Why is Santa so kind to hedge funds? The December return puzzle!

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Abstract

We find that the average hedge fund returns during December are significantly higher than those during the rest of the year. This *December spike* cannot be fully explained by increase in the funds' risk exposures and by higher factor risk premiums in December. We argue that hedge fund contractual features such as performance-linked fee, lockup period, notice period, and redemption period, provide incentives to inflate returns at year-end. Consistent with this notion, we find that the spike is indeed more pronounced among funds with higher incentives. In addition to incentives, we contend that funds with greater opportunities to manage returns, i.e., those with higher volatility and higher exposure to liquidity risk, exhibit greater spike. We find that the spike is indeed higher for funds with greater opportunities to manage returns. Finally, we demonstrate that funds engage in returns management by under-reporting returns earlier in the year and/or by borrowing from January returns in the following year.

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Abstract

We find that the average hedge fund returns during December are significantly higher than those during the rest of the year. This December spike cannot be fully explained by increase in the funds' risk exposures and by higher factor risk premiums in December. We argue that hedge fund contractual features such as performance-linked fee, lockup period, notice period, and redemption period, provide incentives to inflate returns at year-end. Consistent with this notion, we find that the spike is indeed more pronounced among funds with higher incentives. In addition to incentives, we contend that funds with greater opportunities to manage returns, i.e., those with higher volatility and higher exposure to liquidity risk, exhibit greater spike. We find that the spike is indeed higher for funds with greater opportunities to manage returns. Finally, we demonstrate that funds engage in returns management by under-reporting returns earlier in the year and/or by borrowing from January returns in the following year.

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Hedge funds are compensated by incentive fees that are paid at the end of the year based on annual performance exceeding prespecified thresholds.[1] Thus, there exist strong incentives for managers to improve performance as the year comes to a close. Consistent with this notion, we find that in our sample, average December returns are significantly higher than the average return during January to November (see Figure 1, Panel A). We refer to this as the *December spike*.

A potential explanation for the December spike, based on risk, is that funds either increase their risk exposures in December or that the factor risk premiums happen to be higher during December in our sample. We find that this risk-based explanation cannot fully account for the December spike, which leaves us with a somewhat more provocative interpretation that hedge funds may be inflating December returns in order to earn higher compensation. To understand the economic rationale behind such a phenomenon, we exploit the special contractual features of hedge funds, such as performance-based incentive fee, lockup period, notice period, and redemption period.[2] Specifically, we investigate if funds that have higher incentives and greater opportunities to manage returns exhibit greater December spike.

To capture incentives for returns management, we recognize that the performance-based compensation contract provides asymmetric call-option-like payoff. We compute the moneyness and delta of the option and use these as proxies for returns management incentives faced by the

[1] Incentive fees are paid out at the end of the calendar year based on fund performance over 12 months when net asset value (NAV) exceeds a threshold NAV, which in turn depends on the hurdle rate and high-water mark provisions. 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). With a high-water mark provision, the manager earns incentive fees only on new profits, i.e., after recovering past losses, if any.

[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."

fund. Furthermore, hedge funds have lockup and restriction periods that impose impediments on capital withdrawals. Shorter lockup and restriction periods can result in frequent capital outflows. If investors withdraw their capital in response to poor annual performance, then managers may pay excessive attention to short-term performance and potentially engage in returns management. Hence, we also use lockup period and restriction period as additional proxies for returns management incentives.

In addition to incentives, funds also need to have opportunities to manage returns. Funds with higher volatility might mask the returns management with greater ease. Similarly, funds with higher exposure to liquidity risk can more easily influence the prices of securities they own. Thus, we use fund's volatility and its exposure to liquidity risk to proxy for the opportunities available to the fund to engage in returns management.

Consistent with our expectation, we find that funds with higher incentives and greater opportunities do indeed exhibit a greater December spike. In particular, we find that the December spike is the highest for in-the-money funds, followed by near-the-money funds, which in turn exceeds that of out-of-money funds. We also find that funds with higher delta, lower lockup period, lower restriction period, higher volatility, and higher liquidity risk exhibit a higher December spike. The presence of a December spike and the observation that the size of the spike correlates with our proxies for returns management, together suggest that funds manage their reported returns. Following the well-known phenomenon of "earnings management" in corporations, this paper explores, and indeed is the first to document, this phenomenon of "returns management" in hedge funds.

The evidence of returns management and its economic drivers begs the question arises of its modus operandi: What is the mechanism by which hedge funds manage their returns? Specifically, we examine whether funds underreport positive returns in the earlier months of a year to create reserves for a bad state of the world in future months ("saving for the rainy day"), and then add those reserves back in December if the bad state is not realized. Such intrayear smoothing is in contrast to the interyear smoothing observed in corporations. We also examine if some funds "borrow" from their future performance to report higher returns in December in order to earn their incentive fees.[3] We find strong evidence that funds manage returns through both of these mechanisms.

Our findings have important implications for hedge fund regulators and investors by informing the debate on the need for increase in regulation of hedge funds. Recently, the Securities and Exchange Commission (SEC) has initiated the process of regulating hedge funds. The SEC is especially concerned about issues related to accurate valuation of securities in hedge fund portfolios.[4] If some hedge funds inflate returns in December, investors cashing out at year-end benefit at the cost of those entering or remaining in those funds. Our findings can help regulators and investors to focus more closely on funds that have higher incentives and greater opportunities to engage in returns management.

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 investigates our hypothesis related to returns management, while Section VI examines the types of funds that exhibit greater returns management. Section VII sheds light on the modus operandi of returns management, and Section VIII offers concluding remarks.

II. Related Literature

[3] 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.

[4] 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.

In documenting returns management in hedge funds and its relation to economic incentives, our study contributes to literature on earnings management and executive compensation from a very different viewpoint.

There exists a large literature on earnings management in corporations.[5] It shows that (see, e.g., Burgstahler and Dichev (1997), and DeGeorge, Patel, and Zeckhauser (1999)) firms manage earnings toward specific earnings thresholds. In particular, it shows that firms, *inter alia,* manage earnings to avoid reporting losses or avoid earnings decline. 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 extent of returns management in hedge funds is strongly related to the degree of moneyness of their compensation contracts.

The present study also supplements the executive compensation literature examining the relation between earnings management and incentives from compensation.[6] Healy (1985) and Gaver, Gaver, and Austin (1995) relate managers' accrual policies with incentives arising from 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 also can 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. Similar to these findings, our investigation provides evidence that hedge funds with higher delta exhibit a larger December spike.

While documenting the December spike and the returns management in hedge funds, we control for well-documented year-end effects in mutual fund returns. For example, Carhart et al.

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[5] See Healey and Wahlen (1999), Dechow and Skinner (2000), Fields, Lys, and Vincent (2001), and Stolowy and Breton (2004) for surveys on this literature.
[6] See Murphy (1999) and Core, Guay, and Larcker (2003) for a survey of literature on executive compensation.

(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 trade in same securities as mutual funds, hedge fund returns can also be passively inflated in December. Interestingly, even when we allow for such a possibility, we continue to find a significant December spike, suggesting active return management behavior in hedge funds. We believe that the performance-based compensation contract provides hedge funds incentives to engage in returns management. Consistent with this, we find that funds with stronger incentives (moneyness and delta) exhibit larger December spikes.

Chander 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 suggestive evidence that hedge funds with higher exposure to liquidity risk exhibit increased returns management.

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 (2004) demonstrate that it is difficult to detect intentional smoothing of returns by looking at autocorrelations. Despite funds' preference for smoothing returns, the finding of a December spike and the mechanism by which this spike is achieved (saving for the rainy day and borrowing from the future) suggest that the returns management we document is very much real.

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 asymmetric 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 convex compensation scheme motivates the manager to exert effort and improve fund performance, it can also tempt the manager to *inflate* returns. Incentive fees accrue over the year, but are paid at the end of the fiscal year. Since for most funds December is their fiscal-year-end when their accounts are audited, one is more likely to observe returns management during the month of December. This leads us to our first hypothesis.

Hypothesis 1: All else equal, December returns should be higher than the returns during other months.

In the process of examining hypothesis 1, we control for the possibility that 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 for greater compensation. We also allow for the possibility that some funds might passively benefit from portfolio pumping by other institutional investors.

If we find support for the above hypothesis, a question naturally arises as to what types of funds display greater December spike. As discussed in the section on related literature (Section II), we know that incentives can arise from thresholds in case of corporations from the earnings management literature. 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 to proxy for the incentives faced by hedge funds. For example, if by November-end, the incentive-fee 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. Similarly, one would expect funds with higher delta to exhibit greater December spike. In addition to performance-based fee, contractual features such as lockup and restriction periods also provide incentives to manage returns. For example, funds with shorter lockup and restriction periods can experience capital outflows at more frequent intervals. This can result in excessive attention being paid to short-term performance, thus providing greater incentives to engage in inflating returns in December.

In addition to incentives, a fund's motivation to inflate returns also depends on the opportunities available to the fund. Hedge funds with more volatile trading strategies have more opportunities to inflate returns, as it is relatively more difficult to detect such an activity. Furthermore, hedge funds that trade in relatively illiquid securities have more opportunities to influence the prices of securities they own, sometimes for the purpose of inflating returns. These arguments provide us with our second hypothesis:

Hypothesis 2: All else equal, funds that have higher incentives (higher moneyness, higher delta, lower lockup and restriction periods) and funds with greater opportunities (higher volatility and greater illiquidity) should 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 mechanism 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 fact, such behavior is common in corporations according to former SEC chairman, Arthur Levitt (1998) who argues that "companies stash accruals in cookie jar reserves during the good economic times and reach into them when needed in the bad times." In the case of hedge funds, the tendency to create reserves could be driven by investors' preference for funds with fewer loss-making months. 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 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 last-minute buying. This is followed by price reversals in January (see Carhart et al (2002), Bernhardt and Davies (2005)), which effectively amounts to *borrowing* from January returns.[7] It is plausible that hedge funds borrow from January returns in a similar fashion. This provides us with our fourth hypothesis.

Hypothesis 4 (Borrowing Hypothesis): All else equal, higher December returns in a year should be associated with lower January returns in the following year.

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 four large databases, namely, Center for International Securities and Derivative Markets (CISDM), Hedge Fund Research (HFR), Morgan Stanley Capital International (MSCI), and Tremont Advisory Shareholder Services (TASS). This database reports net-of-fee monthly returns, assets under management, and fund characteristics, such as hurdle rate and high-water mark provisions,

[7] 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 for both the short position in the option and the delta-hedge component correctly.

lockup, notice, and redemption periods, incentive fees, management fees, inception date, and fund strategy.[8] This enables us to resolve occasional discrepancies among different databases as well as create a sample that is more representative of the hedge fund industry. Our sample period extends from January 1994 to December 2002. 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.[9] After merging the four databases, we find that there are 7535 hedge funds: 3924 remained live as of December, 2002 while 3611 became defunct during our sample period. In Figure 2, we report the overlap among the four 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. Merging them, therefore, helps to capture a more representative sample of the hedge fund universe.

One challenge in dealing with multiple databases is that they adopt different nomenclature to identify fund strategies. Based on descriptions provided by the database vendors, we classify funds into four broad strategies: Directional, Relative Value, Security Selection, and Multi-Process Traders. This classification is motivated by Fung and Hsieh (1997) and Brown and Goetzmann (2003), which are studies that indicate few distinct style-factors in hedge fund returns. Appendix A describes the mapping between the data vendors' classification and our classification and reports the distribution of hedge funds across the four broad strategies.[10]

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[8] 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.

[9] 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.

[10] We also conduct our analysis at the substrategy level using the original strategy classification in the four databases; we find our results to be robust to using the original classification. These results are available from authors upon request.

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 2002. We compute the gross-of-fee returns from net-of-fee returns following the methodology of Agarwal, Daniel, and Naik (2005) (see Appendix B for details). 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, 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.

To test for December spike, we need to control for the systematic risks of hedge funds. Hence we employ a second measure, $\text{Residual}_{i,m,}$, 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).[11] This is in the spirit of Bollen and Krepely (2004), who estimate the predicted returns from Fung and Hsieh's (2004) seven-factor model and call it 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 some variables that are predicted to be related to accruals (see Jones (1991), 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 1.06%. As expected, the mean monthly residuals are

[11] 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 report these later in Section V.A.

virtually zero.

IV.C. Measures of Risk Exposures

As hedge fund returns are available only on a monthly basis, it is not possible 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 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*.[12] 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 6.02% (5.83%).

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, again using the methodology of Agarwal, Daniel, and Naik (2005) (see Appendix B

[12] 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 .

for details).

Our first measure of returns management incentives is related to the moneyness. 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. 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. In Table I, we observe that the mean (median) moneyness is –0.003 (–0.13) suggesting that, on average, funds are just about at-the-money or out-of-the-money.

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 in our sample. We provide an example to illustrate our classification algorithm. Suppose that the mean (μ) and standard deviation (σ) of a fund's monthly returns are 1% and 5%, respectively. 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.*[13] During our sample period, we find (not reported), on average, that 31% of the funds are near the money, 38% are in the money, and remaining 31% are out of the money.

[13] Our results are robust to reclassification using strategy-level μ and σ instead of fund-level μ and σ.

Our second measure of returns management incentives is the delta of this portfolio. 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, fund volatility.[14] We compute the delta at 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 NAV (see Appendix B for details). From Table I, we find that the mean (median) monthly delta equals $170,000 ($20,000).[15]

Our third and final measure of returns management incentives are lockup period and restriction period. From Table I, we observe that the mean lockup period (restriction period) is 0.13 (0.31) year.

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 4.82% (3.83%). 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 returns on the seven factors of Fung and Hsieh (2004), augmented with the value-weighted liquidity risk factor.[16] A higher beta on the liquidity risk factor implies that the fund has greater liquidity risk and thereby is more illiquid. From Table I, we observe that the mean (median) of the liquidity beta is 0.02 (0.00). The interquartile range of liquidity beta is 0.15 (i.e., 0.09 – (–0.06)) suggests that there is considerable cross-sectional variation in the liquidity risk exposure across different hedge funds.

IV.F. Measures of Reserves

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[14] Black and Scholes (1973) delta equals our dollar delta divided by (0.01× (incentive fee) × (investors' assets)).

[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] All our results are robust to the use of an equally-weighted liquidity risk factor.

To test our *Savings Hypothesis*, we construct a measure of reserves. We define $Reserves_{i,m}$ 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. If the fund manager is indeed adding back reserves in December, then one would expect to see the interaction of the reserves variable and the December dummy to be positive.[17] From Table I, we observe that the mean (median) of the reserves variable is 8.58% (3.56%).

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

V. Is There Evidence of a December Spike in Hedge Funds?

Before conducting a multivariate analysis, we first plot the average monthly gross returns for all the hedge funds in our sample period (1994-2002) in Figure 1, Panel A. As mentioned earlier, the results are striking, as the average December return is more than two-and-a-half times the average return during the January–November period (2.51% compared to 0.96%). We also compare each month's gross return to the gross return in December. We find the December return to be higher in each pairwise comparison and the difference to be statistically significant (results not reported in table). In Figure 1, Panel B, for each year during our sample period, we plot the average returns during the January–November period and during December. In a majority of years, we find that December returns exceed the January–November returns. Thus, this phenomenon appears to be widespread.

To examine if the December spike for hedge funds is due to high December returns for the market, we also plot the average monthly returns for all NYSE, AMEX, and NASDAQ firms during our sample period (1994–2002) in Figure 3, Panel A (overall) and Panel B (year-by-year).

[17] We repeat our analysis using the reserves variable without truncating it at zero. All our results remain unchanged.

We also plot similar figures using monthly gross-of-fee returns for all equity mutual funds from the CRSP mutual fund database in Figure 3, Panels C and D.[18] Although December returns are high for both the market and the mutual funds samples, these plots are not nearly as striking as is Figure 1 for hedge funds.

In Table II, we provide a univariate comparison of gross returns and residual returns of hedge funds in our sample for December and the rest of the year (January–November). Results from *t*-tests suggest that the average gross returns and residuals in December are significantly greater than those for the rest of the year. The December spike is 1.55% in terms of gross returns and 0.25% in terms of residual returns. We also compare the factor premiums between December and rest of the year. Although the factor premiums are higher in December, given that we find a December spike in residual returns suggests that higher factor premiums in December are not completely responsible for this pattern.

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

In this section, we extend our analysis to a multivariate setting. We start our analysis with gross-of-fee returns after controlling for fund characteristics, strategy and year effects. In particular, we estimate the following regression:

$$\begin{aligned}\text{Return}_{i,m} = {} & \lambda_0 + \lambda_1 I(\text{December}_i) + \lambda_2 \text{Return}_{i,m-1} + \lambda_3 \text{Return}_{i,m-2} + \lambda_4 \text{Delta}_{i,m-1} \\ & + \lambda_5 \text{Moneyness}_{i,m-1} + \lambda_6 \text{Lockup}_i + \lambda_7 \text{Restrict}_i + \lambda_8 \text{Size}_{i,m-1} + \lambda_9 \sigma_i \\ & + \lambda_{10} \text{Age}_i + \lambda_{11} \text{MFee}_i + \sum_{s=1}^{3} \lambda_{12}^{s} I(\text{Strategy}_{i,s}) + \sum_{k=1}^{8} \lambda_{13}^{k} I(\text{Year}_{t,k}) + \xi_{i,m}\end{aligned} \qquad \textbf{(1)}$$

where $\text{Return}_{i,m}$ is the return of fund *i* in month *m*, $I(\text{December}_i)$ is an indicator variable that takes the value 1 if the month is December, and 0 otherwise, $\text{Delta}_{i,m-1}$ is the sensitivity of the managers' wealth to a 1% change in NAV for fund *i* as of end of month *m-1*, $\text{Moneyness}_{i,m-1}$ of

[18] Following Sirri and Tufano (1998), we compute the gross returns by adding back expense ratio and one-seventh of the total load fees.

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 fees 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]

Here and throughout the paper, we report the slope coefficients and corresponding p-values after adjusting for heteroskedasticity and fund-level clustering including serial correlation.

We report our findings in Table III. Our results for Model 1 show that the slope coefficient on December dummy is positive (λ_1 = 1.514) and highly significant at 1% level. The coefficient estimates imply that December returns are higher by 1.5%. This result is economically significant given that the average returns are 1.1%. For robustness, we repeat our analysis with net-of-fee returns and find that the slope coefficient on December dummy continues to be positive (λ_1 = 1.272) and significant at the 1% level (see Model 1 results in Appendix C). Consistent with the findings of Agarwal, Daniel, and Naik (2005), 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 Getmansky, Lo, and Makarov (2004), we find that the coefficient on the first lag of returns is positive and significant, although the second lag is positive but not significant.[20]

[19] We winsorize extreme 1% of the independent variables in order to minimize the influence of outliers.

[20] It is plausible that funds may increase the risk during the twelve months leading to December. Since the

As discussed earlier, it is possible that a part of the December spike could result if hedge funds hold the same securities as mutual funds, and those mutual funds 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 extent of the December spike 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 a quarter-end spike in hedge funds, it suggests that hedge funds might be beneficiaries of returns management by mutual funds. For this purpose, we add a quarter-end dummy in regression (1), above. This dummy 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.

The results in Model 2 of Table III show that the quarter-end dummy is positive (coeff. = 0.091) and significant at the 1% level, suggesting that hedge fund returns could be influenced by the inflation of mutual fund returns at quarter-ends. More importantly, December dummy continues to be positive ($\lambda_1 = 1.539$) and highly significant. In the study by Carhart et al. (2002), the ratio of coefficients on the year-end and the quarter-end dummies (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 2 of Table III. However, in our case, this ratio turns out to be considerably higher, 16.9 (i.e., 1.539/0.091), indicating that

regressions consider the volatility during the prior year, it may not capture the increase in risk during the current year. Hence, for the sake of robustness, we repeat our analysis using volatility over twelve months, up to prior month, computed on a rolling basis. We find similar results.

the December spike persists even after allowing for the possibility that hedge funds could passively benefit from the portfolio pumping by mutual funds. Taking the higher ratio of 3.26 and the coefficient on Quarter-end dummy of 0.091, we estimate that free-riding by hedge funds contributes at best 0.3% (0.991 × 3.26) to the December spike.

To allow for the possibility that managers could increase their risk exposures in December, we include the cross-sectional volatility measure, CS Volatility$_m$ in the regression in regression (1) above. We report our results from this regression in Model 3 of Table III. We find the coefficient on cross-sectional volatility is positive (coeff. = 0.066) and significant at the 1% level. This implies that higher cross-sectional volatility is associated with higher returns. The December dummy is still 1.5%, so the increase in risk exposures contributes little to the December spike. Model 4 includes both the quarter-end dummy and the cross-sectional volatility measure, and we still get similar inferences. Most importantly the coefficient on the December dummy continues to be positive ($\lambda_1 = 1.511$) and significant at the 1% level. When we estimate Model 4 with net-of-fee returns, we find that the slope coefficient on the December dummy to be again positive ($\lambda_1 = 1.262$) and significant at the 1% level (see Model 4 results in Appendix C).

It is conceivable that managers gradually adjust their returns and do not limit their manipulations to the month of December. Hence, for robustness, we replace the December dummy with a November–December dummy, which takes the value 1 if month equals November or December. We continue to replicate our previous results, with the slope coefficient on the November–December dummy to be 1.27% (results not reported in table).

In Model 5, we use the residual returns (or discretionary component of returns) estimated using the Fung and Hsieh (2004) seven-factor model as the dependent variable in equation (1). In addition, we replace the two lags of returns with those of residuals in the list of independent variables in equation (1). Residuals strip out the effect of higher returns in December that will result if risk premiums are higher in December. The December spike is now 0.362%. This is still economically significant, given that the average monthly return is 1.06%.[21] For robustness, we repeat our analysis with net-of-fee residuals and find that the slope coefficient on the December dummy continues to be positive (λ_1 = 0.334) and significant at the 1% level (see Model 5 results in Appendix C).

Overall, the results in Table III support the idea that funds could be managing returns at the end of the year.

VI. Do Funds with Greater Incentives and Higher Opportunities to Manage Returns Exhibit a Greater December Spike?

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, and funds that have shorter lockup and restriction periods) should exhibit increased incidence of returns management. We also posited that funds with greater opportunities (funds with higher volatility and funds with more illiquidity) should display greater returns management. To test this notion (hypothesis 2), we first create subsamples based on these key variables. Specifically, we divide the funds into *high* and *low* categories based on the median of these variables at the end of each November.[22] 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 reestimate Models 4 and 5 of Table III for these subsamples of funds. Table IV reports the results. For brevity, we report only the slope coefficients for the December dummy

[21] For robustness, we repeat our analysis in Model 5 by replacing residual by the sum of abnormal return (α) and residual return and find similar results. December dummy is positive (λ_1 = 0.345) and significant at the 1% level. As another robustness check, we add the book-to-market and momentum factors to the Fung and Hsieh (2004) seven-factor model and use the residuals from this nine-factor model. We continue to find the December dummy to be positive (λ_1 = 0.380) and significant at the 1% level.

[22] Please note that some variables, such as lockup period and restriction period, do not change for a fund over time.

(λ_1). We also report the significance of the differences between the coefficients of the December dummy (based on Chow-test) for the high and low groups.

From Table IV, we find the slope coefficient on the December dummy to be higher for in-the-money and near-the-money funds compared to out-of-the-money funds. The coefficient estimates from Model 1 imply that the December spike using returns is greater for in-the-money funds by 1.91% (i.e., 2.281 − 0.371) when compared to out-of-the-money funds. The December spike is also greater for near-the-money funds by 1.457% (1.828 − 0.371) relative to out-of-the-money funds. These results also indicate that the December spike is greater for the in-the-money funds relative to near-the-money funds (2.281% vs 1.828%), a difference that is significant at the 1% level and is intuitive, given the fact that benefits of returns management are highest for in-the-money funds.

Results are similar when we define the December spike in terms of residuals. The December spike is again greater for in-the-money funds by 0.597% (0.566 − (–0.031)) and near-the-money funds by 0.517% (0.486 − (–0.031)) when compared to out-of-the-money funds. Once again, in-the-money funds exhibit a significantly greater December spike relative to near-the-money funds. These figures are economically large, as the average monthly return (residual) is 1.06% (–0.02%) (see Table I); all these differences are also statistically significant at the 1% level.

Next, we repeat our analysis using the second measure of incentives—delta. We find that funds with high delta exhibit a greater December spike compared to funds with low delta. The December spike is higher for the high-delta funds by 0.355% (i.e., 1.642% − 1.287%) in terms of returns, and 0.158% (0.414% − 0.256%) in terms of residuals; both these differences are statistically significant at the 1% level.

Finally, we use our third and fourth measure of incentives—lockup period and restriction period. Results for Model 1 show that funds with shorter lockup periods exhibit higher December spikes compared to the funds with longer lockup periods (1.559% vs 1.164%). We find similar differences with respect to the restriction period (1.556% vs 1.488%). The differences between the long- and short-period groups are statistically significant at the 1% level. Results are qualitatively similar when we use residuals instead of returns.

Overall, the results based on moneyness, delta, lockup period, and restriction period suggest that funds with higher incentives exhibit an increased incidence of returns management, providing support for hypothesis 2.

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 more pronounced December spikes than do funds with low volatility. The December spike is higher for the high-volatility funds by 1.922% (i.e., 2.468% − 0.546%) in terms of returns and 0.380% (0.545% − 0.165%) in terms of residuals. Both these differences are statistically significant at the 1% level.

Next, we classify funds into different groups based on liquidity. From the results in Table IV, we find that the slope coefficient (λ_1) on the December dummy is higher for low-liquidity funds by 0.499% (1.791% − 1.292%) in terms of returns. This suggests that more illiquid funds that have greater opportunities to engage in returns management exhibit higher December spikes. However, in terms of residuals, the December spike for low-liquidity funds seems to be indistinguishable from zero and is lower than that of high-liquidity funds by 0.482%. Overall, results based on liquidity provide mixed evidence on the relation between liquidity and returns management.

Our findings from this section lend support to hypothesis 2, i.e., funds with greater incentives (in-the-money and near-the-money incentive-fee contracts, higher delta, shorter lockup and restriction periods) and funds with higher opportunities (higher volatility and more illiquidity) display greater December spikes.

Our finding of a December spike in Section V and that this December spike is related to economically motivated variables in a meaningful way, suggests that hedge funds manage reported returns.

VII. 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, which they add back in December. We test this by including two additional explanatory variables to Model 4 of Table 3: (a) $\text{Reserves}_{i,m\text{-}1}$, 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 Table V confirm that this is indeed the case, with the coefficient on the interaction being positive (coeff. = 0.112) 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 1.46% 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 unreported 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. = 0.633; 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 4 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 Table V indicate that the coefficient on the interaction of the January dummy and the lagged monthly return is negative (coeff. = –0.040) and significant at the 1% level. This result is also economically significant. A one standard deviation increase in the December returns is associated with a borrowing of 0.39% returns from January of the following year. As before, our results for the other variables remain unchanged. This provides evidence in support of the borrowing hypothesis.

Finally, we test for both *savings* as well as *borrowing* hypotheses together by including the corresponding variables together in Model 3 of Table V. All our inferences remain unchanged. Overall, the results from this section strongly support the hypotheses 3 and 4, namely the savings and borrowing hypotheses.

VIII. Concluding Remarks

Recently, there has been much debate about the quality of disclosure and security valuation in the hedge fund industry. In this paper, we contribute to this debate by examining the issue of potential returns management in hedge funds. Since hedge fund managers earn an incentive fee based on annual performance, they have incentives to manage returns upward as the year draws to a close. Consistent with this notion, our paper demonstrates year-end effects in hedge fund returns. Specifically, we find that December returns are higher by 1.5%. Controlling for risk, we continue to find residual returns to be 0.4% higher. We term this the December spike. As expected, we find that funds with greater incentives (higher moneyness, higher delta, and lower lockup and restriction periods) and with greater opportunities (higher volatility and more illiquidity) engage in returns management and exhibit a larger December spike. When we examine the mechanism potentially employed by hedge funds to manage returns, we find support for the possibility that funds underreport their returns until December (thereby creating reserves) and then add them back in December. Furthermore, we find evidence suggesting that part of the December spike comes from funds borrowing from their January returns of the following year.

Our findings have important implications for hedge fund investors and regulators. If some hedge funds inflate returns in December, investors cashing out at year-end benefit at the cost of those entering or remaining in those funds. Since there is a growing trend of retail investors gaining exposure to hedge funds either directly or indirectly via their pension funds, our findings should be of particular interest to investors as well as regulators.

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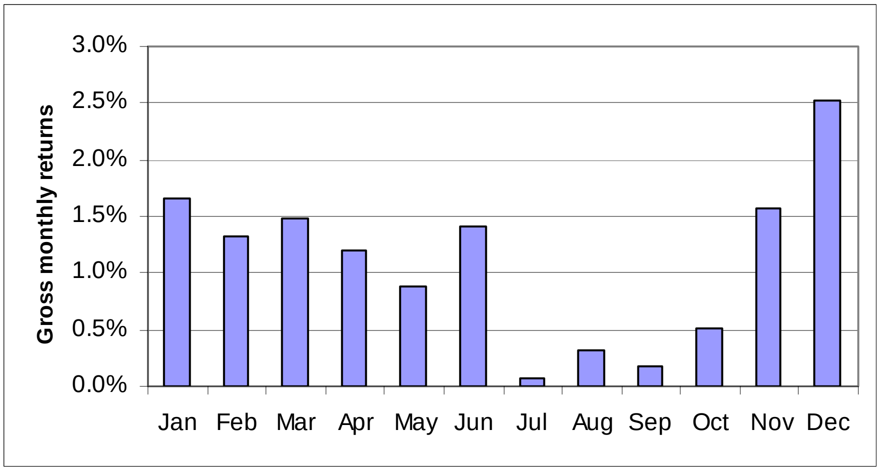
Figure 1: Monthly Gross Returns of Hedge Funds

Panel A plots the average gross monthly fund returns during our sample period, 1994–2002. Panel B plots the average gross monthly fund returns each year for January–November and December periods.

Panel A



Panel B

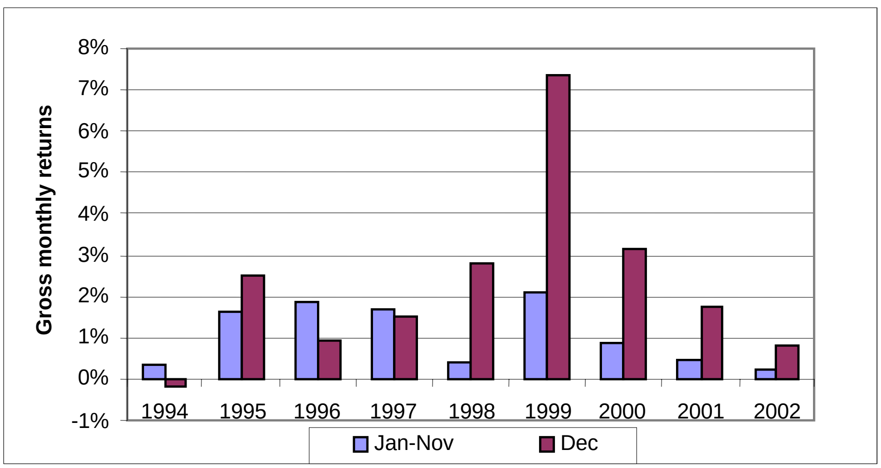


Figure 2: Distribution of Hedge Funds by Data Sources

Depicted is the percentage of hedge funds present in the four databases, namely CISDM, HFR, MSCI, and TASS, at the end of our sample period (2002). Straight lines indicate the origin of fund unions that have been separated for greater legibility, i.e., (HFR + TASS) and (CISDM + MSCI).

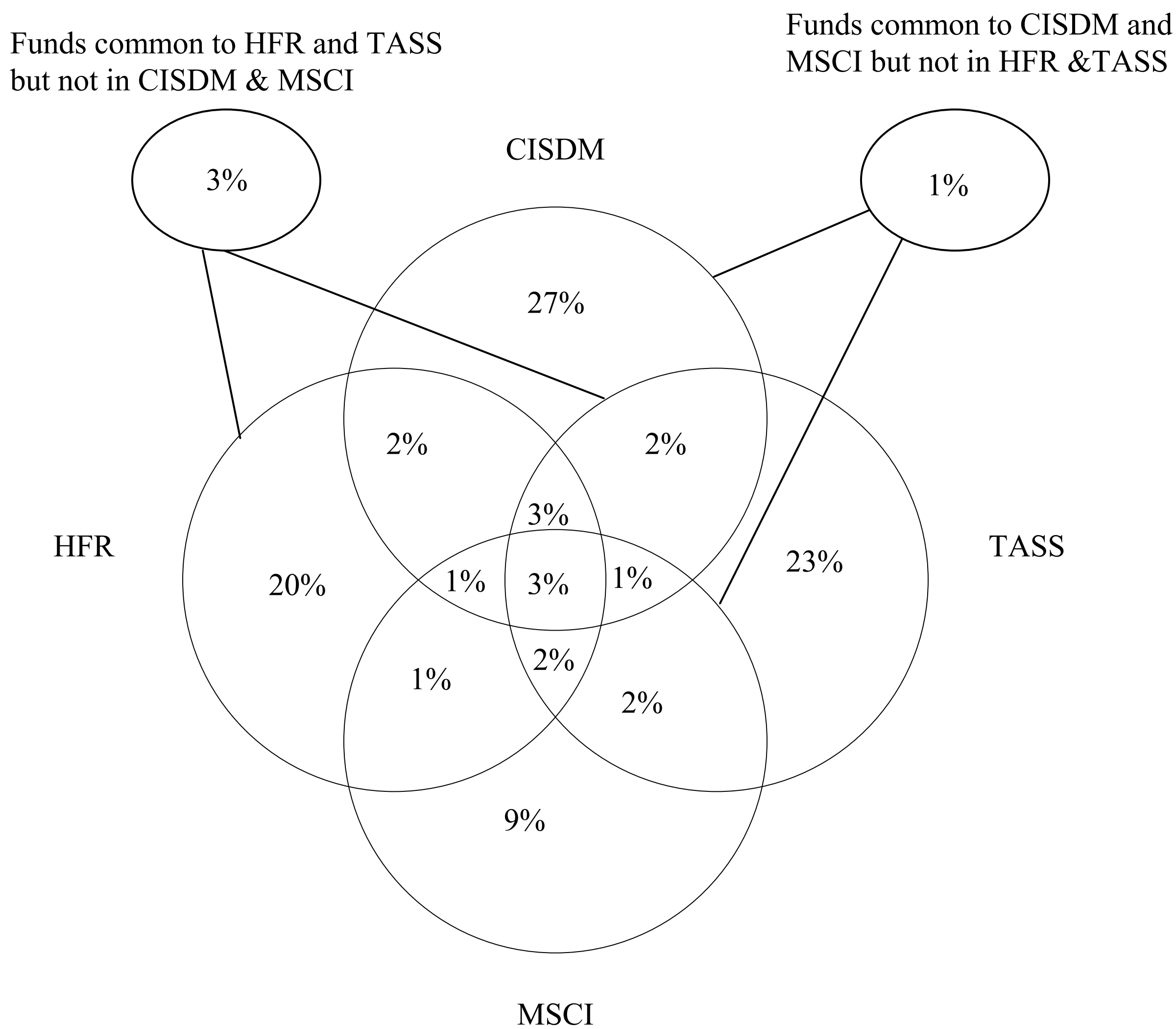


Figure 3: Monthly Gross Returns of Market and Mutual Funds

Panel A plots the average monthly market (all NYSE, AMEX, and NASDAQ firms) returns from Ken French's website during our sample period, 1994–2002. Panel B plots the average monthly market returns each year for January–November and December periods. Panel C plots the average monthly gross-of-fees mutual fund returns from CRSP mutual fund database during our sample period, 1994–2002. Panel D plots the average monthly gross-of-fees returns each year for January–November and December periods for mutual funds in the CRSP mutual fund database.

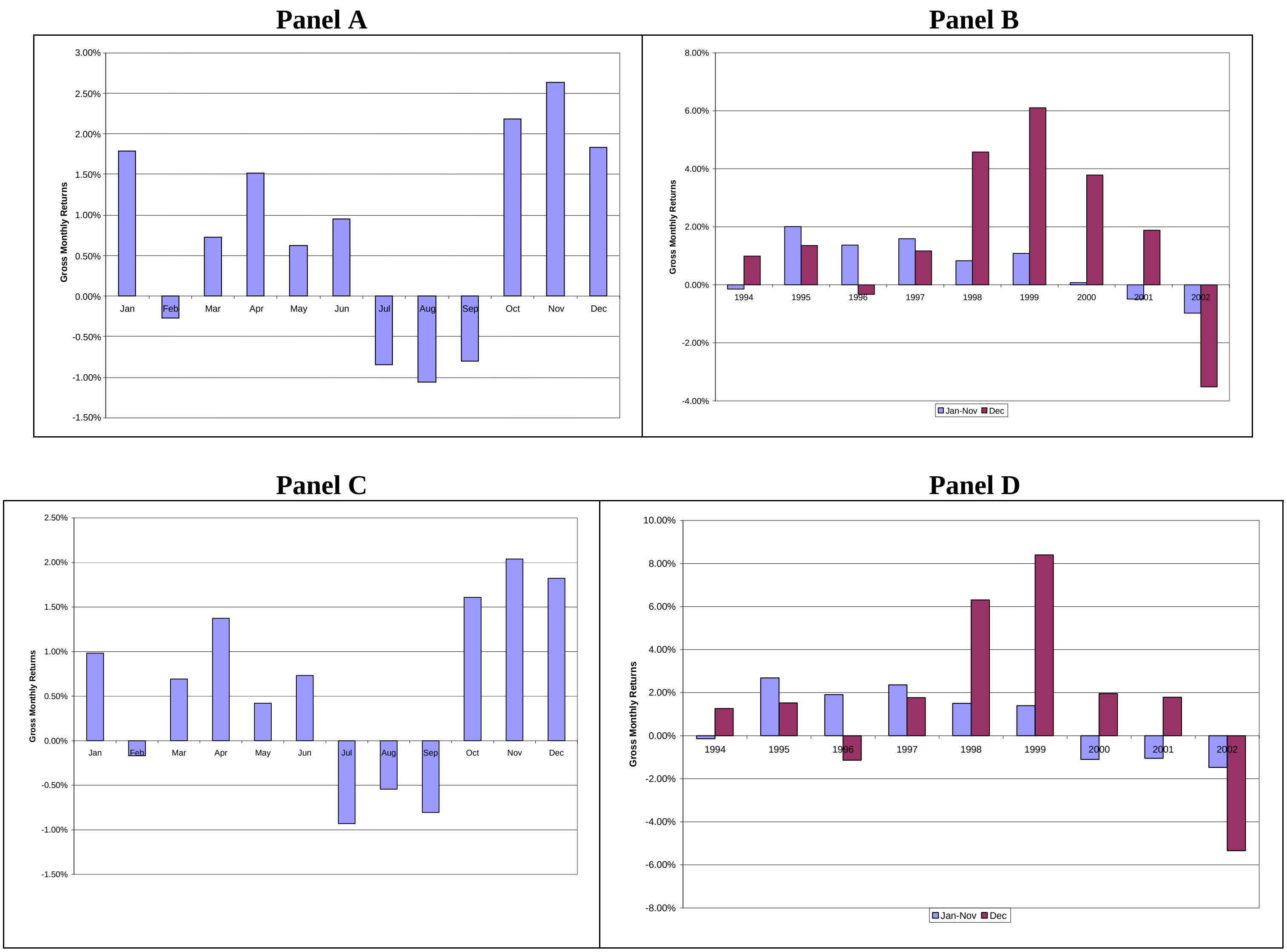


Table I. Summary Statistics

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' 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. Reserves, computed each month, is equal to max (0, Cumulative Returns up to and including current month). 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. 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. AUM is the monthly assets under management. Volatility is standard deviation of monthly gross returns estimated over the calendar year. 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 (%)	1.06	5.63	–1.13	0.84	2.97
Residuals (%)	–0.02	4.19	–1.74	–0.05	1.55
CS-Volatility (%)	6.02	1.90	4.64	5.83	6.61
Moneyness	–0.003	17.87	–6.30	–0.13	7.18
Delta ($ millions)	0.17	0.51	0.002	0.02	0.11
Lockup Period (years)	0.13	0.32	0.00	0.00	0.00
Restriction Period (years)	0.31	0.28	0.16	0.18	0.34
Volatility (%)	4.82	3.95	1.93	3.83	6.52
Liquidity beta	0.02	0.29	–0.06	0.00	0.09
Reserves (%)	8.58	13.20	0.00	3.56	11.58
AUM ($ millions)	131.26	390.89	9.42	29.55	88.84
Age	4.94	3.56	2.17	4.09	6.84
Management Fees	0.01	0.01	0.01	0.01	0.02
Incentive Fees	0.16	0.08	0.15	0.20	0.20

Table II. Do Funds Manage Returns? Univariate Results

This table reports the average gross hedge fund returns, residuals from the time-series regressions of hedge funds' gross returns, using the seven-factor model of Fung and Hsieh (2004), and factor risk premiums for the seven risk factors, S&P 500 (SP), spread between Wilshire Small Cap 1750 index and Wilshire Large Cap 750 index (SCLC), 10-year Treasury (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 right-hand column provides the difference between December values and the average of January–November values and the *t*-statistic (after testing for equality of variances) for the test that this difference equals zero. *t*-statistics are reported in parentheses. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

	Dec	Jan-Nov	Dec minus Jan–Nov (*t*-statistic)
Gross hedge fund returns	2.51%	0.96%	1.55%*** (32.0)
Residual hedge fund returns	0.23%	–0.02%	0.25%*** (6.5)
SP	0.76%	0.46%	0.30% (0.2)
SCLC	2.51%	–0.32%	2.83%** (2.3)
10Y	0.35%	0.25%	0.10% (0.2)
CS	0.36%	0.06%	0.30% (0.7)
BdOpt	3.09%	1.15%	1.94% (0.3)
FXOpt	3.91%	–1.52%	5.43% (0.8)
ComOpt	2.10%	–2.00%	4.10% (0.9)

Table III. Do Funds Exhibit a 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 fund returns on the seven factors of Fung and Hsieh (2004). December (January) dummy equals 1 if the month is December (January), and equals 0 otherwise. Quarter-End dummy equals 1 if the month corresponds to a quarter-end (other than December), and equals 0 otherwise. CS-Volatility$_m$ is the cross-sectional dispersion 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 $m - 2$. Prior Year Volatility is the standard deviation of monthly returns estimated using the previous year's data. 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.

Independent Variables	Expected Sign	Model 1 Returns$_m$	Model 2 Returns$_m$	Model 3 Returns$_m$	Model 4 Returns$_m$	Model 5 Residuals$_m$
December Dummy	+	1.514***	1.539***	1.488***	1.511**	0.362***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Quarter-End Dummy			0.091***		0.082***	0.019
			(0.002)		(0.005)	(0.402)
CS-Volatility$_m$				0.066***	0.066***	0.068***
				(0.000)	(0.000)	(0.000)
Returns$_{m-1}$ (Residuals$_{m-1}$ for Model 5)		0.101***	0.101***	0.101***	0.101***	0.079***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Returns$_{m-2}$ (Residuals$_{m-2}$ for Model 5)		0.002	0.002	0.002	0.002	0.038***
		(0.557)	(0.516)	(0.572)	(0.534)	(0.000)
Delta$_{m-1}$		0.121***	0.120***	0.121***	0.120***	0.080***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Moneyness$_{m-1}$		0.001	0.001	0.001	0.001	–0.005***
		(0.471)	(0.496)	(0.459)	(0.482)	(0.000)
Lockup Period		0.127***	0.127***	0.127***	0.127***	0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.974)
Restriction Period		0.192***	0.192***	0.192***	0.192***	0.029
		(0.000)	(0.000)	(0.000)	(0.000)	(0.130)
Size$_{m-1}$		–0.092***	–0.092***	–0.092***	–0.092***	–0.105***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prior Year Volatility		0.002	0.002	0.002	0.002	–0.039***
		(0.757)	(0.765)	(0.754)	(0.761)	(0.000)
Age$_{m-1}$		–0.029***	–0.029***	–0.029***	–0.029***	0.001
		(0.000)	(0.000)	(0.000)	(0.000)	(0.718)
Management Fee		2.605	2.604	2.601	2.601	0.828
		(0.147)	(0.147)	(0.147)	(0.148)	(0.331)
Intercept, Strategy Dummies, and Year Dummies		Yes	Yes	Yes	Yes	Yes
Observations		195717	195717	195717	195717	195717
Adjusted R^2		3.4%	3.4%	3.4%	3.4%	1.9%

Table IV. What types of funds exhibit greater a greater December spike?

The table reports the slope coefficients for the December dummy for Models 4 and 5 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. For characteristics other than moneyness, we do independent sorts based on Delta as of November end, Lockup, Restriction Period, Volatility, and Liquidity. The High (Low) groups consists 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 High and Low groups. In the case of moneyness, the difference is with respect to out-of-the-money group. 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 2.281 is equal to 2.281%. 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 spike as per Model 4, Table V Returns	Expected Sign	Difference (*p*-value)	Dec spike as per Model 5, Table V Residuals	Expected Sign	Difference (*p*-value)
INCENTIVES TO MANAGE RETURNS						
In the Money	2.281**			0.566***		
	(0.000)	+	1.910*** (0.000)##	(0.000)	+	0.597*** (0.000)##
Near the Money	1.828***			0.486***		
	(0.000)	+	1.457*** (0.000)##	(0.000)	+	0.517* (0.078)##
Out of the Money	0.371***			-0.031		
	(0.000)			(0.680)		
High Delta	1.642***			0.414***		
	(0.000)	+	0.355*** (0.000)	(0.000)	+	0.158*** (0.000)
Low Delta	1.287***			0.256***		
	(0.000)			(0.000)		
Long Lockup	1.164***			0.008		
	(0.000)	–	–0.395*** (0.000)	(0.945)	–	–0.401 (0.945)
Short Lockup	1.559***			0.409***		
	(0.000)			(0.000)		
Long Restriction Period	1.488***			0.322***		
	(0.000)	–	–0.068*** (0.000)	(0.000)	–	–0.099*** (0.000)
Short Restriction Period	1.556***			0.421***		
	(0.000)			(0.000)		
OPPORTUNITIES TO MANAGE RETURNS						
High Volatility	2.468***			0.545		
	(0.000)	+	1.922*** (0.000)	(0.000)	+	0.380*** (0.000)
Low Volatility	0.546***			0.165***		
	(0.000)			(0.000)		
High Liquidity	1.292***			0.584***		
	(0.000)	–	–0.499*** (0.000)	(0.000)	–	0.482*** (0.000)
Low Liquidity	1.791***			0.102		
	(0.000)			(0.104)		

– these differences are relative to out-of-the-money funds

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

The table reports OLS regressions of monthly gross returns ($Returns_m$). See Tables I and III for variable definitions. 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.

Independent Variables	Expected Sign	Model 1	Model 2	Model 3
December Dummy	+	0.144**	1.569***	0.200***
		(0.027)	(0.000)	(0.002)
December Dummy×Reserves $_{m-1}$	+	0.112***		0.111***
		(0.000)		(0.000)
January Dummy×Returns$_{m-1}$	–		–0.040***	–0.044***
			(0.000)	(0.000)
Reserves $_{m-1}$		–0.015***		–0.013***
		(0.000)		(0.000)
January Dummy			0.612***	0.485***
			(0.000)	(0.000)
Quarter-End Dummy		0.094***	0.145***	0.139***
		(0.001)	(0.000)	(0.000)
CS-Volatility$_m$		0.043***	0.067***	0.045***
		(0.000)	(0.000)	(0.000)
Returns $_{m-1}$		0.102***	0.102***	0.104***
		(0.000)	(0.000)	(0.000)
Returns $_{m-2}$		0.008**	0.002	0.008**
		(0.028)	(0.491)	(0.021)
Delta $_{m-1}$		0.118***	0.118***	0.116***
		(0.000)	(0.000)	(0.000)
Moneyness $_{m-1}$		–0.001	0.002	–0.002
		(0.470)	(0.205)	(0.374)
Lockup Period		0.124***	0.129***	0.124***
		(0.001)	(0.001)	(0.001)
Restriction Period		0.186***	0.192***	0.182***
		(0.000)	(0.000)	(0.000)
Size$_{m-1}$		–0.092***	–0.091***	–0.091***
		(0.000)	(0.000)	(0.000)
Prior Year Volatility		0.002	0.003	0.002
		(0.740)	(0.499)	(0.714)
Age$_{m-1}$		–0.028***	–0.027***	–0.027***
		(0.000)	(0.000)	(0.000)
Management Fee		2.762	2.639	2.869
		(0.129)	(0.139)	(0.113)
Intercept, Strategy Dummies, and Year Dummies		Yes	Yes	Yes
Observations		195717	195717	195717
Adjusted R^2		4.3%	3.5%	4.3%

Appendix A: Classification of Hedge Fund Strategies

This table provides the mapping of the strategies provided by different data vendors with the four broad strategies that we use in our study. It also provides a brief definition of each of the four broad strategies and distribution of funds across the four strategies.

Broad Strategy	Vendor's Strategy	Vendor
Directional Traders		
	Dedicated Short Bias	TASS
	Discretionary Trading	MSCI
	Emerging Markets	TASS
	Emerging Markets: Asia	HFR
	Emerging Markets: E. Europe/CIS	HFR
	Emerging Markets: Global	CISDM and HFR
	Emerging Markets: Latin America	HFR
	Foreign Exchange	HFR
	Global Macro	CISDM, HFR, and TASS
	Macro	HFR
	Market Timing	HFR
	Sector	CISDM and HFR
	Short Bias	MSCI
	Short Sales	CISDM and TASS
	Short Selling	HFR
	Systematic Trading	MSCI
	Tactical Allocation	MSCI
Relative Value		
	Arbitrage	MSCI
	Convertible Arbitrage	HFR and TASS
	Equity Market Neutral	HFR and TASS
	Fixed Income: Arbitrage	HFR and TASS
	Fixed Income: Convertible Bonds	HFR
	Fixed Income: High Yield	HFR
	Fixed Income: Mortgage-Backed	HFR
	Long-Short Credit	MSCI
	Market Neutral	CISDM
	Merger Arbitrage	HFR and MSCI
	Relative Value Arbitrage	HFR and TASS

	Statistical Arbitrage	MSCI
Security Selection		
	Equity Hedge	HFR
	Equity Non-Hedge	CISDM and HFR
	Global	CISDM
	Global Established	CISDM
	Global International	CISDM
	Long/Short Equity Hedge	HFR and TASS
	Long Bias	HFR and MSCI
	No Bias	MSCI
	Private Placements	MSCI
	US Opportunistic	CISDM
	Variable Bias	MSCI
Multiprocess		
	Event Driven	CISDM, HFR, MSCI, and TASS
	Fixed Income: Diversified	HFR
	Distressed Securities	CISDM, HFR, and MSCI
	Multi-Process	MSCI and TASS
	Multi-Strategy	HFR

<u>Directional Traders</u> usually bet on the direction of market prices of currencies, commodities, equities, and bonds in the futures and cash markets; 24% of the funds in our sample fall in this category.

<u>Relative Value</u> strategies take positions on spread relationships between prices of financial assets or commodities and aim to minimize market exposure; 23% of the funds in our sample fall in this category.

<u>Security Selection</u> managers take long and short positions in undervalued and overvalued securities, respectively, and reduce the systematic market risks in the process. Usually, they take positions in equity markets; 42% of the funds in our sample fall in this category.

<u>Multiprocess</u> strategy involves multiple strategies employed by the funds, usually involving investments in opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations, and share buybacks. For example, the portfolio of some event-driven managers might shift in majority weighting between merger arbitrage and distressed securities, while others might take a broader scope; 11% of the funds in our sample fall in this category.

Note: We exclude managed futures, natural resources, mutual funds, and “other” hedge funds, since these categories are not usually considered as “typical” hedge funds. We also exclude long-only funds, Regulation D funds, and funds with missing strategy information.

Appendix B: Computation of Gross Returns, Moneyness, and Delta

Incentive fee contracts provide managers with options on the investors' assets under management (AUM). We calculate the option delta based on the formula of Black and Scholes (1973) for valuing European call options, where *manager's option delta* is defined as the sensitivity of the option value to a one-percent change in asset value:

Manager's Option Delta = sensitivity of the option value to a 1% change in asset value

$$= N(Z) \times S \times 0.01 \times I \quad \textbf{(A1)}$$

$Z \quad = \left\{ ln\left(S/X\right) + T\left(r + \sigma^2/2\right) \right\} / \sigma T^{0.5}$

S = spot price (market value of the investor's assets as of end of current year)

X = exercise price (the market value of the investor's assets that must be reached the subsequent year before incentive fees can be paid that year)

T = time to maturity of the option (one year)

r = ln (1+ risk-free interest rate) (i.e., ln (1 + LIBOR rate for the subsequent year))

σ = volatility of monthly net returns (estimated over the year)

I = incentive fee rate (expressed as a fraction)

$N(\ )$ = cumulative distribution function (cdf) of standard normal distribution

The manager's option delta of the fund is the sum of the deltas from different sets of investors, each of whom will have an exercise price depending on when that individual entered the fund. To compute the spot price (S) and exercise price (X) used in the computation of delta, we make the following assumptions:

1) Assets at inception are assumed to be that of the investor.
2) Investors' money flows occur at the end of each year.
3) The dollar inflows from investors are tracked separately for each year. Hence, each investor has an individual exercise price depending on the timing of entering the fund and the hurdle rate and high-water mark provisions.
4) When dollar outflows from investors occur, we adopt first-in–first-out rule to decide which of the investor's money leaves the fund.
5) Hurdle rate is LIBOR for funds with a hurdle rate provision.

6) If no incentive fee is paid for a year due to insufficient returns, the hurdle for next year is based on a geometrically compounded hurdle rate over that time.
7) Management fees cover fixed costs.
8) Incentive fees are paid annually at the end of the year. The manager reinvests all of the incentive fees into the fund after paying personal taxes. Offshore managers pay no personal taxes on incentive fees, whereas onshore managers pay a tax rate of 35%.

We adopt the following steps:

1) Estimate the fund's annual gross returns, given data on net returns.
   a. The first investor enters the fund at the end of year 0, the second investor enters the fund at the end of year 1, and so on.
   b. For the fund's first full year of existence, since there is only one investor (see assumption (1a)), gross returns can be computed as follows:

$$\text{Gross}_t = \begin{cases} \dfrac{\text{Net}_t - \text{Hurdle}_t \times I}{1 - I} & \text{if Net}_t > \text{Hurdle}_t \\ \text{Net}_t \text{ otherwise} \end{cases} \qquad \textbf{(A2)}$$

   where $\text{Hurdle}_t = \text{LIBOR}_t$ if the fund has hurdle rate provision, and = 0 otherwise.

   From the second year onward, the computation of gross returns becomes more involved. Since investor money flow is assumed to occur at the end of the year, the reported net return is the year-end market value of year-beginning AUM after incentive fees have been paid to the AUM divided by the year-beginning AUM. For example, for a given investor *i*, the year-end market value of *i*'s assets net of incentive fees, MVafterINC, is given by

$$\text{MVafterINC}_\text{i} = S_{i,t-1}(1+\text{Gross}_t) - \text{Max}[(S_{i.t-1}(1+\text{Gross}_t) - X_{i.t-1}), 0]\, I$$

   where S_i denotes the market value of assets of investor *i* (i.e., the spot price as of year-end $t-1$), X_i denotes the market value of assets of investor *i* that must be reached (i.e., exercise price as of year-end $t-1$) before incentive fees could be paid out in year *t*, and *I* is the incentive fee rate. The numerator in the net return formula is then the summation of the above over all investors ($\sum \text{MVafterINC}_i$) plus the year-end market value of the manager's year-beginning investment in the fund. Since this is a nonlinear function of gross returns, a closed-form solution for gross returns is not possible. Therefore, we solve this recursive problem iteratively to back out gross returns from the data.

2) Estimate the market value of the manager's investment in the fund (MVmgr). This equals the sum of the year-end market value of the manager's year-beginning investment and the post-tax incentive fees earned in that year.
3) Estimate new money flow into or out of the fund as the difference between the reported year-end AUM and ($\sum \text{MVafterINC}_i + \text{MVmgr}$).
4) If there is net outflow, then the MVafterINC of the earliest investor is reduced by the outflow computed in step 3. If the outflow is greater than MVafterINC of the earliest investor, then the remaining balance is assumed to be withdrawn from the second earliest investor, and so on.
5) Compute the year-end market value of assets for each investor (spot price *S*) and the fund manager.
6) Compute the exercise price for each investor (exercise price *X*), depending on whether the fund has a hurdle rate and/or high-water mark provision.
   a. If the gross return of the fund is sufficiently high such that an investor must pay an incentive fee, then the exercise price is higher than the current market value by the hurdle rate (i.e., LIBOR if the fund has a hurdle rate provision, or 0 if the fund lacks a hurdle rate provision).
   b. If the gross fund return is insufficiently high to require an investor to pay an incentive fee, and if the fund has a high-water mark provision, the new exercise price is higher than the prior year's exercise price by the hurdle rate.
   c. If the gross fund return is insufficiently high to require an investor to pay an incentive fee, and if the fund does not have a high-water mark provision, then the exercise price is higher than the current market value by the hurdle rate.
7) Using the *S* and *X* of various investors' capital in the fund, compute the moneyness as the capital-flow-weighted-average of the moneyness of each option.
8) Using the *S* and *X* of various investors' capital, compute the delta of each and sum them up along with the delta from the manager's investment to estimate the total delta of the fund.
9) The delta of the fund equals the delta from investors' assets (manager's option delta) plus the delta from the manager's stake. Since all the return from the manager's investment is retained, the delta from the manager's stake equals market value of manager's investment in

the fund multiplied by 0.01 (i.e., when fund earns one-percent return, value of the manager's stake goes up by one percent).

Appendix C. Robustness Test with Net-of-Fee returns: Do Funds Manage Returns?

This table reports OLS regressions of monthly net-of-fee returns (Returns$_m$). December (January) dummy equals 1 if the month is December (January), and equals 0 otherwise. Quarter-End dummy equals 1 if the month corresponds to a quarter-end (other than December), and equals 0 otherwise. CS-Volatility$_m$ is the cross-sectional dispersion 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 the spot and exercise prices, divided by the exercise price. Returns$_{m-2}$ and Residuals$_{m-2}$ are gross returns and residual returns during month $m-2$. 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. or Year Volatility is the standard deviation of monthly returns estimated using the previous year's data. 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.

Independent Variables	Expected Sign	Model 1 *RETURNS$_m$*	Model 2 *RETURNS$_m$*	Model 3 *RETURNS$_m$*	Model 4 *RETURNS$_m$*	Model 5 *RESIDUALS$_m$*
December Dummy	+	1.272***	1.282***	1.254***	1.262**	0.334***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Quarter-End Dummy			0.033		0.027	0.033*
			(0.209)		(0.299)	(0.097)
CS-Volatility$_m$				0.046***	0.046***	0.046***
				(0.000)	(0.000)	(0.000)
Returns$_{m-1}$		0.102***	0.103***	0.102***	0.103***	0.077***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Returns$_{m-2}$		–0.002	–0.002	–0.002	–0.002	0.039***
		(0.554)	(0.570)	(0.555)	(0.568)	(0.000)
Delta$_{m-1}$		0.075***	0.075***	0.075***	0.075***	0.073***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Moneyness$_{m-1}$		–0.002*	–0.002*	–0.002*	–0.002*	–0.006***
		(0.058)	(0.056)	(0.059)	(0.057)	(0.000)
Lockup Period		0.111***	0.111***	0.111***	0.111***	0.005
		(0.002)	(0.002)	(0.002)	(0.002)	(0.782)
Restriction Period		0.270***	0.270***	0.270***	0.270***	0.014
		(0.000)	(0.000)	(0.000)	(0.000)	(0.411)
Size$_{m-1}$		–0.075***	–0.075***	–0.075***	–0.075***	–0.093***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prior Year Volatility		–0.008	–0.008	–0.008	–0.008	–0.034***
		(0.114)	(0.113)	(0.115)	(0.114)	(0.000)
Age$_{m-1}$		–0.023***	–0.023***	–0.023***	–0.023***	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.916)
Management Fee		0.166	0.166	0.164	0.164	1.285*
		(0.923)	(0.923)	(0.924)	(0.924)	(0.081)
Intercept, Strategy Dummies, and Year Dummies		Yes	Yes	Yes	Yes	Yes
Observations		195717	195717	195717	195717	195717
Adjusted R^2		3.0%	3.0%	3.1%	3.1%	1.8%