

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

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## Abstract

This paper is the first to document that hedge fund returns during December are significantly higher than those during the rest of the year. This *December spike* cannot be fully explained by increase in the funds' risk exposures or by higher factor risk premiums in December. It contends that the contractual features provide hedge funds incentives to inflate returns at year-end and provides strong evidence in support of this argument. It also shows that the spike is higher for funds with greater opportunities to inflate returns. Finally, it demonstrates that funds inflate December returns by under-reporting returns earlier in the year and/or by borrowing from January returns in the following year.

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### **Abstract**

This paper is the first to document that hedge fund returns during December are significantly higher than those during the rest of the year. This *December spike* cannot be fully explained by increase in the funds' risk exposures or by higher factor risk premiums in December. It contends that the contractual features provide hedge funds incentives to inflate returns at year-end and provides strong evidence in support of this argument. It also shows that the spike is higher for funds with greater opportunities to inflate returns. Finally, it demonstrates that funds inflate December returns by under-reporting returns earlier in the year and/or by borrowing from January returns in the following year.

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

Hedge funds are compensated by incentive fees based on annual performance exceeding prespecified thresholds.<sup>1</sup> Additionally, better annual performance results in more investor inflows into the fund (Agarwal, Daniel, and Naik, 2004). Hence, there exist strong incentives for managers to improve performance as the year comes to a close. Using a comprehensive database of hedge funds, we for the first time show that December returns of hedge funds are significantly higher than their average returns from January to November (see Figure 1, Panel A). We refer to this as the *December spike*.

One potential explanation for the December spike, based on risk, is that funds either increase their risk exposures in December or that the factor risk premiums happen to be higher during December in our sample. We find that this risk-based explanation cannot fully explain the December spike, which leaves us with a somewhat more provocative reason that hedge funds are potentially inflating December returns in order to earn higher compensation.

To understand the economic rationale behind the December spike, we focus on two types of incentives faced by hedge fund managers. First one relates to the promise of rewards for good performance. Second one relates to the threat of penalties in the form of capital withdrawal by investors following poor performance. These incentives motivate funds to report better performance. In this paper, we investigate the relation between incentives and the December spike, and show that the spike is driven by incentives to improve performance.

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

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<sup>1</sup> Incentive fees are based on fund performance over 12 months when net asset value (NAV) exceeds a threshold NAV, which in turn depends on the hurdle rate and high-water mark provisions. With a hurdle rate provision, the manager does not get paid any incentive fee if the fund returns are below the specified hurdle rate, which is usually a cash return like the London Interbank Offered Rate (LIBOR). With a high-water mark provision, the manager earns incentive fees only on new profits, i.e., after recovering past losses, if any.

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

To capture the second set of incentives related to penalties for poor performance, we consider lockup and restriction periods, which determine the severity of threat of capital withdrawals.<sup>2</sup> Shorter lockup and restriction periods imply that investors could withdraw their capital quickly in response to poor performance. Therefore, they act as a disciplining mechanism, which can lead to managers paying excessive attention to short-term performance, thereby providing incentives for returns management. Furthermore, given the flow-performance relation, larger funds that charge higher percentage management fee stand to lose the most from capital withdrawals. Hence, we proxy these incentives by the lockup period, restriction period, and November-end dollar management fee.

In addition to the two types of incentives, arguably funds must also have opportunities to manage returns. For example, funds with higher volatility may be able to hide returns management with greater ease, and therefore may display bigger December spike. Similarly, funds with higher exposure to liquidity risk can more easily influence the security prices to inflate the December returns. In light of this, we proxy the opportunities to manage returns by a fund's volatility and its exposure to liquidity risk.

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

Consistent with the above line of reasoning, we find that funds with higher incentives and greater opportunities exhibit bigger December spike. In particular, we find that the December spike is the highest for funds that are in-the-money as of November-end, followed by near-the-money funds, which in turn exceeds that for out-of-money funds. We also find that funds with higher delta and better relative performance at November-end display greater December spike. These results are consistent with the incentives that reward good performance driving the December spike. Further, we find that funds with shorter lockup and higher dollar management fee exhibit a higher December spike. This supports the idea that incentives that penalize poor performance also affect the December spike. Finally, we observe that funds with more opportunities, i.e., higher volatility and higher liquidity risk, show bigger December spike. The existence of a December spike and its magnitude being correlated with proxies for incentives and opportunities together suggest that hedge funds may be managing their reported returns. This “returns management” phenomenon in hedge funds resembles the well-known “earnings management” phenomenon in corporations.

The evidence of returns management begs the following question: What are the mechanisms by which hedge funds manage their returns? The first mechanism relates to intra-year smoothing of returns, which helps funds to report greater fraction of monthly returns that are positive, an attribute favored by investors.<sup>3</sup> This, in turn, can motivate funds to underreport positive returns realized during the early part of the year to create reserves which can be added to future returns if they happen to be negative (“saving for the rainy day”). Any unused reserves get added to the December returns when financial audit takes place at the end of the year. This can potentially give rise to a December spike. The second mechanism relates to funds “borrowing” from their future performance to report higher returns in December in order to earn their

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<sup>3</sup> Later, we provide evidence in support of this behavior.

incentive fees.<sup>4</sup> Funds can push up the security prices at December-end by last-minute buying. This is followed by price reversals in January, which effectively amounts to borrowing from January returns. We find strong evidence that funds manage returns through both saving and borrowing mechanisms.

Our findings have important implications for hedge fund regulators and investors. Recently, the Securities and Exchange Commission (SEC) has been especially concerned about issues related to accurate valuation of securities in hedge fund portfolios.<sup>5</sup> Return management behavior in hedge funds is important from the point of view of investor welfare, too. If some hedge funds inflate returns in December, investors cashing out at year-end benefit at the cost of those entering and remaining in those funds. Further, if funds save for the rainy day by underreporting in the earlier part of the year, investors cashing out earlier may lose to other investors. Hence, investors entering and leaving the fund at different points in time may get systematically rewarded or penalized as a result of returns management by hedge funds. Our findings can help regulators and investors spend their limited resources to pay particular attention to funds with higher incentives and greater opportunities to manage returns.

The remainder of the paper is organized as follows. Section II shows how our investigation contributes to the existing literature. Section III presents testable hypotheses. Section IV describes the data and construction of variables. Section V investigates our hypothesis related to the existence of December spike, while Section VI examines the types of funds that exhibit greater December spike. Having established returns management in hedge

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<sup>4</sup> In the context of earnings management in corporate firms, DeGeorge, Patel, and Zeckhauser (1999) document saving and borrowing behavior, which they refer to as “saving for a better tomorrow” and “borrowing for a better today”. Bergstresser and Phillipon (2006) document inter-year smoothing of earnings by corporations.

<sup>5</sup> In roundtable discussions held at the SEC office in 2003, one of the panel discussions exclusively focused on issues associated with *valuation*, allocation, use of commissions, and personal trading. See <http://www.sec.gov/spotlight/hedgefunds/hedgeagenda.htm> for more details.

funds, Section VII sheds light on the modus operandi of such returns management. Section VIII offers concluding remarks.

## II. Related Literature and Contributions

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

There exists a large literature on earnings management in corporations.<sup>6</sup> It shows that (see, e.g., Burgstahler and Dichev (1997), and DeGeorge, Patel, and Zeckhauser (1999)) firms manage earnings toward specific earnings thresholds. In particular, it shows that firms, *inter alia*, manage earnings to avoid reporting losses or avoid earnings decline. In case of hedge funds, the threshold to earn incentive fees is the strike price of the option-like incentive fee contract, and the returns necessary to meet that threshold represents the moneyness of the option. Our investigation shows that the magnitude of December spike in hedge funds is larger for funds with in-the-money and near-the-money options relative to those with out-of-the-money options. This is similar to the results of Efendi, Srivastava, and Swanson (2006), who document that the likelihood of misstating financial statements to boost stock prices increases when the CEO owns a sizable holding of in-the-money options.

The present study also supplements the executive compensation literature examining the relation between earnings management and incentives from compensation.<sup>7</sup> Healy (1985) and Gaver, Gaver, and Austin (1995) relate managers' accrual policies with incentives arising from their bonus contracts. Goldman and Sleazak (2006) provide theoretical underpinnings for why

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<sup>6</sup> See Healy and Wahlen (1999), Dechow and Skinner (2000), Fields, Lys, and Vincent (2001), and Stolowy and Breton (2004) for surveys on this literature.

<sup>7</sup> See Murphy (1999) and Core, Guay, and Larcker (2003) for surveys of the literature on executive compensation.

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

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

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

Finally, our paper complements the literature on return smoothing by hedge funds.

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

Having described how our research contributes to the extant literature, we now formalize the hypotheses that we test in this paper.

### **III. Hypotheses Development**

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

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

well as implicit incentives to inflate returns in December. This leads us to our first hypothesis.

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

In the process of examining hypothesis 1, we control for the possibility that factor premiums could be high in December during our sample period and funds could actively increase their risk exposures in December to improve year-end performance. We also allow for the possibility that some funds might passively benefit from portfolio pumping by other institutional investors.

If we find support for the above hypothesis, a question naturally arises as to what types of funds display greater December spike. As discussed in the section on related literature (Section II), we know that incentives can arise from thresholds in case of corporations from the earnings management literature. We also know that incentives arise from the pay-for-performance sensitivity (delta) of the executive compensation contract. Drawing from these insights, we use the distance from the threshold (moneyness) and delta of the call-option-like incentive fee contract to proxy for the explicit incentives faced by hedge funds. For example, if by November-end, the call option of a fund is deep out of the money, inflating returns in December might not help to earn any incentive fee for the year. Hence, one would expect the in-the-money and near-the-money funds to exhibit greater December spike compared to the out-of-the-money funds. Further, in addition to meeting the threshold for earning fees, we also expect funds with greater pay-performance sensitivity (or higher delta) to exhibit greater December spike. In addition to the explicit incentives induced by the incentive fee contract, the response of investors' capital flows to prior performance provides implicit incentives to engage in returns management. We expect that funds with superior relative performance should have higher incentives to inflate year-end returns.

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

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

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

If we find evidence in support of hypotheses 1 and 2, we could then say that hedge funds

engage in returns management. It would then be natural to explore the mechanisms they employ to manage their returns. It is conceivable that hedge funds “*save for the rainy day*” and create reserves by underreporting positive returns earlier in the year and use them during bad months to avoid reporting losses. In fact, such behavior is common in corporations according to former SEC chairman, Arthur Levitt (1998) who argues that “companies stash accruals in cookie jar reserves during the good economic times and reach into them when needed in the bad times.” In the case of hedge funds, the tendency to create reserves could be driven by investors’ preference for funds with fewer loss-making months. In Addendum A, we provide empirical evidence that, all else equal, higher the number of months in which the fund reports positive returns, the more the capital that investors put into the fund. The resulting increase in assets under management will lead to higher fees in the future, and hence funds have an incentive to engage in such behavior. In case some reserves remain unutilized by the end of the year, the manager is forced to include them in December due to auditing reasons, thus leading to the December spike. This leads us to our third hypothesis.

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

It is well-documented that mutual funds push up the prices of securities they hold at December-end by creating a short-term price pressure through purchases during the last few minutes of trading on the last day of the year (see Carhart et al. (2002), Bernhardt and Davies (2005)). This is followed by price reversals in January, which effectively amounts to *borrowing* from January returns. It is plausible that hedge funds borrow from January returns in a similar fashion.<sup>8</sup> By doing so, funds can earn their incentive fees earlier. This provides us with our

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<sup>8</sup> Another way that the hedge fund manager could borrow from future returns is by selling deep out-of-the-money put options on the index and delta-hedging them in December. Selling the puts generates income up front, while the cost of replication through dynamically delta-hedging is incurred over a period that can extend beyond December.

fourth hypothesis.

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

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

## **IV. Data and Variable Construction**

### *IV.A. Data Description*

In this paper, we construct a comprehensive hedge fund database that is a union of four large databases, namely, Center for International Securities and Derivative Markets (CISDM), Hedge Fund Research (HFR), Morgan Stanley Capital International (MSCI), and Tremont Advisory Shareholder Services (TASS). This database reports net-of-fee monthly returns, assets under management, and fund characteristics, such as hurdle rate and high-water mark provisions, lockup, notice, and redemption periods, incentive fee rate, management fee rate, inception date, and fund strategy.<sup>9</sup> 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.<sup>10</sup> After merging the four databases, we find that there are 7535 hedge funds: 3924 remained live as of December, 2002 while 3611 became defunct during our sample

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However, this argument assumes that the computation of NAV does not account simultaneously for both the short position in the option and the delta-hedge component.

<sup>9</sup> The database provides information on contractual features as of the last date for which the fund’s data is available. Following previous researchers, we assume that these contract features hold throughout the life of the fund. Discussions with industry experts suggest that this is a reasonable assumption, as it is easier for a manager to start a new fund with different contract terms instead of going through the legal complications of changing existing contracts with numerous investors.

<sup>10</sup> 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.

period. In Figure 2, we report the overlap among the four databases with a Venn diagram. It highlights the fact that there are a large number of hedge funds that are unique to each of the four databases. Merging them, therefore, helps to capture a more representative sample of the hedge fund universe.

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

#### *IV.B. Measures of Performance*

We consider two performance measures for our study. Our first measure is gross return of fund  $i$  in month  $m$ ,  $\text{Returns}_{i,m}$ , where  $m$  runs from January 1994 to December 2002. We compute the gross-of-fee returns from net-of-fee returns following the methodology of Agarwal, Daniel, and Naik (2006) (see Appendix B for details). The reason for using gross-of-fees returns instead of net-of-fee returns is to mitigate any problems created by the path dependency in the computation of incentive fees, which can induce smoothing in net-of-fee monthly returns (see Getmansky, Lo and Makarov (2004)). Gross returns do not suffer from this problem. In the rest of the paper, for brevity, we simply refer to gross returns as returns. For robustness, we repeat our analysis using net-of-fee returns and obtain similar inferences (we report these results in Section V.B).

To test for December spike, we need to control for the systematic risks of hedge funds. Hence we employ a second measure,  $\text{Residual}_{i,m}$ , which is the residual return of fund  $i$  during

month  $m$ . For this purpose, we estimate fund-level time-series regressions of excess returns on the seven factors of Fung and Hsieh (2004).<sup>11</sup> This is in the spirit of Bollen and Krepely (2007), who estimate the predicted returns from Fung and Hsieh’s (2004) seven-factor model and define it as the nondiscretionary component of hedge fund returns. Thus, the residuals can be thought of as the discretionary component of returns over which the manager may be able to exercise influence. The motivation behind this measure is analogous to that for the discretionary accruals in earnings management literature, which are defined as the residuals from a regression of accruals on some variables (such as change in sales etc.) that are predicted to be related to accruals (see Jones (1991), Ball and Shivakumar (2006)).

In Table I, we report the summary statistics of the performance measures. We find that the mean monthly gross fund returns are 1.06%. As expected, the mean monthly residuals are virtually zero.

#### *IV.C. Measures of Risk Exposures*

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

returns of  $N$  hedge funds during month  $m$ , 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  $m$ .<sup>12</sup> If funds increase

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<sup>11</sup> Our results are robust to computing residuals using a nine-factor model by augmenting the Fung and Hsieh (2004) seven-factor model with book-to-market and momentum factors. We also report these results in Section V.B.

<sup>12</sup> 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 .

their risk exposures, then CS Volatility<sub>m</sub> will increase. Hence, we use CS Volatility<sub>m</sub> to proxy for the risk exposures. From Table I, we observe that the mean (median) cross-sectional volatility of funds' monthly returns is 6.02% (5.83%). As an alternative to cross-sectional volatility, in Section V.B, we allow funds to vary their risk exposures to market factor on a monthly basis. Our results reported later with this control are qualitatively similar.

#### *IV.D. Measures of Incentives to Manage Returns*

Goetzmann, Ingersoll, and Ross (2003) point out that the incentive fee contract in hedge funds provides the manager with a call option and theoretically model the value of this option. When a hedge fund receives capital flows at different points in time, the incentive fee contract resembles a *portfolio* of call options, where each option is related to the capital inflow at a given point in time and has its own strike price (dictated by the NAV at the time of entry and whether the fund has hurdle rate and high-water mark provisions). Following the insights of Goetzmann, Ingersoll, and Ross (2003), we empirically estimate the moneyness and delta of this portfolio of call options, using the methodology of Agarwal, Daniel, and Naik (2006) (see Appendix B for details).

Our first measure of returns management incentives is related to the moneyness. To construct this, we keep track of the capital flows into each fund and the corresponding NAV (the spot price  $S$ ). We then compute the exercise price ( $X$ ) of each option (reset at the beginning of each year) depending on hurdle rate and high-water mark provisions. Finally, we compute the moneyness of each option as the difference in the spot price and exercise price, divided by the exercise price, (i.e.,  $(S - X)/X$ ). This implies that the moneyness of the portfolio of call options would then be equal to the weighted-average moneyness of different options granted by investors' capital inflows at different points in time. In Table I, we observe that the mean (median) month-end moneyness is  $-0.003$  ( $-0.13$ ) suggesting that, on average, funds are just

about at-the-money or out-of-the-money.

Our *Hypothesis 2* states that funds that are in the money and near the money are more likely to engage in returns management compared to funds that are out of the money. For this purpose, we categorize funds into three groups based on the moneyness at the end of November. We first compute the mean ( $\mu$ ) and standard deviation ( $\sigma$ ) of a fund's returns using the entire data in our sample. We provide an example to illustrate our classification algorithm. Suppose a fund has  $\mu$  and  $\sigma$  of 1% and 5%. This fund is deemed to be *near the money* if its moneyness lies between  $-6\%$  [ $-(\mu + \sigma)$ ] and  $+4\%$  [ $-(\mu - \sigma)$ ]. Following this example further, if the fund's moneyness is greater than  $+4\%$ , we define it to be *in the money*, and if the fund's moneyness is less than  $-6\%$ , we define it to be *out of the money*. It is important to note that the use of  $\mu$  and  $\sigma$  for categorizing funds based on moneyness does not depend on the normality of fund return distribution. In fact, during our sample period, we find, on average, 31% of the funds are near the money, 38% are in the money, and remaining 31% are out of the money, suggesting that the return distribution is far from normal. Furthermore, in Section VI.A, we use alternative procedures to classify funds based on their moneyness and demonstrate that our results are robust to different classification criteria.

Our second measure of returns management incentives is the delta of the portfolio of call options endowed to the fund by the incentive fee contract. The delta of each of the call options depends on the current NAV ( $S$ ), the threshold NAV that must be reached before the manager can claim an incentive fee ( $X$ ), and other fund characteristics, such as the fund size and fund volatility. We compute the delta, which equals the expected dollar change in the manager's compensation for a one-percent change in the fund's NAV, at the end of each month (see

Appendix B for details). From Table I, we find that the mean (median) monthly delta equals \$170,000 (\$20,000).<sup>13</sup>

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

As discussed before, moneyness, delta, and fractional rank capture incentives that reward good performance. Our next three measures of incentives belong to the group of incentives that penalizes poor performance. The first two of these returns management incentives are lockup period and restriction period. From Table I, we observe that the mean lockup period (restriction period) is 0.13 (0.31) year. Our last measure is the dollar management fee at the end of November. From Table I, we observe that the average fee is \$2.14 million.

#### *IV.E. Measures of Opportunities to Manage Returns*

Our first measure of opportunities for returns management is fund volatility. From Table I, we observe that the mean (median) fund volatility is 4.82% (3.83%). Our second measure of opportunities is the liquidity of each fund, which we capture by its exposure to the liquidity risk factor of Pastor and Stambaugh (2003). For this purpose, we estimate fund-level time-series regression of returns on the seven factors of Fung and Hsieh (2004), augmented with the liquidity risk factor.<sup>14</sup> A higher beta on the liquidity risk factor implies that the fund has greater exposure to illiquidity and therefore is more illiquid.<sup>15</sup> From Table I, we observe that the mean

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<sup>13</sup> 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).

<sup>14</sup> We use value-weighted liquidity risk factor for our analysis. All our results are robust to the use of equally-weighted liquidity risk factor.

<sup>15</sup> It is the overall liquidity of the fund portfolio rather than the systematic liquidity (proxied by liquidity beta) that affects the opportunities to manage returns. We assume that overall liquidity and systematic liquidity are correlated.

(median) of the liquidity beta is 0.02 (0.00). The interquartile range of liquidity beta is 0.15 (i.e.,  $0.09 - (-0.06)$ ) suggests that there is considerable cross-sectional variation in the liquidity risk exposure across different hedge funds.

#### *IV.F. Measures of Reserves*

To test our *Savings Hypothesis*, we construct a measure of reserves. We define  $\text{Reserves}_{i,m}$  to be the cumulative return from January of each year up to month  $m - 1$  of the same year if positive, and to be zero otherwise. Since the reserves can *only* be used to spike December returns if they are actually available, we consider only the positive cumulative returns. From Table I, we observe that the mean (median) of the reserves variable is 8.58% (3.56%).

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

### **V. Is There Evidence of a December Spike?**

Before conducting a multivariate analysis, we first plot the average monthly gross returns for all the hedge funds in our sample period (1994–2002) in Figure 1, Panel A. As mentioned earlier, the results are striking, as the average December return is more than two-and-a-half times the average return during the January–November period (2.51% compared to 0.96%). In Figure 1, Panel B, for each year during our sample period, we plot the average returns during the January–November period and during December. In a majority of years, we find that December returns exceed the January–November returns. Thus, this phenomenon appears to be persistent.

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

the CRSP mutual fund database in Figure 3, Panels C and D.<sup>16</sup> Although December returns are high for both the market and mutual funds, these plots are not nearly as striking as is Figure 1 for hedge funds.

In Table II, we provide a univariate comparison of gross returns and residual returns of hedge funds in our sample for December and the rest of the year (January–November). Results from  $t$ -tests suggest that the average gross returns and residuals in December are significantly greater than those for the rest of the year. The December spike is 1.55% in terms of gross returns and 0.25% in terms of residual returns.<sup>17</sup> We also compare the factor premiums between December and rest of the year. Although the factor premiums are higher in December, our findings of a December spike in residual returns suggest that higher factor premiums in December cannot completely explain this pattern.

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

In this section, we extend our analysis to a multivariate setting after controlling for fund characteristics, strategy and year effects. In particular, we estimate the following regression<sup>18</sup>:

$$\begin{aligned} \text{Return}_{i,m} = & \lambda_0 + \lambda_1 I(\text{December}) + \lambda_2 \text{Return}_{i,m-1} + \lambda_3 \text{Return}_{i,m-2} + \lambda_4 \text{Delta}_{i,m-1} \\ & + \lambda_5 \text{Moneyiness}_{i,m-1} + \lambda_6 \text{Lockup}_i + \lambda_7 \text{Restrict}_i + \lambda_8 \text{Size}_{i,m-1} + \lambda_9 \sigma_i \\ & + \lambda_{10} \text{Age}_i + \lambda_{11} \text{MFee}_i + \sum_{s=1}^3 \lambda_{12}^s I(\text{Strategy}_{i,s}) + \sum_{k=1994}^{2002} \lambda_{13}^k I(\text{Year}_{i,k}) + \xi_{i,m} \end{aligned} \quad (1)$$

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

<sup>16</sup> Following Sirri and Tufano (1998), we compute the gross returns by adding back expense ratio and one-seventh of the total load fees.

<sup>17</sup> We also compare each month’s gross return to the gross return in December. We find the December gross return to be higher in each of the 11 pair-wise comparisons and the differences to be statistically significant.

<sup>18</sup> We winsorize extreme 1% of all the variables in order to minimize the influence of outliers. Here and throughout the paper, we report the slope coefficients and corresponding p-values after adjusting for heteroskedasticity and fund-level clustering including serial correlation.

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

We report our findings in Table III. Our results for Model 1 show that the slope coefficient on December dummy is positive ( $\lambda_1 = 1.514$ ) and highly significant at 1% level. The coefficient estimates imply that December returns are higher by 1.5%. This result is economically significant given that the average returns are 1.1%. Consistent with the findings of Agarwal, Daniel, and Naik (2006), who estimate cross-sectional regressions of annual returns, we observe that delta, lockup period, and restriction period are positively related to returns. Consistent with the evidence of serial correlation in hedge fund returns documented in the literature, we find that the coefficient on the first lag of returns is positive and significant. The coefficient on the second lag is positive but not significant.

As discussed earlier, it is possible that a part of the December spike could result if hedge funds trade in the same securities as mutual funds that engage in year-end return manipulation. In the absence of high-frequency holdings data, it is not possible to precisely quantify the magnitude of active and passive portfolio pumping during December. However, we can estimate the extent of the December spike that could be due to hedge funds taking advantage of mutual

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<sup>19</sup> We also conduct our analysis at the substrategy level using the original strategy classification in the four databases and find qualitatively similar results.

fund behavior. This is possible because, unlike mutual funds, hedge funds are unlikely to have an active interest in managing returns at quarter-ends, since they are not subject to portfolio disclosure requirements. Thus, if we find a quarter-end spike in hedge funds, it suggests that hedge funds might be beneficiaries of returns management by mutual funds. For this purpose, to regression (1) above, we add a quarter-end dummy. This dummy takes a value of 1 if the month corresponds to a quarter-end other than December, (i.e., March, June, or September), and equals 0 otherwise.

The results in Model 2 of Table III show that the quarter-end dummy is positive (coeff. = 0.091) and significant at the 1% level, suggesting that hedge fund returns could be influenced by the inflation of mutual fund returns at quarter-ends. More importantly, December dummy continues to be positive ( $\lambda_1 = 1.539$ ) and highly significant. In the study by Carhart et al. (2002), the ratio of coefficient on the year-end dummy to the coefficient on the quarter-end dummy ( $b_1/b_3$ ) is 3.26 (i.e., 53.01/16.27) and 2.57 (29.6/11.54) for *all* funds (see Table II, Panels A and B, of Carhart et al. (2002): page 671). If hedge funds were passively benefiting from the gaming behavior of mutual funds by holding the same securities, then one would expect a similar ratio of coefficients on year-end and quarter-end dummies (as a rough approximation) in Model 2 of Table III. However, in our case, this ratio is substantially higher, 16.9 (i.e., 1.539/0.091), indicating that the hedge fund returns exhibit a considerably bigger December spike even after allowing for the possibility that they could be passively benefiting from portfolio pumping activity of mutual funds. Taking the higher ratio of 3.26 and the coefficient on Quarter-end dummy of 0.091, we estimate that portfolio pumping at year ends by mutual funds contributes at best 0.3% ( $0.091 \times 3.26$ ) to the December spike of 1.539% observed in hedge fund returns. The balance of the December spike could be due to active returns management by hedge funds driven by incentives and opportunities, as we examine in the next section.

To allow for the possibility that managers could increase their risk exposures in December, we include the cross-sectional volatility measure,  $CS\ Volatility_m$  in regression (1) above. We report our results from this regression in Model 3 of Table III. We find the coefficient on cross-sectional volatility is positive (coeff. = 0.066) and significant at the 1% level. This implies that higher cross-sectional volatility is associated with higher returns. The December dummy is still 1.5%, so the increase in risk exposures cannot explain the December spike. Model 4 includes both the quarter-end dummy and the cross-sectional volatility measure, and we still get similar inferences. Most importantly the coefficient on the December dummy continues to be positive ( $\lambda_1 = 1.511$ ) and significant at the 1% level.

In Model 5, we re-estimate Model 4 but with the residual returns (or discretionary component of returns) as the dependent variable. In addition, we replace the two lags of returns with those of residuals. Residuals strip out the effect of higher returns in December that will result if risk premiums are higher in December. The December spike is now 0.362%. This is still economically significant, given that the average monthly return is 1.06%.

Overall, the results in Table III suggest that hedge fund returns exhibit a December spike.

### *V. B. Robustness*

In this section, we demonstrate that our results are robust to several alternative specifications. Appendix C, Panel A reports only the December spike based on the two comprehensive models (Models 4 and 5 using returns and residuals as dependent variables, respectively) of Table III for various specifications. For brevity, we do not report the coefficients on control variables.

First, we use net returns instead of gross returns. Row 1 reports the results. Second, as Figure 1, Panel B shows that the December spike is highest during the year 1999, we exclude that year and re-estimate Models 4 and 5. Row 2 reports the results. Third, to better control for

changes in risk in the current year, we replace prior year volatility with volatility estimated over the twelve months ending November of the current year. Row 3 reports the results. Fourth, we repeat our analysis in Model 5 by replacing the residual with the sum of residual and the intercept from the Fung and Hsieh (2004) model. Row 4 reports the results. Fifth, 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. Row 5 reports the results.

Sixth, we allow for time-varying risk loadings in estimating residuals. Specifically, to allow for the incentives to increase risk (embedded in the flow-performance relation), we allow the monthly loading on the market factor to be a function of the performance of the fund relative to its peers. We hypothesize this relation to be of the following functional form.

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

where  $\beta_t$  is the loading on the market factor in month  $t$  and  $Frank_{t-1}$  is the fractional rank based on fund's returns from January to month  $t-1$  relative to other funds following the same strategy within a given year. For January,  $Frank$  is assumed to be zero for all funds because there are no tournament-related incentives at the start of the year.<sup>20</sup> Empirical implementation effectively amounts to re-estimating residuals by augmenting Fung and Hsieh (2004) model with the interaction of  $Frank_{t-1}$  and  $R_{mt} - R_{ft}$ . Row 6 reports the results.<sup>21</sup>

Finally, it is conceivable that managers gradually adjust their returns and do not limit their manipulations to the month of December. Hence, we replace the December dummy with a November–December dummy, which takes the value 1 if month equals November or December. Row 7 reports the results.

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<sup>20</sup> A number of papers (Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997) among others) document tournament behavior in mutual funds.

<sup>21</sup> As further robustness checks, we also allow betas to vary with lagged moneyness and lagged delta (instead of lagged fractional rank). We continue to find December spike in the residuals of 0.263% and 0.344% respectively, both significant at the 1% level.

Overall, we document that our main finding of a statistically and economically significant December spike is robust to all these alternative specifications.

## **VI. Do Funds with Higher Incentives and Greater Opportunities to Manage Returns**

### **Exhibit a Bigger December Spike?**

In Section III, we hypothesized that funds that have higher incentives (funds that are in the money and near the money, funds that have higher delta, funds that have better relative performance, funds that have shorter lockup and restriction periods, and funds that earn significant dollar management fees) should exhibit increased incidence of returns management. We also posited that funds with greater opportunities (funds with higher volatility and funds with more exposure to liquidity risk factor) should display greater returns management. To test this notion (hypothesis 2), we first create subsamples based on these key variables. Specifically, each year, we divide the funds into *high* and *low* categories based on the median of these variables at the end of each November.<sup>22</sup> For example, if a fund's delta is greater than or equal to (less than) the median delta, we classify it as a *high (low) delta* fund.

We re-estimate Models 4 and 5 of Table III for these subsamples of funds. Table IV reports the results. For brevity, we report only the slope coefficients for the December dummy (the December spike). We also report the difference between the coefficients of the December dummy for the high and low groups and the corresponding p-value (based on Chow-test).

From Table IV, we find the slope coefficient on the December dummy to be higher for in-the-money and near-the-money funds compared to out-of-the-money funds. The coefficient estimates from Column 1 imply that the December spike using returns is greater for in-the-money funds by 1.910% (i.e.,  $2.281 - 0.371$ ) when compared to out-of-the-money funds. The

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<sup>22</sup> Please note that some variables, such as lockup period and restriction period, do not change for a fund over time.

December spike is also greater for near-the-money funds by 1.457% ( $1.828 - 0.371$ ) relative to out-of-the-money funds. These results also indicate that the December spike is greater for the in-the-money funds relative to near-the-money funds (2.281% versus 1.828%), a difference that is significant at the 1% level and is intuitive, given the fact that benefits of returns management are highest for in-the-money funds.

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

Next, we repeat our analysis using the second measure of incentives—delta. We find that funds with high delta exhibit a greater December spike compared to funds with low delta. The December spike is significantly higher for the high-delta funds by 0.355% (i.e.,  $1.642\% - 1.287\%$ ) in terms of returns, and by 0.158% ( $0.414\% - 0.256\%$ ) in terms of residuals.

Third, we use the November-end fractional rank. We form three groups, with the top 20% in one group, the bottom 20% in the second group, and the middle 60% in the third group.<sup>23</sup> Consistent with our expectations, we find that the December spike in terms of returns is highest for the top 20%, followed by the funds in the middle 60%, with the bottom 20% having the lowest spike. The results based on residuals are similar, but with one exception – the top 20% funds do not exhibit the highest December spike.

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<sup>23</sup> We get similar results to those reported below if we form 3 groups based on top 25%, middle 50%, and bottom 25%.

Fourth, we use lockup period and restriction period. Since only 19% of the funds have lockup period, the low-lockup period group effectively consists of firms that impose no lockup provisions. Results in Column (1) show that funds with shorter lockup periods exhibit higher December spikes compared to the funds with longer lockup periods (1.559% versus 1.164%). We find similar differences with respect to the restriction period (1.555% versus 1.488%). The differences between the long- and short-period groups are statistically significant at the 1% level for lockup period but not for restriction period. Results are qualitatively similar when we use residuals instead of returns.

Finally, we sort funds into two groups based on dollar management fee as of November-end. We find that the funds that earn larger fees show a significantly higher December spike in terms of both returns and residuals by 0.174% and 0.175%, significant at the 10% and 5% levels respectively.

We next examine the role of opportunities in the returns management behavior. We use two distinct proxies for opportunities, namely volatility and liquidity. From results in Table IV, we find that funds with high volatility exhibit more pronounced December spikes than do funds with low volatility. The December spike is higher for the high-volatility funds by 1.922% (i.e., 2.468% – 0.546%) in terms of returns and 0.380% (0.545% – 0.165%) in terms of residuals.<sup>24</sup> Both these differences are statistically significant at the 1% level.

Next, we classify funds into different groups based on exposure to illiquidity. From the results in Table IV, we find that the slope coefficient on the December dummy is higher for low-liquidity funds by 0.499% (1.791% – 1.292%) in terms of returns. This suggests that more illiquid funds that have greater opportunities to engage in returns management exhibit higher

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<sup>24</sup> High-volatility funds are likely to exhibit spikes unrelated to returns management, but these spikes are equally likely to occur in any of the 12 months. Only if there is returns management do we expect to see this December spike.

December spikes.<sup>25</sup> However, in terms of residuals, the December spike for low-liquidity funds is lower than that of high-liquidity funds. Overall, results provide weaker evidence on the relation between liquidity and returns management.

#### *VI. A. Robustness*

In this section, we document the robustness of results linking incentives to December spike. Panel B of Appendix C reports the results.

First, we reclassify funds as in-the-money, near-the-money, and out-of-the-money using strategy-level  $\mu$  and  $\sigma$  (instead of fund-level  $\mu$  and  $\sigma$ ). Row 1 reports the results. Second, we ignore  $\mu$  and  $\sigma$  and sort firms into three groups based on moneyiness with respect to zero: (i) those that are positive as of November-end (in-the-money), (ii) those that are negative but in the top half (near-the-money), and (iii) those that are negative but in the bottom half (out-of-the-money). Row 2 reports the results. In both cases, we find that our result that the December spike is higher for in-the-money and near-the-money funds remains unchanged.

Higher delta could result, among other things, due to higher percentage incentive fee. We therefore sort funds into three groups based on percentage incentive fee: those above 20%, those that charge exactly 20% (72% of our sample), and those that charge below 20%. Row 3 reports the results. We find that percentage incentive fee is not linked to December spike. Thus, we conclude that it is delta, and not the percentage incentive fee, that drives our results.

Earlier, we showed that funds that earn higher dollar management fees exhibit a greater December spike. Both size (assets under management) and percentage management fee rate

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<sup>25</sup> Hedge funds trading in illiquid assets sometimes keep some of these investments in “side pockets”, which are valued only at the time of sale and may not be reflected in monthly NAV computations. Arguably, these side pockets can be used to hide poorly performing assets. If this is indeed true and if at a later stage, there is a reversal in the performance of these assets, they can be brought back into the main portfolio, thereby resulting in a boost in the fund performance. If this happens exclusively in or more often in December, it could lead to a December spike. Although it is not possible to disentangle the liquidity-based and poor-performance-based rationales for side pockets, to the extent that we find funds with greater illiquidity exhibiting bigger December spike, we believe it perhaps captures the side-pocket effect to some extent.

contributes to higher dollar management fee. We therefore do two independent sorts based on November-end fund size and percentage management fee. Row 4 reports the results for subsamples based on fund size, while Row 5 reports the results for groups based on percentage management fee. We find that neither size nor the percentage management fee by itself has an impact on December spike, thus confirming that the incentives captured by the dollar management fee are driving the December spike.<sup>26</sup>

Our findings from this section lend support to hypothesis 2, i.e., funds with greater incentives and funds with higher opportunities display greater December spikes. Our finding of a December spike in Section V and that this December spike is related to economically motivated variables in a meaningful way, suggests that hedge funds manage reported returns.

## **VII. What is the Modus Operandi that Funds Use for Returns Management?**

Given the evidence of returns management, we next investigate the mechanism employed by funds to accomplish such management. Toward that end, we test hypotheses 3 and 4 (*savings* and *borrowing* hypotheses) developed in Section III. To recall, the *savings hypothesis* posits that funds underreport positive returns up to November to create reserves to add to months with negative returns. The unused reserves are then added back in December. We test this by including two additional explanatory variables to Model 4 of Table 3: (a)  $\text{Reserves}_{i,m-1}$ , the cumulative return from January up to month  $m - 1$  if positive, and 0 otherwise, and (b) the interaction of this variable with the December dummy. If the fund manager is adding those reserves from previous months in December, then one would expect to see this interaction term

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<sup>26</sup> Similar to incentive fee, we also construct three groups based on management fee with one group corresponding to median management fee of 1% and the other two corresponding to above and below median values. We find similar results with the three groups.

to be positive.<sup>27</sup> Our results for Model 1 in Table V confirm that this is indeed the case, with the coefficient on the interaction being positive (coeff. = 0.112) and significant at the 1% level. This result is also economically significant. One standard deviation change in the Reserves variable results in an increase of 1.46% in December returns.

An alternative way to compute reserves is to determine the difference between true returns (which are unobservable) and observed returns. Getmansky, Lo and Makarov (2004) show that, due to return smoothing, observed returns can be expressed as a MA(2) process in true returns. Following their insights, for robustness, we also construct an alternative measure of reserves—cumulative difference between the unobserved true returns and the observed returns up to month  $m - 1$  if positive, and 0 otherwise. In untabulated results, we find that when we use this alternative measure of reserves, its interaction with the December dummy is significantly positive for Model 1 (coeff. = 0.633; significant at the 1% level). These findings, once again, lend strong support to the savings hypothesis.

Next, we test our *borrowing hypothesis*, which addresses the possibility that portfolio pumping by funds causes December returns to be higher at the expense of January returns. In this scenario, one would expect to see a lower January return in the next year following a high December return in the current year. To test this hypothesis, we include two additional variables to Model 4 of Table III: (a) a January dummy that takes the value 1 if the month is January of next year, and 0 otherwise, and (b) the interaction of the January dummy with returns during the previous month. As per the borrowing hypothesis, one would expect to observe a negative coefficient for the interaction term. Results reported in Model 2 of Table V indicate that the coefficient on the interaction of the January dummy and the lagged monthly return is negative

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<sup>27</sup> We repeat our analysis using the reserves variable without truncating it at zero. All our results remain unchanged.

(coeff. =  $-0.040$ ) and significant at the 1% level.<sup>28</sup> This result is also economically significant. A one standard deviation increase in the December returns is associated with a borrowing of 0.39% returns from January of the following year. As before, our results for the other variables remain unchanged. This provides evidence in support of the borrowing hypothesis.

Finally, we test for both *savings* as well as *borrowing* hypotheses together by including the corresponding variables together in Model 3 of Table V. We find that both the interaction terms (i.e., December dummy with reserves up to the previous month-end, and January dummy with previous month's return) are significant at the 1% level. This suggests that funds employ *both* savings and borrowing mechanisms to boost December returns. Overall, the results from this section strongly support hypotheses 3 and 4.

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

In this subsection, we provide additional tests of the borrowing hypothesis using the equity holdings data of hedge funds. In particular, we follow the approach in Carhart et al. (2002), who examine year-end inflation in equities held by mutual funds. Unlike mutual funds, hedge funds do not need to disclose their portfolio holdings on a quarterly basis. However, SEC requires that all funds with assets exceeding \$100 million and holding large positions in stocks (more than 10,000 shares or \$200,000) need to submit 13f filings. This enables us to obtain equity holdings data of 161 hedge funds from our sample.<sup>29</sup>

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

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<sup>28</sup> We find that the slope coefficient on January dummy itself is positive (coeff.=0.612) and significant at the 1% level in Model 2 of Table V. This is consistent with the well-documented January effect in stock returns. Interestingly, the average January hedge fund returns in Figure 1, Panel A, are the second-highest in the year, despite the borrowing activity of the funds suggested by the negative and significant interaction of January dummy and the lagged monthly return.

<sup>29</sup> We follow a procedure similar to Brunnermeier and Nagel (2004) who identify equity holdings of 52 hedge funds. Recently, Griffin and Xu (2005) have also used holdings data of hedge funds to determine presence of skill.

stocks into five quintiles based on market capitalization on the second-last day of the year. This yields us with 25 return-size portfolios.

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

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

Following Carhart et al. (2002), we compute return inflation as the return on each of the 25 long-short stock portfolios on the last day of the year minus its return on the first day of next year. To examine whether this inflation is significantly different from zero, we first compute this return inflation for every non-overlapping 2-day period in the year. We then compute a z-statistic for return inflation for each of the 25 portfolios for each year as the return inflation minus the

average of all possible 2-day returns during that year, divided by the standard deviation of the two-day returns over that year. For the sake of brevity, we report in Table VI, the average end-of-year inflation across 25 return-size portfolios over the 9-year period. The z-statistic for this overall average is the sum of the z-statistic over the 225 portfolio-year combinations divided by square root of 225. The reported p-value is the probability of obtaining a z-statistic greater than this overall z-statistic.

Results in Table VI indicate that funds with higher moneyness, greater delta, superior relative performance, larger dollar management fee, and lower restriction periods exhibit abnormally high year-end return followed by a reversal on the first day in January. These findings suggest that a subgroup of hedge funds facing stronger incentives inflate year-end returns by borrowing from January returns.

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

### **VIII. Concluding Remarks**

In this paper, we uncover a new empirical regularity of hedge fund returns in December being systematically higher than their average returns during the rest of the year. We refer to this phenomenon as the December spike. Since risk-based explanations cannot fully explain this phenomenon, we conduct a detailed investigation of the possibility of hedge funds inflating their December returns as a response to the two types of incentives to deliver superior performance.

First one relates to rewards for good performance. These include explicit incentives from the incentive fee contract and implicit incentives from investors chasing better performance. Second one relates to penalties in form of capital withdrawals following poor performance. These penalties are greater for funds with shorter lockup and restriction periods, and for funds that earn higher dollar management fee. Both these incentives motivate funds to inflate returns at the end of the year. Consistent with this notion, we find that funds with greater incentives (higher moneyness, higher delta, better relative performance, shorter lockup periods, and higher dollar management fees) exhibit a larger December spike.

In addition, we also investigate the role of opportunities in explaining the disproportionately higher returns in December. We argue that funds with higher volatility and greater exposure to illiquidity have more opportunities to inflate December returns. Consistent with this argument, we find that funds with greater opportunities exhibit a larger December spike. Taken together, these two results suggest that hedge funds may be engaging in returns management, similar to the well-documented phenomenon of earnings management in corporations.

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

Our findings have important implications for regulators and investors. Regulatory bodies

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

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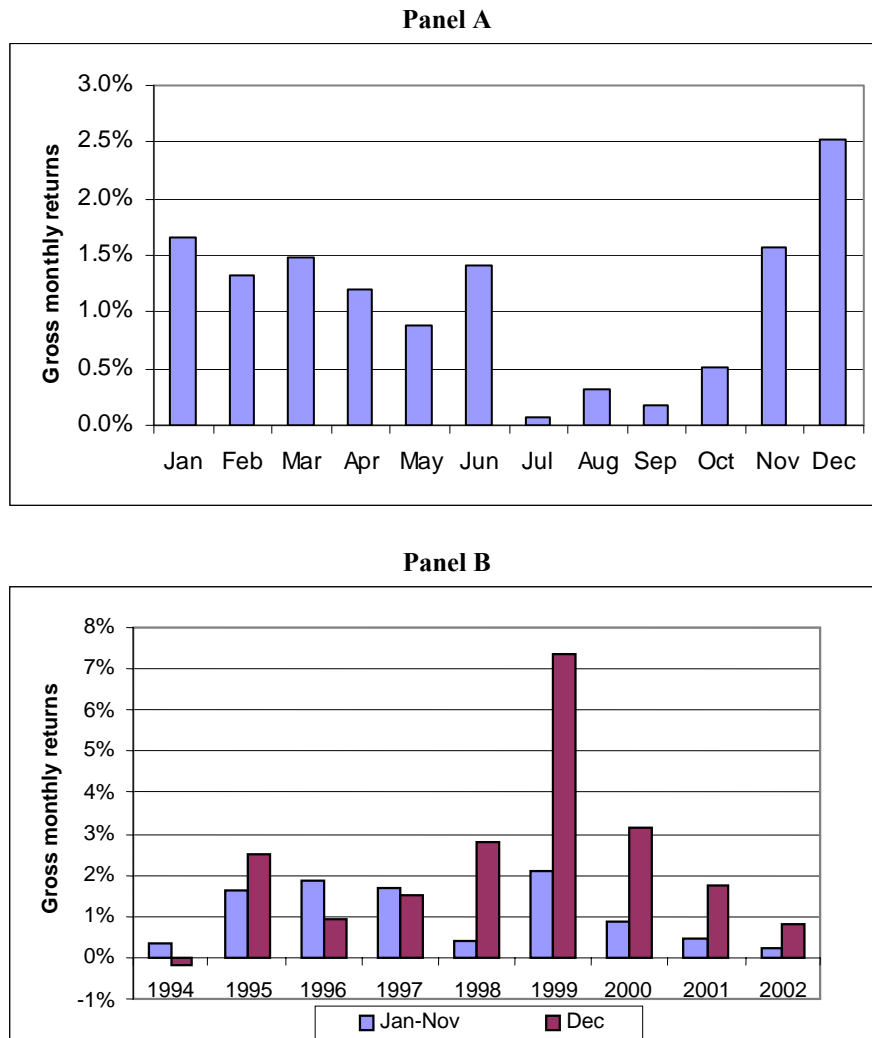
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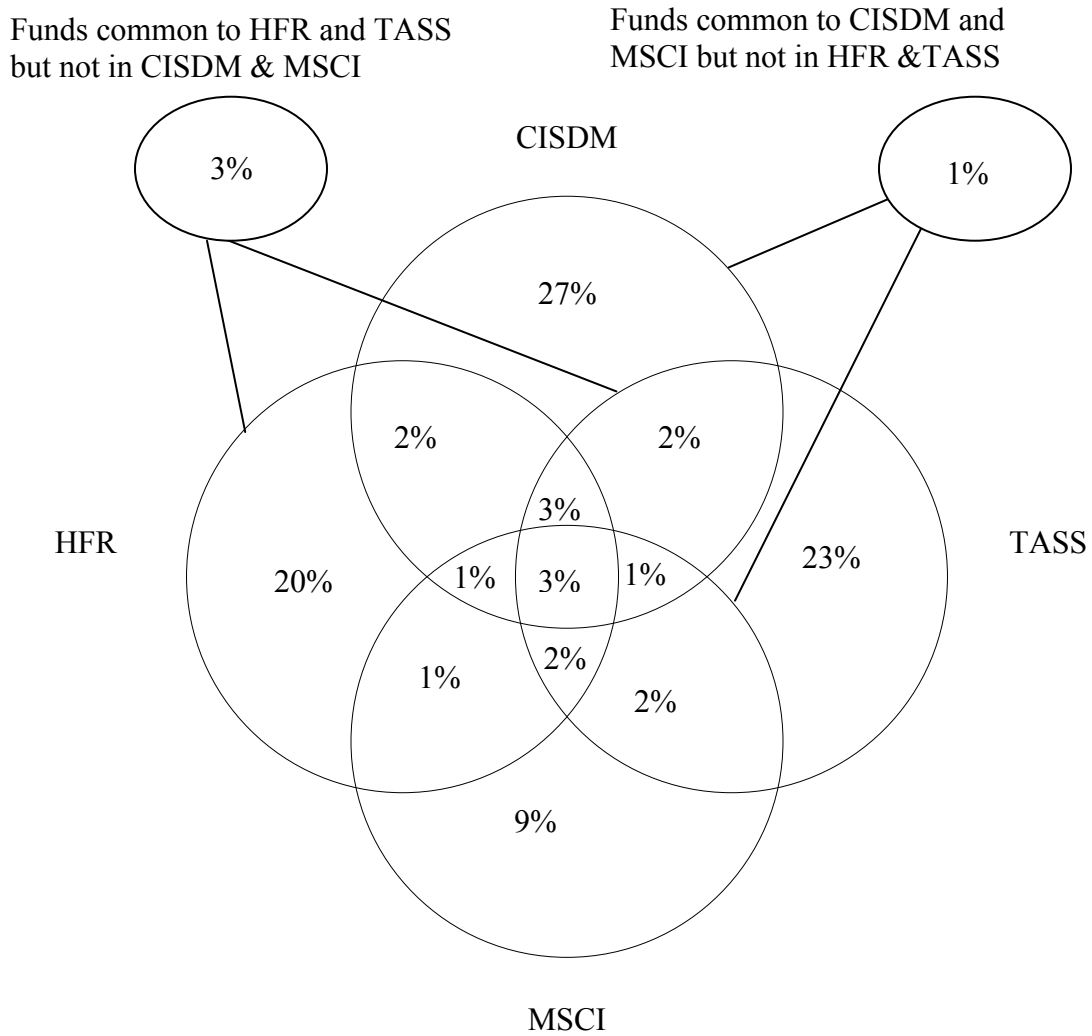
## Figure 1: Monthly Gross Returns of Hedge Funds

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



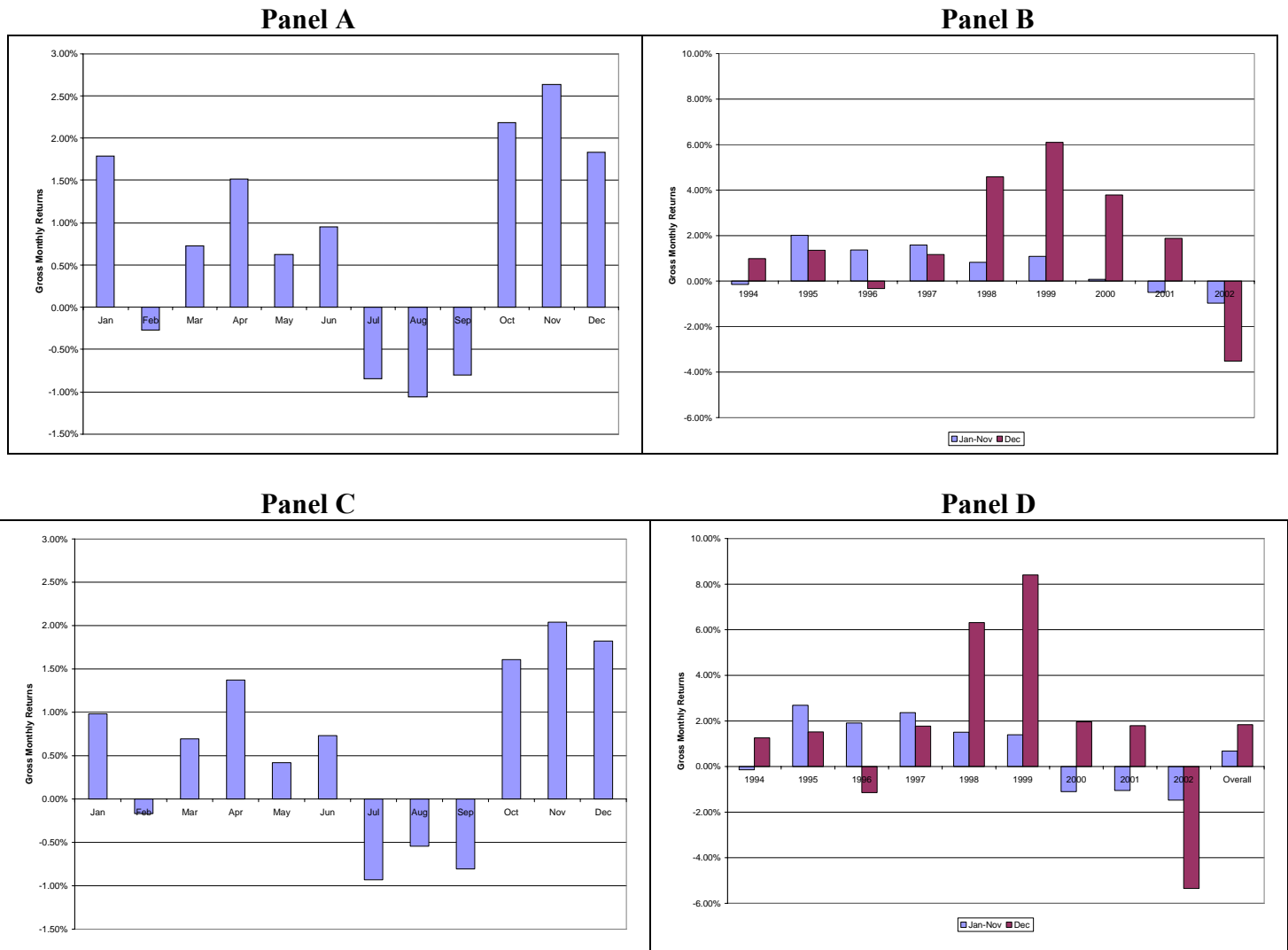
## Figure 2: Distribution of Hedge Funds by Data Sources

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



### Figure 3: Monthly Gross Returns of Market and Mutual Funds

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



## Table I. Summary Statistics

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

<b>Fund Characteristics</b>	<b>Mean</b>	<b>SD</b>	<b>25<sup>th</sup> Percentile</b>	<b>Median</b>	<b>75<sup>th</sup> Percentile</b>
<b>Returns (%)</b>	1.06	5.63	-1.13	0.84	2.97
<b>Residuals (%)</b>	-0.02	4.19	-1.74	-0.05	1.55
<b>CS-Volatility (%)</b>	6.02	1.90	4.64	5.83	6.61
<b>Moneyness</b>	-0.003	17.87	-6.30	-0.13	7.18
<b>Delta (\$ millions)</b>	0.17	0.51	0.002	0.02	0.11
<b>Nov-end Fractional Rank</b>	0.50	0.29	0.25	0.50	0.75
<b>Lockup Period (years)</b>	0.13	0.32	0.00	0.00	0.00
<b>Restriction Period (years)</b>	0.31	0.28	0.16	0.18	0.34
<b>Nov-end Dollar Management fee (\$ millions)</b>	2.14	17.72	0.05	0.27	0.95
<b>Volatility (%)</b>	4.82	3.95	1.93	3.83	6.52
<b>Liquidity beta</b>	0.02	0.29	-0.06	0.00	0.09
<b>Reserves (%)</b>	8.58	13.20	0.00	3.56	11.58
<b>AUM (\$ millions)</b>	131.26	390.89	9.42	29.55	88.84
<b>Age</b>	4.94	3.56	2.17	4.09	6.84
<b>Management Fees</b>	0.01	0.01	0.01	0.01	0.02
<b>Incentive Fees</b>	0.16	0.08	0.15	0.20	0.20

## Table II. Do Funds Manage Returns? Univariate Results

This table reports the average gross hedge fund returns, residuals from the time-series regressions of hedge funds' gross returns, using the seven-factor model of Fung and Hsieh (2004), and factor risk premiums for the seven risk factors, S&P 500 (SP), spread between Wilshire Small Cap 1750 index and Wilshire Large Cap 750 index (SCLC), 10-year Treasury (10Y), credit spread, i.e., difference between CSFB High-Yield index returns and 10-year Treasury returns (CS), lookback straddles on bond futures (BdOpt), lookback straddles on currency futures (FXOpt), and lookback straddles on commodity futures (ComOpt). The right-hand column provides the difference between December values and the average of January–November values and the *t*-statistic (after testing for equality of variances) for the test that this difference equals zero. *t*-statistics reported in parentheses are corrected for fund-level clustering. Figures marked with \*\*\*, \*\*, and \* are significant at the 1%, 5%, and 10% levels, respectively.

	Dec	Jan-Nov	Dec minus Jan–Nov ( <i>t</i> -statistic)
<b>Gross hedge fund returns</b>	2.51%	0.96%	1.55%*** (34.3)
<b>Residual hedge fund returns</b>	0.23%	−0.02%	0.25%*** (6.9)
<b>SP</b>	0.76%	0.46%	0.30% (0.2)
<b>SCLC</b>	2.51%	−0.32%	2.83%** (2.3)
<b>10Y</b>	0.35%	0.25%	0.10% (0.2)
<b>CS</b>	0.36%	0.06%	0.30% (0.7)
<b>BdOpt</b>	3.09%	1.15%	1.94% (0.3)
<b>FXOpt</b>	3.91%	−1.52%	5.43% (0.8)
<b>ComOpt</b>	2.10%	−2.00%	4.10% (0.9)

**Table III. Do Funds Exhibit a December Spike? Multivariate Results**

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

Independent Variables	Expected Sign	Model 1 Returns $_m$	Model 2 Returns $_m$	Model 3 Returns $_m$	Model 4 Returns $_m$	Model 5 Residuals $_m$
December Dummy ( $\lambda_1$ )	+	1.514*** (0.000)	1.539*** (0.000)	1.488*** (0.000)	1.511*** (0.000)	0.362*** (0.000)
Quarter-End Dummy			0.091** (0.002)		0.082*** (0.005)	0.019 (0.402)
CS-Volatility $_m$				0.066*** (0.000)	0.066*** (0.000)	0.068*** (0.000)
Returns $_{m-1}$ (Residuals $_{m-1}$ for Model 5)		0.101*** (0.000)	0.101*** (0.000)	0.101*** (0.000)	0.101*** (0.000)	0.079*** (0.000)
Returns $_{m-2}$ (Residuals $_{m-2}$ for Model 5)		0.002 (0.557)	0.002 (0.516)	0.002 (0.572)	0.002 (0.534)	0.038*** (0.000)
Delta $_{m-1}$		0.121*** (0.000)	0.120*** (0.000)	0.121*** (0.000)	0.120*** (0.000)	0.080*** (0.000)
Money $_{m-1}$		0.001 (0.471)	0.001 (0.496)	0.001 (0.459)	0.001 (0.482)	-0.005*** (0.000)
Lockup Period		0.127*** (0.001)	0.127*** (0.001)	0.127*** (0.001)	0.127*** (0.001)	0.001 (0.974)
Restriction Period		0.192*** (0.000)	0.192*** (0.000)	0.192*** (0.000)	0.192*** (0.000)	0.029 (0.130)
Size $_{m-1}$		-0.092*** (0.000)	-0.092*** (0.000)	-0.092*** (0.000)	-0.092*** (0.000)	-0.105*** (0.000)
Prior Year Volatility		0.002 (0.757)	0.002 (0.765)	0.002 (0.754)	0.002 (0.761)	-0.039*** (0.000)
Age $_{m-1}$		-0.029*** (0.000)	-0.029*** (0.000)	-0.029*** (0.000)	-0.029*** (0.000)	0.001 (0.718)
Management Fee Rate		2.605 (0.147)	2.604 (0.147)	2.601 (0.147)	2.601 (0.148)	0.828 (0.331)
Intercept, Strategy Dummies, and Year Dummies		Yes	Yes	Yes	Yes	Yes
Observations		195717	195717	195717	195717	195717
Adjusted R <sup>2</sup>		3.4%	3.4%	3.4%	3.4%	1.9%

**Table IV. What Types of Funds Exhibit a Greater December Spike?**

The table reports the slope coefficients for the December dummy for Models 4 and 5 in Table III for the various subsamples listed in the first column. Funds are classified into three groups based on their moneyness as of November end, where moneyness is computed as the difference between spot and exercise price divided by the exercise price. Out-of-the-money funds are those whose moneyness is less than  $-(\mu + \sigma)$ . Near-the-money funds are those whose moneyness is between  $-(\mu + \sigma)$  and  $-(\mu - \sigma)$ . In-the-money funds are those whose moneyness is greater than  $-(\mu - \sigma)$ .  $\mu$  is the average monthly fund return, and  $\sigma$  is the standard deviation of monthly fund returns using the entire return history for each fund. Fractional rank is the rank (between 0 and 1) of the fund at November-end each year based on its performance from January to November, relative to all funds within a strategy, i.e., fractional relative rank. Following Sirri and Tufano (1998), we divide the funds into top 20%, middle 60%, and bottom 20% based on their fractional relative rank as of November-end. Dollar management fee at the end of November is the management fee rate multiplied by the fund size at November-end. For characteristics other than moneyness, we do independent sorts based on Delta as of November end, Lockup, Restriction Period, Dollar Management Fee as of November end, Volatility, and Liquidity. The High (Low) groups consist of funds whose characteristic is greater than or equal to (less than) the median value that year; similarly for Long (Short) periods in all instances. The difference in the December spike is between the High and Low groups. In the case of moneyness, the difference is with respect to out-of-the-money group. The  $p$ -values given in parentheses adjacent to the difference values are based on Chow-tests that examine whether this difference is significantly different from zero. The “expected sign” is the hypothesized sign for the difference in December spikes. All figures are in percentage, e.g., a coefficient of 2.281 is equal to 2.281%. Figures marked with \*\*\*, \*\*, and \* are significant at the 1%, 5%, and 10% levels, respectively. Standard errors are corrected for heteroskedasticity and fund-level clustering with  $p$ -values reported in parentheses.

Subsample	Dec spike as per	Expected	Difference	Dec spike as per	Expected	Difference
	Model 4, Table III			Model 5, Table III		
	Returns	Sign	( $p$ -value)	Residuals	Sign	( $p$ -value)
<i><b>INCENTIVES TO MANAGE RETURNS</b></i>						
<b>In the Money</b>	2.281*** (0.000)	+	1.910*** (0.000)	0.566*** (0.000)	+	0.597*** (0.000)
<b>Near the Money</b>	1.828*** (0.000)	+	1.457*** (0.000)	0.486*** (0.000)	+	0.517*** (0.000)
<b>Out of the Money</b>	0.371*** (0.000)			-0.031 (0.680)		
<b>High Delta</b>	1.642*** (0.000)	+	0.355*** (0.000)	0.414*** (0.000)	+	0.158* (0.055)
<b>Low Delta</b>	1.287*** (0.000)			0.256*** (0.000)		
<b>Top 20% Fractional rank</b>	2.129*** (0.000)	+	0.820*** (0.000)	0.071 (0.485)	+	-0.234 (0.105)
<b>Mid 60% Fractional rank</b>	1.677*** (0.000)	+	0.368*** (0.003)	0.605*** (0.000)	+	0.300*** (0.000)
<b>Bottom 20% Fractional rank</b>	1.309*** (0.000)			0.305*** (0.003)		
<b>Long Lockup</b>	1.164*** (0.000)	-	-0.395*** (0.006)	0.008 (0.945)	-	-0.401*** (0.001)
<b>Short Lockup</b>	1.559*** (0.000)			0.409*** (0.000)		
<b>Long Restriction Period</b>	1.488*** (0.000)	-	-0.067 (0.517)	0.322*** (0.000)	-	-0.099 (0.238)
<b>Short Restriction Period</b>	1.555*** (0.000)			0.421*** (0.000)		
<b>High \$ Management Fee</b>	1.599*** (0.000)	+	0.174* (0.076)	0.442*** (0.000)	+	0.175** (0.027)
<b>Low \$ Management Fee</b>	1.425*** (0.000)			0.267*** (0.003)		

**Table IV. (contd.) What Types of Funds Exhibit a Greater December Spike?**

<b>Subsample</b>	<b>Dec spike as per Model 4, Table III</b>	<b>Expected Sign</b>	<b>Difference (p-value)</b>	<b>Dec spike as per Model 5, Table III</b>	<b>Expected Sign</b>	<b>Difference (p-value)</b>
	<b>Returns</b>			<b>Residuals</b>		
<i><u>OPPORTUNITIES TO MANAGE RETURNS</u></i>						
<b>High Volatility</b>	2.468*** (0.000)	+	1.922*** (0.000)	0.545*** (0.000)	+	0.380*** (0.000)
<b>Low Volatility</b>	0.546*** (0.000)			0.165*** (0.000)		
<b>High Liquidity</b>	1.292*** (0.000)	-	-0.499*** (0.000)	0.584*** (0.000)	-	0.482*** (0.000)
<b>Low Liquidity</b>	1.791*** (0.000)			0.102 (0.104)		

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

The table reports OLS regressions of monthly gross returns ( $\text{Returns}_m$ ). See Tables I and III for variable definitions. Figures marked with \*\*\*, \*\*, and \* are significant at the 1%, 5%, and 10% levels, respectively. Standard errors are corrected for heteroskedasticity and autocorrelation with  $p$ -values reported in parentheses.

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

**Table VI. Tests of borrowing hypothesis based on stock holdings data**

This table reports the average year-end inflation of stocks held by hedge funds. The analysis follows that in Table VII of Carhart et al. (2002). Each year, stocks are sorted into five quintiles based on 6-month returns up to the second-last day of the year. Stocks are also sorted into five quintiles based on market capitalization based on the second-last day of the year. This yields us  $9 \times 5 \times 5 = 225$  portfolio-year combinations. Within each portfolio, we then perform independent sorts based on various fund characteristics such as November-end moneyness, November-end delta, lockup period, restriction period, fractional relative rank, November-end dollar management fee, volatility of fund returns, and liquidity beta of the fund. Funds are classified into three groups based on their moneyness as of November end, where moneyness is computed as the difference between spot and exercise price divided by the exercise price. Out-of-the-money (OTM) funds are those whose moneyness is less than  $-(\mu + \sigma)$ . Near-the-money (NTM) funds are those whose moneyness is between  $-(\mu + \sigma)$  and  $-(\mu - \sigma)$ . In-the-money (ITM) funds are those whose moneyness is greater than  $-(\mu - \sigma)$ .  $\mu$  is the average monthly fund return, and  $\sigma$  is the standard deviation of monthly fund returns using the entire return history for each fund. Following Sirri and Tufano (1998), funds are classified into three groups based on their fractional relative rank as of November end – top 20%, middle 60%, and bottom 20%. The High (Low) groups consist of funds whose characteristic is greater than or equal to (less than) the median value that year. In each of the 200 portfolios, we go long on stocks in the hedge fund with higher incentives (ITM and NTM, high delta, low lockup and restriction periods, top 20% and middle 60% relative rank, and high dollar management fee) and higher opportunities (high volatility and low liquidity beta) and short on stocks in hedge funds with lower incentives (OTM, low delta, high lockup and restriction periods, bottom 20% relative rank, and low dollar management fee) and lower opportunities (low volatility and high liquidity beta) to manage returns. Year-end Return Inflation is calculated as the return on this long-short portfolio on the last day of the year minus the portfolio return on the first day of next year. To compute the z-statistic for this, for each portfolio, we first compute the return inflation for every non-overlapping 2-day period in that year. The z-statistic each portfolio is given by: (Year-end Return Inflation minus the mean of all possible 2-day returns for that portfolio) divided by the standard deviation of the two-day returns for that portfolio. For the sake of brevity, we report only the average year-end inflation across the 225 portfolio-year combinations. The z-statistic for this overall average is the sum of the z-statistic of the 225 portfolio-years divided by the square root of 225. The reported p-value is the probability of obtaining a z-statistic greater than this overall z-statistic assuming a standard normal distribution. Figures marked with \*\*\*, \*\*, and \* are significant at the 1%, 5%, and 10% levels, respectively.

	All Stocks	Long ITM and NTM Short OTM	Long High-Delta Short Low-Delta	Long High-Rank Short Low-Rank	Long High-Dollar management fee Short Low-Dollar management fee	Long Low-Lockup Short High-Lockup	Long Low-Restriction Short High-Restriction	Long High-Volatility Short Low-Volatility	Long Low-Liquidity Short High-Liquidity
Average Inflation	0.38%***	0.63%*	0.76%**	0.75%**	0.60%**	-0.41%	0.61%**	0.35%	-0.32%
p-value	0.000	0.062	0.032	0.021	0.043	0.955	0.050	0.303	0.889

## Appendix A: Classification of Hedge Fund Strategies

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

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

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

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.

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

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

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

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

$$\begin{aligned} \text{Manager's Option Delta} &= \text{sensitivity of the option value to a 1\% change in asset value} \\ &= N(Z) \times S \times 0.01 \times I \end{aligned} \tag{A1}$$

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

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

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

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

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

$\sigma$  = volatility of monthly net returns (estimated over the year)

$I$  = incentive fee rate (expressed as a fraction)

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

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

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

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

We adopt the following steps:

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

$$\text{Gross}_t = \left\{ \begin{array}{l} \frac{\text{Net}_t - \text{Hurdle}_t \times I}{1 - I} \text{ if } \text{Net}_t > \text{Hurdle}_t \\ \text{Net}_t \text{ otherwise} \end{array} \right\} \quad (\text{A2})$$

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

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

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

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

- 2) Estimate the market value of the manager's investment in the fund ( $MV_{mgr}$ ). This equals the sum of the year-end market value of the manager's year-beginning investment and the post-tax incentive fees earned in that year.
- 3) Estimate new money flow into or out of the fund as the difference between the reported year-end AUM and  $(\sum MV_{afterINC_i} + MV_{mgr})$ .
- 4) If there is net outflow, then the  $MV_{afterINC}$  of the earliest investor is reduced by the outflow computed in step 3. If the outflow is greater than  $MV_{afterINC}$  of the earliest investor, then the remaining balance is assumed to be withdrawn from the second earliest investor, and so on.
- 5) Compute the year-end market value of assets for each investor (spot price  $S$ ) and the fund manager.
- 6) Compute the exercise price for each investor (exercise price  $X$ ), depending on whether the fund has a hurdle rate and/or high-water mark provision.
  - a. If the gross return of the fund is sufficiently high such that an investor must pay an incentive fee, then the exercise price is higher than the current market value by the hurdle rate (i.e., LIBOR if the fund has a hurdle rate provision, or 0 if the fund lacks a hurdle rate provision).
  - b. If the gross fund return is insufficiently high to require an investor to pay an incentive fee, and if the fund has a high-water mark provision, the new exercise price is higher than the prior year's exercise price by the hurdle rate.
  - c. If the gross fund return is insufficiently high to require an investor to pay an incentive fee, and if the fund does not have a high-water mark provision, then the exercise price is higher than the current market value by the hurdle rate.
- 7) Using the  $S$  and  $X$  of various investors' capital in the fund, compute the moneyness as the capital-flow-weighted-average of the moneyness of each option.
- 8) Using the  $S$  and  $X$  of various investors' capital, compute the delta of each and sum them up along with the delta from the manager's investment to estimate the total delta of the fund.
- 9) The delta of the fund equals the delta from investors' assets (manager's option delta) plus the delta from the manager's stake. Since all the return from the manager's investment is retained, the delta from the manager's stake equals market value of manager's investment in the fund multiplied by 0.01 (i.e., when fund earns one-percent return, value of the manager's stake goes up by one percent).

## Appendix C. Robustness Tests

Panel A reports the coefficient of December dummy from Models 4 and 5 of Table III for various alternative specifications. See Section V.B for the description of various robustness tests. Panel B reports the coefficient of December dummy from Models 4 and 5 of Table III for various subsamples. Section VI.A for the description of various robustness tests. Figures marked with \*\*\*, \*\*, and \* are significant at the 1%, 5%, and 10% levels, respectively.

### Panel A: Replicating Models 4 and 5 of Table III

Row	December spike as per Model 4, Table III	December spike as per Model 5, Table III
1. Net Return	1.262*** (0.000)	0.334*** (0.000)
2. Excluding 1999	1.042*** (0.000)	0.164*** (0.000)
3. Contemporaneous volatility	1.501*** (0.000)	0.314*** (0.000)
4. Residual + Intercept		0.345*** (0.000)
5. Two additional factors		0.380*** (0.000)
6. Time-varying risk exposure		0.329*** (0.000)
7. November-December spike	1.272*** (0.000)	0.140*** (0.000)

## Appendix C. (contd.) Robustness Tests

**Panel B: Replicating Table IV for various subsamples**

Row	Subsample	Dec spike as per Model 4, Table III	Difference ( <i>p</i> -value)	Dec spike as per Model 5, Table III	Difference ( <i>p</i> -value)
		Returns		Residuals	
1. Strategy level $\mu$ and $\sigma$	In the Money	2.456*** (0.000)	2.015*** (0.000)	0.597*** (0.000)	0.628*** (0.000)
	Near the Money	1.446*** (0.000)		0.465*** (0.000)	
	Out of the Money	0.441*** (0.000)		-0.031 (0.700)	
2. Moneyness with respect to zero	In the Money (Moneyness $\geq 0$ )	2.322*** (0.000)	2.130*** (0.000)	0.594*** (0.000)	0.822*** (0.000)
	Near the Money (Moneyness < 0, Top half)	1.248*** (0.000)		0.525*** (0.000)	
	Out of the Money (Moneyness < 0, Bottom half)	0.192 (0.127)		-0.228** (0.026)	
3. Incentive fee rate	Incentive fee rate > 20%	1.731*** (0.000)	0.186 (0.458)	0.594*** (0.002)	0.176 (0.381)
	Incentive fee rate = 20%	1.478*** (0.000)		0.318*** (0.000)	
	Incentive fee rate < 20%	1.545*** (0.000)		-0.067 (0.539)	
4. Fund size	High Fund Size	1.514*** (0.000)	-0.008 (0.936)	0.412*** (0.000)	0.112 (0.165)
	Low Fund Size	1.522*** (0.000)		0.300*** (0.000)	
5. Management fee rate	High Management Fee	1.529*** (0.000)	0.091 (0.437)	0.348*** (0.000)	-0.077 (0.426)
	Low Management Fee	1.438*** (0.000)		0.425*** (0.000)	

## Addendum A: Do investor flows depend on the number of positive months?

This table reports OLS estimates using  $Flow_t$  as the dependent variable. Sample period is from 1994 to 2002. Flow is the annual investors' dollar flow scaled by assets. The independent variables include lagged delta ( $\Delta_{t-1}$ ), hurdle rate and high-water mark dummies, lockup period and restriction period, lagged performance measures, lagged flow ( $Flow_{t-1}$ ), number of positive months (NPM) during year  $t$ , lagged size computed as the logarithm of AUM ( $Size_{t-1}$ ), lagged return volatility ( $Volatility_{t-1}$ ), lagged age ( $Age_{t-1}$ ), management fees, contemporaneous returns ( $Return_t$ ), strategy and year dummies. Fractional rank quintiles are based on annual returns of funds following a particular strategy (relative ranks) during year  $t-1$ . These are constructed as in Sirri and Tufano (1998). NPM is the number of months in a year that were positive. Figures marked with \*\*\*, \*\*, and \* are significant at the 1%, 5%, and 10% respectively. p-values corrected for heteroskedasticity and fund-level clustering are reported in parentheses.

	Expected Sign	Dependent variable: $Flow_t$	
<b>Delta<sub>t-1</sub></b>	+	0.155*** (0.000)	0.156*** (0.000)
<b>Hurdle Rate</b>	+	0.034 (0.115)	0.031 (0.139)
<b>High-Water Mark</b>	+	0.073*** (0.002)	0.069*** (0.004)
<b>Lockup Period</b>	-	-0.032 (0.312)	-0.027 (0.388)
<b>Restriction Period</b>	-	-0.086*** (0.009)	-0.096*** (0.004)
<b>Rank<sub>t-1</sub> - Bottom Quintile</b>		0.134 (0.584)	0.259 (0.283)
<b>Rank<sub>t-1</sub> - 4<sup>th</sup> Quintile</b>	+	0.626*** (0.002)	0.661*** (0.001)
<b>Rank<sub>t-1</sub> - 3<sup>rd</sup> Quintile</b>	+	1.028*** (0.000)	1.047*** (0.000)
<b>Rank<sub>t-1</sub> - 2<sup>nd</sup> Quintile</b>	+	0.465** (0.045)	0.578** (0.012)
<b>Rank<sub>t-1</sub> - Top Quintile</b>	+	0.867** (0.015)	0.971*** (0.007)
<b>NPM<sub>t-1</sub></b>	+	0.023*** (0.000)	
<b>NPM<sub>t</sub></b>	+		0.056*** (0.000)
<b>Size<sub>t-1</sub></b>		-0.191*** (0.000)	-0.192*** (0.000)
<b>Flow<sub>t-1</sub></b>		0.064*** (0.000)	0.065*** (0.000)
<b>Volatility<sub>t-1</sub></b>		-3.097*** (0.000)	-2.421*** (0.000)
<b>Age<sub>t-1</sub></b>		-0.015*** (0.000)	-0.014*** (0.000)
<b>Management Fee Rate</b>		1.664 (0.284)	1.834 (0.236)
<b>Return<sub>t</sub></b>		0.620*** (0.000)	0.378*** (0.000)
<b>Intercept</b>		0.472*** (0.000)	0.220*** (0.003)
<b>Strategy dummies</b>		Yes	Yes
<b>Year dummies</b>		Yes	Yes
<b>Adjusted R<sup>2</sup></b>		12.8%	13.2%
<b>Observations</b>		16,901	16,901