly average during the rest of the year (January–November). Results from *t*-tests suggest that the average gross returns in December are significantly greater than those for the rest of the year. The December return-spike is 1.26%. This spike could be partly due to factor premiums being higher in December (see table). After controlling for this, we find the December residual-spike to be 0.44%. Although the factor premiums are higher in December, our findings of a significant

[17] It is the overall liquidity of the fund portfolio rather than the systematic liquidity (proxied by liquidity beta) that affects the opportunities to manage returns. We assume that overall liquidity and systematic liquidity are correlated.

December spike in residual returns suggest that higher factor premiums in December cannot completely explain this pattern.

Figure 2, Panels A and B illustrate the December return and residual for each of the 13 years of our sample. We find that the return-spike exists for 11 of 13 years (exception: 1994 and 1996) and the residual-spike exists for 10 of 13 years (exceptions: 1994, 1996, and 2000). Thus, the phenomenon we document is wide-spread and is not driven by a small subsample of years. Figure 2, Panel C illustrates the monthly average return and residual. We find that the return in December is the highest of the 12 months and the residual in December is the 2nd highest.[18] Thus, the spike appears to be driven by return inflation in December.

V.A. Multivariate analysis using gross-of-fee returns and residuals

In this section, we extend our analysis to a multivariate setting after controlling for fund characteristics, strategy and year effects. In particular, we estimate the following regression:

$$\begin{aligned}\text{Return}_{i,m} = {} & \lambda_0 + \lambda_1 I(\text{December}) + \lambda_2 I(\text{Non-Dec Quarter-End}) + \lambda_3 (\text{CSVol})_m \\ & + \lambda_4 \text{Delta}_{i,m-1} + \lambda_5 \text{Moneyness}_{i,m-1} + \lambda_6 \text{Lockup}_i + \lambda_7 \text{Restrict}_i \\ & + \lambda_8 \text{Size}_{i,m-1} + \lambda_9 \sigma_i + \lambda_{10} \text{Age}_i + \lambda_{11} \text{MFee}_i + \lambda_{12} \text{Return}_{i,m-1} \\ & + \lambda_{13} \text{Return}_{i,m-2} + \sum_{s=1}^{3} \lambda_{14}^{s} I(\text{Strategy}_{i,s}) + \sum_{k=1994}^{2006} \lambda_{15}^{k} I(\text{Year}_{t,k}) + \xi_{i,m}\end{aligned} \tag{1}$$

where $\text{Return}_{i,m}$ is the gross-of-fee return of fund *i* in month *m*, $I(\text{December})$ is an indicator variable that takes the value 1 if '*m*' is December, and 0 otherwise, $I(\text{Non-Dec Quarter-End})$ is an indicator variable takes a value of 1 if the month corresponds to a quarter-end other than December, (i.e., March, June, or September), and equals 0 otherwise, CSVol_m is the cross-sectional volatility during month *m*, $\text{Delta}_{i,m-1}$ is the sensitivity of the managers' wealth to a 1%

[18] We also compare each month's gross return and residual to the gross return and residual in December. We find the December gross return to be significantly higher in each of the 11 pair-wise comparisons and the December residual to be significantly higher in 9 out of 11 cases.

change in NAV for fund *i* as of end of month *m-1*, $\text{Moneyness}_{i,m-1}$ of fund *i* at the end of month *m-1*, Lockup_i and Restrict_i are the lockup and restriction periods for fund *i*, $\text{Size}_{i,m-1}$ is the size of the fund measured as the natural logarithm of the assets under management (AUM) for fund *i* for month *m-1*, σ_i is the standard deviation of prior year's monthly returns of fund *i*, Age_i is the age in years of fund *i* at the end of prior year, MFee_i is the management fee rate charged by fund *i*, $I\left(\text{Strategy}_{i,s}\right)$ are strategy dummies that take the value 1 if fund *i* belongs to strategy *s*, and 0 otherwise, $I\left(\text{Year}_{t,k}\right)$ are year dummies, and $\xi_{i,m}$ is the error term.[19]

We report our findings in Table III.[20] Our results for Model 1 show that the slope coefficient on December dummy is positive (λ_1 = 1.067) and highly significant at 1% level. This *December return-spike* of 1.067% is economically significant given that the average returns are 1.15% per month.

As discussed earlier, it is possible that a part of the December returns could result if hedge funds trade in the same securities as mutual funds that engage in year-end return manipulation. In the absence of high-frequency holdings data, it is not possible to precisely quantify the magnitude of active and passive portfolio pumping during December. However, we can estimate the fraction of the December return that could be due to hedge funds taking advantage of mutual fund behavior. This is possible because, unlike mutual funds, hedge funds are unlikely to have an active interest in managing returns at quarter-ends, since they are not subject to portfolio disclosure requirements. Thus, if we find higher quarter-end returns for

[19] We also conduct our analysis at the substrategy level using the original strategy classification in the four databases and find qualitatively similar results.

[20] We winsorize extreme 1% of all the variables in order to minimize the influence of outliers. Here and throughout the paper, we report the p-values after adjusting for heteroskedasticity, clustering at the fund-level, and including year dummies. Petersen (2006) shows through simulations that estimating standard errors clustered on one dimension and including dummies for the other yield results similar to clustering on two dimensions. Following Petersen (2006), we cluster standard errors on more frequent fund clusters than the time clusters that are less frequent in our sample (11,305 funds compared to 156 months).

hedge funds, it would suggest that hedge funds might be beneficiaries of returns management by mutual funds. For this purpose, we included a non-December quarter-end dummy.

The results in Model 1 of Table III show that the non-December quarter-end dummy is positive (coeff. = 0.009) but not statistically significant, suggesting that hedge fund returns at quarter-ends are only marginally influenced by the inflation of mutual fund returns. In the study by Carhart et al. (2002), the ratio of coefficient on the year-end dummy to the coefficient on the quarter-end dummy (b_1/b_3) is 3.26 (i.e., 53.01÷16.27) and 2.57 (29.6÷11.54) for *all* funds (see Table II, Panels A and B, of Carhart et al. (2002): page 671). If hedge funds were passively benefiting from the gaming behavior of mutual funds by holding the same securities, then one would expect a similar ratio of coefficients on year-end and quarter-end dummies (as a rough approximation) in Model 1 of Table III. However, in our case, this ratio is substantially higher, 118.56 (i.e., 1.067÷0.009), indicating that the hedge fund returns exhibit a considerably bigger December return-spike even after allowing for the possibility that they could be passively benefiting from portfolio pumping activity of mutual funds. Taking the higher ratio of 3.26 and the coefficient on Quarter-end dummy of 0.009, we estimate that portfolio pumping at year-ends by mutual funds contributes at best 0.03% (0.009 × 3.26) to the December return-spike of 1.067% observed in hedge fund returns. The balance of the December return-spike could be due to active returns management by hedge funds driven by incentives and opportunities, as we examine in the next section.

To allow for the possibility that managers could increase their risk exposures in December, we also included the cross-sectional volatility measure, CS Volatility_m. We find the coefficient on cross-sectional volatility is positive (coeff. = 0.009) and significant at the 1% level. This implies that higher cross-sectional volatility is associated with higher returns.

Consistent with the findings of Agarwal, Daniel, and Naik (2009), who estimate cross-sectional regressions of annual returns, we observe that delta, lockup period, and restriction period are positively related to returns. Consistent with the evidence of serial correlation in hedge fund returns documented in the literature, we find that the coefficient on the first lag of returns is positive and significant. The coefficient on the second lag is positive but not significant.

In Model 2, we re-estimate Model 1 but with the residual returns (or discretionary component of returns) as the dependent variable. In addition, we replace the two lags of returns with those of residuals. Residuals strip out the effect of higher returns in December that will result if risk premiums are higher in December. We find that the slope coefficient on December dummy is significantly positive. This December residual-spike of 0.437% is economically significant given that the average monthly return is 1.15%.[21]

Overall, this section has shown how we estimate the December return-spike and the December residual-spike for the overall sample. This sets the stage for us to investigate our two hypotheses.

VI. Do funds mange their reported returns?

In Section III, we hypothesized that funds that have higher incentives (funds that are in the money and near the money, funds that have higher delta, funds that have better relative performance, funds that have shorter lockup and restriction periods, and funds that earn

[21] We did several robustness tests. First, to better control for changes in risk in the current year, we replace prior year volatility with volatility estimated over the twelve months ending November of the current year. Our December spikes remain unaffected. Secondly, it is conceivable that managers gradually adjust their returns and do not limit their manipulations to the month of December. Hence, we include November dummy in addition to the December dummy. We find a November return-spike of 1.089% ($p < 0.01$) and a residual-spike of 0.033% ($p = 0.28$) while the magnitude of the December spikes remain virtually unaffected. Thus, it appears that return management is primarily a December phenomenon. Third, we include more six lags of residuals. Only the first three lags are statistically significant, but our December dummy coefficient remains virtually the same. Finally, we estimated p-values using Newey-West corrected standard errors using 6 lags and 11 lags. In both cases, we continue to find a significant coefficient on December dummy.

significant dollar management fees) should exhibit positive December spike. We also posited that funds with greater opportunities (funds with higher volatility and funds with more exposure to liquidity risk factor) should display positive December spike. Secondly, we hypothesized that funds that have higher incentives (opportunities) should exhibit greater December spike that those with low incentives (opportunities).

To test our hypotheses, we first create subsamples based on these key variables. Specifically, each year, we divide the funds into *high* and *low* categories based on the median of these variables at the end of each November. For example, if a fund's delta is greater than or equal to (less than) the median delta, we classify it as a *high (low) delta* fund.

We re-estimate Table III for these subsamples of funds. Table IV reports the results for the subsamples. For brevity, we report only the slope coefficients for the December dummy (the return-spike and residual-spike). We also report the difference between the coefficients of the December dummy for the high and low groups and the corresponding p-value. For brevity, we comment on only the residual-spike (Columns 3 and 4) because the inferences using return-spike are similar.

From Table IV, we find the December residual-spike to be significantly positive (0.700%) for in-the-money funds, consistent with hypothesis 1. Moreover, consistent with hypothesis 2, we find this spike for in-the-money funds is significantly greater than that for out-of-the-money funds (difference = 0.700 – (–0.263) = 0.963%). We find similar results when we look at near-the-money funds. The December return-spike for near-the-money funds is also significantly positive (= 0.537%), and this spike is significantly greater than that for out-of-the-money funds by 0.800%. The spikes and differential spikes are economically large, as the average monthly return (residual) is 1.15% (−0.03%). These results are intuitive given the fact that benefits of returns management are highest for in-the-money funds and, to a lesser extent, for near-the-money funds.[22]

Next, we repeat our analysis using the second measure of incentives—delta. We find that funds with high delta exhibit a significantly positive December residual-spike of 0.562%. Also, this spike is significantly greater compared to funds with low delta by 0.241%.[23]

Third, we use the November-end fractional rank. We form three groups, with the top 20% in one group, the bottom 20% in the second group, and the middle 60% in the third group. Consistent with our expectations, we find that the December residual-spike is significantly positive for both the top 20% and the middle 60%. However, the difference in December residual-spike between the top 20% and bottom 20% is not significantly positive, though the difference in spike between the funds in the middle 60% and the bottom 20% is significantly positive.

Fourth, we use lockup period and restriction period. Since only 25% of the funds have lockup period, the low-lockup period group effectively consists of firms that impose no lockup provisions. Results in Column (3) show that funds with shorter lockup periods exhibit a significantly positive spike of 0.556%. This spike is higher compared to the funds with longer lockup periods (difference = 0.117%), though this difference is not statistically significant (p-value = 0.21). The results with restriction period are stronger. We find that funds with shorter restriction periods exhibit a significantly positive spike of 0.587%, which in turn is significantly higher compared to the funds with longer restriction periods (difference = 0.258%).

[22] We do two robustness tests. First, we reclassify funds as in-the-money, near-the-money, and out-of-the-money using strategy-level μ and σ (instead of fund-level μ and σ). Second, we ignore μ and σ and sort firms into three groups based on moneyness with respect to zero: (i) those that are positive as of November-end (in-the-money), (ii) those that are negative but in the top half (near-the-money), and (ii) those that are negative but in the bottom half (out-of-the-money). In both cases, our inferences remain unchanged.

[23] Higher delta could result, among other things, due to higher percentage incentive fee. We therefore sort funds into three groups based on percentage incentive fee: those above 20%, those that charge exactly 20% (80% of our sample), and those that charge below 20%. We find that higher percentage incentive fee have higher December residual-spike and this spike is significantly greater than that exhibited by low incentive fee funds.

Finally, we sort funds into two groups based on dollar management fee as of November-end. We find that the funds that earn larger fees show a significant December residual-spike of 0.551%. This spike is also significantly higher than that for the low-fee funds by 0.237%.[24]

We next examine the role of opportunities in the returns management behavior. We use two distinct proxies for opportunities, namely volatility and liquidity. From results in Table IV, we find that funds with high volatility exhibit a significantly positive residual-spike of 0.662%, and this is significantly more pronounced than for funds with low volatility (0.662% vs. 0.211%).[25, 26]

Next, we classify funds into different groups based on exposure to illiquidity. From results in Table IV, we find that the December residual-spike for low-liquidity funds is significantly positive (0.562%) and is also significantly higher than that for high-liquidity funds by 0.232% (0.562% – 0.330%).[27, 28]

Overall, we find convincing evidence that funds that have higher incentives and greater

---

[24] Both size (assets under management) and percentage management fee rate contributes to higher dollar management fee. We therefore do two independent sorts based on November-end fund size and percentage management fee. We find that both subsamples – funds that are larger and funds that charge a higher rate – exhibit positive December spike. However, while the larger funds exhibit a significantly bigger December residual-spike compared to smaller funds, the higher-fee funds exhibit significantly smaller December residual-spike compared to the smaller-fee funds. Thus, it appears that $ management fees are the important driver of returns management.

[25] High-volatility funds are likely to exhibit spikes unrelated to returns management, but these spikes are equally likely to occur in any of the 12 months. Only if there is returns management do we expect to see this December spike.

[26] Alternatively, we use strategy level volatility to sort funds into two groups and get similar results, where strategy-level volatility is defined as the standard deviation of monthly strategy returns estimated by taking a simple average of returns of the funds belonging to that strategy. We limit this analysis to those strategies that have a minimum of 50 funds.

[27] Hedge funds trading in illiquid assets sometimes keep some of these investments in "side pockets", which are valued only at the time of sale and may not be reflected in monthly NAV computations. Arguably, these side pockets can be used to hide poorly performing assets. If this is indeed true and if at a later stage, there is a reversal in the performance of these assets, they can be brought back into the main portfolio, thereby resulting in a boost in the fund performance. If this happens exclusively in or more often in December, it could lead to a December spike. Although it is not possible to disentangle the liquidity-based and poor-performance-based rationales for side pockets, to the extent that we find funds with greater illiquidity exhibiting bigger December spike, we believe it perhaps captures the side-pocket effect to some extent.

[28] We also use strategy level liquidity to sort funds into two groups, where strategy level liquidity beta is obtained by regressing excess returns on the seven factors of Fung and Hsieh (2004) model and the liquidity factor of Pastor and Stambaugh (2003). We find the funds belong to low-liquidity strategies exhibit a significantly positive December residual-spike and this spike is greater than the spike for the sample of funds belong to high-liquidity strategies, though this difference is not statistically significant.

opportunities are the ones that manage their reported returns.

VII. Robustness

In this section, we document the robustness of our primarily result from Section VI that funds manage their reported returns. Table V reports the results for each of the tests we perform. For brevity, we report the overall December residual-spike from Model 2 of Table III, the December residual-spike for the higher incentives and opportunities subsamples from Column 3 of Table IV (test of hypothesis 1), and the difference in December residual-spike between the higher incentives and opportunities groups and their corresponding lower incentives and opportunities counterparts from Column 4 of Table IV (test of hypothesis 2). For ease of comparison, Column 1 reports the base case numbers from Tables III and IV. As per hypotheses 1 and 2, we expect rows 2 – 21 to be significantly positive.

First we consider the possibility that there might be an (omitted) factor with December seasonality that has the power to explain hedge fund returns. For this omitted factor to be the main driver of returns management, it must be the case that (i) high-incentives and high-opportunities funds should load on this omitted factor (which would result in a December spike for these subsamples, consistent with hypothesis 1) and (ii) this loading must be greater than the loading for low-incentives and low-opportunities funds (which would result in the high incentives and opportunities funds having a greater December spike than their low-incentives and low-opportunities counterparts, consistent with hypothesis 2). This seems difficult to argue. Thus, we do not think an omitted factor can fully explain away the return management that we document.

Nevertheless, we allow for the possibility that such an omitted factor might give rise to evidence that may be interpreted as returns management. We perform additional tests (described below) and the results from these tests suggest that an omitted factor could not be responsible for the return management that we document.

(i) If there is an omitted factor, it is likely to be relevant for funds belonging to strategies where the seven factors do a poor job of explaining fund returns. To this end, we first estimate the time series of monthly returns for each strategy by taking a simple average of returns of the funds belonging to that strategy, regress the excess strategy return on the seven factors of Fung and Hsieh (2004), and obtain the adjusted R^2.[29] We then sort the strategies into two bins based on adjusted R^2 and re-estimate Model 2 of Table III for these two groups. We find that the subsample of funds belonging to strategies that exhibit low adjusted R^2 have a December residual-spike of 0.294%, which is in fact significantly lower that for the subsample of funds belonging to strategies that exhibit high adjusted R^2 (0.357%). Thus, we do not think that an omitted factor is responsible for the results we document.

Nevertheless, given that equity long-short constitutes 1/3rd of our sample, we concentrate on including more equity-oriented factors to the 7-factor Fung and Hsieh (2004) model.

(ii) We augment the 7-factor model with the book-to-market and momentum factors and repeat our analysis with the residuals from the 9-factor model. Column 2 of Table V reports the results. We continue to find a significant December spike for the funds with high incentives and opportunities and this spike is significantly greater than that for funds with low incentives and opportunities.

(iii) We augment the 7-factor model with the option factor of Agarwal and Naik (2004) and the VIX factor of Hasanhodzic and Lo (2007). We repeat our analysis using residuals obtained after inclusion of the above two factors. Column 3 of Table V reports the results. All our

[29] We consider only the strategies that had at least 50 funds and we also exclude strategies that are mixed strategies such as Multi-strategy and Managed Futures.

inferences continue to hold.

Second, if our controls for risk-taking in December are inadequate, it is possible that one might observe a December spike. However, to document return management, it must be the case that the omitted control must lead to a greater spike for higher incentives and higher opportunities funds. This is hard to argue.

If funds take more risk in December, it is likely to get reflected in fatter tails in the cross-sectional distribution of fund residuals. Specifically, we expect excess kurtosis of December residuals to be positive and for it to be significantly greater than the excess kurtosis of January-to-November residuals. We don't find this to be the case. The excess kurtosis of December residuals is 138.5 (p-value = 0.20) and is not significantly different (p-value = 0.91) from the excess kurtosis of residuals in the other months (kurtosis = 128.4). Nevertheless, we do two additional things to control for risk-taking – one in the cross-sectional setting and the other in the time-series setting.

(i) We include prior month's vega – the sensitivity of manager's compensation for a 1% point change in volatility – as an additional control in in Model 2 of Table III. Vega has been used as a proxy for risk-taking incentives (Guay, 1999; Coles, Daniel, Naveen, 2006). By including vega, we allow performance to vary with risk-taking incentives. We then perform all our subsample analysis (Table IV) using this enhanced Model 2 regression. Results are reported in Column 4 of Table V. All our results go through.

(ii) We allow for time-varying risk loadings in estimating residuals. Specifically, we let the monthly loading on the market factor to be a function of managerial incentives. We hypothesize this relation to be of the following functional form.

$$\beta_{i,t} = \kappa_{i,1} + \kappa_{i,2} Incentives_{i,t-1}$$

where $\beta_{i,t}$ is the loading on the market factor for fund i in month t and $Incentives_{i,t-1}$ is the incentives of the manager of fund *i* as of month *t-1*. We first consider the implicit incentives to increase risk (embedded in the flow-performance relation). i.e.,

$$\beta_{i,t} = \kappa_{i,1} + \kappa_{i,2} Frank_{i,t-1}$$

where $Frank_{i,t-1}$ is the fractional rank based on fund *i* returns from January to month *t-1* relative to other funds following the same strategy within a given year. For January, *Frank* is assumed to be zero for all funds because there are no tournament-related incentives at the start of the year.[30] Empirical implementation effectively amounts to re-estimating residuals by augmenting Fung and Hsieh (2004) model with the interaction of $Frank_{i,t-1}$ and $R_{mt} - R_{ft}$. Based on the coefficient estimates ($\kappa_{i,1}, \kappa_{i,2}$) from the fund-level time-series regressions and the fund's relative performance as of November, one can compute the beta of the market factor in December.

$$\beta_{i,December} = \kappa_{i,1} + \kappa_{i,2} Frank_{i,November}$$

Similarly, one can compute the betas for the other months of the year. We find that December beta is significantly higher than the average beta for the rest of the year (0.32 vs. 0.24, p = 0.02). To document return management, we then re-estimate cross-sectional regressions of residuals obtained using the above method for the full sample (Model 2 of Table III) and for various subsamples (Table IV). Column 5 of Table 5 reports the results. We continue to find support for returns management.

As further robustness checks, we also allow loadings on the market factor to vary with lagged moneyness, lagged delta, and lagged dollar management fee (instead of lagged fractional rank). In unreported tables, we continue to find results similar to that reported in Column 5 of Table V.

Third, we control for the possibility that all managers work especially hard in December

[30] A number of papers (Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997) among others) document tournament behavior in mutual funds. Shouldn't we have a hedge fund paper reference?

– similar to students burning the midnight oil prior to exams. We do not believe this to be the case because the incentive fees depend not only on whether the manager beats a threshold but also on the magnitude by which he beats the threshold. Therefore, the manager has an incentive to work hard all the time (assuming the manager has no utility from leisure), and not just in December, as fees are increasing in the profits he makes for investors. If we assume all managers work harder in December than in other months, then those managers with higher incentives are likely to work harder than those with lower level of incentives, and this in turn could potentially explain a *subset* of our results, viz., that high-incentives managers exhibit a positive December spike (Hypothesis 1) and that the high-incentives managers exhibit a greater December spike compared to the low-incentives managers (Hypothesis 2). It is hard, however, to argue why high-opportunities managers work harder in December compared to the low-opportunities managers. Hence working-hard story cannot explain all of our results.

One way to test whether hard work is in play is to examine skewness. We find that skewness of residuals in December is not significantly positive (skew = 2.7; p-value = 0.32) and it is not significantly different (p-value = 0.52) from the skewness of residuals for the January-November period (skew = 1.1). Thus, it does not appear to be the case that managers work particularly harder in December. Nevertheless, we make an attempt to control for this unobserved hard work that managers might be putting in December. Specifically, we model this as follows:

$$Residual_{it} = Function\{December, Controls\} + \varepsilon_{it}$$

$$\varepsilon_{it} = Hard\,Work_i + \eta_{it}$$

Hard Work$_i$ represent the fund-specific time-invariant unobserved variable that captures hard work of manager '*i*'. Since we do not have a good proxy for hard work, the effect of hard work on performance is reflected in the error term. If managers work hard in December, then this implies that the error term is correlated with the December dummy, and hence the OLS regressions are invalid. A simple econometric solution to this correlated-omitted-variable problem is to estimate fund fixed effects. We therefore estimate Model 2 of Table III using fund fixed effects and then replicate Table IV using this model. Column 6 of Table V reports the results. All our inferences remain unchanged.

Fourth, we try to control for backfilling bias. We have included the performance history of defunct funds (36% of fund-year observations) in our analysis, and hence we believe that survivorship bias is not a major concern. To tackle backfilling bias, we follow Ackermann, McEnally, and Ravenscraft (1999) and exclude the first two years' data of each fund from the analysis. We report the results in the Column 7 of Table V. All our inferences continue to hold.

Fifth, we use net returns instead of gross returns to estimate the residuals using Fung and Hsieh (2004) regressions. We then estimate Model 2 of Table III for the overall sample and for various subsamples using these residuals. Column 8 of Table V reports the results. The results are consistent with our hypotheses except that the differential spike between the top 20% funds and bottom 20% funds is negative.

The central take-away from this section is that our inference that funds manage returns is robust to several alternative interpretations.

VIII. What is the Modus Operandi that Funds Use for Returns Management?

Given the evidence of returns management, we next investigate the mechanism employed by funds to accomplish such management. Toward that end, we test Hypotheses 3 and 4 (*savings* and *borrowing* hypotheses) developed in Section III. To recall, the *savings hypothesis* posits that funds underreport positive returns up to November to create reserves to add to months with negative returns. The unused reserves are then added back in December. We test this by including two additional explanatory variables to Model 1 of Table III: (a) $\text{Reserves}_{i,m-1}$, the cumulative return from January up to month $m-1$ if positive, and 0 otherwise, and (b) the interaction of this variable with the December dummy. If the fund manager is adding those reserves from previous months in December, then one would expect to see this interaction term to be positive. Our results for Model 1 in Panel A of Table VI confirm that this is indeed the case, with the coefficient on the interaction being positive (coeff. = 0.074) and significant at the 1% level. This result is also economically significant. One standard deviation change in the Reserves variable results in an increase of 0.97% in December returns.

An alternative way to compute reserves is to determine the difference between true returns (which are unobservable) and observed returns. Getmansky, Lo and Makarov (2004) show that, due to return smoothing, observed returns can be expressed as a MA(2) process in true returns. Following their insights, for robustness, we also construct an alternative measure of reserves—cumulative difference between the unobserved true returns and the observed returns up to month $m-1$ if positive, and 0 otherwise. In untabulated results, we find that when we use this alternative measure of reserves, its interaction with the December dummy is significantly positive for Model 1 (coeff. = 0.667; significant at the 1% level). These findings, once again, lend strong support to the savings hypothesis.

Next, we test our *borrowing hypothesis*, which addresses the possibility that portfolio pumping by funds causes December returns to be higher at the expense of January returns. In this scenario, one would expect to see a lower January return in the next year following a high December return in the current year. To test this hypothesis, we include two additional variables to Model 1 of Table III: (a) a January dummy that takes the value 1 if the month is January of next year, and 0 otherwise, and (b) the interaction of the January dummy with returns during the previous month. As per the borrowing hypothesis, one would expect to observe a negative coefficient for the interaction term. Results reported in Model 2 of Panel A of Table VI indicate that the coefficient on the interaction of the January dummy and the lagged monthly return is negative (coeff. = –0.014), but is not statistically significant.[31] Thus, we don't find support for the borrowing hypothesis.

Finally, we test for both *savings* as well as *borrowing* hypotheses by including the corresponding variables together in Model 3 of Panel A of Table VI. We continue to find support for the saving hypothesis but not for the borrowing hypothesis.

Panel B of Table VI reports the two coefficients from Model 3, Panel A, Table VI that test the saving and borrowing hypotheses but for the high-incentives and high-opportunities subsamples.[32] We find consistent support for the saving hypothesis across all subsamples, but the evidence in favor of borrowing hypothesis is weak at best.

VII. A. Additional test of the borrowing hypothesis based on portfolio holdings

In this subsection, we provide additional tests of the borrowing hypothesis using the equity holdings data of hedge funds. In particular, we follow the approach in Carhart et al. (2002), who examine year-end inflation in equities held by mutual funds. Unlike mutual funds, hedge funds do not need to disclose their portfolio holdings on a quarterly basis. However, SEC requires that all funds with assets exceeding $100 million and holding large positions in stocks (more than 10,000 shares or $200,000) need to submit 13f filings. This enables us to obtain equity holdings data of 206 hedge funds from our sample.[33]

---

[31] We find that the slope coefficient on January dummy itself is positive (coeff.=0.518) and significant at the 1% level in Model 2 of Table VI. This is consistent with the well-documented January effect in stock returns.

[32] If saving and borrowing were the only mechanisms by which funds could manage their returns, then we should find that either borrowing effect or the saving effect has to be significantly greater for the high incentives and high opportunities groups compared to their low incentive and low opportunities counterparts. Since there could be other mechanisms that might also result in returns management, we have no hypothesis concerning the strength of the borrowing and saving effect of the high groups compared to the low groups. Hence, we only report the borrowing coefficient and the saving coefficient for the high groups only.

[33] We follow a procedure similar to Brunnermeier and Nagel (2004) who identify equity holdings of 52 hedge funds. Recently, Griffin and Xu (2008) have also used holdings data of hedge funds to determine presence of skill.

We report the average year-end inflation of stocks held by hedge funds in Table VII. Our analysis follows that in Table VII of Carhart et al. (2002). Each year, we sort stocks into five quintiles based on 6-month returns up to the second-last day of the year. We then sort these stocks into five quintiles based on market capitalization on the second-last day of the year. This provides us 25 return-size portfolios.

Next, we determine the year-end inflation in these stocks held by hedge funds that have higher incentives and greater opportunities to inflate December returns. For this purpose, we form groups of funds based on their characteristics such as moneyness, delta, fractional rank, and dollar management fees at the end of November. We also use other attributes such as lockup period, restriction period, volatility of fund returns, and fund's exposure to illiquidity to segregate funds into different sub-samples. For example, using November-end moneyness, as before, we divide the funds into three groups: in the money, near the money, and out of the money. Using November-end fractional rank, as in Sirri and Tufano (1998), we divide funds into three groups: top 20%, middle 60%, and bottom 20%. For all remaining characteristics, we form two groups (High and Low) using the median value each year as the cutoff.

For each of the 25 return-size portfolios, we take long positions in the stocks held by funds with higher incentives and greater opportunities and short positions in the stocks held by other funds. As described before, funds with higher incentives are the ones that are in-the-money and near-the-money, have high delta, have high fractional rank (top 20% and middle 60%), have low lockup and low restriction periods, and have high dollar management fees. Similarly, the funds with greater opportunities to inflate returns are the ones with high volatility and high exposure to illiquidity.

Following Carhart et al. (2002), we compute return inflation as the return on each of the 25 long-short stock portfolios on the last day of the year net of its return on the first day of next year. To examine whether this inflation is significantly different from zero, we first compute this return inflation for every non-overlapping 2-day period in the year. We then compute a z-statistic for return inflation for each of the 25 portfolios for each year as the return inflation net of the average of all possible 2-day returns during that year, divided by the standard deviation of the two-day returns over that year. For the sake of brevity, we report in Table VII, the average end-of-year inflation across 25 return-size portfolios over the 9-year period. The z-statistic for this overall average is the sum of the z-statistic over the 225 portfolio-year combinations divided by square root of 225. The reported p-value is the probability of obtaining a z-statistic greater than this overall z-statistic.

Results in Table VII indicate that funds with higher moneyness, greater delta, superior relative performance, and larger dollar management fee exhibit abnormally high year-end return inflation followed by a reversal on the first day in January. We do not find that illiquid funds engage in borrowing from the future. While on the surface this may appear surprising, it must be noted that the funds that are forced to report their equity holdings are large equity-oriented funds, and their typical holdings are not invested in illiquid securities. Overall, these findings suggest that a subgroup of hedge funds facing stronger incentives inflate year-end returns by borrowing from January returns.

A couple of caveats are in order here. First, this holdings-based test sheds light only on the borrowing hypothesis and does not preclude the possibility of funds also saving for the rainy day, which can also contribute to the December spike. Second, these results are based on a sub-sample of hedge funds that are required to report large equity holdings, which are likely to be liquid. Arguably, if one had access to non-equity holdings of hedge funds, some of which are likely to be more illiquid, one may find even stronger evidence of borrowing from January returns.

IX. Concluding Remarks

In this paper, we provide strong evidence of hedge funds inflating their returns in an opportunistic fashion to increase their compensation. Specifically, we find funds that stand to gain the most from good performance, the funds that stand to lose the most from poor performance, and the funds that have greater opportunities to engage in return inflation exhibit the greatest spike in December returns. These results are robust to controlling for potentially higher December factor premium and various fund characteristics including their risk-taking behavior at year-ends.

We also provide evidence on two potential mechanisms employed by hedge funds to manage returns. First method involves funds underreporting their returns in the early part of the year in order to create reserves for possible poor performance later in the year (saving for the rainy day). In case some of these reserves are left unutilized, they get added to the December returns resulting in the spike. Second mechanism involves funds borrowing from their January returns of the subsequent year to improve their December returns. This can be achieved by funds pushing up the security prices at December-end by last-minute buying, which is followed by price reversals in January.

Our findings have important implications for regulators and investors. Regulatory bodies in the US such as the SEC have been recently concerned about issues related to accurate security valuation in hedge funds. Our findings have important implications for investor welfare, too. If the reported NAVs of some hedge funds differ from their true NAVs, then some investors may benefit at the expense of others depending on their timing of entry into and exit from the funds. Our results can help regulators and investors better understand the potential returns management phenomenon in the hedge fund industry.

*** *** ***

References

Ackermann, C., R. McEnally, and D. Ravenscraft, 1999, The performance of hedge funds: Risk, return and incentives, *Journal of Finance* 54, 833-874.

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

Agarwal, Vikas, Naveen D. Daniel, and Narayan Y. Naik, 2004, Flows, performance, and managerial incentives, Working Paper, Georgia State University, Purdue University, and London Business School.

Agarwal, Vikas, Naveen D. Daniel, and Narayan Y. Naik, 2009, Role of managerial incentives and discretion in hedge fund performance, *Journal of Finance*, Forthcoming.

Ball, R., and L. Shivakumar, 2006, The role of accruals in asymmetrically timely gain and loss recognition, *Journal of Accounting Research*, 44(2), 207–242.

Bergstresser, D., and T. Philippon, 2006, CEO incentives and earnings management, *Journal of Financial Economics*, 80(3), 511–529.

Bernhardt, D., and Ryan J. Davies, 2005, Painting the tape: Aggregate evidence, *Economic Letters*, 89, 306–311.

Black, Fischer, and Myron Scholes, 1973, The pricing of options and corporate liabilities, *Journal of Political Economy*, 81(3), 637–654.

Bollen, N. P. B., and V. Krepely, 2007, Fraud detection in the hedge fund industry, *Journal of Financial and Quantitative Analysis,* Forthcoming.

Brown, S. J., and W. N. Goetzmann, 2003, Hedge funds with style, *Journal of Portfolio Management*, 29(2), 101–112.

Brown, S. J., W. N. Goetzmann, and J. Park, 2001, Careers and Survival: Competition and Risk in the Hedge Fund and CTA Industry, *Journal of Finance*, 56(5), 1869–1886.

Brown, K.C., W. V. Harlow, and L.T. Starks, 1996, Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry, *Journal of Finance*, 51(1), 85-110.

Brunnermeier, M., and S. Nagel, 2004, Hedge funds and the technology bubble, *Journal of Finance*, 59(5), 2013-2040.

Burgstahler, D., and I. Dichev, 1997, Earnings management to avoid earnings decreases and losses, *Journal of Accounting and Economics*, 24, 99–126.

Burns, Natasha, and Simi Kedia, 2006, The impact of performance-based compensation on misreporting, *Journal of Financial Economics*, 79, 35–67.

Campbell, John Y., Martin Lettau, Burton Malkiel, and Yexiao Xu, 2001, Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk, *Journal of Finance*, 56(1), 1–43.

Carhart, Mark M., Ron Kaniel, David K. Musto, and Adam V. Reed, 2002, Leaning for the tape: evidence of gaming behavior in equity mutual funds, *Journal of Finance*, 57(2), 661–693.

Chandar, Nandini, and Robert Bricker, 2002, Incentives, discretion, and asset valuation in closed-end mutual funds, *Journal of Accounting Research*, 40(4), 1037–1070.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy*, 105, 1167-1200.

Coles, Jeffrey L., Naveen D. Daniel, and Lalitha Naveen, 2006, Managerial incentives and risk-taking, *Journal of Financial Economics*, 79(2), 431–468.

Core, J. E., W. R. Guay, and David F. Larcker, 2003, Executive equity compensation and incentives: A survey, *Federal Reserve Bank of New York Economic Policy Review*, 9(1), 27–50.

Daniel, N., D. Denis, and L. Naveen, 2008, Do firms manage earnings to meet dividend thresholds?, *Journal of Accounting and Economics*, 45, 2-26.

Dechow, P. M., and D. J. Skinner, 2000, Earnings management: Reconciling the views of accounting academics, practitioners, and regulators, *Accounting Horizons*, 14, 235–250.

Degeorge, F., J. Patel, and R. Zeckhauser, 1999, Earnings management to exceed thresholds, *Journal of Business*, 72, 1–33.

Efendi, J., A. Srivastava, and E. Swanson, 2006, Why do corporate managers misstate financial statements? The role of option compensation and other factors, *Journal of Financial Economics,* 85(3), 667-708.

Fields, T. D., T. Z. Lys, and L. Vincent, 2001, Empirical research on accounting choice, *Journal of Accounting and Economics*, 31, 255–307.

Fung, W., and D. A. Hsieh, 1997, Empirical characteristics of dynamic trading strategies: The case of hedge funds, *Review of Financial Studies*, 10(2), 275–302.

Fung, W., and D. A. Hsieh, 2000, Performance characteristics of hedge funds and CTA funds: natural versus spurious biases, *Journal of Financial and Quantitative Analysis*, 35(3), 291–307.

Fung, W., and D. A. Hsieh, 2004, Hedge fund benchmarks: A risk-based approach, *Financial Analysts Journal*, 60(5), 65–80.

Gaver, Jennifer J., Kenneth M. Gaver, and Jeffrey R. Austin, 1995, Additional evidence on bonus plans and income management, *Journal of Accounting and Economics*, 19, 3–28.

Getmansky, Mila, Andrew W. Lo, and Igor Makarov, 2004, An econometric model of serial correlation and illiquidity in hedge fund returns, *Journal of Financial Economics*, 74(3), 529–609.

Goetzmann, W. N., J. Ingersoll, and S. A. Ross, 2003, High-water marks and hedge fund management contracts, *Journal of Finance*, 58(4), 1685–1718.

Goldman, E., and S. L. Slezak, 2006, An equilibrium model of incentive contracts in the presence of information manipulation, *Journal of Financial Economics*, 80(3), 603–626.

Griffin, John M., and Jin Xu, 2008, How smart are the smart guys? A unique view from hedge fund stock holdings, *Review of Financial Studies* forthcoming.

Guay, W. R., 1999, The sensitivity of CEO wealth to equity risk: An analysis of the magnitude and determinants, *Journal of Financial Economics*, 53, 43-71.

Hasanhodzic, J., and A. Lo, 2007, "Can Hedge Fund Returns be Replicated? The Linear Case," Journal of Investment Management, 5, 5–45.

Healy, Paul M., 1985, The effect of bonus schemes on accounting decisions, *Journal of Accounting and Economics*, 7, 85–107.

Healy, P. M., and J. M. Wahlen, 1999, A review of the earnings management literature and its implications for standard setting, *Accounting Horizons*, 13(4), 365–383.

Jones, J., 1991, Earnings management during import relief investigation, *Journal of Accounting Research*, 29, 193–228.

Liang, B., 2003, Hedge Fund Returns: Auditing and Accuracy, *The Journal of Portfolio Management* 29, 111-122.

Levitt, A., 1998, Speech by SEC chairman: A financial partnership. November 16, 1998.

Murphy, K., 1999, Executive compensation, in Orley Ashenfelter and David Card, eds.: *Handbook of Labor Economics*, Vol. 3b, (Elsevier Science, North Holland), Chapter 38: 2485–2563.

Pastor, Lubos, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy*, 111, 642–685.

Pulliam, Susan, Randall Smith, and Michael Siconolfi, 2007, U.S. Investors Face An Age of Murky Pricing, *The Wall Street Journal*, October 12.

Silva, Harinder de, Steven Sapra, and Steven Thorley, 2001, Return dispersion and active management, *Financial Analysts Journal*, 57(5), 29–42.

Sirri, Erik, and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance*, 53, 1589–1622.

Solnik, Bruno, and Jacques Roulet, 2000, Dispersion as cross sectional correlation, *Financial Analysts Journal*, 56(1), 54–61.

Stolowy, H., and G. Breton, 2004, Accounting manipulation: A literature review and proposed conceptual framework, *Review of Accounting and Finance*, 3, 5–65.

Figure 1. Hedge Fund Database

The hedge fund database we cobble together by merging five databases – CISDM, Eureka, HFR, MSCI, and TASS – contains 11,305 hedge funds This figure shows the percentage of funds covered by each database individually and by all possible combinations of multiple databases.

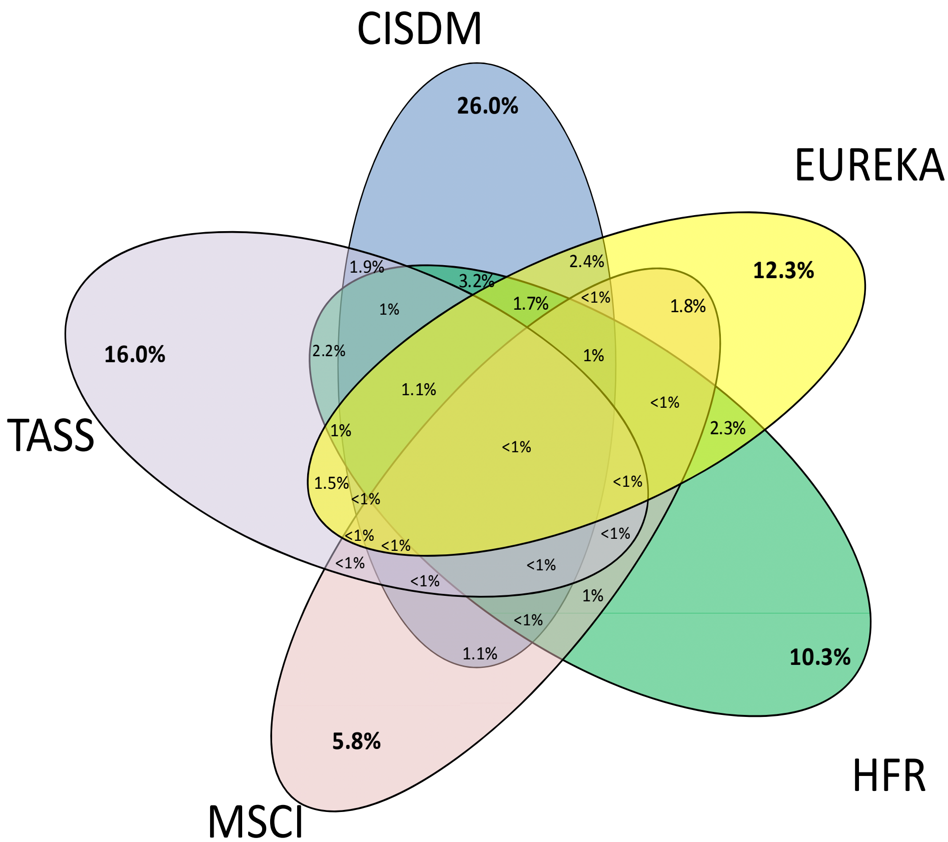
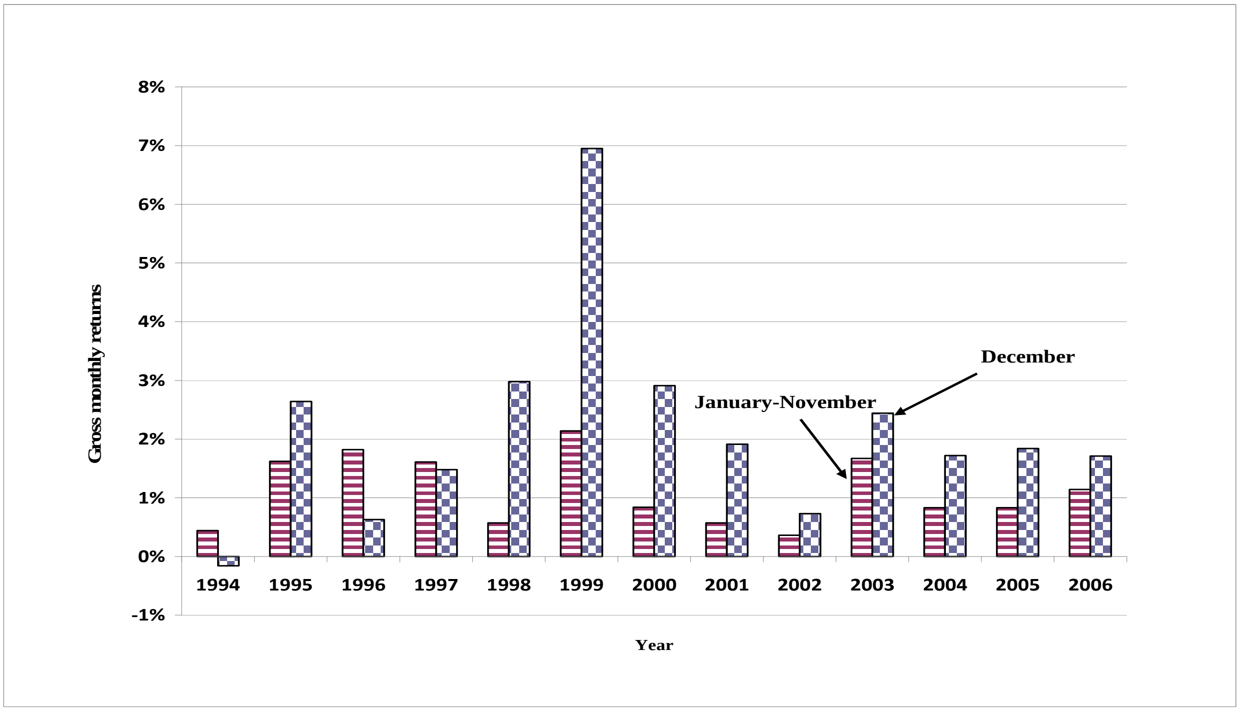


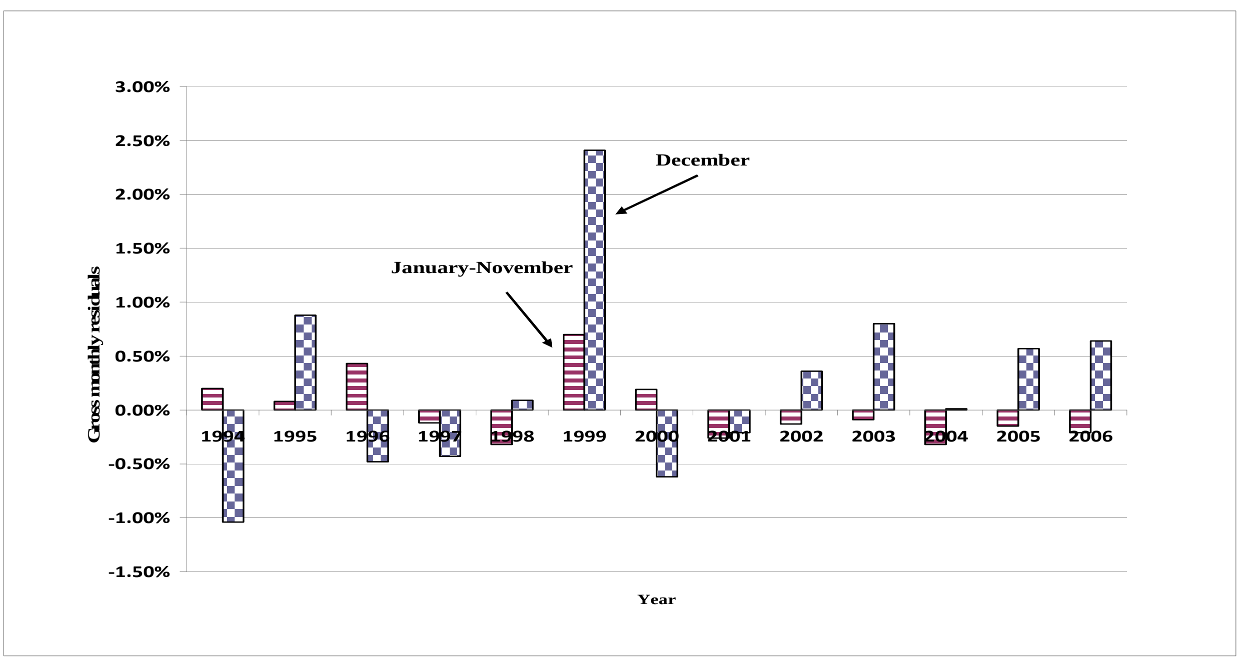
Figure 2. Average returns and residuals

The average return (Panel A) and the average residual (Panel B) for both the January to November period and the month of December are presented on an annual basis. Panel C presents the average return and average residual for each month. Returns are the monthly gross fund returns. Residuals are the residuals from the time-series regressions of funds' gross returns using the seven-factor model of Fung and Hsieh (2004).

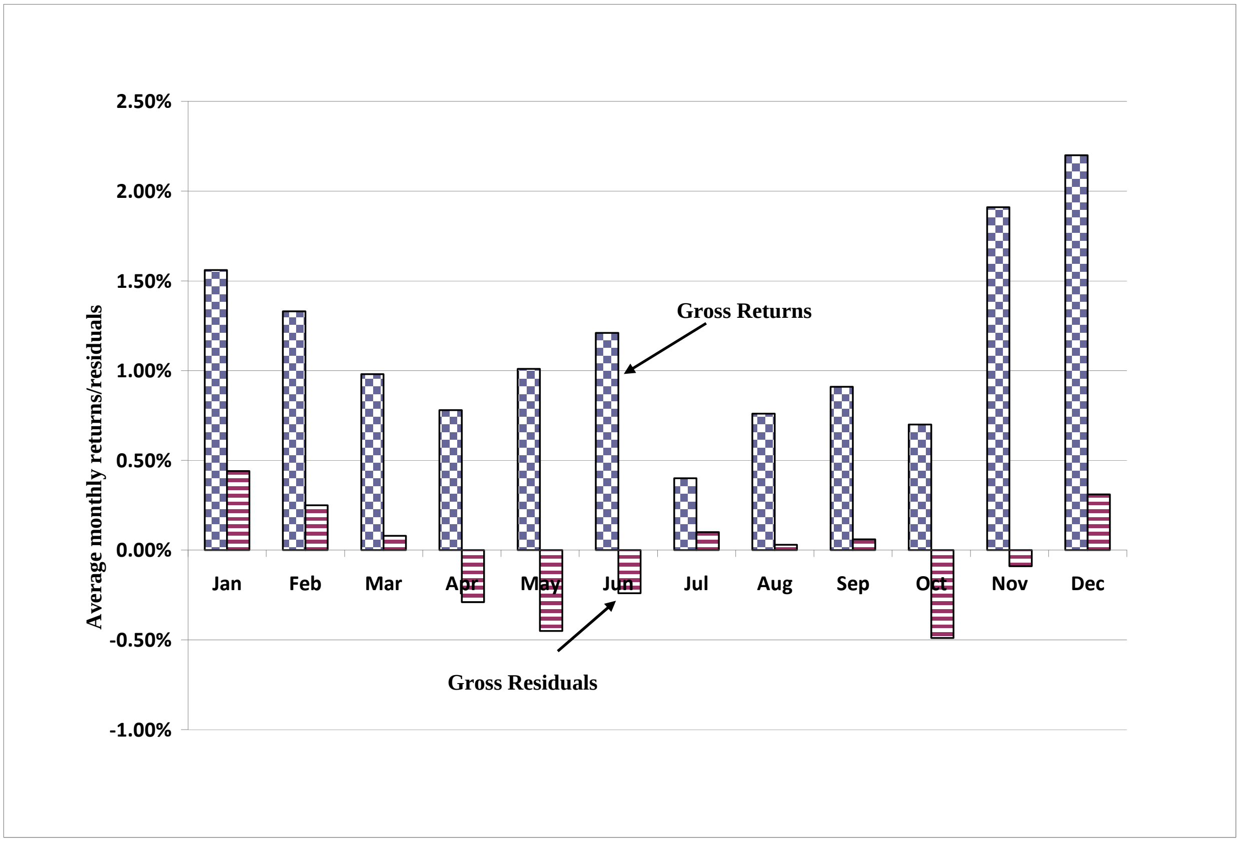
Panel A



Panel B



Panel C



Average monthly returns/residuals
2.50%
2.00%
1.50%
1.00%
0.50%
0.00%
-0.50%
-1.00%
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Gross Returns
Gross Residuals

Table I. Summary Statistics

The table reports the summary statistics of select fund characteristics. Returns are the monthly gross fund returns. Residuals are the residuals from the time-series regressions of funds' excess gross returns using the seven-factor model of Fung and Hsieh (2004). CS-Volatility is the monthly cross-sectional dispersion in fund returns. Moneyness is defined on a monthly basis as the difference between the spot price and the exercise price, divided by the exercise price. Delta is the expected dollar change in manager's wealth for a 1% change in NAV. Fractional rank is the rank (between 0 and 1) of the fund at November-end each year based on its performance from January to November, relative to all funds within a strategy, i.e., fractional relative rank. Lockup period is the minimum time that an investor must wait (after making an investment) before being permitted to withdraw money. Restriction Period is given by the sum of the Notice Period and the Redemption Period, where Notice Period is the duration of the time the investor has to give notice to the fund about an intention to withdraw money from the fund, and Redemption Period is the time that the fund takes to return the money after the Notice Period is over. Dollar management fee at the end of November is the percentage management fee multiplied by the fund size at November-end. Volatility is standard deviation of monthly gross returns estimated over the calendar year. Liquidity beta is the exposure to the value-weighted liquidity risk factor of Pastor and Stambaugh (2003) in the augmented Fung and Hsieh (2004) seven-factor model. Reserves, computed each month, is equal to max (0, Cumulative Returns up to and including current month). AUM is the monthly assets under management. Age is the age of the fund in years. Lockup period, restriction period, management fee, and incentive fee are time-invariant.

Fund Characteristics	**Mean**	**SD**	**25th Percentile**	**Median**	**75th Percentile**
Returns (%)	1.15	5.17	–0.84	0.84	2.84
Residuals (%)	–0.03	3.97	–1.55	–0.07	1.39
CS-Volatility (%)	7.81	4.04	4.78	6.43	9.24
Moneyness	1.63	16.51	–4.47	0.60	7.50
Delta ($ millions)	0.21	0.53	0.01	0.04	0.15
Nov-end Fractional Rank	0.50	0.29	0.25	0.50	0.75
Lockup Period (years)	0.16	0.39	0.00	0.00	0.00
Restriction Period (years)	0.28	0.28	0.11	0.16	0.36
Nov-end Dollar Management fee ($ millions)	2.34	52.94	0.09	0.37	1.32
Volatility (%)	4.20	3.77	1.62	3.10	5.52
Liquidity beta	0.05	0.88	–0.07	0.01	0.11
Reserves (%)	8.11	12.97	0.00	3.25	10.54
AUM ($ millions)	117.78	256.80	7.95	29.10	100.00
Age	4.64	3.64	1.88	3.59	6.42
Management Fees	0.01	0.01	0.01	0.01	0.02
Incentive Fees	0.19	0.05	0.20	0.20	0.20

Table II. December Spike in Fund Returns and Risk Factors

This table reports the average gross hedge fund returns, residuals from the time-series regressions of hedge funds' excess gross returns using the seven-factor model of Fung and Hsieh (2004), and the seven risk factors: excess return on S&P 500 (SP), spread between Wilshire Small Cap 1750 index and Wilshire Large Cap 750 index (SCLC), 10-year Treasury return (10Y), credit spread, i.e., difference between CSFB High-Yield index returns and 10-year Treasury returns (CS), lookback straddles on bond futures (BdOpt), lookback straddles on currency futures (FXOpt), and lookback straddles on commodity futures (ComOpt). The last column provides the difference between the average December values and the average of January–November values and the *p*-values in parentheses for the test that this difference equals zero after correcting the standard errors for clustering at the fund-level. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	Dec Average	Jan-Nov Average	December Spike (*p*-value)
Gross hedge fund returns	2.40%	1.14%	1.26%*** (0.000)
Residual hedge fund returns	0.40%	–0.04%	0.44%*** (0.000)
SP	1.21%	0.57%	0.64% (0.589)
SCLC	1.61%	–0.13%	1.74% (0.111)
10Y	0.30%	0.16%	0.14% (0.815)
CS	0.43%	0.21%	0.22% (0.514)
BdOpt	1.18%	–1.39%	2.57% (0.557)
FXOpt	2.13%	–0.41%	2.54% (0.649)
ComOpt	–0.43%	–0.75%	0.32% (0.934)

Table III. December Spike: Multivariate Results

This table reports OLS regressions of monthly gross returns ($Returns_m$) and residual returns ($Residuals_m$), where the residuals are estimated from fund-level time-series regressions of excess gross returns on the seven factors of Fung and Hsieh (2004). December dummy equals 1 if the month is December, and equals 0 otherwise. Non-December Quarter-End dummy equals 1 if the month corresponds to a quarter-end (other than December), and equals 0 otherwise. $CS\text{-}Volatility_m$ is the cross-sectional volatility of fund returns during month m. $Returns_{m-1}$, $Residuals_{m-1}$, $Delta_{m-1}$, $Moneyness_{m-1}$, $Size_{m-1}$, and Age_{m-1} are as of prior month $m - 1$. Moneyness is computed as the difference between spot and exercise prices, divided by the exercise price. $Returns_{m-2}$ and $Residuals_{m-2}$ are gross returns and residual returns during month $m - 2$. Volatility is the standard deviation of monthly returns during the year. Remaining variables are as defined in Table I. Returns are in percentage terms. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively. Standard errors are corrected for heteroskedasticity and fund-level clustering with *p*-values reported in parentheses.

	Dependent Variable:	
Independent Variables	**$Returns_m$ Model 1**	**$Residuals_m$ Model 2**
December Dummy (λ_1)	1.067^{***}	0.437^{***}
	(0.000)	(0.000)
Non-December Quarter-End Dummy	0.009	0.044^{**}
	(0.721)	(0.031)
$CS\text{-}Volatility_m$	0.009^{**}	0.022^{***}
	(0.024)	(0.000)
$Delta_{m-1}$	0.102^{***}	0.030^{**}
	(0.000)	(0.025)
$Moneyness_{m-1}$	0.006^{***}	-0.002^{**}
	(0.000)	(0.033)
Lockup Period	0.101^{***}	0.026^{***}
	(0.001)	(0.007)
Restriction Period	0.266^{***}	0.021
	(0.000)	(0.142)
$Size_{m-1}$	-0.056^{***}	-0.051^{***}
	(0.000)	(0.000)
Volatility	0.086^{***}	0.012^{***}
	(0.000)	(0.000)
Age_{m-1}	-0.018^{***}	-0.015^{***}
	(0.000)	(0.000)
Management Fee Rate	–0.745	–0.799
	(0.720)	(0.386)
$Returns_{m-1}$ ($Residuals_{m-1}$ for Model 2)	0.102^{***}	0.076^{***}
	(0.000)	(0.000)
$Returns_{m-2}$ ($Residuals_{m-2}$ for Model 2)	0.004	0.026^{***}
	(0.331)	(0.000)
Intercept, Strategy Dummies, and Year Dummies	Yes	Yes
Observations	229501	229501
Adjusted R^2	3.5%	1.4%

Table IV. Do funds manage their reported returns?

The table reports the slope coefficients for the December dummy for Models 1 and 2 in Table III for the various subsamples listed in the first column. Funds are classified into three groups based on their moneyness as of November end, where moneyness is computed as the difference between spot and exercise price divided by the exercise price. Out-of-the-money funds are those whose moneyness is less than $-(\mu + \sigma)$. Near-the-money funds are those whose moneyness is between $-(\mu + \sigma)$ and $-(\mu - \sigma)$. In-the-money funds are those moneyness is greater than $-(\mu - \sigma)$. μ is the average monthly fund return, and σ is the standard deviation of monthly fund returns using the entire return history for each fund. Fractional rank is the rank (between 0 and 1) of the fund at November-end each year based on its performance from January to November, relative to all funds within a strategy, i.e., fractional relative rank. Following Sirri and Tufano (1998), we divide the funds into top 20%, middle 60%, and bottom 20% based on their fractional relative rank as of November-end. Dollar management fee at the end of November is the management fee rate multiplied by the fund size at November-end. For characteristics other than moneyness, we do independent sorts based on Delta as of November end, Lockup, Restriction Period, Dollar Management Fee as of November end, Volatility, and Liquidity. The High (Low) groups consist of funds whose characteristic is greater than or equal to (less than) the median value that year; similarly for Long (Short) periods in all instances. The difference in the December spike is between the 1st group and the 2nd group. In the case of moneyness, the difference is with respect to out-of-the-money group. In the case of fractional rank, the difference is with respect to bottom 20%. The *p*-values given in parentheses adjacent to the difference values are based on Chow-tests that examine whether this difference is significantly different from zero. The "expected sign" is the hypothesized sign for the difference in December spikes. All figures are in percentage, e.g., a coefficient of 1.483 is equal to 1.483%. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively. Standard errors are corrected for heteroskedasticity and fund-level clustering with *p*-values reported in parentheses.

Subsample	Dec return-spike as per Model 1, Table III 1	Difference in spike (*p*-value) 2	Dec residual-spike as per Model 2, Table III 3	Difference in spike (*p*-value) 4
INCENTIVES TO MANAGE RETURNS				
In the Money	1.483***		0.700***	
	(0.000)	1.626*** (0.000)	(0.000)	0.963*** (0.000)
Near the Money	1.138***		0.537***	
	(0.000)	1.281*** (0.000)	(0.000)	0.800*** (0.000)
Out of the Money	–0.143		–0.263***	
	(0.123)		(0.001)	
High Delta	1.234***		0.562***	
	(0.000)	0.310*** (0.000)	(0.000)	0.241*** (0.000)
Low Delta	0.924***		0.321***	
	(0.000)		(0.000)	
Top 20% Fractional rank	1.321***		0.335***	
	(0.000)	0.066 (0.646)	(0.000)	–0.168 (0.169)
Mid 60% Fractional rank	1.359***		0.699***	
	(0.000)	0.104 (0.318)	(0.000)	0.196** (0.024)
Bottom 20% Fractional rank	1.255***		0.503***	
	(0.000)		(0.000)	
Short Lockup	1.071***		0.556***	
	(0.000)	0.171 (0.111)	(0.000)	0.117 (0.210)
Long Lockup	0.900***		0.439***	
	(0.000)		(0.000)	
Short Restriction Period	1.165***		0.587***	
	(0.000)	0.174** (0.038)	(0.000)	0.258*** (0.000)
Long Restriction Period	0.991***		0.329***	
	(0.000)		(0.000)	
High $ Management Fee	1.212***		0.551***	
	(0.000)	0.283*** (0.001)	(0.000)	0.237*** (0.000)
Low $ Management Fee	0.929***		0.314***	
	(0.000)		(0.000)	

Table IV. (contd.) Do funds manage their reported returns?

Subsample	Dec return-spike as per Model 1, Table III 1	Difference in spike (*p*-value) 2	Dec residual-spike as per Model 2, Table III 3	Difference in spike (*p*-value) 4
OPPORTUNITIES TO MANAGE RETURNS				
High Volatility	1.745*** (0.000)	1.361*** (0.000)	0.662*** (0.000)	0.451*** (0.000)
Low Volatility	0.384*** (0.000)		0.211*** (0.000)	
Low Liquidity	1.458*** (0.000)	0.666*** (0.000)	0.562*** (0.000)	0.232*** (0.002)
High Liquidity	0.792*** (0.000)		0.330*** (0.000)	

Table V. Do funds manage their reported returns? Robustness

For various robustness tests, the table reports the residual spike for the overall sample (Model 2 of Table III), the residual spike for the various subsamples (Column 3 of Table IV), and the difference in December residual-spike between various subsamples (Column 4 of Table IV). "Base Case" reported in Column 1 corresponds to the numbers reported in Tables III and IV using residuals estimated from gross returns. "Additional factors: BM + Momentum" reported in Column 2 uses the residual obtained using the 7 factors of Fung and Hsieh (2004) and two additional factors: book-to-market and momentum. "Additional factors: DVIX + OTM Put" reported in Column 3 uses the residual obtained using the 7 factors of Fung and Hsieh (2004) and two additional factors: VIX factor of Lo and Hasanhodzic and Lo (2007) and the option factor of Agarwal and Naik (2004). "Including Vega" reported in Column 4 uses the residuals obtained from Model 2 of Table III but augmented by included vega as an additional control variable. "Time-varying Risk Exposure" reported in Column 5 uses the residuals obtained by allowing the monthly market beta in the 7 factor model of Fung and Hsieh (2004) to vary with the relative year-to-prior month performance of the fund with respect to its peer group. "Fund Fixed Effects" reported in Column 6 are based on estimating Model 2 of Table III for the overall sample and for various subsamples using fund fixed effects. "Adjustment for Backfilling Bias" reported in Column 7 is based on results excluding the first two years of data of each fund. "Net Residual" reported in Column 8 is based on using net returns instead of gross returns to estimate the residuals. Funds are classified into three groups based on their moneyness as of November end, where moneyness is computed as the difference between spot and exercise price divided by the exercise price. Out-of-the-money funds are those whose moneyness is less than $-(\mu + \sigma)$. Near-the-money funds are those whose moneyness is between $-(\mu + \sigma)$ and $-(\mu - \sigma)$. In-the-money funds are those moneyness is greater than $-(\mu - \sigma)$. μ is the average monthly fund return, and σ is the standard deviation of monthly fund returns using the entire return history for each fund. Fractional rank is the rank (between 0 and 1) of the fund at November-end each year based on its performance from January to November, relative to all funds within a strategy, i.e., fractional relative rank. Following Sirri and Tufano (1998), we divide the funds into top 20%, middle 60%, and bottom 20% based on their fractional relative rank as of November-end. Dollar management fee at the end of November is the management fee rate multiplied by the fund size at November-end. For characteristics other than moneyness, we do independent sorts based on Delta as of November end, Lockup, Restriction Period, Dollar Management Fee as of November end, Volatility, and Liquidity. The High (Low) groups consist of funds whose characteristic is greater than or equal to (less than) the median value that year; similarly for Long (Short) periods in all instances. The *p*-values given in parentheses adjacent to the difference values are based on Chow-tests that examine whether this difference is significantly different from zero. The "expected sign" is the hypothesized sign for the difference in December spikes. All figures are in percentage, e.g., a coefficient of 0.437 is equal to 0.437%. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively. Standard errors are corrected for heteroskedasticity and fund-level clustering with *p*-values reported in parentheses.

	Base Case: Gross Residual	Additional factors: BM + Momentum	Additional factors: DVIX + OTM Put	Including Vega	Time-varying Risk Exposure	Fund Fixed Effects	Adjustment for Backfilling Bias	Net Residual
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. Overall December spike	0.437***	0.877***	1.371***	0.436***	0.382***	0.615***	0.441***	0.395***
2. December spike: In the Money	0.700***	1.397***	1.878***	0.694***	0.619***	0.797***	0.708***	0.568***
3. Differential Dec spike: In the Money Less Out of the Money	0.963***	1.926***	1.770***	0.960***	0.899***	0.920***	0.969***	0.814***
4. December spike: Near the Money	0.537***	0.967***	1.472***	0.543***	0.475***	0.889***	0.530***	0.483***
5. Differential Dec spike: Near the Money Less Out of the Money	0.800***	1.495***	1.364***	0.809***	0.755***	0.848***	0.791***	0.729***
6. December spike: High Delta	0.562***	1.005***	1.544***	0.565***	0.496***	0.714***	0.564***	0.478***
7. Differential Dec spike: High Delta Less Low Delta	0.241***	0.235***	0.316***	0.312***	0.231***	0.224***	0.233***	0.209***
8. December spike: Top 20%	0.335***	1.193***	1.715***	0.345***	0.200**	0.326***	0.322***	0.307***
9. Differential Dec spike: Top 20% Less Bottom 20%	–0.168	0.017	0.190	–0.149	–0.269**	–0.024	–0.187	–0.197*
10. December spike: Mid 60%	0.699***	1.200***	1.716***	0.693***	0.637***	0.759***	0.698***	0.572***
11. Differential Dec spike: Mid 60% Less Bottom 20%	0.196**	0.024	0.191*	0.198**	0.169**	0.340**	0.188**	0.068
12. December spike: Short Lockup Period	0.556***	0.967***	1.388***	0.551***	0.513***	0.721***	0.561***	0.480***
13. Differential Dec spike: Short Lockup Period Less Long Lockup Period	0.117	–0.004	0.565	0.116	0.118	0.128	0.122	0.116
14. December spike: Short Restriction Period	0.587***	1.061***	1.539***	0.589***	0.524***	0.733***	0.590***	0.511***
15. Differential Dec spike: Short Restriction Period Less Long Restriction Period	0.258***	0.243***	0.247***	0.265***	0.256***	0.272***	0.258***	0.244***
16. December spike: High $ Management Fee	0.551***	0.994***	1.516***	0.556***	0.493***	0.681***	0.554***	0.466***
17. Differential Dec spike: High $ Management Fee Less Low $ Management Fee	0.237***	0.229***	0.278***	0.242***	0.243***	0.211***	0.236***	0.202***
18. December spike: High Volatility	0.662***	1.567***	2.052***	0.665***	0.555***	0.891***	0.665***	0.567***
19. Differential Dec spike: High Volatility Less Low Volatility	0.451***	1.432***	1.390***	0.455***	0.359***	0.479***	0.447***	0.393***
20. December spike: Low Liquidity	0.562***	1.231***	1.699***	0.566***	0.471***	0.847***	0.561***	0.476***
21. Differential Dec spike: Low Liquidity Less High Liquidity	0.232***	0.775**	0.687***	0.241***	0.146**	0.400***	0.220***	0.198***

Table VI. How do Funds Manage Returns? Tests of Saving and Borrowing Hypotheses

Panel A reports OLS regressions of monthly gross returns ($Returns_m$). See Tables I and III for variable definitions. Panel B reports the coefficient of December Dummy×Reserves $_{m-1}$ (test of savings hypothesis) and January Dummy×$Returns_{m-1}$ (test of borrowing hypothesis) from Model 3 of Panel A for various subsamples. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively. Standard errors are corrected for heteroskedasticity and autocorrelation with *p*-values reported in parentheses.

Panel A

Independent Variables	**Expected Sign**	**Model 1 (Saving Hypothesis)**	**Model 2 (Borrowing Hypothesis)**	**Model 3 (Saving and Borrowing Hypothesis)**
December Dummy	+	0.087	1.109***	0.134**
		(0.109)	(0.000)	(0.014)
December Dummy×Reserves $_{m-1}$	+	0.074***		0.072***
		(0.000)		(0.000)
January Dummy×$Returns_{m-1}$	–		–0.014	–0.018
			(0.248)	(0.157)
Reserves $_{m-1}$		–0.010***		–0.008***
		(0.000)		(0.003)
January Dummy			0.518***	0.429***
			(0.000)	(0.000)
Non-December Quarter-End Dummy		0.009	0.057**	0.047*
		(0.708)	(0.021)	(0.053)
CS-$Volatility_m$		0.011***	0.017***	0.017***
		(0.004)	(0.000)	(0.000)
Returns $_{m-1}$		0.105***	0.101***	0.104***
		(0.000)	(0.000)	(0.000)
Returns $_{m-2}$		0.007*	0.003	0.006
		(0.058)	(0.492)	(0.109)
Delta $_{m-1}$		0.105***	0.103***	0.106***
		(0.000)	(0.000)	(0.000)
Moneyness $_{m-1}$		0.004*	0.007***	0.004*
		(0.056)	(0.000)	(0.074)
Lockup Period		0.099***	0.101***	0.099***
		(0.001)	(0.001)	(0.001)
Restriction Period		0.259***	0.266***	0.256***
		(0.000)	(0.000)	(0.000)
$Size_{m-1}$		–0.057***	–0.058***	–0.058***
		(0.000)	(0.000)	(0.000)
Volatility		0.087***	0.086***	0.086***
		(0.000)	(0.000)	(0.000)
Age_{m-1}		–0.019***	–0.018***	–0.019***
		(0.000)	(0.000)	(0.000)
Management Fee Rate		–0.564	–0.753	–0.490
		(0.783)	(0.717)	(0.811)
Intercept, Strategy Dummies, and Year Dummies		Yes	Yes	Yes
Observations		229501	229501	229501
Adjusted R^2		4.0%	3.6%	4.0%

Panel B

Subsamples	SAVING Dec Dummy* Reserves	BORROWING Jan Dummy*Returns$_{m-1}$
In-the-Money	0.066***	0.748***
	(0.000)	(0.000)
High Delta	0.090***	–0.053***
	(0.000)	(0.002)
Top 20% Jan-Nov fractional rank	0.091***	0.065**
	(0.000)	(0.018)
High Nov-end dollar Management fee	0.087***	–0.034*
	(0.000)	(0.052)
Low Lockup Period	0.071***	–0.009
	(0.000)	(0.641)
Low Restriction Period	0.085***	0.034*
	(0.000)	(0.076)
High Volatility	0.075***	–0.001
	(0.000)	(0.927)
Low Liquidity	0.093***	–0.004
	(0.000)	(0.836)

Table VII. Tests of borrowing hypothesis based on stock holdings data

This table reports the average year-end inflation of stocks held by hedge funds. The analysis follows that in Table VII of Carhart et al. (2002). Each year, stocks are sorted into five quintiles based on 6-month returns up to the second-last day of the year. Stocks are also sorted into five quintiles based on market capitalization based on the second-last day of the year. This yields us 13×5×5 = 325 portfolio-year combinations. Within each portfolio, we then perform independent sorts based on various fund characteristics such as November-end moneyness, November-end delta, lockup period, restriction period, fractional relative rank, November-end dollar management fee, volatility of fund returns, and liquidity beta of the fund. Funds are classified into three groups based on their moneyness as of November end, where moneyness is computed as the difference between spot and exercise price divided by the exercise price. Out-of-the-money (OTM) funds are those whose moneyness is less than $-(\mu + \sigma)$. Near-the-money (NTM) funds are those whose moneyness is between $-(\mu + \sigma)$ and $-(\mu - \sigma)$. In-the-money (ITM) funds are those whose moneyness is greater than $-(\mu - \sigma)$. μ is the average monthly fund return, and σ is the standard deviation of monthly fund returns using the entire return history for each fund. Following Sirri and Tufano (1998), funds are classified into three groups based on their fractional relative rank as of November end – top 20%, middle 60%, and bottom 20%. The High (Low) groups consist of funds whose characteristic is greater than or equal to (less than) the median value that year. In each of the 25 portfolios, we go long on stocks in the hedge fund with higher incentives (ITM and NTM, high delta, low lockup and restriction periods, top 20% and middle 60% relative rank, and high dollar management fee) and higher opportunities (high volatility and low liquidity beta) and short on stocks in hedge funds with lower incentives (OTM, low delta, high lockup and restriction periods, bottom 20% relative rank, and low dollar management fee) and lower opportunities (low volatility and high liquidity beta) to manage returns. Year-end Return Inflation is calculated as the return on this long-short portfolio on the last day of the year minus the portfolio return on the first day of next year. To compute the z-statistic for this, for each portfolio, we first compute the return inflation for every non-overlapping 2-day period in that year. The z-statistic each portfolio is given by: (Year-end Return Inflation minus the mean of all possible 2-day returns for that portfolio) divided by the standard deviation of the two-day returns for that portfolio. For the sake of brevity, we report only the average year-end inflation across the 325 portfolio-year combinations. The z-statistic for this overall average is the sum of the z-statistic of the 325 portfolio-years divided by the square root of 325. The reported p-value is the probability of obtaining a z-statistic greater than this overall z-statistic assuming a standard normal distribution. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	All Stocks	Long ITM and NTM Short OTM	Long High-Delta Short Low-Delta	Long High-Rank Short Low-Rank	Long Short-Lockup Short Long-Lockup	Long Short-Restriction Short Long-Restriction	Long High-Dollar management fee Short Low-Dollar management fee	Long High-Volatility Short Low-Volatility	Long Low-Liquidity Short High-Liquidity
Average Inflation	0.51%***	0.48%*	0.64%**	0.59%*	–0.25%	0.32%	0.65%*	0.06%	–0.01%
p-value	0.000	0.099	0.032	0.061	0.105	0.145	0.053	0.413	0.460

Appendix A. Do investor flows depend on the number of positive months?

This table reports OLS estimates using $Flow_t$ as the dependent variable. Sample period is from 1994 to 2006. Flow is the annual investors' dollar flow scaled by assets. The independent variables include number of positive months (NPM) during year *t-1* and year *t*, lagged performance measures (fractional rank quintiles), lagged delta ($Delta_{t-1}$), hurdle rate and high-water mark dummies, lockup period and restriction period, lagged flow ($Flow_{t-1}$), lagged size computed as the logarithm of AUM ($Size_{t-1}$), lagged return volatility ($Volatility_{t-1}$), lagged age (Age_{t-1}), management fees, contemporaneous returns ($Return_t$), strategy and year dummies. Fractional rank quintiles are based on annual returns of funds following a particular strategy (relative ranks) during year *t-1*. These are constructed as in Sirri and Tufano (1998). Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% respectively. p-values corrected for heteroskedasticity and fund-level clustering are reported in parentheses.

	Expected Sign	Dependent variable: $Flow_t$	
NPM_{t-1}	+	0.036^{***} (0.000)	
NPM_t	+		0.066^{***} (0.000)
$Rank_{t-1}$ - Bottom Quintile		0.350 (0.298)	0.495 (0.124)
$Rank_{t-1}$ - 4th Quintile		0.833^{***} (0.002)	0.997^{***} (0.000)
$Rank_{t-1}$ - 3rd Quintile		1.132^{***} (0.000)	1.125^{***} (0.000)
$Rank_{t-1}$ - 2nd Quintile		0.724^{**} (0.028)	0.886^{***} (0.006)
$Rank_{t-1}$ - Top Quintile		0.716 (0.171)	0.877^{*} (0.089)
$Delta_{t-1}$		0.196^{***} (0.000)	0.196^{***} (0.000)
Hurdle Rate		–0.034 (0.252)	–0.029 (0.327)
High-Water Mark		0.101^{***} (0.005)	0.098^{***} (0.005)
Lockup Period		–0.021 (0.526)	–0.028 (0.392)
Restriction Period		-0.137^{***} (0.001)	-0.155^{***} (0.000)
$Size_{t-1}$		-0.231^{***} (0.000)	-0.231^{***} (0.000)
$Flow_{t-1}$		0.055^{***} (0.000)	0.057^{***} (0.000)
$Volatility_{t-1}$		-0.030^{***} (0.000)	-0.025^{***} (0.000)
Age_{t-1}		-0.019^{***} (0.000)	-0.019^{***} (0.000)
Management Fee Rate		3.108 (0.312)	2.372 (0.418)
$Return_t$		0.008^{***} (0.000)	0.005^{***} (0.000)
Intercept		0.235^{**} (0.018)	0.283^{**} (0.017)
Strategy dummies		Yes	Yes
Year dummies		Yes	Yes
Adjusted R^2		11.1%	11.5%
Observations		15,059	15,421

cfr working paper series

centre for financial research cologne

cfr working papers are available for download from **www.cfr-cologne.de**.

Hardcopies can be ordered from: centre for financial research (cfr), Albertus Magnus Platz, 50923 Koeln, Germany.

2012

No.	Author(s)	Title
12-06	A. Kempf, A. Pütz, F. Sonnenburg	Fund Manager Duality: Impact on Performance and Investment Behavior
12-05	R. Wermers	Runs on Money Market Mutual Funds
12-04	R. Wermers	A matter of style: The causes and consequences of style drift in institutional portfolios
12-03	C. Andres, A. Betzer, I. van den Bongard, C. Haesner, E. Theissen	Dividend Announcements Reconsidered: Dividend Changes versus Dividend Surprises
12-02	C. Andres, E. Fernau, E. Theissen	Is It Better To Say Goodbye? When Former Executives Set Executive Pay
12-01	L. Andreu, A. Pütz	Are Two Business Degrees Better Than One? Evidence from Mutual Fund Managers' Education

2011

No.	Author(s)	Title
11-16	V. Agarwal, J.-P. Gómez, R. Priestley	Management Compensation and Market Timing under Portfolio Constraints
11-15	T. Dimpfl, S. Jank	Can Internet Search Queries Help to Predict Stock Market Volatility?
11-14	P. Gomber, U. Schweickert, E. Theissen	Liquidity Dynamics in an Electronic Open Limit Order Book: An Event Study Approach
11-13	D. Hess, S. Orbe	Irrationality or Efficiency of Macroeconomic Survey Forecasts? Implications from the Anchoring Bias Test
11-12	D. Hess, P. Immenkötter	Optimal Leverage, its Benefits, and the Business Cycle
11-11	N. Heinrichs, D. Hess, C. Homburg, M. Lorenz, S. Sievers	Extended Dividend, Cash Flow and Residual Income Valuation Models – Accounting for Deviations from Ideal Conditions
11-10	A. Kempf, O. Korn, S. Saßning	Portfolio Optimization using Forward - Looking Information

11-09	V. Agarwal, S. Ray	Determinants and Implications of Fee Changes in the Hedge Fund Industry
11-08	G. Cici, L.-F. Palacios	On the Use of Options by Mutual Funds: Do They Know What They Are Doing?
11-07	V. Agarwal, G. D. Gay, L. Ling	Performance inconsistency in mutual funds: An investigation of window-dressing behavior
11-06	N. Hautsch, D. Hess, D. Veredas	The Impact of Macroeconomic News on Quote Adjustments, Noise, and Informational Volatility
11-05	G. Cici	The Prevalence of the Disposition Effect in Mutual Funds' Trades
11-04	S. Jank	Mutual Fund Flows, Expected Returns and the Real Economy
11-03	G.Fellner, E.Theissen	Short Sale Constraints, Divergence of Opinion and Asset Value: Evidence from the Laboratory
11-02	S.Jank	Are There Disadvantaged Clienteles in Mutual Funds?
11-01	V. Agarwal, C. Meneghetti	The Role of Hedge Funds as Primary Lenders

2010

No.	Author(s)	Title
10-20	G. Cici, S. Gibson, J.J. Merrick Jr.	Missing the Marks? Dispersion in Corporate Bond Valuations Across Mutual Funds
10-19	J. Hengelbrock, E. Theissen, C. Westheide	Market Response to Investor Sentiment
10-18	G. Cici, S. Gibson	The Performance of Corporate-Bond Mutual Funds: Evidence Based on Security-Level Holdings
10-17	D. Hess, D. Kreutzmann, O. Pucker	Projected Earnings Accuracy and the Profitability of Stock Recommendations
10-16	S. Jank, M. Wedow	Sturm und Drang in Money Market Funds: When Money Market Funds Cease to Be Narrow
10-15	G. Cici, A. Kempf, A. Puetz	The Valuation of Hedge Funds' Equity Positions
10-14	J. Grammig, S. Jank	Creative Destruction and Asset Prices
10-13	S. Jank, M. Wedow	Purchase and Redemption Decisions of Mutual Fund Investors and the Role of Fund Families
10-12	S. Artmann, P. Finter, A. Kempf, S. Koch, E. Theissen	The Cross-Section of German Stock Returns: New Data and New Evidence
10-11	M. Chesney, A. Kempf	The Value of Tradeability
10-10	S. Frey, P. Herbst	The Influence of Buy-side Analysts on Mutual Fund Trading
10-09	V. Agarwal, W. Jiang, Y. Tang, B. Yang	Uncovering Hedge Fund Skill from the Portfolio Holdings They Hide
10-08	V. Agarwal, V. Fos, W. Jiang	Inferring Reporting Biases in Hedge Fund Databases from Hedge Fund Equity Holdings
10-07	V. Agarwal, G. Bakshi,	Do Higher-Moment Equity Risks Explain Hedge Fund

	J. Huij	Returns?
10-06	J. Grammig, F. J. Peter	Tell-Tale Tails
10-05	K. Drachter, A. Kempf	Höhe, Struktur und Determinanten der Managervergütung- Eine Analyse der Fondsbranche in Deutschland
10-04	J. Fang, A. Kempf, M. Trapp	Fund Manager Allocation
10-03	P. Finter, A. Niessen-Ruenzi, S. Ruenzi	The Impact of Investor Sentiment on the German Stock Market
10-02	D. Hunter, E. Kandel, S. Kandel, R. Wermers	Endogenous Benchmarks
10-01	S. Artmann, P. Finter, A. Kempf	Determinants of Expected Stock Returns: Large Sample Evidence from the German Market

2009

No.	Author(s)	Title
09-17	E. Theissen	Price Discovery in Spot and Futures Markets: A Reconsideration
09-16	M. Trapp	Trading the Bond-CDS Basis – The Role of Credit Risk and Liquidity
09-15	A. Betzer, J. Gider, D.Metzger, E. Theissen	Strategic Trading and Trade Reporting by Corporate Insiders
09-14	A. Kempf, O. Korn, M. Uhrig-Homburg	The Term Structure of Illiquidity Premia
09-13	W. Bühler, M. Trapp	Time-Varying Credit Risk and Liquidity Premia in Bond and CDS Markets
09-12	W. Bühler, M. Trapp	Explaining the Bond-CDS Basis – The Role of Credit Risk and Liquidity
09-11	S. J. Taylor, P. K. Yadav, Y. Zhang	Cross-sectional analysis of risk-neutral skewness
09-10	A. Kempf, C. Merkle, A. Niessen-Ruenzi	Low Risk and High Return – Affective Attitudes and Stock Market Expectations
09-09	V. Fotak, V. Raman, P. K. Yadav	Naked Short Selling: The Emperor`s New Clothes?
09-08	F. Bardong, S.M. Bartram, P.K. Yadav	Informed Trading, Information Asymmetry and Pricing of Information Risk: Empirical Evidence from the NYSE
09-07	S. J. Taylor , P. K. Yadav, Y. Zhang	The information content of implied volatilities and model-free volatility expectations: Evidence from options written on individual stocks
09-06	S. Frey, P. Sandas	The Impact of Iceberg Orders in Limit Order Books
09-05	H. Beltran-Lopez, P. Giot, J. Grammig	Commonalities in the Order Book
09-04	J. Fang, S. Ruenzi	Rapid Trading bei deutschen Aktienfonds: Evidenz aus einer großen deutschen Fondsgesellschaft
09-03	A. Banegas, B. Gillen, A. Timmermann, R. Wermers	The Performance of European Equity Mutual Funds

09-02	J. Grammig, A. Schrimpf, M. Schuppli	Long-Horizon Consumption Risk and the Cross-Section of Returns: New Tests and International Evidence
09-01	O. Korn, P. Koziol	The Term Structure of Currency Hedge Ratios

2008

No.	Author(s)	Title
08-12	U. Bonenkamp, C. Homburg, A. Kempf	Fundamental Information in Technical Trading Strategies
08-11	O. Korn	Risk Management with Default-risky Forwards
08-10	J. Grammig, F.J. Peter	International Price Discovery in the Presence of Market Microstructure Effects
08-09	C. M. Kuhnen, A. Niessen	Public Opinion and Executive Compensation
08-08	A. Pütz, S. Ruenzi	Overconfidence among Professional Investors: Evidence from Mutual Fund Managers
08-07	P. Osthoff	What matters to SRI investors?
08-06	A. Betzer, E. Theissen	Sooner Or Later: Delays in Trade Reporting by Corporate Insiders
08-05	P. Linge, E. Theissen	Determinanten der Aktionärspräsenz auf Hauptversammlungen deutscher Aktiengesellschaften
08-04	N. Hautsch, D. Hess, C. Müller	Price Adjustment to News with Uncertain Precision
08-03	D. Hess, H. Huang, A. Niessen	How Do Commodity Futures Respond to Macroeconomic News?
08-02	R. Chakrabarti, W. Megginson, P. Yadav	Corporate Governance in India
08-01	C. Andres, E. Theissen	Setting a Fox to Keep the Geese - Does the Comply-or-Explain Principle Work?

2007

No.	Author(s)	Title
07-16	M. Bär, A. Niessen, S. Ruenzi	The Impact of Work Group Diversity on Performance: Large Sample Evidence from the Mutual Fund Industry
07-15	A. Niessen, S. Ruenzi	Political Connectedness and Firm Performance: Evidence From Germany
07-14	O. Korn	Hedging Price Risk when Payment Dates are Uncertain
07-13	A. Kempf, P. Osthoff	SRI Funds: Nomen est Omen
07-12	J. Grammig, E. Theissen, O. Wuensche	Time and Price Impact of a Trade: A Structural Approach
07-11	V. Agarwal, J. R. Kale	On the Relative Performance of Multi-Strategy and Funds of Hedge Funds
07-10	M. Kasch-Haroutounian, E. Theissen	Competition Between Exchanges: Euronext versus Xetra
07-09	V. Agarwal, N. D. Daniel, N. Y. Naik	Do hedge funds manage their reported returns?

07-08	N. C. Brown, K. D. Wei, R. Wermers	Analyst Recommendations, Mutual Fund Herding, and Overreaction in Stock Prices
07-07	A. Betzer, E. Theissen	Insider Trading and Corporate Governance: The Case of Germany
07-06	V. Agarwal, L. Wang	Transaction Costs and Value Premium
07-05	J. Grammig, A. Schrimpf	Asset Pricing with a Reference Level of Consumption: New Evidence from the Cross-Section of Stock Returns
07-04	V. Agarwal, N.M. Boyson, N.Y. Naik	Hedge Funds for retail investors? An examination of hedged mutual funds
07-03	D. Hess, A. Niessen	The Early News Catches the Attention: On the Relative Price Impact of Similar Economic Indicators
07-02	A. Kempf, S. Ruenzi, T. Thiele	Employment Risk, Compensation Incentives and Managerial Risk Taking - Evidence from the Mutual Fund Industry -
07-01	M. Hagemeister, A. Kempf	CAPM und erwartete Renditen: Eine Untersuchung auf Basis der Erwartung von Marktteilnehmern

2006

No.	Author(s)	Title
06-13	S. Čeljo-Hörhager, A. Niessen	How do Self-fulfilling Prophecies affect Financial Ratings? - An experimental study
06-12	R. Wermers, Y. Wu, J. Zechner	Portfolio Performance, Discount Dynamics, and the Turnover of Closed-End Fund Managers
06-11	U. v. Lilienfeld-Toal, S. Ruenzi	Why Managers Hold Shares of Their Firm: An Empirical Analysis
06-10	A. Kempf, P. Osthoff	The Effect of Socially Responsible Investing on Portfolio Performance
06-09	R. Wermers, T. Yao, J. Zhao	Extracting Stock Selection Information from Mutual Fund holdings: An Efficient Aggregation Approach
06-08	M. Hoffmann, B. Kempa	The Poole Analysis in the New Open Economy Macroeconomic Framework
06-07	K. Drachter, A. Kempf, M. Wagner	Decision Processes in German Mutual Fund Companies: Evidence from a Telephone Survey
06-06	J.P. Krahnen, F.A. Schmid, E. Theissen	Investment Performance and Market Share: A Study of the German Mutual Fund Industry
06-05	S. Ber, S. Ruenzi	On the Usability of Synthetic Measures of Mutual Fund Net-Flows
06-04	A. Kempf, D. Mayston	Liquidity Commonality Beyond Best Prices
06-03	O. Korn, C. Koziol	Bond Portfolio Optimization: A Risk-Return Approach
06-02	O. Scaillet, L. Barras, R. Wermers	False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas
06-01	A. Niessen, S. Ruenzi	Sex Matters: Gender Differences in a Professional Setting

2005

No.	Author(s)	Title
05-16	E. Theissen	An Analysis of Private Investors´ Stock Market Return Forecasts

05-15	T. Foucault, S. Moinas, E. Theissen	Does Anonymity Matter in Electronic Limit Order Markets
05-14	R. Kosowski, A. Timmermann, R. Wermers, H. White	Can Mutual Fund „Stars“ Really Pick Stocks? New Evidence from a Bootstrap Analysis
05-13	D. Avramov, R. Wermers	Investing in Mutual Funds when Returns are Predictable
05-12	K. Griese, A. Kempf	Liquiditätsdynamik am deutschen Aktienmarkt
05-11	S. Ber, A. Kempf, S. Ruenzi	Determinanten der Mittelzuflüsse bei deutschen Aktienfonds
05-10	M. Bär, A. Kempf, S. Ruenzi	Is a Team Different From the Sum of Its Parts? Evidence from Mutual Fund Managers
05-09	M. Hoffmann	Saving, Investment and the Net Foreign Asset Position
05-08	S. Ruenzi	Mutual Fund Growth in Standard and Specialist Market Segments
05-07	A. Kempf, S. Ruenzi	Status Quo Bias and the Number of Alternatives - An Empirical Illustration from the Mutual Fund Industry
05-06	J. Grammig, E. Theissen	Is Best Really Better? Internalization of Orders in an Open Limit Order Book
05-05	H. Beltran-Lopez, J. Grammig, A.J. Menkveld	Limit order books and trade informativeness
05-04	M. Hoffmann	Compensating Wages under different Exchange rate Regimes
05-03	M. Hoffmann	Fixed versus Flexible Exchange Rates: Evidence from Developing Countries
05-02	A. Kempf, C. Memmel	Estimating the Global Minimum Variance Portfolio
05-01	S. Frey, J. Grammig	Liquidity supply and adverse selection in a pure limit order book market

2004

No.	Author(s)	Title
04-10	N. Hautsch, D. Hess	Bayesian Learning in Financial Markets – Testing for the Relevance of Information Precision in Price Discovery
04-09	A. Kempf, K. Kreuzberg	Portfolio Disclosure, Portfolio Selection and Mutual Fund Performance Evaluation
04-08	N.F. Carline, S.C. Linn, P.K. Yadav	Operating performance changes associated with corporate mergers and the role of corporate governance
04-07	J.J. Merrick, Jr., N.Y. Naik, P.K. Yadav	Strategic Trading Behaviour and Price Distortion in a Manipulated Market: Anatomy of a Squeeze
04-06	N.Y. Naik, P.K. Yadav	Trading Costs of Public Investors with Obligatory and Voluntary Market-Making: Evidence from Market Reforms
04-05	A. Kempf, S. Ruenzi	Family Matters: Rankings Within Fund Families and Fund Inflows
04-04	V. Agarwal, N.D. Daniel, N.Y. Naik	Role of Managerial Incentives and Discretion in Hedge Fund Performance
04-03	V. Agarwal, W.H. Fung, J.C. Loon, N.Y. Naik	Risk and Return in Convertible Arbitrage: Evidence from the Convertible Bond Market
04-02	A. Kempf, S. Ruenzi	Tournaments in Mutual Fund Families

04-01	I. Chowdhury, M. Hoffmann, A. Schabert	Inflation Dynamics and the Cost Channel of Monetary Transmission

centre for financial research
cfr/university of cologne
Albertus-Magnus-Platz
D-50923 cologne
Fon +49(0)221-470-6995
Fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de