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

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Abstract

We observe that the average hedge fund returns during December are almost three times of their average returns during the rest of the year. In this paper, we examine the reasons for the disproportionately higher returns during December, or the December 'bonanza'. We investigate two competing explanations for this bonanza. The first risk-based explanation suggests that underwater funds increase their risk exposures in December to catch up or that the risk exposures of the funds remain the same but factor risk premium realizations happen to be large in December. Second, somewhat provocative explanation can be that the underwater funds manipulate their returns in December in order to earn incentive fees. We find that the risk-based explanation is unable to completely explain the December bonanza. Our results suggest that fund managers engage in managing their returns towards the end of the year in order to earn incentive fees. We find that fund managers whose incentive fee contracts are near-the-money are more likely to engage in such *returns management*. However, it appears that investors can see through this as we find that investors direct less flows into such funds that engage in returns management.

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Preliminary investigation of hedge fund returns reveals that average December returns are almost three times compared to the average monthly return during the remaining eleven months of the year (2.5% compared to 1.0%) (see Panel A of Figure 1). This plot is in sharp contrast to what we typically see with stocks, where year-end tax loss selling results in low December returns but high January returns. In this paper, we examine the reasons for disproportionately high returns in December or December *bonanza*. In particular, we distinguish between two possible explanations for this December bonanza. Our first explanation, based on risk, is that funds that are just underwater as of November-end increase their risk exposures in December to catch up, or that their risk exposures remain the same but factor risk premium realizations happen to be large in December during our sample. An alternative explanation, somewhat more provocative, is that hedge funds that are just underwater manipulate returns so that they come out ahead at the end of the calendar year in order to be eligible to earn incentive fees. This possibility of "*returns management*" is similar to earnings management in firms, where the compensation structures have interesting similarities with those for hedge fund managers (see Agarwal, Daniel, and Naik, 2005 for more details).

If there is evidence of "returns management", then other natural questions follow: Can December spike be explain by funds under-reporting their positive returns in the earlier months (to create reserves for a bad state of the world in future) and then adding those reserves back in December when the bad state is not realized? Do funds borrow from their future performance for reporting higher returns in December to earn fees? Which fund characteristics determine returns management? Is it more prone in certain hedge fund strategies? Are the funds involved in trading illiquid or hard-to-price securities more likely to manage returns, as they have more discretion in valuing securities in absence of reliable market prices? Are the funds with less sophisticated administrators and less reputed auditors more likely to manage returns? Are the funds whose managers have high incentives (and thus stand to gain if investors cannot see through such behavior) more likely to manage returns? Finally, we examine if investors are fooled by such behavior. Do hedge fund investors, who are considered to be smart, see through such returns management? If investors are not deceived, do funds that engage in returns management experience lower net money flows, all else equal? We also address these related research questions in this paper.

Similar to shareholders of corporate firms facing agency problem, hedge fund investors also face agency problem. While investors would like the manager to maximize wealth creation, the manager would like to take actions that maximize her compensation. Hedge funds are unique with respect to the asymmetric performance-linked incentive compensation provided to its fund managers due to the hurdle rate and high-water mark provisions.[1] Since this kind of compensation structure allows manager to only participate in the profits with no downside participation, it resembles a call option on the assets under management. Incentive fees are paid out the end of the calendar year based on fund performance over the twelve months and only when the net asset value (NAV) exceeds the exercise price, which depends on the hurdle rate and high-water mark provisions. Further, due to these two provisions, money flows coming into the fund at different points in time are associated with different NAVs , and therefore different strike prices. As a result, the incentive fee contract of the manager resembles a *portfolio* of call options where each option is related to the flow each year having its own exercise price, which is reset

[1] 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.

annually based on contract provisions. If the options are just out-of-the-money, i.e., the fund is just *underwater*, as the year draws to a close, the manager may be tempted to manipulate returns such that the NAV exceeds the exercise price and she earns incentive fees.

Our research builds on various strands of corporate finance and accounting literature and applies them to the hedge fund industry. There is a large literature on earnings management and its implications for regulators. A number of survey articles have been written on this topic.[2] Most of this literature documents earnings management in firms where the managers have some discretion in reporting accruals. Specifically, Burgstahler and Dichev (1997) and DeGeorge, Patel, and Zeckhauser (1998) examine the distribution of reported earnings around zero, and show that there is a higher-than-expected frequency of slightly positive earnings and a lower-than-expected frequency of slightly negative earnings. This is consistent with earnings management. In case of hedge funds, the threshold would be the returns necessary to overcome the hurdle rate and high-water mark benchmarks. In a similar manner, we examine the degree of moneyness of hedge fund returns to detect returns management, if any, for funds that are near-the-money. In a different setting, Chander and Bricker (2002) study earnings management in closed-end mutual funds by using discretion in valuation of restricted securities. Such kind of discretion in financial reporting is likely to be higher for hedge funds that invest in illiquid securities, are lightly regulated, and offer limited disclosure. Our paper contributes to the extant literature by examining the role of such discretion and evidence of returns management in the hedge fund industry.

There is also a large literature relating incentives from compensation to earnings management. Healy (1985) and Gaver, Gaver, and Austin (1995) relate managers' accrual

[2] For example, see Barnea, Ronen and Sadan (1976), Imhoff (1977), Ronen and Sadan (1981), Buckmaster (1992, 1997), Healey and Wahlen (1999), Dechow and Skinner (2000), Fields, Lys, and Vincent (2001), and Stolowy and Breton (2004).

policies with incentives arising from their bonus contracts. Goldman and Sleazak (2003) theoretically model the tradeoff between the costs and benefits of stock-based compensation, where the benefits arise from managers exerting more effort while costs result from managers fraudulently misrepresenting performance in presence of high pay-for-performance sensitivity. Bergstresser and Phillippon (2004) document that firms with CEOs having high incentives, i.e., high delta, have higher degree of earnings management. Our paper also contributes to this strand of literature by examining the role of incentives (arising from the hedge fund manager's compensation) in returns management in hedge funds.

Our paper also builds on another strand of literature studying serial correlation in hedge fund returns. Getmansky, Lo, and Makarov (2004) find positive autocorrelations in monthly returns, and conclude that it is driven by hedge funds' exposure to illiquidity and smoothing of returns by hedge fund managers. Bollen and Krepely (2004) demonstrate that the power to detect returns management using return autocorrelations is poor. Both these papers focus on the serial correlation in returns while our focus in this paper is different. We examine if hedge funds engage in returns management by focusing on their returns at the end of the year and relating them to the moneyness of the portfolio of call options implicit in the managerial compensation contract. However, following insights from these papers, we also relate the spike in December returns to funds intentionally smoothing their returns through the year.[3] It is plausible that funds report returns lower than the true returns when returns are positive. This creates reserves, which provides them an option to use them in case they have negative returns in the future (a phenomenon sometimes referred to as "*saving* for the rainy day"). However, if funds do not have significant negative returns by the end of November, they are forced to add back those reserves

[3] Interestingly, in a different setting, Gaver, Gaver, and Austin (1996) and Burgstahler and Dichev (1997) find evidence of earnings management consistent with income smoothing in corporate firms.

in December (as they may not be able to carry them over to next fiscal year), resulting in the December spike. A related scenario can be that funds may need to "*borrow*" from returns during January of the following year when they have insufficient reserves. We examine these possibilities through our *saving* and *borrowing* hypotheses.

We have several interesting findings. First, we find that disproportionately high returns in December cannot be entirely explained by the increase in risk exposures or higher factor risk premiums in December. This indicates that funds may be engaging in managing returns towards the end of the year to earn incentive fees. Second, we find results consistent with our savings hypothesis with higher returns in December being related to the idea of funds "saving for the rainy day", as described above. Third, we find that funds may also be borrowing from their January returns in the following year in case they do not have reserves from the current year. Fourth, we find that funds that are near-the-money are more likely to manage returns as these funds clearly have higher incentives to benefit from returns management. Finally, we find that investors are smart enough to figure out the funds engaged in returns management and therefore direct less money to such funds. This shows that in presence of such internal governance mechanisms, there may be limited role for external governance mechanisms such as regulation by outside authorities such as the Securities and Exchange Commission (SEC).

Our results 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 discretion lies at the hands of the managers, one would expect a higher incidence of returns

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

management. Further, our results shed light on the factors driving returns management, which can help regulators and investors to focus more closely on funds involved in such activity. Finally, returns management may not be worrisome if there is a market mechanism that sees through such behavior and penalizes such funds. We examine one such mechanism, namely, investor flows. Our result of investors directing lesser flows into funds that engage in returns management suggests that the role for regulation is diminished since smart investors can figure it all out. In addition to the policy implications for governance, our findings also have implications for security valuation in hedge funds, managerial compensation structure, and disclosure in the hedge fund industry.

The rest of the paper is organized as follows. Section I presents the related literature and testable hypotheses. Section II describes the data and construction of variables. Section III investigates our Hypothesis 1 relating to evidence of returns management in hedge funds while Section IV tests our Hypothesis 2 relating to types of funds that are more likely to manage returns. Section V investigates our Hypothesis 3 regarding investors' response to potential returns management in hedge funds by examining the money flows into such funds. Section VI offers concluding remarks and suggestions for future research.

I. Related Literature and Hypotheses Development

As discussed earlier, our paper is broadly related to earnings management in corporate firms. There is a large accounting and finance literature on this subject with a number of survey articles being written on it (see Barnea, Ronen, and Sadan, 1976; Imhoff, 1977; Ronen and Sadan, 1981; Buckmaster, 1992, 1997; Healey and Wahlen, 1999; Dechow and Skinner, 2000; Fields, Lys, and Vincent, 2001; Stolowy and Breton, 2004). Earnings management literature documents managers using discretion in reporting accruals to benefit personally. For example, Bergstresser and Phillippon (2004) show that corporate firms in which the CEOs have higher incentives, i.e., high delta, are engaged in greater amount of earnings management (see also Healy, 1985; Goldman and Sleazak, 2003).[5]

Despite the large literature on earnings management in firms, the literature on discretion in financial reporting by investment companies is limited. Recently, Getmansky, Lo, and Makarov (2004) find positive autocorrelations in monthly returns, and conclude that it is driven by hedge funds' exposure to illiquidity and smoothing of returns by hedge fund managers. Bollen and Krepely (2004) demonstrate that the power to detect returns management using return autocorrelations is poor. Both these papers focus on the serial correlation in returns while our focus in this paper is different. We examine if hedge funds engage in returns management by focusing on their returns at the end of the year and relating them to the moneyness of the portfolio of call options implicit in the managerial compensation contract.

Our paper is closely related to Chander and Bricker (2002), who examine a similar issue as in this paper for closed-end mutual funds, where managers have some discretion in valuing restricted securities in their portfolios. We build on their study by examining similar issues in the hedge fund industry where the problem of returns management is expected to be more acute as hedge funds differ from closed-end funds in at least three ways. First, hedge funds invest in much more illiquid securities such as distressed debt, convertible bonds, and emerging markets. Second, hedge funds are lightly regulated and there is limited disclosure by hedge fund managers, which can entice the manager to engage in managing returns. Finally, hedge fund

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[5]Erickson, Hanlon, and Maydew (2003), Johnson, Ryan, and Tian (2003), Ke (2003), and Kedia (2003) provide empirical evidence on the positive relation between stock-based compensation and either manipulation of accounting statements or fraudulent managerial behavior.

managers have different incentives arising from their unique compensation structure. Unlike closed-end fund managers that are compensated based on performance relative to a passive benchmark, hedge fund managers are compensated based on absolute returns with benchmark determined by hurdle rate and high-water mark provisions. Therefore, our study offers interesting insights on returns management in the hedge fund industry, which has been attracting a lot of money recently along with attention from regulators for more disclosure and transparency in financial reporting.

Next, we turn to the main hypotheses tested in this paper. Our first hypothesis relates to providing evidence on and explaining the disproportionately high hedge fund returns during December (i.e., December *bonanza*). There can be two possible explanations for this bonanza. The first explanation is related to risk, which suggests that the hedge funds may be increasing their risk exposures during December or the factor risk premiums may be high during December.[6] The second explanation is related to return manipulation, which suggests that hedge funds manage returns during December. Recently, Agarwal, Daniel, and Naik (2005) show that hedge fund returns are higher for funds with better managerial incentives (delta of the call-option-like incentive fee contract) and higher managerial flexibility (lockup and restriction period) after controlling for several fund characteristics such as size, age, volatility, management fee, fund strategy, and past money flows. If after controlling for these characteristics as well as controlling for the possibility of increase in risk exposures and factor risk premiums, we continue to observe high returns in December, it would lend support to our first hypothesis, i.e., *returns management* hypothesis.

[6] Interestingly, Getmansky, Lo, and Makarov (2004) also consider the possibility of time-varying expected returns as one of the explanations for autocorrelation in monthly returns. They show that such variation in expected returns is unable to explain the magnitude of serial correlation observed in monthly hedge fund returns. In this paper, we explore this possibility to explain a different phenomenon – disproportionately high returns towards the end of the year.

Hypothesis 1: Controlling for risk (higher risk exposures and factor risk premiums), managerial incentives, managerial flexibility, and fund characteristics, December returns are higher than the returns during any other month.

It is plausible that hedge fund managers may "save for the rainy day" by under-reporting positive returns so that they can use these reserves for a bad month in the future. Such smoothing of returns will lead to a downward bias in the return volatility and upward bias in Sharpe ratio. This argument has been made in the seminal work on serial autocorrelation in hedge fund returns by Getmansky, Lo, and Makarov (2004). If this indeed is the case, what happens when the bad month that the manager is saving for does not happen till end of November? In such a scenario, manager may be forced to add all the *reserves* in December as she may not be able to carry those forward to the next fiscal year. This can result in lumpiness in December returns especially during the good years when bad outcomes do not occur before December. This leads us to our next sub-hypothesis – *savings hypothesis*.

Hypothesis 1a: Controlling for risk (higher risk exposures and factor risk premiums), managerial incentives, managerial flexibility, and fund characteristics, December returns are higher than the returns during any other month when cumulative returns up to December are large, i.e., there are higher reserves.

Following the argument made in our savings hypothesis, it is also plausible that managers may not have enough reserves available at the beginning of December to reach the benchmark for earning incentive fee. This is likely to be the case during a year where the fund has not done well leading up to December. In this scenario, manager may be tempted to borrow against future returns to earn her fees. So, a peak in December returns may be followed by a trough in January returns. This leads to our second sub-hypothesis – *borrowing hypothesis*.

Hypothesis 1b: Controlling for risk (higher risk exposures and factor risk premiums), managerial incentives, managerial flexibility, and fund characteristics, higher December returns in a year are associated with lower January returns in the following year.

If we find support to the returns management hypothesis and the two sub-hypotheses above, a natural question is about the type of funds that are likely to engage in such an activity. Our next hypothesis relates to fund characteristics associated with returns management or in other words, determinants of returns management. If the fund is deep out-of-the-money by November end, managing returns slightly upwards in December may not help the manager to earn incentive fee for the year. Also, if the fund is in-the-money by November-end, manager has no incentives to engage in returns management. Hence, the incentives to manage returns are highest for funds that are just underwater or *near-the-money*. 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 incentives to manipulate the share price to increase her benefits. Following these arguments, one would expect to observe funds with higher managerial incentives (or delta) to be more likely to engage in returns management. Further, funds having higher exposure to illiquid assets are more likely to engage in returns management as these funds have more discretion in valuing illiquid securities for which market prices are not readily available, thus providing more avenue for managing returns.[7] These arguments lead us to our second hypothesis:

[7] We are currently in the process of constructing a measure of illiquidity similar to the smoothing index in Getmansky, Lo, and Makarov (2004).

Hypothesis 2: All else equal, funds that are near-the-money, have higher managerial incentives (delta), and have higher illiquidity exposure are more likely to engage in returns management.

Our third and final hypothesis is related to investor behavior in response to returns management by hedge funds. If investors are rational and smart enough to see through the manipulation of returns by hedge fund managers, they will take this into account and allocate less capital to such funds, all else equal. This provides us the following hypothesis:

Hypothesis 3: All else equal, funds that engage in returns management will receive lower money flows.

We test these three main hypotheses and two sub-hypotheses in the rest of this paper.

II. Data and Variable Construction

A. 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 has net-of-fee monthly returns, assets under management, and other 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.[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

[8] 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.

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, 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. We also conduct our analysis at the sub-strategy level using the original strategy classification in the four databases to examine the relation between illiquidity exposure and returns management.

B. 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, $Returns_{i,m,t}$. Getmansky, Lo, and Makarov (2004) demonstrate that the path dependency in the computation of incentive fees can naturally induce smoothing in net-of-fee monthly returns. Therefore, we conduct our analysis using gross returns that do not suffer

[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.

from this problem. Since we need to rule out the risk-based explanation to examine our *returns management hypothesis*, we also employ a second measure, residual return of each fund *i* during each month *m* in each year *t* of our sample period, $Residual_{i,m,t}$.[10] For this purpose, we use the seven-factor model of Fung and Hsieh (2004). The seven asset-based style factors include two equity factors (equity market and size factors), two fixed-income factors (bond market and credit spread factors), and the three trend-following factors for bond, currency, and commodity markets.[11] In particular, following the methodology in Brennan, Chordia, and Subrahmanyam (1998), we estimate $Residual_{i,m,t}$ from the following regression over our sample period:

$$\begin{aligned} Return_{i,m,t} = {} & Alpha_i + \beta_1 SP_t + \beta_2 SCLC_t + \beta_3 10Y_t + \beta_4 CS_t + \beta_5 BdOpt_t + \beta_6 FXOpt_t \\ & + \beta_7 ComOpt_t + Residual_{i,m,t} \end{aligned} \quad \textbf{(1)}$$

where $Return_{i,m,t}$ is the return for fund *i* in excess of the risk-free rate during month *m* of year *t*, $Alpha_i$ is the abnormal return for fund *i*, SP_t is the monthly S&P 500 return in excess of risk-free rate, $SCLC_t$ is the spread between Wilshire Small Cap 1750 index and Wilshire Large Cap 750 index return, $10Y_t$ is monthly return on 10-year Treasury in excess of risk-free rate, CS_t is the difference in the monthly returns of CSFB High Yield index and 10-year Treasury, $BdOpt_t$ is the monthly return on a portfolio of lookback straddles on bond futures in excess of risk-free rate, $FXOpt_t$ is the monthly return on a portfolio of lookback straddles on currency futures in excess of risk-free rate, $ComOpt_t$ is the monthly return on a portfolio of lookback straddles on commodity futures in excess of risk-free rate, and $Residual_{i,m,t}$ is the residual of fund *i* during month *m* of year *t*.

[10] For robustness, we are also currently repeating our analysis by using a sum of abnormal return (alpha) and residual return. We also plan to use Agarwal and Naik (2004) option-based factor model to estimate the alphas of equity-oriented hedge fund strategies.
[11] We thank Bill Fung and David Hsieh for generously providing us the data on these factors.

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, $DIFFRET_{i,y}$, for each fund i in year y, is based on raw returns. It relates to the magnitude of returns management and is computed as the difference between returns for fund i during December of year y and the average returns over January-November period for the same fund during the same year. Our second measure based on raw returns is a dummy variable, $RETMGMT_{i,y}$, which takes a value 1 if $DIFFRET_{i,y}$ is positive, and 0 otherwise. Clearly, when $RETMGMT_{i,y}$ equals 1, it will correspond to the case where fund i's December return in year y is greater than the average return from January to November during that year. Our next two measures are based on risk-adjusted returns. First, we compute $DIFFRES_{i,y}$, for each fund i in year y, as the difference between residual returns (from the seven-factor model of Fung and Hsieh, 2004) during December of year y and the average residual returns over January-November period for the same fund during the same year. Second, we construct a dummy variable, $RESMGMT_{i,y}$, which takes a value 1 if $DIFFRES_{i,y}$ is positive, and 0 otherwise. In other words, $RESMGMT_{i,y}$ equals 1 when fund i's December residual return in year y is greater than the average residual return from January to November during that year.

In Table I, we report the summary statistics of performance measures and returns management. We find that the mean (median) monthly gross fund returns are 1.06% (0.84%) while the mean (median) monthly risk-adjusted returns, residuals are -0.02% (-0.05%). Further, mean (median) of our returns management measure based on raw returns, $DIFFRET_{i,y}$, is 1.55% (0.55%) suggesting that the average gross December returns are higher than the average gross returns during the rest of the year by roughly 1.6%, on average. Mean value of 0.59 for our indicator variable, $RETMGMT_{i,y}$, suggests that 59% of the fund-years in our sample have average

December gross returns higher than the average gross January-November returns. Finally, the summary statistics of our returns management measure based on risk-adjusted returns suggest that mean (median) residual returns are higher in December compared to January-November period by 0.25% (0.04%), as implied by the figures for $DIFFRES_{i,y}$ in Table I. Also, an average value of 0.51 for our indicator variable, $RESMGMT_{i,y}$, suggests that 51% of the fund-years in our sample have average December residual returns higher than the average gross January-November residual returns.

C. Measures for Increase in Risk Exposures and Moneyness

To investigate whether funds increase their risk exposures in December, we compute the cross-sectional dispersion in returns ($CS\ Volatility_{m-1}$) on a month-by-month basis. As hedge fund returns are available, at best, only on a monthly basis, it is not possible to use a time-series approach to estimate betas on a month to month basis using a multifactor model for changes in risk exposures. Therefore, we use a cross-sectional approach to determine the change in the risk exposures. If funds increase their risk exposures, then $CS\ Volatility_{m-1}$ will increase.[12] Hence, $CS\ Volatility_{m-1}$ proxies for the increase in risk exposures. It captures the cross-sectional dispersion of fund returns for a given month *m*. It is computed as $\sqrt{\sum_{i=1}^{N}(r_{i,m}-\bar{r}_m)^2}$ where $r_{i,m}$ is the return of fund *i* in month *m*, and $\bar{r}_m$ is the cross-sectional average of fund returns in month *m*.

Next, we compute the moneyness of the option-like incentive fee contract. For this purpose, we compute the percentage deviation of the manager's portfolio of call options from the

[12] Cross-sectional dispersion has been studied in different contexts in the extant literature. For example, Bessembinder, Chan, and Seguin (1996) use security return dispersion as a proxy for company-specific information flows, 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 .

benchmark, which in turn, depends on the hurdle rate and high-water mark provisions in the compensation contract. Specifically, we compute the moneyness at the end of each month as the difference in the spot price and exercise price, divided by the exercise price. Our *Hypothesis 2* suggests that funds that are near-the-money are more likely to engage in returns management. For this purpose, we categorize moneyness into three groups based on the moneyness at the end of November: out-of-the-money, near-the-money, and in-the-money. For this purpose, we first compute the average (μ) and standard deviation (σ) of monthly returns using the entire return history of each fund since 1994. We consider the funds whose moneyness is greater than $-(\mu - \sigma)$ to be "in-the-money" and funds whose moneyness is less than $-(\mu + \sigma)$ to be "out-of-the-money". Therefore, those funds whose moneyness is between $-(\mu + \sigma)$ and $-(\mu - \sigma)$ are considered as "near-the-money". Let us consider an example to make this clear. Suppose that the average and standard deviation of moneyness, μ and σ, are 2% and 5%, respectively. This means that about 66% of the times, moneyness will lie between $(\mu - \sigma)$ or -3%, and $(\mu + \sigma)$ or +7%. This implies that a fund can have moneyness between -7% $[-(\mu + \sigma)]$ and +3% $[-(\mu - \sigma)]$ to be near the money, i.e., zero moneyness. Following this example further, if the fund has moneyness greater than +3% $[-(\mu - \sigma)]$, it will be in-the-money and if the fund has moneyness less than -7% $[-(\mu + \sigma)]$, it will clearly be out-of-the-money.

In Table I, we observe that the mean (median) cross-sectional volatility of funds' monthly returns are 6.02% (5.83%) while the mean (median) moneyness is 0.03 (-0.13) suggesting that on average, funds are just about at-the-money or slightly out-of-the-money. Mean of 0.31 for near-the-money indicator variable suggests that 31% of the funds are near-the-money, on average.

D. Measures for Managerial Incentives and Money Flows

As described earlier, incentive fee contract endows the manager with a portfolio of call options, which provides incentives to deliver superior performance. Following the procedure outlined in Agarwal, Daniel, and Naik (2005), we proxy these incentives by the delta of the portfolio of call options, which equals the expected dollar change in the manager's compensation for a one percent change in the fund's NAV. 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.[13] We follow Agarwal, Daniel, and Naik (2005) to compute delta at the end of each month.

Following Chevalier and Ellison (1997), Sirri and Tufano (1998), and Goetzmann et al. (2003), we compute money flows as the scaled dollar flow into the fund.

$$Flow_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1}\left(1 + Returns_{i,t}\right)}{AUM_{i,t-1}} \qquad \textbf{(2)}$$

where $AUM_{i,t}$ and $AUM_{i,t-1}$ are the assets-under-management of fund *i* at the end of period *t* and *t-1* and $Returns_{i,t}$ is the return for fund *i* during period *t*.

From Panel A of Table I, we find that the mean (median) monthly delta equals \$170,000 (\$20,000).[14] Further, in our sample, mean (median) percentage annual money flows for the funds are 60.66% (5.89%) suggesting that the flows are positively skewed with a few funds receiving large percentage flows, most likely the case for smaller funds.

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

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

[14] Coles, Daniel, and Naveen (2004) 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.

III. Do funds manage returns?

In this section, we test our *Hypothesis 1* by examining if funds engage in returns management. 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 much higher than average return during any other month. In fact, the average return during December is almost one-and-a-half times the next highest return during January (2.52% versus 1.65%) and almost three times the average return during January-November period (2.52% versus 0.96%). We also compare each month's gross return to December gross return. 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 Panel B of Figure 1, we also show for each year during our sample period, the average returns during January-November and December periods. With the exception of three years (1994, 1996, and 1997), we find that for each year, December returns exceed January-November returns. These plots motivate us to examine the reasons behind the disproportionately high December returns.

Univariate plots in Figure 1 do not control for the alternative risk-based explanation as well as managerial incentives, managerial flexibility, and various fund characteristics that have been shown to be associated with performance (Agarwal, Daniel, and Naik, 2005). Therefore, we next examine if there is evidence of returns management at the end of the year using a multivariate approach. Towards that end, we estimate the following pooled time-series cross-sectional regression:

$$
\begin{aligned}
Return_{i,m,t} = {} & \lambda_0 + \lambda_1 I(December_{i,t}) + \lambda_2 Return_{i,m-1,t} + \lambda_3 Return_{i,m-2,t} + \lambda_4 CS\_Volatility_{m-1,t} \\
& + \lambda_5 Delta_{i,m-1,t} + \lambda_6 Moneyness_{i,m-1,t} + \lambda_7 Lockup_i + \lambda_8 Restrict_i + \lambda_9 Size_{i,m-1,t} \\
& + \lambda_{10} Flow_{i,m-1,t} + \lambda_{11} \sigma_{i,t-1} + \lambda_{12} Age_{i,m-1,t-1} + \lambda_{13} MFee_i + \sum_{s=1}^{3} \lambda_{14}^{s} I(Strategy_{i,s}) \qquad \textbf{(3)} \\
& + \sum_{k=1}^{8} \lambda_{15}^{k} I(Year_{t,k}) + \xi_{i,t}
\end{aligned}
$$

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*, $CS\_Volatility_{m-1,t}$ is the cross-sectional variance in month *m-1* for 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*, $Flow_{i,m-1,t}$ is the money-flow in fund *i* during month *m-1* in 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.[15] We report the slope coefficients and corresponding p-values after adjusting for heteroskedasticity and autocorrelation in Table II. Following Getmansky, Lo, and Makarov

[15] We winsorize top 1% of the independent variables in order to minimize the influence of outliers. Throughout this paper, all the t-statistics and p-values are adjusted for heteroskedasticity and autocorrelation.

(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.

Our results for Model 1 in Table II show that the slope coefficient on December dummy is positive (coeff.=1.496) and highly significant at 1% level (t-stat=32.7). This suggests that December returns are higher by 1.5% compared to any other month even after controlling for lagged monthly returns, moneyness, cross-sectional volatility, and other fund-specific characteristics such as delta, lockup period, and restriction period. Further, we find the coefficient on cross-sectional volatility is positive (coeff.=0.067) and significant at 1% level (t-stat=6.4). This implies that higher cross-sectional volatility in previous month is associated with higher returns. So, increase in risk exposures contribute partly to the higher returns but cannot fully explain December bonanza as the December dummy comes out positive even after controlling for cross-sectional volatility. 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 Getmansky, Lo, and Makarov (2004). Following Agarwal, Daniel, and Naik (2005), we also control for other variables that determine performance such as lagged delta, moneyness, lockup period, restriction period, size, flow, volatility, age, management fee, and strategy and year effects. Like them, we find a positive relation between performance and managerial incentives (delta), and between performance and managerial flexibility (lockup period and restriction period).[16] Overall, these results support our returns management hypothesis (*Hypothesis 1*) suggesting that funds may be engaging in managing returns at the end of the year.

Next, we test our two sub-hypotheses. Our first sub-hypothesis, *savings hypothesis*,

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[16] Agarwal, Daniel, and Naik (2005) use hurdle rate and high-water mark to capture moneyness. Since we use moneyness directly in this paper for all specifications, we do not include hurdle rate and high-water mark as additional variables.

suggests that managers create reserves by saving for the rainy day through under-reporting positive returns up to December. They add these reserves to December returns in case the rainy day does not arrive! To test savings hypothesis, we include two additional explanatory variables in the regression in equation (3) – (a) *reserves* variable, $CumRetOpt_{i,m-1,t}$ that is computed as $Max(0, CumRet_{i,m-1,t})$, where $CumRet_{i,m-1,t}$ is the cumulative return up to month *m-1* in year *t* and (b) interaction of *reserves* variable, $CumRetOpt_{i,m-1,t}$ with December dummy, $I(December_{i,t})$. If $CumRetOpt_{i,m-1,t}$ is non-zero, it implies that the fund has had positive cumulative returns up to the previous month. Please note that in order for the fund manager to have reserves available to save for the rainy day; she needs to have positive returns in the first place. So, if the fund manager is indeed adding those reserves from previous months in December, then one would expect to see the interaction of reserves variable and December dummy to be positive. Our results for Model 2 in Table II confirm that this is indeed the case with the coefficient on the interaction being positive (coeff.=0.111) and significant (t-stat=25.4). Our results for the other control variables are similar to those for Model 1 before.

Our second sub-hypothesis, *borrowing hypothesis*, addresses the possibility that fund managers may not have enough reserves available at the beginning of December and may sometimes be tempted to *borrow* from January returns in the following year. 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 again include two additional variables in our regression in equation (3) – (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. Our results in Model 3 of Table II provide evidence in support of the *borrowing hypothesis*. We find the coefficient on the interaction of January dummy and lagged monthly return to be negative (coeff.=-0.041) and significant at 1% level (t-stat=3.9). As before, our results for the other variables remain unchanged.

Finally, we test for both our sub-hypotheses (*Savings* and *Borrowing*) together and include the corresponding variables altogether in Model IV of Table II. We continue to find December dummy to be positive (coeff.=0.178) and significant at 1% level (t-stat=2.9) supporting our *returns management hypothesis*. Further, we continue to find strong support for *savings hypothesis* with interaction of $CumRetOpt_{i,m-1,t}$ with December dummy to be positive (coeff.=0.110) and significant at 1% level (t-stat=25.1). Finally, our results are also consistent with the *borrowing hypothesis* as the interaction of January dummy and lagged returns is negative (coeff.=-0.046) and significant at 1% level (t-stat=4.3). Overall, these results suggest that hedge funds may be engaging in returns management and they seem to save for adverse outcome in the future as well as borrow from their future performance to earn incentive fees.

Until now, we control for the increase in risk exposures in December by using cross-sectional dispersion in fund returns. One can argue that the results in Table II do not control for the possibility of higher factor risk premiums in December compared to those in other months. To allow for this possibility, we first compute the residual returns of each fund during our sample period using the seven-factor model of Fung and Hsieh (2004) as specified in equation (1) earlier. We then follow the methodology in Brennan, Chordia, and Subrahmanyam (1998) to estimate the following pooled time-series cross-sectional regression:

$$
\begin{aligned}
Residual_{i,m,t} = {} & \lambda_0 + \lambda_1 I(December_{i,t}) + \lambda_2 Residual_{i,m-1,t} + \lambda_3 Residual_{i,m-2,t} \\
& + \lambda_4 CS\_Volatility_{m-1,t} + \lambda_5 Delta_{i,m-1,t} + \lambda_6 Moneyness_{i,m-1,t} + \lambda_7 Lockup_i \\
& + \lambda_8 Restrict_i + \lambda_9 Size_{i,m-1,t} + \lambda_{10} Flow_{i,m-1,t} + \lambda_{11} Age_{i,m-1,t-1} + \lambda_{12} MFee_i \\
& + \sum_{s=1}^{3} \lambda_{13}^{s} I(Strategy_{i,s}) + \sum_{k=1}^{8} \lambda_{14}^{k} I(Year_{t,k}) + \xi_{i,t}
\end{aligned} \qquad \textbf{(4)}
$$

where $Residual_{i,m,t}$ is the residual return of fund i in month m of year t from a time-series regression of fund i's monthly excess returns on the monthly excess returns of the seven factors identified in Fung and Hsieh (2004). Considering that hedge funds use dynamic trading strategies, one can make a case for allowing the risk exposures or betas to change over time. However, even if one uses a rolling regression approach to allow for intertemporal variation in betas, it is still not going to capture the change in risk during a particular month. Hence, to control for month-to-month changes in risk exposures, we use cross-sectional volatility and include it as an independent variable in our regression in equation (4). As in the case of regression using raw returns in equation (3), we control for managerial incentives, managerial flexibility, and other fund characteristics following Agarwal, Daniel, and Naik (2005). We also allow for serial correlation in residual returns by taking two lags, following Getmansky, Lo, and Makarov (2004), in addition to adjusting p-values for autocorrelation. We report the results from this regression in Table III.

Again, our results in Table III show that the coefficient on December dummy is positive (coeff. = 0.309) and significant at 1% level (t-stat = 9.2), after controlling for increase in risk exposures through cross-sectional volatility, which is also positive and significant as before (coeff.=0.077 and t-stat=11.9). This result further supports our *returns management hypothesis* (*Hypothesis 1*) with risk-adjusted returns also being higher for the month of December after controlling for both increase in factor risk premiums and increase in risk exposures (through cross-sectional volatility). As before, we continue to find a positive relation between performance and delta, our proxy for managerial incentives.

Overall, our results using both gross returns and residual returns lend strong support to our *Hypothesis 1* that hedge funds potentially engage in returns management at the end of the year. Following this evidence on returns management, in the next section, we go on to examine our second hypothesis related to the kind of funds that are likely to engage in such activity.

IV. What types of funds are more likely to manage returns?

We hypothesize that funds that are near-the-money, have higher managerial incentives (delta), and have higher exposure to illiquidity are more likely to manage returns. If the fund is deep out-of-the-money by November-end, managing returns slightly upwards in December may not help the manager to earn incentive fee for the year. Also, if the fund is in-the-money by November-end, manager has no incentives to engage in returns management. Hence, the incentives to manage returns are highest for funds that are just underwater or *near-the-money*. Therefore, we hypothesize a positive relation between our measures of returns management and *Near-the-Money* variable. Further, following the theoretical model of Bergstresser and Philippon (2004) and their empirical results, we also expect the funds with high managerial incentives to be more likely to engage in returns management. Thus, we hypothesize a positive relation between returns management and delta. Finally, funds having higher exposure to illiquid assets are more likely to engage in returns management as these funds have more discretion in valuing illiquid securities for which market prices are not readily available, thus providing more avenue for managing returns. In order to test our *Hypothesis 2*, we estimate the following pooled time-series cross-sectional regression using yearly data:

$$DIFFRET_{i,y} = \lambda_0 + \lambda_1 Near-the-Money_{Nov,y} + \lambda_3 \sigma_{i,t-1} + \lambda_4 Delta_{Nov,y} + \lambda_5 Size_{Nov,y} + \lambda_6 Flow_{Nov,y} + \lambda_7 Age_{Nov,y} + \lambda_8 MFee_i + \sum_{s=1}^{3} \lambda_9^s I(Strategy_{i,s}) + \sum_{k=1}^{8} \lambda_{10}^k I(Year_{t,k}) + \xi_{i,t} \quad \textbf{(5)}$$

where $DIFFRET_{i,y}$ measures the magnitude of returns management and is given by the difference between returns for fund *i* during December of year *y* and the average returns over January-November period for the same fund during the same year. All the other variables are as defined earlier for regression in equation (3) except that for this regression we need yearly data and the explanatory variables are measured as of November-end for each fund-year. We report the results from this regression in Model 1 of Table IV under "OLS".

We find the coefficient on near-the-money variable to be positive (coeff. = 0.445) and significant at 1% level (t-stat=3.8). This is consistent with our *Hypothesis 2*, which predicts that funds that are near-the-money are more likely to manage returns. The coefficient on delta is positive (coeff.=0.113) but not significant (t-stat=1.6). So, we do not observe funds with higher managerial incentives significantly engaging in higher returns management. It seems like that high-powered incentives do not seem to have perverse effects similar to those observed in corporate firms as in Bergstresser and Philippon (2004).

Next, we repeat our analysis by using a risk-adjusted returns management measure, $DIFFRES_{i,y}$ given by the difference between residual returns (from the seven-factor model of Fung and Hsieh, 2004) for fund *i* during December of year *y* and the average residual returns over January-November period for the same fund during the same year. For this purpose, we replace $DIFFRET_{i,y}$ with $DIFFRES_{i,y}$ as the dependent variable in the regression in equation (5) above and report our results in Model 2 of Table IV under "OLS".

Again, we find similar results as in Model 1 with the coefficient on near-the-money variable being positive (coeff. = 0.436) and significant at 1% level (t-stat=4.2). This is consistent with our *Hypothesis 2*, which predicts that funds that are near-the-money are more likely to manage returns. Like before, the coefficient on delta is positive (coeff.=0.038) but not significant. So, we do not find evidence supporting our hypothesis of funds with higher managerial incentives to be engaging in higher returns management.

To allow for the possibility that our hypothesized variables may be non-linearly related to our returns management measures, we also adopt a logistic regression approach. The dependent variable here is $RETMGMT_{i,y}$ is a variable that takes a value 1 if $DIFFRET_{i,y}$ is positive, and 0 otherwise. Towards that end, we estimate the following logistic regression:

$$\begin{aligned} RETMGMT_{i,y} = \lambda_0 + \lambda_1 Near-the-Money_{Nov,y} + \lambda_3 \sigma_{i,t-1} + \lambda_4 Delta_{Nov,y} + \lambda_5 Size_{Nov,y} \\ + \lambda_6 Flow_{Nov,y} + \lambda_7 Age_{Nov,y} + \lambda_8 MFee_i + \sum_{s=1}^{3} \lambda_9^s I(Strategy_{i,s}) \qquad \textbf{(6)} \\ + \sum_{k=1}^{8} \lambda_{10}^k I(Year_{t,k}) + \xi_{i,t} \end{aligned}$$

We report the results from this regression under “LOGISTIC” in Model 3 of Table IV.

Consistent with our *Hypothesis 2*, we find that the coefficient on near-the-money is positive (coeff.=0.280) and significant at 1% level (t-stat=6.4). However, as in the OLS regression, delta turns out to be positive (coeff.=0.025) but not significant (t-stat=0.7).

Following our earlier approach, we repeat our analysis using risk-adjusted returns management measure, $RESMGMT_{i,y}$ instead of $RETMGMT_{i,y}$ as dependent variable in logistic regression in equation (6) and report our results in Model 4 of Table IV. Our results continue to support *Hypothesis 2* suggesting that near-the-money funds are more likely to engage in returns management as suggested by positive and significant coefficient on near-the-money (coeff.=0.185; t-stat=4.5). However, we do not find support for our hypothesis that funds with higher managerial incentives engage in higher returns management with delta turning out to be negative and insignificant (coeff.=-0.017; t-stat=0.5).

In summary, our findings in Table IV based on OLS and logistic specifications suggest that funds that are near-the-money are more likely to manage returns, a result consistent with our *Hypothesis 2*. Based on our findings, it seems that increase in risk (through higher risk exposures and/or bigger factor risk premiums) is not able to explain the December bonanza and that funds that are near-the-money are more likely to exhibit disproportionately high December returns. If hedge funds are involved in manipulating returns, regulators such as the SEC will be naturally concerned about this phenomenon and will advocate the use of external governance mechanism in terms of regulating hedge funds. However, if hedge fund investors are smart enough to see through such manager behavior, they should allocate less money flows to such funds. This kind of internal governance mechanism will obviate the need for an external mechanism calling for strict regulation of hedge funds. In the following section, we examine these issues by analyzing investor behavior in response to potential returns management in hedge funds.

V. Do investors penalize funds that manage returns?

Our last hypothesis (*Hypothesis 3*) predicts that hedge fund investors respond rationally and are sophisticated enough to realize if funds manage returns and penalize them by allocating less money to such funds. In order to test this hypothesis, we estimate the following pooled time-series cross-sectional regression[17]:

[17] We also estimate median regressions to examine the robustness of our results to outliers. We find similar results as with the OLS regressions.

$$
\begin{aligned}
FLOW_{i,y} = {} & \lambda_0 + \lambda_1 ReturnMgmtMeasure_{i,y} + \lambda_2 Delta_{i,y-1} + \lambda_3 Moneyness_{i,y-1} \\
& + \lambda_4 Lockup_i + \lambda_5 Restrict_i + \lambda_6 Return_{i,y-1} + \lambda_7 Return_{i,y} + \lambda_8 Size_{i,y-1} \\
& + \lambda_9 Flow_{i,y-1} + \lambda_{10}\sigma_{i,t-1} + \lambda_{11} Age_{i,y-1} + \lambda_{12} MFee_i + \sum_{s=1}^{3} \lambda_{13}^{s} I(Strategy_{i,s}) \\
& + \sum_{k=1}^{8} \lambda_{14}^{k} I(Year_{t,k}) + \xi_{i,t}
\end{aligned} \tag{7}
$$

where, $ReturnMgmtMeasure_{i,y}$ can be one of the four measures defined in Section II before, namely, *DIFFRET*$_y$, *RETMGMT*$_y$, *DIFFRES*$_y$, and *RESMGMT*$_y$. All the other variables are as defined before except that we consider them here at the end of year *y-1* as regression in equation (7) is estimated using yearly data.

Our *Hypothesis 3* posits that the slope coefficient on returns management measure should be negative and significant suggesting that investors allocate less money to funds that are likely to be involved in returns management. Our results from the above regressions in Models 1 to 4 of Table V strongly support our *Hypothesis 3*. First, using the returns management measures based on raw returns, as hypothesized, we find in Models 1 and 2, the coefficients on *DIFFRET*$_y$ and *RETMGMT*$_y$ to be negative (coeffs.=-1.175 and -12.660) and significant at 1% level (t-stats=5.8 and 6.4). Next, using the returns management measures based on risk-adjusted returns, *DIFFRES*$_y$ and *RESMGMT*$_y$, in Models 3 and 4 of Table V, we again find the coefficient to be negative for the two returns management measures (coeffs.=-0.392 and -7.308) and significant (t-stats=1.8 and 3.8).

Overall, these results suggest that investors direct less money towards funds which potentially engage in returns management. Following Agarwal, Daniel, and Naik (2005), we control for other cross-sectional determinants of flows such as lagged managerial incentives (delta), lagged moneyness, lockup and restriction period, lagged and contemporaneous yearly returns, lagged size, lagged flows, lagged volatility, lagged age, and management fee in the above regression. We find similar signs for these control variables as hypothesized in their paper. Overall, these results confirm the prediction of *Hypothesis 3* that investors allocate less capital to funds that are potentially manipulating returns. Our result indicates that such internal governance mechanism seems to work and there is not always the need for an external governance mechanism in form of regulation by authorities such as the SEC.

VI. 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 inform this debate by examining the issue of returns management in hedge funds and contribute to the broad literature on earnings management in corporate firms. We use a comprehensive database of hedge funds to explain the disproportionately high returns during December or December *bonanza*.

We test three main hypotheses and two sub-hypotheses related to December effect in hedge funds. Our first hypothesis (*returns management hypothesis*) suggests that hedge funds may be managing returns if even after controlling for higher risk (through increase in risk exposures or higher factor risk premiums) towards the end of the year and other fund characteristics, we observe high fund returns during December. Our two sub-hypotheses related to December bonanza are the *savings* and *borrowing* hypotheses. In *savings hypothesis*, we posit that December bonanza may be related to managers smoothing returns during the year by under-reporting their positive returns till December (thereby creating reserves) and then being forced to add these reserves in December if they did not need to use them earlier in the year. In *borrowing hypothesis*, we conjecture that funds may be borrowing from future returns in January of the following year when they do not have enough reserves in terms of unreported returns. Our second main hypothesis corresponds to near-the-money and highly incentivized funds managing returns at the end of the year in order to earn incentive fees. Our third and final hypothesis examines investor behavior in response to potential returns management by funds. We hypothesize that investors are rational and smart to figure out this activity and allocate less capital to funds that may be managing returns. We document several new and interesting findings from the tests of these hypotheses.

First, we find that risk-based explanation alone cannot explain the disproportionately high returns in December and it appears that funds manage returns towards the end of the year. Second, we observe that December bonanza can be explained to some extent by the funds' tendency to save for the rainy day by under-reporting their positive returns and then being forced to add back the unreported returns in December when they don't need to use the reserves, i.e., unreported returns during the year. Third, it appears that funds borrow from their future returns in January of the following year to meet any shortfall in December of the current year. Fourth, we observe that near-the-money funds are more likely to manage returns. Such funds have higher incentives to benefit from returns management as they are just lagging behind and by managing returns upwards they can exceed the threshold to earn incentive fees. Finally, we find that investors are not naïve and are able to detect returns management. We show that it may be costly for funds to engage in returns management as investors penalize such funds by directing less money to them.

Our results have several important implications for policy issues related to security valuation, disclosure, regulation, and compensation design. On one hand, our findings suggest a need for appropriate disclosure environment to curb any returns management. This may be achieved by increasing the transparency and valuation of securities that are subject to managerial discretion. On the other hand, considering that hedge fund investors are able to decipher returns management in hedge funds, our results indicate that there is limited role for external governance mechanisms such as regulation by outside authorities as investors seem to sophisticated enough to infer any returns management and penalize such funds.

Our research is broadly related to the evidence of earnings management in corporate firms where similar incentives arise from the compensation schemes of top executives. But due to the challenges in the measuring earnings management through discretionary accruals (Beneish, 2001), it is harder to study such issues in corporate firms. This, in addition to the growing importance of professional fund management, makes our study important and suggests the need for more future research in this area.

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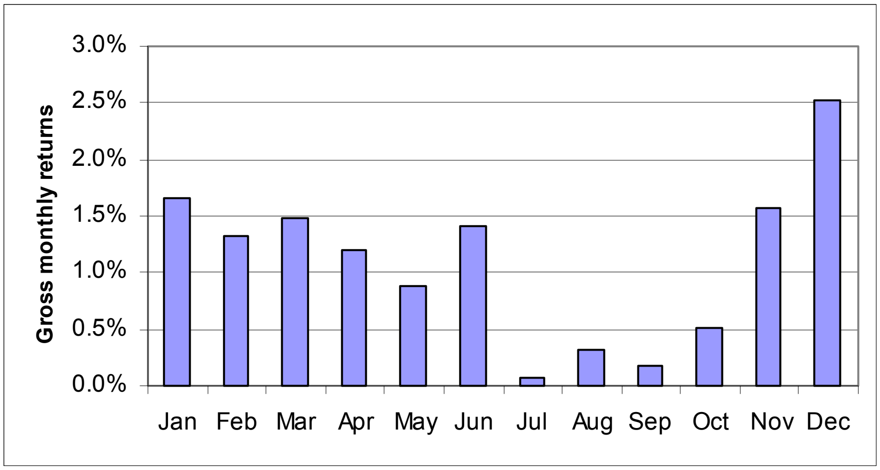
Figure 1: Monthly Gross Returns

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

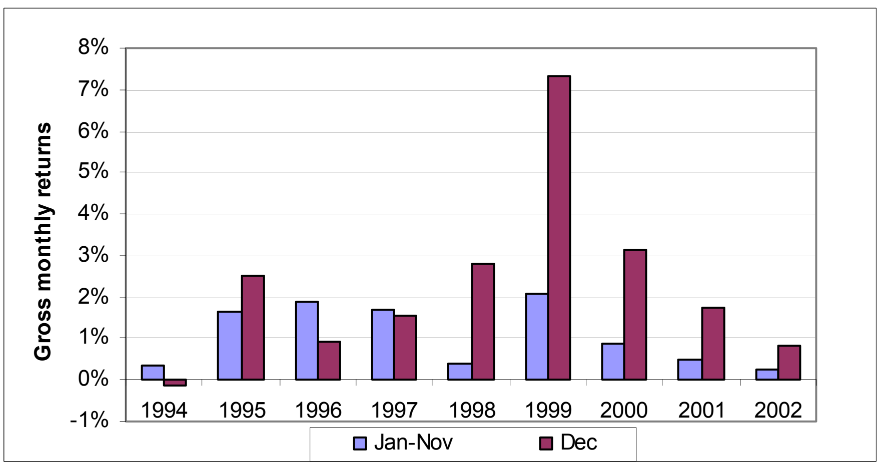


Figure 2: Distribution of Hedge Funds by Data Sources

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

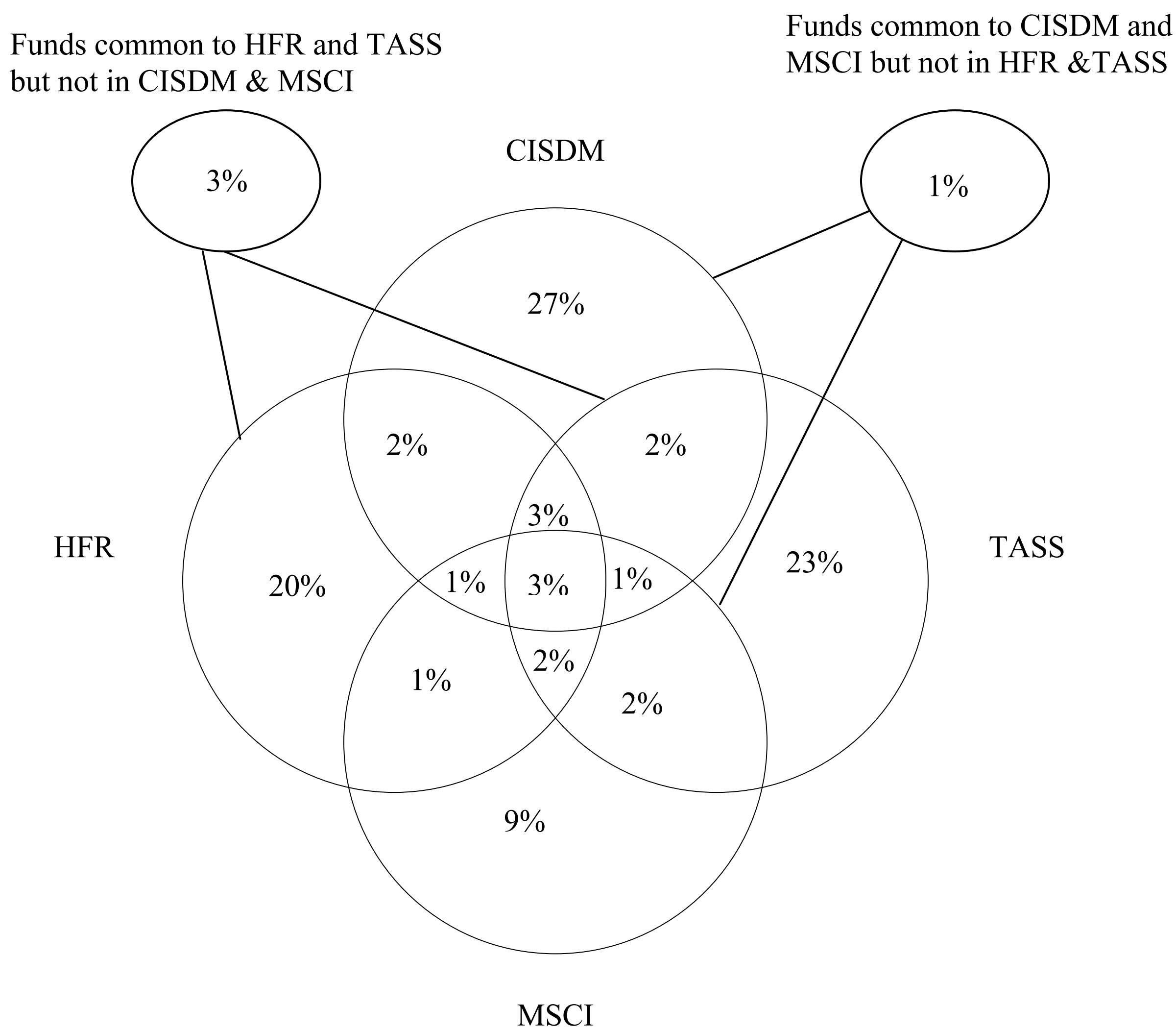


Table I: Summary statistics

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 fund's returns using the seven-factor model of Fung and Hsieh (2004). Annual Flows are the investors' dollar flow scaled by assets. *DIFFRETy* (*DIFFRESy*) is the difference between December raw returns (residual returns from seven-factor model of Fung and Hsieh, 2004) and the average raw return (residual returns from seven-factor model of Fung and Hsieh, 2004) over January to November of the same year *y*. *RETMGMTy* (*RESMGMTy*) equals 1 if the DIFFRET (*DIFFRESy*) is positive and 0 otherwise. CS Volatility is the monthly cross-sectional dispersion in fund returns. Near-the-money takes a value of 1 when moneyness is between $-(\mu + \sigma)$ and $-(\mu - \sigma)$, where μ is the time-series average of the monthly return and σ is the standard deviation of monthly return using the entire return history for each fund since 1994. 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. 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	5.64	-1.14	0.84	2.98
Residuals (%)	-0.02	4.19	-1.73	-0.05	1.56
Annual Flows (%)	60.66	192.27	-14.26	5.89	54.55
***DIFFRETy* (%)**	1.55	5.95	-1.05	0.55	3.12
RETMGMTy	0.59	0.49	0.00	1.00	1.00
***DIFFRESy* (%)**	0.25	4.99	-1.72	0.04	1.87
RESMGMTy	0.51	0.50	0.00	1.00	1.00
CS Volatility (%)	6.02	1.90	4.64	5.83	6.61
Near-the-Money	0.31	0.46	0.00	0.00	1.00
Moneyness	0.03	17.90	-6.30	-0.13	7.19
Delta ($ millions)	0.17	0.51	0.00	0.02	0.10
Lockup Period (years)	0.13	0.32	0.00	0.00	0.00
Restriction Period (years)	0.31	0.28	0.16	0.16	0.33
AUM ($ millions)	129.94	387.39	9.30	29.35	88.21
Volatility (%)	4.83	3.95	1.95	3.84	6.53
Age	4.91	3.55	2.12	4.01	6.76
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? Multivariate results

This table reports OLS regressions of monthly gross returns ($RETURNS_m$). December (January) dummy equals 1 if the month is December (January), and equals 0 otherwise. $CumRetOpt_{m-1}$ is equal to max(0, Cumulative Returns up to month *m-1*). CS $Volatility_{m-1}$ is the cross-sectional dispersion of fund returns during month *m-1*. $Returns_{m-1}$, CS $Volatility_{m-1}$ (cross-sectional volatility), $Delta_{m-1}$, $Moneyness_{m-1}$, $Size_{m-1}$, $Flow_{m-1}$, 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*. Prior Year Volatility is standard deviation of monthly returns estimated using previous year's data. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% respectively. t-statistics corrected for heteroskedasticity and autocorrelation are reported in parentheses.

Independent Variables	Expected Sign	Model 1	Model 2	Model 3	Model 4
December Dummy	+	1.496^{***}	0.140^{**}	1.533^{***}	0.178^{***}
		(32.7)	(2.2)	(33.8)	(2.9)
December Dummy*$CumRetOpt_{m-1}$	+		0.111^{***}		0.110^{***}
			(25.4)		(25.1)
January Dummy*$Returns_{m-1}$	-			-0.041^{***}	-0.046^{***}
				(3.9)	(4.3)
$CumRetOpt_{m-1}$			-0.015^{***}		-0.014^{***}
			(6.3)		(5.6)
January Dummy				0.575^{***}	0.445^{***}
				(12.1)	(9.3)
$Returns_{m-1}$		0.100^{***}	0.101^{***}	0.101^{***}	0.104^{***}
		(25.3)	(26.3)	(24.2)	(25.4)
$Returns_{m-2}$		0.001	0.007^{*}	0.001	0.007^{**}
		(0.2)	(1.9)	(0.3)	(2.1)
CS $Volatility_{m-1}$		0.067^{***}	0.045^{***}	0.069^{***}	0.046^{***}
		(6.4)	(4.4)	(6.5)	(4.5)
$Delta_{m-1}$		0.133^{***}	0.130^{***}	0.132^{***}	0.130^{***}
		(5.8)	(5.7)	(5.8)	(5.6)
$Moneyness_{m-1}$		0.002	-0.001	0.002	-0.001
		(1.2)	(0.4)	(1.5)	(0.5)
Lockup Period		0.131^{***}	0.129^{***}	0.132^{***}	0.129^{***}
		(3.5)	(3.4)	(3.5)	(3.4)
Restriction Period		0.188^{***}	0.182^{***}	0.188^{***}	0.178^{***}
		(4.6)	(4.4)	(4.6)	(4.3)
$Size_{m-1}$		-0.101^{***}	-0.101^{***}	-0.102^{***}	-0.100^{***}
		(10.8)	(10.7)	(10.8)	(10.7)
$Flow_{m-1}$		0.006^{***}	0.006^{***}	0.007^{***}	0.006^{***}
		(6.5)	(6.3)	(6.9)	(6.6)
Prior Year Volatility		0.003	0.003	0.005	0.004
		(0.6)	(0.6)	(0.9)	(0.7)
Age_{m-1}		-0.027^{***}	-0.027^{***}	-0.025^{***}	-0.026^{***}
		(7.8)	(7.7)	(7.3)	(7.4)
Management Fee		2.166	2.358	2.194	2.441
		(1.2)	(1.3)	(1.2)	(1.4)
Intercept, Strategy Dummies, and Year Dummies		Yes	Yes	Yes	Yes
Observations		199365	199365	199365	199365
Adjusted R-square		3.5%	4.3%	3.5%	4.3%

Table III: Do funds manage returns? A look at residual returns

The table reports OLS regressions of 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 dummy equals 1 if the month is December, and equals zero otherwise. $Residual_{m-1}$, CS $Volatility_{m-1}$ (cross-sectional volatility), $Delta_{m-1}$, $Moneyness_{m-1}$, $Size_{m-1}$, $Flow_{m-1}$, 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. $Residual_{m-2}$ are residual returns during month *m-2*. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% respectively. t-statistics corrected for heteroskedasticity and autocorrelation are reported in parentheses.

Independent Variables	Expected Sign	$RESIDUALS_m$
December Dummy	+	0.309^{***}
		(9.2)
$Residual_{m-1}$		0.076^{***}
		(21.6)
$Residual_{m-2}$		0.030^{***}
		(8.7)
CS $Volatility_{m-1}$		0.077^{***}
		(11.9)
$Delta_{m-1}$		0.064^{***}
		(5.3)
$Moneyness_{m-1}$		-0.004^{***}
		(4.3)
Lockup Period		-0.014
		(1.2)
Restriction Period		0.040^{***}
		(3.1)
$Size_{m-1}$		-0.083^{***}
		(18.5)
$Flow_{m-1}$		0.002^{***}
		(2.7)
Age_{m-1}		-0.005^{***}
		(3.1)
Management Fee		0.412
		(0.6)
Intercept, Strategy Dummies, and Year Dummies		Yes
Observations		245875
Adjusted R-square		1.8%

Table IV: What types of funds are more likely to manage returns?

The table reports OLS regressions of *DIFFRETy* and *DIFFRESy* as well as logistic regressions of *RETMGMTy* and *RESMGMTy*, where *DIFFRETy* (*DIFFRESy*) is the difference between December raw returns (residual returns from seven-factor model of Fung and Hsieh, 2004) and the average raw return (residual returns from seven-factor model of Fung and Hsieh, 2004) over January to November of the same year *y*. *RETMGMTy* (*RESMGMTy*) equals 1 if the DIFFRET (*DIFFRESy*) is positive, and 0 otherwise. Delta, Near-the-Money, Size, Flow, Volatility, and Age are as of November of year *y*. Near-the-money takes a value of 1 when moneyness is between $-(\mu + \sigma)$ and $-(\mu - \sigma)$, where μ is the time-series average of the monthly return and σ is the standard deviation of monthly return using the entire return history for each fund since 1994. Moneyness is computed as the difference between spot and exercise price divided by the exercise price. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% respectively. t-statistics corrected for heteroskedasticity and autocorrelation are reported in parentheses.

	OLS			LOGISTIC		
Independent Variables	**Expected Sign**	**Model 1 *$DIFFRET_y$***	**Model 2 *$DIFFRES_y$***	**Expected Sign**	**Model 3 *$RETMGMT_y$***	**Model 4 *$RESMGMT_y$***
Near-the-money$_{nov,y}$	+	0.445***	0.436***	+	0.280***	0.185***
		(3.8)	(4.2)		(6.4)	(4.5)
Delta$_{nov,y}$	+	0.113	0.038	+	0.025	-0.017
		(1.6)	(0.6)		(0.7)	(0.5)
Size$_{nov,y}$		-0.068**	-0.084***		0.001	-0.008
		(2.0)	(2.9)		(0.1)	(0.7)
Flow$_{nov,y}$		-0.001	-0.005		-0.002	-0.004***
		(0.2)	(1.2)		(1.2)	(2.6)
Prior Year Volatility		0.210***	-0.088***		0.019***	-0.029***
		(11.5)	(5.5)		(4.0)	(6.4)
Age$_{nov,y}$		0.067***	0.067***		0.036***	0.028***
		(5.0)	(6.1)		(6.7)	(5.6)
Management Fee		12.991**	10.112*		-3.050	-0.913
		(2.0)	(1.7)		(1.2)	(0.4)
Intercept, Strategy Dummies, and Year Dummies		Yes	Yes		Yes	Yes
Observations		16564	16564		16564	16564
Adjusted R-square / Pseudo R-square		10.9%	4.1%		3.1%	2.5%

Table V: Do investors penalize funds that manage returns?

This table reports OLS regressions of $FLOW_y$, estimated as annual dollar flow scaled by assets. *DIFFRETy* (*DIFFRESy*) is the difference between December raw returns (residual returns from seven-factor model of Fung and Hsieh, 2004) and the average raw return (residual returns from seven-factor model of Fung and Hsieh, 2004) over January to November of the same year *y*. *RETMGMTy* (*RESMGMTy*) equals 1 if the *DIFFRETy* (*DIFFRESy*) is positive, and 0 otherwise. Delta, Moneyness, Size, Flow, Volatility, and Age are as of previous year. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% respectively. t-statistics corrected for heteroskedasticity and autocorrelation are reported in parentheses.

Independent Variables	Expected Sign	Model 1	Model 2	Model 3	Model 4
$DIFFRET_y$	-	-1.175***			
		(5.8)			
$RETMGMT_y$	-		-12.660***		
			(6.4)		
$DIFFRES_y$	-			-0.392*	
				(1.8)	
$RESMGMT_y$	-				-7.308***
					(3.8)
$Delta_{y-1}$		14.548***	14.589***	14.589***	14.584***
		(10.9)	(10.9)	(10.9)	(10.9)
$Moneyness_{y-1}$		0.342***	0.364***	0.331***	0.337***
		(3.3)	(3.5)	(3.2)	(3.2)
Lockup Period		-2.020	-1.911	-1.630	-1.698
		(0.7)	(0.6)	(0.5)	(0.5)
Restriction Period		-3.102	-2.853	-2.850	-2.840
		(1.0)	(0.9)	(0.9)	(0.9)
$Return_{y-1}$		0.570***	0.583***	0.587***	0.590***
		(13.2)	(13.5)	(13.6)	(13.6)
$Return_y$		0.722***	0.663***	0.661***	0.656***
		(12.7)	(12.6)	(12.1)	(12.4)
$Size_{y-1}$		-18.565***	-18.535***	-18.650***	-18.627***
		(17.5)	(17.5)	(17.5)	(17.5)
$Flow_{y-1}$		0.068***	0.067***	0.067***	0.068***
		(11.0)	(10.9)	(10.9)	(10.9)
$Volatility_{y-1}$		-3.246***	-3.416***	-3.547***	-3.560***
		(10.6)	(11.4)	(11.7)	(11.7)
Age_{y-1}		-1.481***	-1.475***	-1.553***	-1.528***
		(4.9)	(4.9)	(5.2)	(5.1)
Management Fee		75.1848	53.130	67.629	61.966
		(0.5)	(0.4)	(0.4)	(0.4)
Intercept, Strategy Dummies, and Year Dummies		Yes	Yes	Yes	Yes
Observations		16901	16901	16901	16901
Adjusted R-square		11.8%	11.7%	11.5%	11.6%

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.