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

Vikas Agarwal
Georgia State University

Naveen D. Daniel
Purdue University

and

Narayan Y. Naik
London Business School

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Abstract

Hedge fund managers are compensated by incentive fees and the investors' money flows into hedge funds are based on their prior performance. These provide managers with both explicit and implicit incentives to improve performance as the year draws to a close. Consistent with this, we document that the average returns during December are two-and-a-half times their average returns during the rest of the year. We find that this December spike cannot be fully explained by increase in the funds' risk exposures, or by higher factor risk premiums, or by funds' free-riding on end-of-year gaming by mutual funds. Our results suggest that this spike arises due to funds potentially managing their returns upwards in December. This spike seems to be achieved by (i) adding back in December the under-reported returns during earlier months of the year, and (ii) by borrowing from future returns. We find that the spike is more pronounced among funds whose incentive fee contracts are near-the-money and whose performance lags their peers, indicating that incentives may be driving the return management behavior.

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: +1-404-651-2699. Fax: +1-404-651-2630. Naveen Daniel is from Purdue University, Krannert School of Management, 403, W. State St., West Lafayette, IN 47907, USA. email: nav@purdue.edu. Tel: +1-765-494-4461. Fax: +1-765-494-9658. Narayan Y. Naik is from London Business School, Sussex Place, Regent's Park, London NW1 4SA, United Kingdom: e-mail: nnaik@london.edu Tel: +44-207-262-5050, extension 3579 Fax: +44-207-724-3317. We would like to thank Nick Bollen, Stephan Dieckmann, Julian Franks, Jason Greene, Jayant Kale, Omesh Kini, Iwan Meier, Igor Osobov, Lalitha Naveen, Henri Servaes, Hongjun Yan and seminar participants at Arizona State University, Georgia State University, HEC Montreal, IAE Sorbonne, and London Business School for many helpful comments and constructive suggestions. We are grateful for funding from BSI Gamma. 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.

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1. Introduction

Hedge funds are compensated by incentive fees that are paid at the end of the year based on annual performance exceeding pre-specified thresholds.[1] In addition, investors direct more money into funds whose prior performance is better relative to their peers (Agarwal, Daniel, and Naik, 2005). Thus, there exist both explicit and implicit 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 two-and-half times the average monthly return during January to November (2.5% compared to 1.0%) (see Panel A of Figure 1). Our paper is the first to document year-end effects in hedge funds, a phenomenon which we refer to as *December spike*.

We investigate three possible explanations for the December spike. First, a passive strategy could give rise to this spike to the extent that hedge funds free-ride on mutual funds year-end gaming behavior documented by Carhart, Kaniel, Musto, and Reed (2002) or if factor risk premia happened to be greater in December during our sample period. A second explanation, based on risk, is that funds whose incentive compensation is just underwater or funds whose performance is lagging behind their peers as of November-end increase their risk exposures in December to catch up. While the above two explanations have some empirical support, the December spike continues to remain large and economically significant. This leaves us with a somewhat more provocative explanation that hedge funds may be managing returns upwards in

[1] Incentive fees are paid out at the end of the calendar year based on fund performance over twelve months only 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 LIBOR. With a high-water mark provision, the manager earns incentive fees only on new profits, i.e., after recovering past losses, if any.

order to report better performance. We term this as "*returns management.*" This behavior is similar to the well-known phenomena of "earnings management" in corporations.[2]

Given the evidence of "returns management", two related questions follow naturally. First, what is the mechanism by which funds manage returns? Specifically, we examine whether funds under-report positive returns in the earlier months of a year to create reserves for a bad state of the world in future ("saving for the rainy day"), and then add those reserves back in December if the bad state is not realized.[3] We also examine if some funds "borrow" from their future performance to report higher returns in December in order to earn their incentive fees. We find strong evidence that funds employ both these mechanisms for returns management.

Second, do funds that have greater incentives (explicit and implicit) and higher reserves as of November-end exhibit higher degree of returns management? In particular, we investigate whether funds whose call-option-like incentive fee contract is near-the-money, funds with higher pay-performance sensitivity (delta) in their compensation contract, funds with poor relative performance, and funds with more reserves at the end of November display greater degree of returns management. With the exception of delta, we find results that suggest that funds with greater incentives and higher reserves are associated with larger amount of returns management.

Our findings have important implications for hedge fund investors and regulators. Our results inform the debate on the need for increase in regulation of hedge funds. Recently, the SEC has been debating about regulating hedge funds and has been especially concerned about issues related to accurate valuation of securities in hedge fund portfolios.[4] To the extent that at

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[2] We use the terms, returns management, return inflation, marking up, and portfolio pumping interchangeably in this paper. Some of these terms have been used in the prior literature on other institutional investors such as mutual funds.

[3] Such behavior is very common in corporations too. According to former SEC chairman, Arthur Levitt (1998), *companies stash accruals in 'cookie jar' reserves during the good economic times and reach into them when needed in the bad times*.

[4] In a 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

least some discretion lies in the hands of the fund managers, one would expect a higher incidence of returns management. Further, our results shed light on the factors driving returns management, which can help regulators and investors to focus more closely on funds that are likely to be involved in such activity. Clearly, if hedge funds do inflate returns in December, it provides an opportunity for some investors to sell at higher prices and others to lose out in the process. In addition to the policy implications for governance, our findings also have implications for disclosure, security valuation, and design of managerial compensation contracts in the hedge fund industry.

Our study contributes to various strands of literature on mutual funds, earnings management, executive compensation, and return smoothing by hedge funds. Our study is closely related to the pioneering work of Carhart, Kaniel, Musto, and Reed (2002) (henceforth CKMR) in the area of mutual funds. They find that US equity mutual funds inflate year-end portfolio prices and this inflation is highest for the stocks held by the funds that have the most incentives to inflate prices. They document that it is possible for funds to influence the end-of-day prices by trading at the last minute, a practice often referred to as "painting the tape" or "marking up" or "portfolio pumping". This is done by buying a small quantity of a security at a high price to influence the value of a large long position in their portfolios. Since hedge funds invest in relatively more illiquid securities, it provides them with even more opportunities to engage in such marking up activity. This does not imply that all hedge funds *actively* mark up their returns as some of them can *passively* benefit holding securities in which other institutional investors (such as mutual funds and pension funds) engage in portfolio pumping. Our work is also related to Chander and Bricker (2002) study of earnings management in closed-end mutual funds through discretion in valuation of restricted securities. Such kind of discretion in financial

http://www.sec.gov/spotlight/hedgefunds/hedgeagenda.htm for more details.

reporting is likely to be higher for hedge funds that invest in exotic securities often traded in over-the-counter markets. Since we do not have high-frequency holdings data, we are unable to show active marking up, but our empirical results are consistent with the portfolio pumping explanation.

Our paper also contributes to a large literature on earnings management.[5] Burgstahler and Dichev (1997) and DeGeorge, Patel, and Zeckhauser (1998) show that firms manage earnings towards specific earnings thresholds. In particular, they find that firms avoid reporting losses, avoid reporting earnings decline, and avoid missing analysts' forecasts by managing earnings. For hedge funds, the threshold would be determined by explicit incentives (level of NAV required to earn incentive fees) and implicit incentives (outperforming peers to attract greater capital flows and thus higher compensation). Furthermore, our paper supplements the executive compensation literature studying the relation between earnings management and incentives from compensation. Healy (1985) and Gaver, Gaver, and Austin (1995) relate managers' accrual policies with incentives arising from their bonus contracts. Goldman and Sleazak (2003) 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 fraudulently exaggerate performance. Bergstresser and Phillippon (2004) report that firms with CEOs having high incentives (high delta of executive stock options) are associated with higher degree of earnings management. Burns and Kedia (2004) find that the delta of CEO's option portfolio is positively related to the propensity of misreporting.[6] In light of this evidence, we examine the relation between delta (from the incentive fee contract) and extent of returns management in hedge funds, but find no evidence that delta contributes to such

[5] For example, 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] Peng and Roell (2003), in their study relating executive compensation and shareholder litigation, show that manipulation of earnings significantly explains fraud allegations.

behavior in hedge funds. However, we do find that funds whose incentive-fee-call-options are near-the-money are more likely to manage returns upwards in December.

Finally, our paper complements the literature on return smoothing by hedge funds. Getmansky, Lo, and Makarov (2004) (henceforth GLM) 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 the autocorrelations. Our methodology doesn't require us to examine autocorrelation. We still show that the *December spike* could arise from intentional smoothing of returns through the year. We find evidence that funds under-report their returns when returns are positive, thereby creating a reserve, which can be used in case of subsequent negative returns, i.e., "*saving*" for the rainy day. However, if the rainy day does not come, they add back the reserves in December resulting in the *December spike*. Further, we find that funds exhibiting the spike report lower returns in January of the following year, which is equivalent to them "*borrowing*" from their future returns.[7]

The rest of the paper is organized as follows. Section 2 presents testable hypotheses. Section 3 describes the data and construction of variables. Section 4 investigates our hypothesis relating to evidence of returns management in hedge funds and the two sub-hypotheses exploring savings and borrowing possibilities. Section 5 tests our hypothesis relating to the types of funds that are more likely to manage returns. Section 6 offers concluding remarks and suggestions for future research.

[7] CKMR (2002) also examine how marking up results in borrowing from future returns. They show that inflation in returns during year-ends is followed by reversals on the following day, i.e., beginning of the following year. Interestingly, in the context of earnings management, DeGeorge, Patel, and Zeckhauser (1999) refer to saving and borrowing behavior as "saving for a better tomorrow" and "borrowing for a better today".

2. Hypotheses Development

Like shareholders of corporate firms, hedge fund investors also face 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. Following the earnings management literature, we refer this phenomenon as *returns management.* Incentive fees accrue over the year but are paid at the end of the fiscal year. Since, most funds have December as their fiscal-year-end when their accounts are audited, one is more likely to detect returns management by looking at December returns.[8]

In addition to such explicit incentives embedded in the compensation contracts, fund managers also face implicit incentives to improve performance. Agarwal, Daniel, and Naik (2005) document that capital flows into hedge funds are positively related to prior performance. Higher assets under management would also yield higher compensation in the form of management fees, and potentially higher incentive fees. Thus, hedge funds face both explicit and implicit incentives to manage returns in December. This leads us to our first hypothesis.

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

In the process of examining the above hypothesis, we allow for the possibility that some funds may be passively benefiting from portfolio pumping by other institutional investors. For

[8] According to MSCI database, over 95% of the funds have December as their fiscal-year-end.

example, if hedge funds invest in the same securities that mutual funds engage in return inflation, then one could observe such a spike. If factor premiums happen to be high in December during our sample period and if funds have a positive exposure to these risk factors, then one could also observe a December spike. Finally, funds may actively increase their risk exposures in order to improve their performance for the year.

After controlling for these possibilities, if we find evidence in support of *Returns Management Hypothesis*, a natural question would be to determine the mechanism employed by funds to manage their returns. It is conceivable that hedge funds "*save for the rainy day*" and create reserves by under-reporting positive returns earlier in the year and use them during bad months to avoid reporting losses. In fact, such behavior is very common in corporations too. Former SEC chairman, Arthur Levitt (1998) 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 case of hedge funds, the tendency to create reserves is driven by investors' preference for funds with lower volatility and/or funds with fewer loss-making months. In case, some reserves remain unutilized by the end of the year, the manager can always include them in December returns, thus leading to the December spike. This leads us to our first sub-hypothesis, which we call as the *Savings Hypothesis*.

Hypothesis 1a (Savings Hypothesis): All else equal, December returns should be higher when reserves leading up to December are higher.

It is plausible that hedge funds may also be *borrowing* from January returns in the following way. It is well-documented that if funds engage in portfolio pumping, i.e., pushing up the security prices at December-end by last-minute buying, it is followed by price reversals in early January (see CKMR, 2002 and Bernhardt and Davies, 2005). This is equivalent to *borrowing* from January returns.[9] This leads to our second sub-hypothesis, which we refer to as the *Borrowing Hypothesis*.

Hypothesis 1b (Borrowing Hypothesis): Controlling for risk, higher December returns in a year should be associated with lower January returns in the following year.

If we find support for the *Returns Management Hypothesis*, a question naturally arises as to what types of funds display greater degree of returns management. We develop several hypotheses which take into account the expected benefits versus the expected costs of returns management. We know from literature on mutual fund, earnings management, and executive compensation, that incentives play an important role in determining the incidence of earnings/returns management. For example, if by November-end, the incentive-fee call option of a fund is deep out-of-the-money, then managing returns slightly upwards in December may not be of much help in earning the incentive fee for the year. Similarly, if the incentive-fee call option of a fund is deep in-the-money by November-end, then the fund may have little incentive to engage in returns management. Clearly, there are costs and benefits associated with returns management. Engaging in returns management increases the compensation but can result in loss of reputation and/or human capital (career concerns). Arguably, benefits may exceed the costs for a fund that is near-the-money. If this is the case, then one would expect funds that are *near-the-money* to engage more in returns management.

Bergstresser and Philippon (2004) theoretically model and empirically show that earnings management is more pronounced in firms where CEOs have higher exposure to their firms' equity. Clearly, if a CEO's compensation is more sensitive to firm's share price, she has more

[9] One of the ways that managers can 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 upfront while the cost of replication through dynamically delta-hedging is incurred over a period that may 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.

incentives to manipulate the share price to increase her benefits. Following these arguments, one would expect to observe funds with higher managerial incentives (proxied by the pay-performance sensitivity, or delta of the call-option-like incentive fee contract) to be more likely to engage in returns management.

In addition to such explicit incentives, the sensitivity of investors' capital flows to prior performance provides implicit incentives to engage in returns management. Therefore, we hypothesize that funds that are lagging behind their peers will try to catch up in order to improve their year-end ranking. Hence, such funds should display greater returns management.

A fund's decision to manage returns also depends on the ease with which it could be accomplished. For example, funds that have built up reserves through the year by under-reporting the returns (premise of our *Savings Hypothesis*), would find it easy to manage returns upwards, and therefore should exhibit greater degree of returns management. These arguments provide us our second hypothesis:

Hypothesis 2: All else equal, funds that have higher incentives (funds with near-the-money incentive-fee contracts, funds with greater delta, funds with poor performance relative to their peers) and funds that have higher reserves should exhibit greater degree of returns management.

Having developed our hypotheses, we next describe our data and key variables that we use to test these hypotheses.

3. Data and Variable Construction

3.1. Data Description

In this paper, we construct a comprehensive hedge fund database that is a union of four large databases, namely, CISDM, HFR, MSCI, and TASS. This database reports net-of-fee monthly returns, assets under management, and fund characteristics such as hurdle rate and high-water mark provisions, lockup, notice, and redemption periods, incentive fees, management fees, inception date, and fund strategy.[10] 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.[11] After merging the four databases, we find that there are 7535 hedge funds, out of which 3924 are 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 and thus, merging them helps in capturing a more representative sample of the hedge fund universe.

One of the challenges in dealing with multiple databases is that they adopt different nomenclature to identify fund strategies. Based on description 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) studies which show that there are 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.[12]

[10] The database provides information on contractual features as of the last available 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.

[11] 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.

[12] We also conduct our analysis at the sub-strategy level using the original strategy classification in the four databases and find our results to be robust to using original classification. These results are available from authors upon request.

3.2. Measures of Performance and Returns Management

We consider two performance measures for our study. Our first measure is gross return of fund *i* in month *m* of year *t*, $Returns_{i,m,t}$. We compute the gross-of-fee returns from net-of-fee returns following Agarwal, Daniel, and Naik (2005) methodology (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 GLM, 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. Further, in order to test our *returns management hypothesis*, we need to control for the systematic risks of hedge funds. Hence, we employ a second measure, residual return of fund *i* during month *m* in year *t*, $Residual_{i,m,t}$. For this purpose, we estimate fund-level time-series regressions of the seven-factor model of Fung and Hsieh (2004).[13] 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 non-discretionary 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. This measure is equivalent to 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, 2005).

Our next variable of key interest is returns management measure. Similar to performance measures, we use both raw-return-based and risk-adjusted-return-based measures of returns management. Our first measure, based on raw returns, is $DIFFRET_{i,t}$. It relates to the magnitude of returns management and is computed as the difference between returns for fund *i* during December of year *t* and the average returns over January-November period for the same fund

[13] Our results are robust to computing residual 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 4.1.

during the same year. Our second measure, based on residual returns, is $DIFFRES_{i,t}$, is computed in the same way as our first measure, except using residual returns.

In Table 1, we report the summary statistics of performance measures and returns management. We find that the average monthly gross fund returns are 1.06%. As expected, the mean monthly residuals are virtually zero. Further, mean of our returns management measure based on raw returns, *DIFFRET*, is 1.54% suggesting that the average gross December returns are substantially higher than the average gross returns during the rest of the year. Finally, the mean residual returns, *DIFFRES*, are also higher in December compared to January-November period by 0.24%.

3.3. 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 changes in risk exposures from month to month 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*.[14] If funds increase their risk exposures, then $CS\ Volatility_m$ will increase. Hence, $CS\ Volatility_m$ proxies for the risk exposures. From Table 1, we observe that the mean (median) cross-sectional volatility of funds' monthly returns are 6.02% (5.83%).

[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 .

3.4. Measures of Incentives

Our first measure of explicit incentives is related to the moneyness of the option-like incentive fee contract, which we compute at the end of each month. For this purpose, we follow Agarwal, Daniel, and Naik (2005), who recognize that the incentive fee contract grants the manager a portfolio of call options. We compute the moneyness of option as the difference in the spot price (*S*) and exercise price (*X*), divided by the exercise price, (i.e., *(S-X)/X*) where the exercise price depends on the hurdle rate and high-water mark provisions. In Table 1, 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 near-the-money are more likely to engage in returns management. For this purpose, we categorize funds into three groups based on the moneyness at the end of November: out-of-the-money, near-the-money, and in-the-money. We first compute the mean (μ) and standard deviation (σ) of a fund's returns in our sample. We define the ranges of moneyness in terms of μ and σ. We provide an example to illustrate the breakpoints. Suppose that the mean (μ) and standard deviation (σ) of a fund's monthly returns are 1% and 5%, respectively. For this fund, we define *near-the-money* as the range of moneyness lying between -6% [-(μ + σ)] and +4% [-(μ - σ)]. Following this example further, if the fund has moneyness greater than +4% [-(μ - σ)], we define it to be *in-the-money* and if the fund has moneyness less than -6% [-(μ + σ)], we define it to be *out-of-the-money*.[15] During our sample period, we find (not reported) on average, 31% of the funds are near-the-money, 38% are in-the-money, and remaining 31% are out-of-the-money.

As described earlier, incentive fee contract endows the manager with a portfolio of call options, which provides incentives to deliver superior performance. Our second measure of

[15] Our results are robust to alternative breakpoints for near-the-moneyness using strategy-level μ and σ instead of fund-level μ and σ .

explicit incentives is the delta of the portfolio of call options. The delta of each of the call options depends on the current NAV (spot price), the threshold NAV that has to be reached before the manager can claim incentive fee (exercise price), and other fund characteristics such as the fund size, fund volatility etc.[16] We follow Agarwal, Daniel, and Naik (2005) to 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 1, we find that the mean (median) monthly delta equals $170,000 ($20,000).[17]

Our measure of implicit incentives is the fractional rank of the fund at November-end of each year. We compute this rank for all funds each year based on their January-November returns relative to the other funds within the same strategy. 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. We notice in Table 1, as expected, the mean fractional rank as of November-end is 0.5.

3.5. Measures of Reserves

To test our *Savings Hypothesis*, we construct a measure of reserves. We define $Reserves_{i,m,t}$, to be the cumulative return from January up to month *m-1* in year *t* if positive, else zero. The reason for considering only the positive cumulative returns is that the reserves can *only* be used, if they are there in the first place! So, if the fund manager is indeed adding back reserves in December, then one would expect to see the interaction of reserves variable and December dummy to be positive.[18] From Table 1, we observe that the mean (median) of the reserves variable is 8.58% (3.56%).

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

[17] 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). See Murphy (1999) and Core, Guay, and Larcker (2003) for a survey of literature on executive compensation.

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

An alternative way of computing reserves can be to determine the difference between true returns (which are unobservable) and observed returns. GLM (2004) show that due to return smoothing, observed returns can be expressed as a MA(2) process in true returns. Following their insights, for the sake of robustness, we also construct an alternative measure of reserves – cumulative difference between the unobserved returns and the observed returns up to month *m-1* in year *t* if positive, else zero.

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

4. Do hedge funds manage returns?

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

To examine if *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). We also plot similar figures using monthly gross-of-fee returns for all equity mutual funds from CRSP mutual fund database in Panels C and D of Figure 3.[19] Although December returns are high for both market and mutual funds, these plots are not nearly as striking as Figure 1 for hedge funds.

In Table 2, we also provide a univariate comparison of gross returns and residual returns of hedge funds in our sample for December and rest of the year (Jan-Nov). 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. We also compare and contrast our results for hedge funds with those for open-ended equity mutual funds in CRSP mutual fund database. The figures in Table 2 confirm the inflation of returns and residuals (using the four-factor model of Carhart, 1997) in December for mutual funds, consistent with CKMR (2002). These figures suggest that it is possible that some hedge funds free ride on the portfolio pumping practice in mutual funds by taking positions in the same securities that are marked up by mutual funds. We investigate such passive behavior later in this section.

We also compare the cross-sectional volatility and factor risk premia between December and rest of the year. With the exception of the size factor (SCLC), none of the differences are statistically significant different at conventional levels. These results already point that the December spike is unlikely to be driven by hedge funds increasing their risk in December or by higher factor risk premia in December.

4.1. 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 well-known determinants of hedge fund performance (See Agarwal, Daniel, and Naik, 2005).[20] In particular, we estimate the following regression:

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

[20] Agarwal, Daniel, and Naik (2005) use hurdle rate and high-water mark to capture moneyness. Since we use

$$
\begin{aligned}
Return_{i,m,t} = {} & \lambda_0 + \lambda_1 I(December_{i,t}) + \lambda_2 Return_{i,m-1,t} + \lambda_3 Return_{i,m-2,t} + \lambda_4 Delta_{i,m-1,t} \\
& + \lambda_5 Moneyness_{i,m-1,t} + \lambda_6 Lockup_i + \lambda_7 Restrict_i + \lambda_8 Size_{i,m-1,t} + \lambda_9 \sigma_{i,t-1} \\
& + \lambda_{10} Age_{i,m-1,t-1} + \lambda_{11} MFee_i + \sum_{s=1}^{3} \lambda_{12}^{s} I(Strategy_{i,s}) + \sum_{k=1}^{8} \lambda_{13}^{k} I(Year_{t,k}) + \xi_{i,t}
\end{aligned} \qquad \textbf{(1)}
$$

where $Return_{i,m,t}$ is the return of fund *i* in month *m* of year *t*, $I(December_{i,t})$ is an indicator variable that takes the value 1 if the month is December of year *t*, and 0 otherwise, $Return_{i,m-1,t}$ and $Return_{i,m-2,t}$ are the returns of fund *i* in months *m-1* and *m-2* of year *t*, $Delta_{i,m-1,t}$ is the sensitivity of the managers' wealth to a 1% change in NAV for fund *i* as of end of month *m-1* in year *t*, $Moneyness_{i,m-1,t}$ of fund *i* at the end of month *m-1* of year *t*, computed as the difference in the spot and exercise price divided by exercise price, $Lockup_i$ and $Restrict_i$ are the lockup and restriction periods for fund *i*, $Size_{i,m-1,t}$ is the size of the fund measured as the natural logarithm of the AUM for fund *i* for month *m-1* of year *t*, $\sigma_{i,t-1}$ is the standard deviation of the monthly returns of fund *i* estimated using monthly returns of year *t-1*, $Age_{i,t-1}$ is the age of fund *i* at the end of year *t-1*, $MFee_i$ is the management fees charged by fund *i*, $I\left(Strategy_{i,s}\right)$ are strategy dummies that take the value 1 if fund *i* belongs to strategy *s*, and 0 otherwise, $I\left(Year_{t,k}\right)$ are year dummies, and $\xi_{i,t}$ is the error term.[21]

Here and throughout the paper, we report the slope coefficients and corresponding p-values after adjusting for heteroskedasticity and autocorrelation. Following GLM (2004), we also control for any serial correlation in the monthly returns by including two lags of the monthly returns, in addition to adjusting the p-values for autocorrelation.

We report our findings in Table 3. Our results for Model 1 show that the slope coefficient

---

moneyness directly in this paper for all specifications, we do not include hurdle rate and high-water mark as additional variables.

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

on December dummy is positive (coeff.=1.514) and highly significant at 1% level. This result is economically significant too suggesting that December returns are higher by 1.5% compared to any other month even after controlling for the well-known determinants of returns. As in Agarwal, Daniel, and Naik (2005), we find that delta, lockup period, restriction period, and size are related to returns. We also find that the coefficient on the first lag of returns is positive and significant, although the second lag is positive but not significant. This is consistent with the evidence of serial correlation in hedge fund returns as documented in GLM (2004).[22]

As discussed earlier, in order to establish whether Dec spike is due to active portfolio pumping by hedge funds, one needs high-frequency holdings data, which is not available. However, one can shed light on the passive effect by examining the impact of portfolio pumping during other times in the year. To test whether hedge funds *passively* benefit from year-end gaming behavior of other institutional investors such as mutual funds and pension funds, we include Quarter-end dummy in equation (1) above. This dummy takes a value of 1 if the month corresponds to a quarter-end other than December, (i.e, March, June, and September), and equals 0 otherwise. This test is predicated on the fact that unlike mutual funds for which quarter-ends are important for reporting purposes, it is not the same for hedge funds. Therefore, hedge funds are unlikely to have active interest in managing returns at quarter-ends. So, if one does find the hedge fund returns to be higher at quarter-ends, it would indicate that they may be passively benefiting from the gaming behavior of mutual funds.

The results in Model 2 of Table 3 show that the quarter-end dummy is positive (coeff=0.091) and significant at 1% level, suggesting that hedge fund returns may be influenced by mutual funds' return inflation at quarter-ends. More importantly, December dummy continues

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

to be positive (coeff=1.539) and highly significant. The relatively higher coefficient for December dummy suggests that the magnitude of return inflation seems to be higher during year-ends compared to quarter-ends. This is consistent with hedge funds having greater incentives to engage in marking up practice at year-end rather than at quarter-ends. This finding is also consistent with CKMR's (2002), who also find stronger results for year-ends compared to quarter-ends.[23] In CKMR (2002), the ratio of coefficients on the year-end and the quarter-end dummies (b_1/b_3) is 3.26 (=53.01/16.27) and 2.57 (=29.6/11.54) for *All* funds (see Panels A and B of their Table II on 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 (as a rough approximation) in Model 2 of our Table III. However, in our case, this ratio turns out to be considerably higher, 16.9 (=1.539/0.091), indicating that the December spike persists even after allowing for the possibility that hedge funds may be passively benefiting from the portfolio pumping by mutual funds.

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 equation (1) above. We report our results from this regression in Model 3 of Table 3. We find the coefficient on cross-sectional volatility is positive (coeff.=0.066) and significant at 1% level. This implies that higher cross-sectional volatility is associated with higher returns. The Dec 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.

[23] Such window-dressing (e.g., Haugen and Lakonishok, 1988; Lakonishok, Shleifer, Thaler, and Vishny, 1991; Musto, 1997, 1999) at quarter-ends could be related to the frequency of reporting holdings to stakeholders in the fund and to the implicit incentives arising from flow-performance and tournaments literature (e.g., Ippolito, 1992; Brown, Harlow, and Starks, 1996; Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Brown, Goetzmann, and Park, 2001).

It is conceivable that managers may increase their risk exposures gradually and this may not be reflected entirely in the month of December. Hence, for robustness, we combine the returns for last two months, November and December, and then repeat our analysis. We continue to find similar results as before with the slope coefficient on dummy for Nov-Dec to be 1.27% (results not reported in table).

In Model 5, we use the residual returns (or discretionary component of returns) estimated using 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 around 1%.[24] Further, the ratio of coefficients on December and quarter-end dummies, (0.362/0.019=19.1) continues to be substantially higher than observed in case of mutual funds by CKMR (2002). This reinforces our finding that December spike cannot be entirely explained away by hedge funds' passively benefiting from the gaming behavior of mutual funds.

Overall, the results in Table 3 support our *Returns Management Hypothesis* suggesting that funds may be engaging in managing returns at the end of the year.

4.2 What mechanism can funds use to spike up December returns?

How is return management accomplished by fund managers? We test the *Savings* and *Borrowing* hypotheses developed in Section 2. To recall, the *Savings Hypothesis* posits that managers under-report positive returns up to November to create reserves, which they add back

[24] For robustness, we repeat our analysis in Model 5 by replacing residual by the sum of abnormal return (alpha) and residual return and find similar results. December dummy is positive (coeff.=0.345) and significant at 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 December dummy to be positive (coeff.=0.380) and significant at 1% level.

in December. We test this by including two additional explanatory variables to equation (1): (a) $Reserves_{i,m\text{-}1,t}$, the cumulative return from January up to month *m-1* in year *t* if positive, else zero, and (b) interaction of this variable with 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 4 confirm that this is indeed the case with the coefficient on the interaction being positive (coeff.=0.112) and significant at 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. For the sake of robustness, we also use our alternative measure of reserves based on GLM (2004). In unreported results, we find that when we use this measure, its interaction with the December dummy is significantly positive for Model 1 (coeff.=0.633 and significant at 1% level). These findings 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 year *t+1* following a high December return in year *t*. To test this hypothesis, we include two additional variables to Model 4 of Table 1: (a) January dummy that takes the value 1 if the month is January of year *t+1*, and 0 otherwise, and (b) interaction of January dummy with returns during the previous month of year $t, Return_{i,m-1,t}$. If funds are indeed *borrowing* from January returns in the year following December of a particular year, then one would expect to observe a negative coefficient for the interaction term. Results reported in Model 2 of Table 4 indicate that the coefficient on the interaction of January dummy and lagged monthly return is negative (coeff.=-0.040) and significant at 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 4. All our inferences remain unchanged. Overall, the results from this section strongly support the *Returns Management Hypothesis* and the two sub-hypotheses, namely *Savings* and *Borrowing* hypotheses.

Following this evidence on returns management, in the next section, we examine our second hypothesis related to the kind of funds that should engage in greater degree of returns management.

5. Do funds with higher incentives and reserves exhibit greater degree of returns management?

In Section 2, we hypothesized that funds that have higher incentives (funds whose call-option-like incentive fee contracts are near-the-money and have higher delta, and funds that have worse relative performance) and have larger reserves should exhibit greater degree of returns management. In order to test our *Hypothesis 2*, we estimate the regressions of $DIFFRET_{i,t}$ and $DIFFRES_{i,t}$, our measures of returns management. As described in Section 3, $DIFFRET_{i,t}$ measures the magnitude of returns management and is given by the difference between returns for fund i during December of year t and the average returns over January-November period for the same fund during the same year. Similarly, $DIFFRES_{i,t}$ measures the difference between December residual and the average residual in the first eleven months. Since these are annual measures, we estimate the following regressions using yearly data:

$$DIFFRET_{i,t}(DIFFRES_{i,t}) = \theta_0 + \theta_1 Near-the-Money_{Nov,t} + \theta_2 Delta_{Nov,t} + \theta_3 Frank_{Nov,t} + \theta_4 Reserves_{Nov,t}$$
$$+\theta_5 In-the-Money_{Nov,t} + \theta_6 Return_{i,t-1} + \theta_7 Lockup_i + \theta_8 Restrict_i + \theta_9 Size_{Nov,t} \quad \textbf{(2)}$$
$$+\theta_{10}\sigma_{i,t-1} + \theta_{11} Age_{Nov,t} + \theta_{12} MFee_i + \sum_{s=1}^{3}\theta_{13}^{s} I(Strategy_{i,s}) + \sum_{k=1}^{8}\theta_{14}^{k} I(Year_{t,k}) + \omega_{i,t}$$

where $Near-the-money_{Nov,t}$ and $In-the-money_{Nov,t}$ are indicator variables that take value of 1 when fund is near-the-money and in-the-money at the end of November of year *t*, $Delta_{Nov,t}$ is the manager's pay-performance sensitivity as of end of November of year t, $Frank_{Nov,t}$ is the fractional rank of the fund at the end of November of year *t* based on its performance (January-November returns during that year) relative to its peer group as defined by its fund strategy, and $Return_{i,t-1}$ is the annual return of fund *i* during year *t-1*. All the other variables are as defined earlier for regression in equation (1) except that for this regression we need yearly data and the explanatory variables are measured as of Nov-end for each fund-year. [25]

In addition to our key independent variables used to test our hypothesis, we include other explanatory variables that could capture the costs of engaging in return management. In what follows, we briefly discuss how they may be related to returns management. First, funds with lower ability may have an incentive to engage in returns management in order to make themselves look better. We proxy for ability with prior year's returns and expect a negative coefficient. Second, larger funds and older funds stand to lose more by way of reputation if they are caught, and hence should engage in such behavior to a lesser extent. Therefore, we expect negative coefficients on size and age variables. Third, funds with higher volatility may find it easy to hide returns management and hence such funds face reduced probability of being caught (in turn, face lower expected costs). So, we expect a positive coefficient on volatility. Fourth, lockup and restriction periods could impact returns management in a complex way. If the

[25] We compute fractional rank ranging between 0 and 1 following the methodology in Sirri and Tufano (1998). Our results are also robust to the use of fractional rank computed across all funds rather than within a strategy, i.e., *absolute* fractional rank rather than *relative* fractional rank.

lockups are higher, the funds will have more flexibility to invest in illiquid assets. A relatively illiquid asset portfolio makes it easy to camouflage returns management. In contrast, funds with longer lockups may not have to worry about capital outflows in response to short-term performance, and hence lockups may reduce the temptation to engage in such short-termist behavior. Thus, it is an open empirical question as to whether higher lockups and higher restriction periods are associated with greater degree of returns management. Finally, higher the management fee, higher are the expected benefits from the additional fee earned on incremental flows arising from reporting higher returns (since flows chase past performance). Therefore, we expect a positive relation between management fees and extent of returns management.

We report our results from the regression in equation (2) using $DIFFRET_{i,t}$ and $DIFFRES_{i,t}$ as the dependent variables in Models 1 and 2 of Table 5. We find the coefficient on near-the-money variable to be significantly positive in both models. The coefficient estimates from Model 1 (Model 2) imply that, when compared to out-of-the-money funds, near-the-money funds have December returns (residuals) that exceed the average return (residuals) during January-November period by 0.822% (0.345%). This is a significant figure as the average monthly return (residual) in our sample is 1.06% (-0.02%) (see Table 1).

The coefficient on delta is positive but not significant in either models. It appears that high-powered incentives do not seem to have perverse effects similar to those documented for corporations by Bergstresser and Philippon (2004). This may be due to the fact that CEOs in corporations who can have greater influence on share price of their firms by painting a rosier picture of future growth opportunities.

The coefficient on fractional rank is significantly negative (coeff.=-2.050) in Model 1 ($p < 0.01$) but only weakly so in Model 2 ($p = 0.14$). Our result in Model 1 is also economically meaningful with one standard-deviation change in the fractional rank resulting in a decrease of

0.59% in December returns relative to Jan-Nov average. This finding suggests that funds respond to their implicit incentives inherent in the flow-performance relationship. In unreported results, for robustness, when we use fractional ranks computed across all funds each year rather than those computed using funds within a particular strategy (i.e., *absolute* ranks compared to *relative* ranks), we find our results continue to hold, with the coefficient on the absolute fractional rank being negative (coeff.=-1.305) and significant in Model 1.

Finally, we find the coefficient on Reserves to be positive (coeff.=0.052) and highly significant in Model 1 and positive but not significant in Model 2. The role of Reserves in Model 1 is also economically significant as one standard deviation increase in the Reserves is associated with an increase of 0.69% (a significant number considering average monthly return is 1.06%) in December returns relative to the Jan-Nov average. As before, for robustness, we repeat our analysis using the alternative measure of reserves based on GLM (2004) and we find our results are qualitatively similar.

Although, we do not find that delta is significantly related to returns management, other findings from this section lend strong support to *Hypothesis 2*, i.e., funds with greater incentives (funds with near-the-money incentive-fee contracts and worse performance relative to their peers) and funds with higher reserves display greater degree of returns management.

With respect to the control variables, consistent with our expectation, the degree of returns management is negatively related to prior returns and positively related to returns management fees. We find that the coefficient on lockup period is negative. Thus, while funds with lockup periods could more easily mask returns management, it appears that they are less likely to do so, perhaps because they are less concerned with capital withdrawals in response to poor performance. Finally, we find mixed evidence for volatility.

6. Concluding Remarks

Recently, there has been a lot of debate about 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. Hedge funds face both explicit and implicit incentives to manage returns upwards as the year draws to a close. Consistent with this notion, our paper is the first to document that hedge funds exhibit disproportionately higher returns during December - 2.5% compared to the average of 1% during the first eleven months. This result is robust to the possibility that factor risk premiums may be larger in December, that funds may be increasing their risk exposures in December, and/or free-riding on year-end return pumping by mutual funds.

We then test two hypotheses relating to the possible modus operandi of returns management. Consistent with our *Savings Hypothesis*, we find that funds under-report their positive returns till December (thereby creating reserves) and then add them back in December. Consistent with our *Borrowing Hypothesis*, we find that funds borrow from January returns of the following year. Finally, our results show that incentives can explain the returns management behavior in hedge funds. In particular, we find that funds with greater incentives (funds with near-the-money compensation contracts and with poor performance relative to their peers) engage in returns management to a greater extent.

Our results have important implications for policy issues related to security valuation, disclosure, regulation, and compensation design. Our findings complement the evidence of earnings management in corporations where top executives also face similar incentives arising from their compensation contracts. This suggests that economic agents respond similarly to their incentive contracts even though they may be operating in very different environments.

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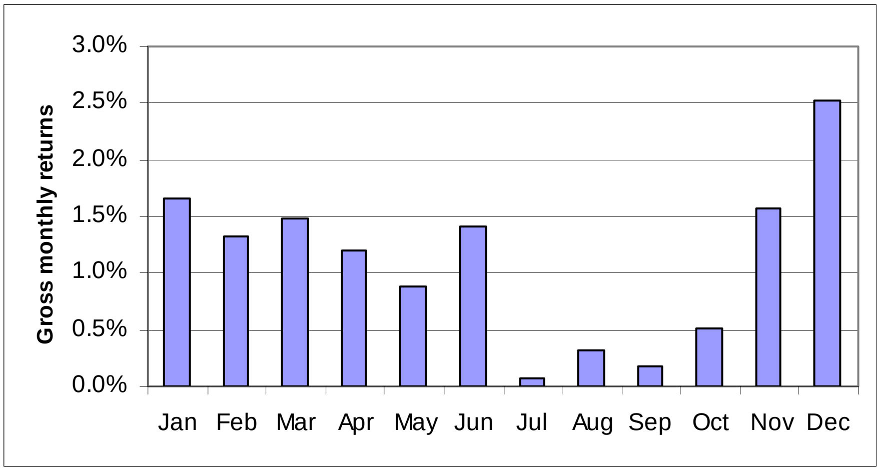
Figure 1: Monthly Gross Returns of Hedge Funds

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

Panel A



Panel B

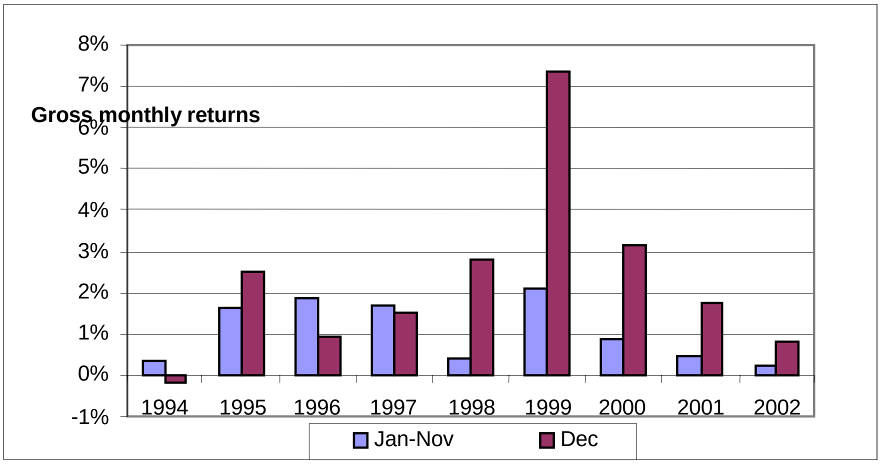


Figure 2: Distribution of Hedge Funds by Data Sources

This figure shows the percentage of hedge funds from the four databases namely CISDM, HFR, MSCI, and TASS at the end of our sample period (2002).

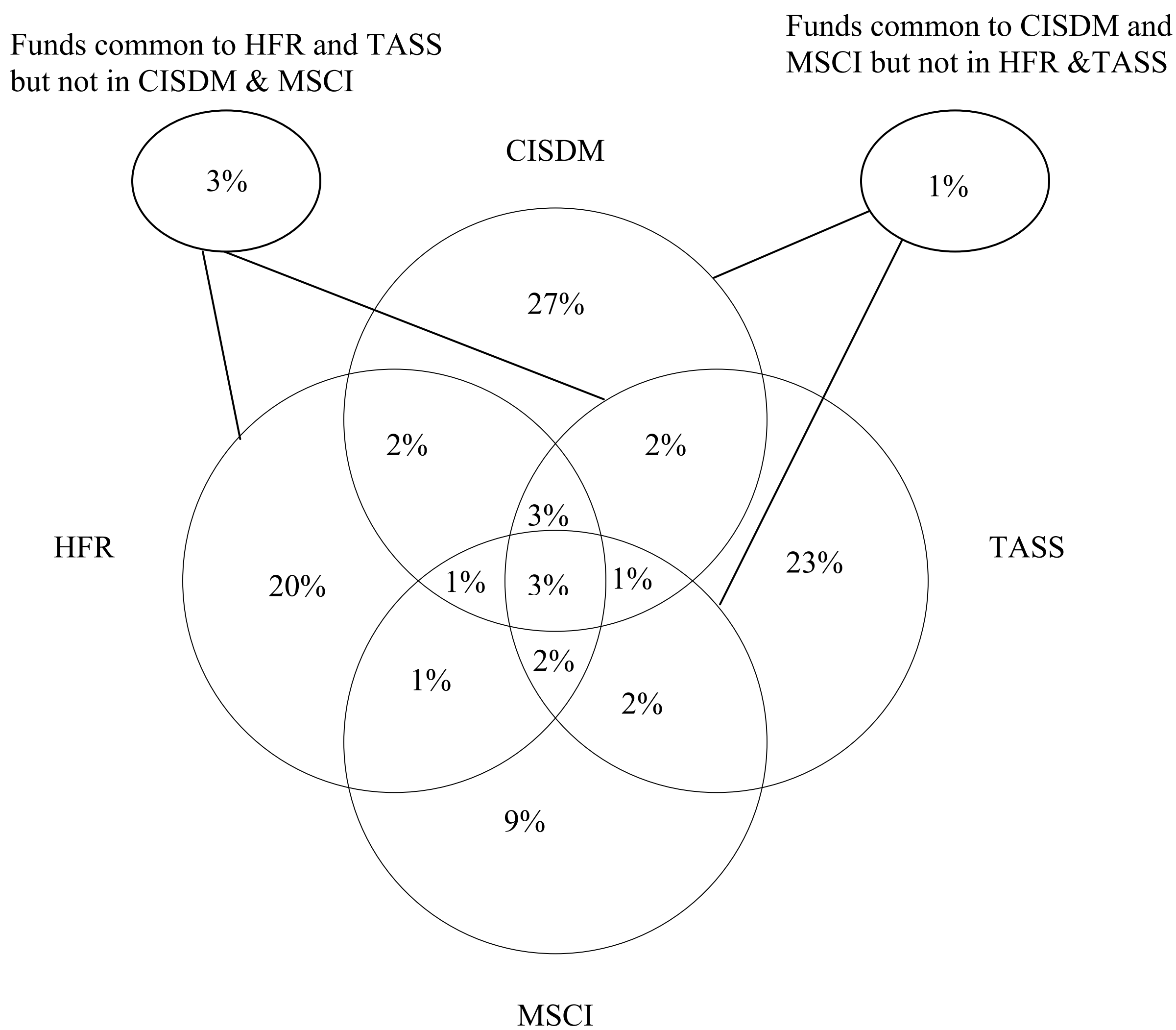
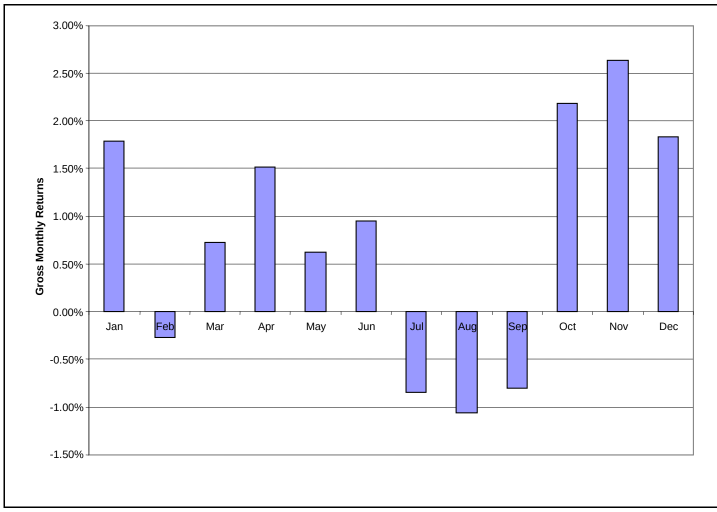


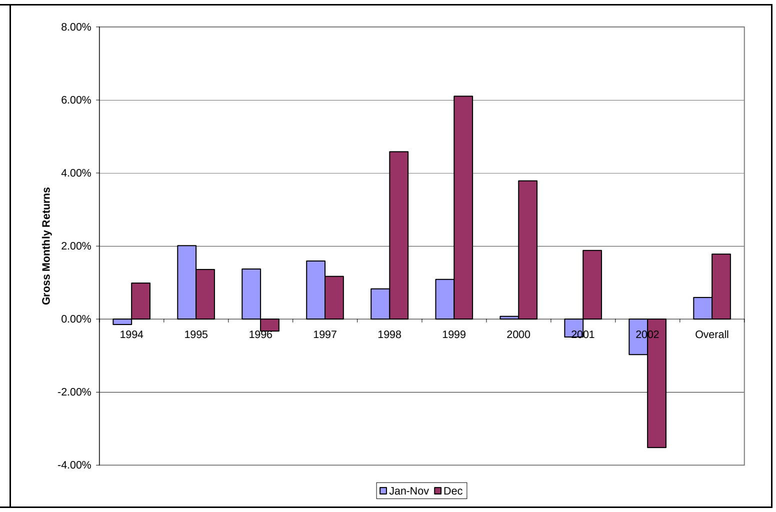
Figure 3: Monthly Gross Returns of Market and Mutual Funds

Figure in 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. Figure in Panel B plots the average monthly market returns each year for January-November and December periods. Figure in Panel C plots the average monthly gross-of-fees mutual fund returns from CRSP mutual fund database during our sample period, 1994-2002. Figure in 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.

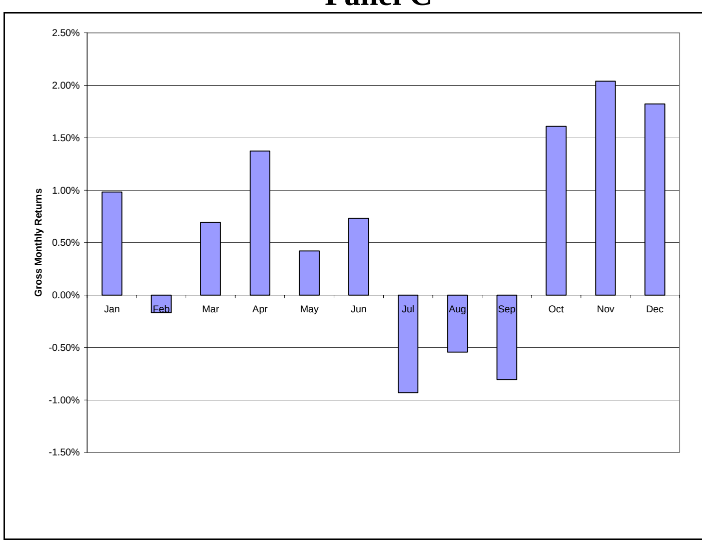
Panel A



Panel B



Panel C



Panel D

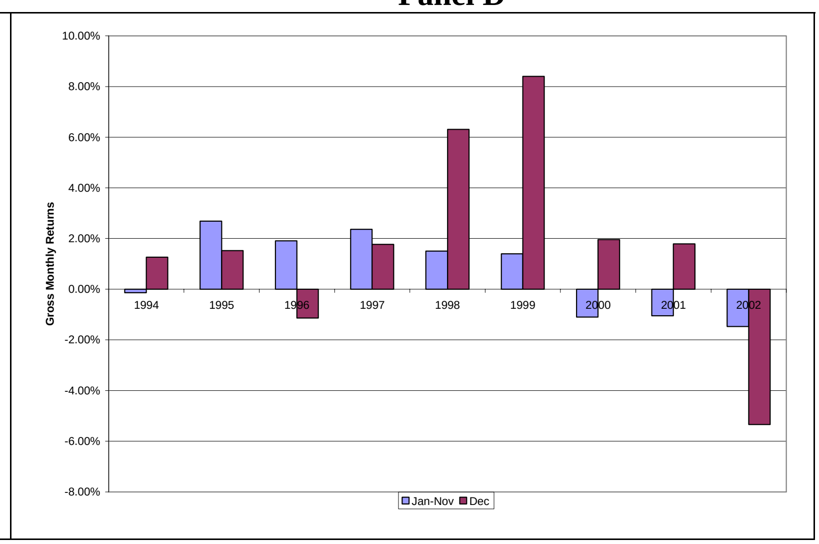


Table 1. Summary statistics

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 fund's gross returns using the seven-factor model of Fung and Hsieh (2004). *DIFFRET* is the difference between December raw returns and the average raw return over January to November of the same year. Similarly, *DIFFRES* is the difference between Dec residual and the average residual over Jan-Nov. CS Volatility is the monthly cross-sectional dispersion in fund returns. Moneyness is defined on a monthly basis as spot price minus 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., relative fractional rank. Reserves_{m-1} is equal to max (0, Cumulative Returns up to month *m-1*). Lockup period is the minimum time that an investor has to wait (after making her investment) before she can withdraw her 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 her 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
***DIFFRET* (%)**	1.54	5.94	-1.05	0.54	3.10
***DIFFRES* (%)**	0.24	5.03	-1.72	0.02	1.88
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
Fractional Rank	0.50	0.29	0.25	0.50	0.75
Reserves (%)	8.58	13.20	0.00	3.56	11.58
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
AUM ($ millions)	131.26	390.89	9.42	29.55	88.84
Volatility (%)	4.82	3.95	1.93	3.83	6.52
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 2. Do funds manage returns? Univariate Results

This table reports the average gross hedge fund returns, gross mutual fund returns, residuals from the time-series regressions of hedge fund's gross returns using the seven-factor model of Fung and Hsieh (2004), residuals from the time-series regressions of mutual fund's gross returns using the four-factor model of Carhart (1997), cross-sectional volatility (CS Volatility), 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 last column provides the results from t-tests (after testing for equality of variances) comparing the average values for December (Dec) with January-November (Jan-Nov) period with t-statistics reported in parentheses. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% respectively.

Independent Variables	Dec	Jan-Nov	Diff. (Dec minus Jan-Nov) (t-statistic)
Gross hedge fund returns	2.51%	0.96%	1.55%*** (32.00)
Gross mutual fund returns	1.82%	0.49%	1.33%*** (41.86)
Residual hedge fund returns	0.23%	-0.02%	0.25%*** (6.5)
Residual mutual fund returns	0.14%	-0.01%	0.15%*** (10.9)
CS Volatility	6.04	6.00	0.04 (0.1)
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 3. Do funds manage returns? 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 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 o therwise. 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 price 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 has to wait (after making her investment) before she can withdraw her 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 her 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. Prior Year Volatility is standard deviation of monthly returns estimated using previous year's data. All figures are in percent, e.g., a coefficient of 1.514 is equal to 1.514%. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% respectively. Standard errors are corrected for heteroskedasticity and autocorrelation with p-values being 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 $RESIDUALS_m$
Dec 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-square		3.4%	3.4%	3.4%	3.4%	1.9%

Table 4. How do funds manage returns? Tests of Saving and Borrowing Hypotheses

The table reports OLS regressions of monthly gross returns ($RETURNS_m$). December (January) dummy equals 1 if the month is December (January), and equals zero otherwise. $Reserves_{m-1}$ is equal to max (0, Cumulative Returns up to month *m-1*). Quarter-End dummy equals 1 if the month corresponds to a quarter-end (other than December), and equals 0 otherwise. CS $Volatility_m$ (cross-sectional volatility) is the cross-sectional dispersion of fund returns during month *m*. $Returns_{m-1}$, $Delta_{m-1}$, $Moneyness_{m-1}$, $Size_{m-1}$, and Age_{m-1} are as of prior month *m-1*. Moneyness is computed as the difference between spot and exercise price divided by the exercise price. $Returns_{m-2}$ are gross returns during month *m-2*. Lockup period is the minimum time that an investor has to wait (after making her investment) before she can withdraw her 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 her 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. All figures are in percent, e.g., a coefficient of 0.144 is equal to 0.144%. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% respectively. Standard errors are corrected for heteroskedasticity and autocorrelation with p-values being reported in parentheses.

Independent Variables	Expected Sign	Model 1	Model 2	Model 3
Dec Dummy	+	0.144**	1.569***	0.200***
		(0.027)	(0.000)	(0.002)
Dec 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-square		4.3%	3.5%	4.3%

Table 5. Do funds with higher incentives and reserves exhibit greater degree of returns management?

The table reports OLS regressions of *DIFFRETy* and *DIFFRESy*, where *DIFFRETy* (*DIFFRESy*) is the difference between December gross returns (residual returns from seven-factor model of Fung and Hsieh, 2004) and the average gross return (residual returns from seven-factor model of Fung and Hsieh, 2004) over January to November of the same year *y*. Moneyness is computed as the difference between spot and exercise price divided by the exercise price. Near-the-money indicator variable takes a value of 1 when moneyness is between $-(\mu + \sigma)$ and $-(\mu - \sigma)$, else 0. In-the-money indicator variable takes a value of 1 when moneyness is greater than $-(\mu - \sigma)$, else 0. μ is the time-series average of the monthly return and σ is the standard deviation of monthly returns using the entire return history for each fund since 1994. $\text{Reserves}_{nov,y}$ is equal to max (0, Cumulative Returns up to November of year *y*). $\text{FRank}_{nov,y}$ is the fractional rank of a fund *within a strategy* at the end of November, computed using January-November returns during year *y*. Near-the-Money, In-the-Money, Delta, Fractional Rank, Reserves, Size, Volatility, and Age are as of November of year *y*. All figures are in percent, e.g., a coefficient of 0.505 is equal to 0.505%. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% respectively. Standard errors are corrected for heteroskedasticity and autocorrelation with p-values being reported in parentheses.

Independent Variables	Expected Sign	Model 1 $DIFFRET_y$	Model 2 $DIFFRES_y$
$\text{Near-the-money}_{nov,y}$	+	0.822***	0.345**
		(0.000)	(0.007)
$\text{Delta}_{nov,y}$	+	0.087	0.071
		(0.226)	(0.244)
$\text{FRank}_{nov,y}$	-	-2.050***	-0.535
		(0.000)	(0.142)
$\text{Reserves}_{nov,y}$	+	0.052***	0.003
		(0.000)	(0.669)
$\text{In-the-money}_{nov,y}$		0.099	-0.259*
		(0.535)	(0.063)
Returns_{y-1}		-0.023***	-0.024***
		(0.000)	(0.000)
Lockup Period		-0.332**	-0.232*
		(0.021)	(0.060)
Restriction Period		-0.072	0.081
		(0.661)	(0.550)
$\text{Size}_{nov,y}$		-0.002	-0.008
		(0.950)	(0.773)
Prior Year Volatility		0.212***	-0.041**
		(0.000)	(0.027)
$\text{Age}_{nov,y}$		0.052***	0.026**
		(0.000)	(0.014)
Management Fee		12.601*	10.245*
		(0.062)	(0.081)
Intercept, Strategy Dummies, and Year Dummies		Yes	Yes
Observations		16260	16260
Adjusted R-square		12.8%	5.5%

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

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

Directional Traders 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.

Relative Value 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.

Security Selection 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.

Multi-Process 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 may shift in majority weighting between Merger Arbitrage and Distressed Securities, while others may 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 and Delta

Incentive fee contacts provide managers with options on the investors' assets under management (AUM). We calculate the option delta based on Black-Scholes (1973) formula for valuing European call options.

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

$$= N(Z) * S * 0.01 * I \qquad \textbf{(1)}$$

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

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

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

T = time to maturity of the option (= 1 year)

r = natural log of 1+ risk-free interest rate (= log of (1+LIBOR) rate for next year)

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

I = incentive fee rate (expressed as a fraction)

N( ) = cdf of standard normal distribution

Manager's option delta of the fund is the sum of delta from different sets of investors', each of whom will have their own exercise price depending on when they enter the fund. To compute the spot price (S) and exercise price (X) used in the computation of delta above, 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 his own exercise price depending on when he enters 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 hurdle rate provision.
6) In case, no incentive fee is paid for a year due to insufficient returns, the hurdle for next year is based on 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 taxes @35%.

We adopt the following steps:

1) Estimate fund's annual gross returns given data on net returns.

   The 1st investor enters the fund at the end of year 0, the 2nd investor enters the fund at the end of year 1, the 3rd investor enters the fund at the end of year 2, and so on….

For the fund's first full year of existence, since there is only one investor (assumption 1), gross returns can be computed as follows:

$$gross_t = \begin{Bmatrix} \dfrac{net_t - hurdle_t * I}{1 - I} \text{ if } net_t > hurdle_t \\ net_t \text{ otherwise} \end{Bmatrix} \quad \textbf{(2)}$$

where $hurdle_t = libor_t$ if the fund has hurdle rate provision, and = 0 otherwise.

From the second year onwards, 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 has been paid to the AUM divided by the year-beginning AUM. For example, for a given investor '*i*', the year-end market value of his assets net of incentive fees, *MVafterINC*, is given by

$$MVafterINC_i = S_{i,t-1}(1+gross_t) - Max[(S_{i.t-1}(1+gross_t) - X_{i.t-1}), 0]\ I$$

where S_i denotes market value of assets of investor '*i*' ("spot price" as of year-end '*t-1*'), X_i denotes the market value of assets of investor '*i*' that has to be reached ("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 ($\sum MVafterInc_i$) plus the year-end market value of manager's year-beginning investment in the fund. Since this is a non-linear 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 manager's investment in the fund (*MVmgr*). This equals the year-end market value of her year-beginning investment plus 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 less ($\sum MVafterInc_i + MVmgr$).

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 high-enough such that an investor has to pay incentive fee, then the exercise price is higher than the current market value by the hurdle rate (=LIBOR if the fund has hurdle rate provision, and = 0 if the fund does not have the hurdle rate provision)

b) If the gross fund return is not sufficient enough that an investor has to pay incentive fee and if the fund has high-water mark provision, the new exercise price is higher than the last year's exercise price by the hurdle rate

c) If the gross fund return is not sufficient enough that an investor has to pay incentive fee and if the fund does not have the 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 delta of each and sum them up along with the delta from manager's investment in the fund to estimate the total delta of the fund.

The delta of the fund equals delta from investors' assets (manager's option delta) plus the delta from manager's stake. Since manager retains all the return on his own investment, delta from manager's stake equals market value of manager's investment in the fund * 0.01 (i.e., when fund earns one percent return, value of the manager's stake goes up by one percent).