Do Hedge Funds Manage Their Reported Returns?

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For funds with high incentives and more opportunities to inflate returns, we find that (i) returns during December are significantly higher than returns during the rest of the year, even after controlling for risk in both the time series and the cross-section; and (ii) this *December spike* is greater than for funds with lower incentives and fewer opportunities to inflate returns. These results suggest that hedge funds manage their returns upward in an opportunistic fashion in order to earn higher fees. Finally, we find strong evidence that funds inflate December returns by underreporting returns earlier in the year but only weak evidence that funds borrow from January returns in the following year. (*JEL* G10, G19, G23, G30)

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

As the incentive to inflate returns is highest in December, we first estimate what we term as the "December residual spike"—the return in December less the average return from January to November after controlling for risk in the time series (such as factor premiums and factor loadings) and in the cross-section (such as volatility). We find that the magnitude of the December spike is systematically related to the benefits and costs associated with returns management.

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

To capture the first set of incentives—rewards for good performance—we recognize that performance-based compensation contracts provide asymmetric, call-option-like payoffs. We use the moneyness and delta (pay-performance sensitivity) of the incentive-fee call option as of the end of November as proxies for these incentives. In addition, incentives arise from flow-performance sensitivity, as investors direct more money into hedge funds that outperform their peer group (see, e.g., Agarwal, Daniel, and Naik 2004). We use the performance rank for each fund based on January–November returns relative to its peer group as a proxy for these incentives.

To capture the second set of incentives—penalties for poor performance—we first consider lockup and restriction periods, which determine the severity of the threat of capital withdrawals.[2] Shorter lockup and restriction periods imply that investors can withdraw their capital quickly in response to poor performance. Therefore, such periods act as disciplining mechanisms, which

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

[2] The lockup period represents the minimum time the investor must commit the capital. After the lockup period is over, an investor wishing to withdraw must give advance notice (notice period) and then wait an additional period of time to receive the money (redemption period). As the notice and redemption periods are applied back to back, we combine them and simply refer to this combined period as the "restriction period."

can lead to managers paying excessive attention to short-term performance and thereby create incentives for returns management. Furthermore, given the flow-performance relation, larger funds that charge higher management fees stand to lose the most from capital withdrawals. We use the dollar management fee (= management fee rate × assets) at the end of November as a proxy for such an incentive.

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

We find that funds with higher incentives (in-the-money, higher delta, top-20% performers, shorter lockup periods, shorter restriction periods, higher dollar management fees) and greater opportunities (higher volatility, lower liquidity): (i) exhibit a significantly positive December residual spike of 34bp to 70bp; and (ii) this residual spike is greater than it is for funds with lower incentives and fewer opportunities by up to 96bp. Both of these findings are consistent with returns management. Our results are robust to controlling for omitted risk factors, time-varying factor loadings, and the possibility that managers might work harder in December.

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

[3] Later, we provide evidence in support of this investor behavior.

[4] It is important to note that "saving for a rainy day" is associated with a December spike only when the fund has had significant positive returns in the earlier part of the year with which to create reserves. If this is not the case, the manager will be tempted to inflate returns earlier in the year, resulting in lower December returns. Our empirical tests account for these reserves.

[5] In the context of earnings management in corporate firms, Degeorge, Patel, and Zeckhauser (1999) document saving and borrowing behavior, which they refer to as "saving for a better tomorrow" and "borrowing for a better today." Bergstresser and Philippon (2006) document the inter-year smoothing of earnings by corporations.

reversals then follow in January, which effectively amounts to borrowing from January returns. We find strong evidence in support of the savings hypothesis but only weak evidence in favor of the borrowing hypothesis.

Our findings contribute to the stream of literature that explores the effect of managerial incentives on earnings management (Healy 1985; Bergstresser and Philippon 2006; Burns and Kedia 2006). We are the first to show a similar effect in hedge funds. Our findings have important implications for hedge fund regulators and investors. In fact, the Securities and Exchange Commission (SEC) has recently been concerned about issues related to the accurate valuation of securities in hedge fund portfolios.[6] Returns management behavior in hedge funds is important from the point of view of investor welfare as well. If some hedge funds inflate returns in December, investors that cash out at year-end benefit at the cost of those that enter and those that remain in the funds. Furthermore, if funds save for rainy days by underreporting early in the year, those investors who cash out earlier in the year may lose relative to other investors. Hence, investors entering and leaving the fund at different points in time may be systematically rewarded or penalized as a result of returns management. Our findings can help regulators and investors focus on funds with higher incentives and greater opportunities to manage returns.

The remainder of the article is organized as follows. Section 1 shows how our investigation contributes to the existing literature, and Section 2 presents testable hypotheses. Section 3 describes the data and the construction of the variables. Section 4 demonstrates how we estimate the December spike. Section 5 provides evidence related to the tests of our key hypotheses, while Section 6 discusses the robustness of the results to several alternative interpretations. Section 7 sheds light on the modus operandi of returns management, and Section 8 offers concluding remarks.

1. Related Literature

Our study contributes to the literature on earnings management and executive compensation by documenting the existence of returns management in hedge funds.

The literature on earnings management in corporations is extensive.[7] It shows that firms manage earnings to reach specific earnings thresholds (see, e.g., Burgstahler and Dichev 1997; Degeorge, Patel, and Zeckhauser 1999; and Daniel, Denis, and Naveen 2008). In particular, prior research shows that firms, *inter alia*, manage earnings to avoid reporting losses, avoid earnings declines, or meet dividend thresholds. For hedge funds, the threshold to earn incentive

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

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

fees is the strike price of the option-like incentive fee contract, and the returns necessary to meet that threshold represent the moneyness of the option. Our investigation shows that the magnitude of the 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 presented by Efendi, Srivastava, and Swanson (2007), who document that the likelihood of misstating financial statements to boost stock prices increases when the CEO owns a sizable holding of in-the-money options.

The present study also adds to the executive compensation literature that examines the relation between earnings management and compensation-based incentives.[8] Healy (1985) and Gaver, Gaver, and Austin (1995) relate managers' accrual policies to incentives arising from their bonus contracts. Goldman and Slezak (2006) provide a theoretical explanation for why stock-based compensation can induce earnings management. Although stock-based compensation motivates managers to exert more effort, it can also tempt them to exaggerate their performance. Burns and Kedia (2006) find that the delta of a 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 a higher delta for their call-option-like incentive fee contracts exhibit a higher December spike.

When 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 be passively inflated in December. However, unlike mutual funds, hedge funds have explicit incentives at the end of the year, which arise 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 incentive fees. Our finding that the magnitude of the spike at year-end relative to spikes at quarter-ends is substantially higher for hedge funds than for 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 determining year-end effects.

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

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

Finally, our article complements the literature on return smoothing by hedge funds. Asness, Krail, and Liew (2001) show that hedge funds' investments in illiquid securities can lead to underestimations of hedge fund risk. Getmansky, Lo, and Makarov (2004) document positive autocorrelation in monthly returns, and attribute it to hedge funds' exposure to illiquidity and the potential smoothing of returns. Bollen and Pool (2008) demonstrate that it is difficult to detect intentional smoothing of returns by looking at autocorrelations. In this article, we uncover one effect of return smoothing on hedge fund return distribution: Hedge funds can intentionally smooth returns during the earlier part of the year by underreporting their positive returns (saving for a rainy day). This, in turn, can result in a December spike when the underreported returns are added back at the end of the year.

2. Hypotheses Development

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

In addition to the explicit incentives embedded in compensation contracts, fund managers also face implicit incentives to improve 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). An increase in assets under management also yields higher compensation arising from asset-based management fees. Thus, hedge funds face both explicit and implicit incentives to inflate returns.

Typically, incentive fees are paid once a year based on annual performance. As the end of the year draws nearer, managers are better able to judge whether their funds' performance will be sufficiently greater in the remaining periods in that the year-end NAV will be greater than the threshold NAV. This suggests that if a fund is close to the threshold NAV or above it, a manager is likely to engage in returns management to benefit from additional incentive fees. Such returns management is more likely to be evident in December. Thus, after controlling for several fund characteristics that have been shown to affect returns, we expect December returns to be higher than average returns during the other 11 months. We term this the *December return spike*. In addition, we control for the possibilities that fund returns in December could be high because factor premiums are high and that funds might actively increase their risk exposures in December to improve year-end performance. We term the difference in returns between December and the rest of the year after including these controls as the *December residual spike*. Of course, these December spikes (return or residual) are observed only for the subsample of funds that have the incentives and the opportunities to manage returns. This yields our first hypothesis:

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

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

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

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

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

If we find evidence in support of hypotheses 1 and 2, we could say that hedge funds engage in returns management. It would then be natural to explore the mechanisms that funds employ to manage returns. It is conceivable that hedge funds "save for a rainy day" in that they create reserves by underreporting positive returns earlier in the year and using them during periods of poorer performance to avoid reporting losses. For hedge funds, the tendency to create reserves could be driven by investors' preferences for funds with fewer loss-making months. While saving for a rainy day does not lead to higher reported annual returns or higher incentive fees in the current year, it could lead to higher fees in the future. In Appendix A, we provide empirical evidence that, all else equal, the higher the number of months in a calendar year in which the fund reports positive returns, the greater the capital inflow into that fund from investors. The resulting increase in assets under management leads to higher fees in the future, which gives funds an incentive to engage in returns management behavior. If some reserves remain un-utilized at the end of the year, the manager is forced to include them in December for auditing purposes, which leads 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 accrued over the months prior to December are higher.

It is well documented that mutual funds push up the prices of securities they hold at the end of December by creating short-term price pressure through purchases made during the last few minutes of trading on the last day of the year (see, e.g., Carhart et al. 2002; Bernhardt and Davies 2005). Price reversals then follow in January, which effectively amounts to *borrowing* from January returns. It is plausible that hedge funds borrow from January returns in a similar

9 Recently, declining valuations of securities backed by subprime mortgages have fueled the debate on accurate valuation of illiquid securities. Pulliam, Smith, and Siconolfi (2007) discuss this issue and how it can provide an incentive to "inflate marks." Their article also mentions the three levels of precision set by the Financial Accounting Standards Board (FASB) to value securities: "marking to market" (most precise), "marking to matrix," and "marking to model" (least precise). Bollen and Pool (2009) provide evidence on discontinuity in returns around zero resulting from overstating the returns.

fashion in order to earn their incentive fees earlier.[10] This provides us with our fourth hypothesis:

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

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

3. Data and Variable Construction

3.1 Data description

In this article, we use a comprehensive hedge fund database that is a union of five large databases from the Center for International Securities and Derivative Markets (CISDM), Hedge Fund Research (HFR), Morgan Stanley Capital International (MSCI), Tremont Advisory Shareholder Services (TASS) (now Lipper), and Eurekahedge. The databases report net-of-fee monthly returns; assets under management; and fund characteristics, such as hurdle rates and high-water-mark provisions, incentive fee rates, management fee rates, inception dates, fund strategies, and lockup, notice, and redemption periods.[11]

Our sample period extends from January 1994 to December 2006. We focus on the post-1994 period to mitigate potential survivorship bias, as most of the databases start reporting information on "defunct" funds only after 1994.[12] After merging the five databases, we have a sample of 11,305 hedge funds. Of these, 6,976 still existed as of December 2006, while 4,329 became defunct during the sample period. Figure 1 illustrates the overlap among the five databases and highlights the fact that there are a large number of hedge funds that are unique to each of the databases. 70.4% of the funds are found in just one of the five databases, and less than 1% of the sample is found in all five databases. The combination of these databases, therefore, captures a more representative sample of the hedge fund universe and to resolve occasional discrepancies. As in Agarwal, Daniel, and Naik (2009), we classify

[10] Another way that a 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. The sale of the puts generates income upfront, while the cost of replication through dynamically delta hedging is incurred over a period that can extend beyond December. However, this argument assumes that the computation of NAV does not simultaneously account for both the short position in the option and the delta-hedge component.

[11] The database provides information on contractual features as of the last date for which the fund's data are 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 than to go through the legal complications of changing existing contracts with numerous investors.

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

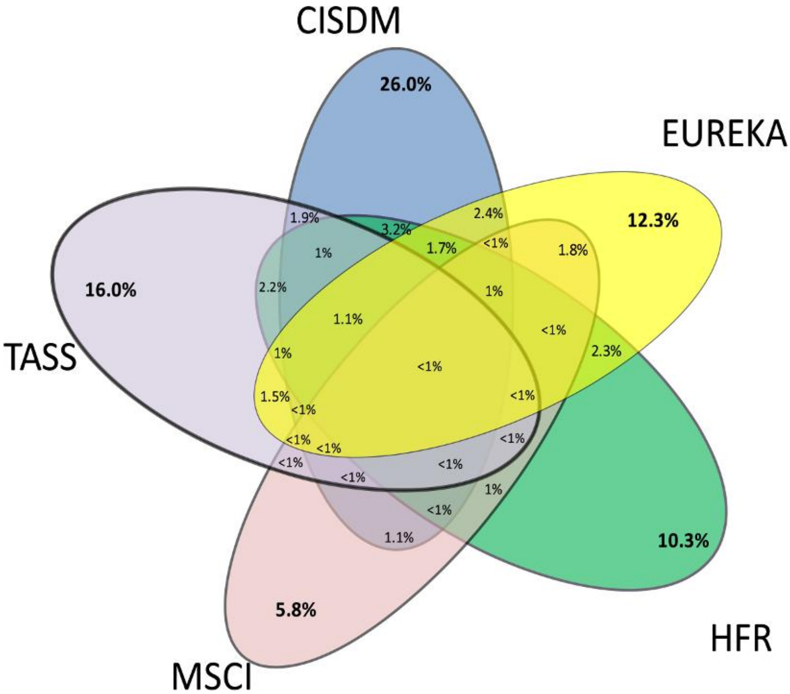

Figure 1
Hedge fund database
The hedge fund database is the result of the merger of five databases from the Center for International Securities and Derivative Markets (CISDM), Eurekahedge, Hedge Fund Research (HFR), Morgan Stanley Capital International (MSCI), and Tremont Advisory Shareholder Services (TASS) (now Lipper). It contains 11,305 hedge funds. This figure shows the percentage of funds covered by each database individually and by all possible combinations of multiple databases.

funds according to four broad strategies: Directional, Relative Value, Security Selection, and Multi-Process Traders.

3.2 Measures of performance

We consider two performance measures in our study. The first is the gross return of fund i in month m, $\text{Returns}_{i,m}$, where m runs from January 1994 to December 2006. We compute the gross-of-fee returns from net-of-fee returns following the methodology suggested by Agarwal, Daniel, and Naik (2009). Although investors (and, therefore, managers) care about net-of-fee returns, we use gross-of-fees returns to mitigate any problems created by path dependency in the computation of incentive fees, which can induce smoothing in net-of-fee monthly returns (see Getmansky, Lo, and Makarov 2004). For the remainder of this article, we simply refer to gross returns as returns. For robustness, we repeat our analysis using net-of-fee returns and obtain similar inferences (see Section 6).

To test for the December spike, we need to control for the systematic risks of hedge funds. Hence, we employ a second measure, Residual$_{i,m}$, which is the residual return of fund i during month m. For this purpose, we estimate fund-level time-series regressions of excess returns on the seven factors of Fung and Hsieh (2004).[13] In this regard, we follow Bollen and Pool (2008), who estimate predicted returns from Fung and Hsieh's (2004) seven-factor model and define them 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 discretionary accruals in earnings management literature, which are defined as the residuals from a regression of accruals on explanatory variables (such as change in sales, etc.) that are predicted to be related to accruals (see, for example, Jones 1991; Ball and Shivakumar 2006).

In Table 1, we report the summary statistics for the performance measures. We find that the mean monthly gross fund return is 1.15%. As expected, the average monthly residuals are virtually zero.

3.3 Measures of risk exposure

As hedge fund returns are available only on a monthly basis, it is difficult to use a time-series approach to estimate month-to-month risk exposure using a multifactor model. Therefore, we use a cross-sectional approach to determine the variation in risk exposure over time. In particular, 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.[14] If funds increase their risk exposure, then CS Volatility$_m$ will increase. Hence, we use CS Volatility$_m$ as a proxy for risk exposure. Table 1 shows that the mean (median) cross-sectional volatility of funds' monthly returns is 7.81% (6.43%). As an alternative to cross-sectional volatility, we allow funds to vary their risk exposures to market factor on a monthly basis in Section 6. With this control, our results are qualitatively similar.

3.4 Measures of incentives to manage returns

Goetzmann, Ingersoll, and Ross (2003) point out that the incentive fee contract for a hedge fund provides the manager with a call option. They theoretically

13 Our results are robust to computing residuals using a nine-factor model by augmenting the Fung and Hsieh (2004) seven-factor model with book-to-market and momentum factors. We report these results in Section 6.

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

Table 1
Summary statistics

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

The table reports the summary statistics of select fund characteristics. Returns are the monthly gross fund returns. Residuals are the residuals from the time-series regressions of funds' excess gross returns using the seven-factor model of Fung and Hsieh (2004). CS-Volatility is the monthly cross-sectional dispersion in fund returns. Moneyness is defined on a monthly basis and is the returns necessary to reach the threshold NAV before incentive fees are paid. Delta is the expected dollar change in manager's wealth given a 1% change in NAV. Fractional rank is the rank (between 0 and 1) of the fund at the end of November each year based on its performance from January to November relative to all funds using a specific 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. Nov-end Dollar Management Fee is the percentage management fee multiplied by the fund size at the end of November. Volatility is the 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, are equal to the maximum of either (0 or the 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.

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 by whether the fund has hurdle rate and high-water-mark provisions). On the basis of these insights, we empirically estimate the moneyness and delta of this portfolio of call options using the methodology suggested by Agarwal, Daniel, and Naik (2009).

Our first measure of returns management incentives is related to the moneyness of the call option portfolio. To construct this measure, we track 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 the exercise price, divided by the exercise price ($(S-X)/X$). This implies that the moneyness of the portfolio of call options is equal to the weighted-average moneyness of different options granted by the capital inflows from investors at different points in time.

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

Our second measure of returns management incentives is the delta of the portfolio of call options endowed to the fund by the incentive fee contract. The delta of each of the call options depends on the current NAV (S), the threshold NAV that must be reached before the manager can claim an incentive fee (X), and other fund characteristics, such as the fund size and fund volatility. We follow Agarwal, Daniel, and Naik (2009) to compute the delta at the end of each month, which equals the expected dollar change in the manager's compensation given a 1% change in the fund's month-end NAV. Table 1 shows that the mean (median) delta equals \$210,000 (\$4,000).[15]

Our third measure of incentives is the fractional rank of the fund at the end of November 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 to November returns relative to other funds following the same strategy. As expected, the mean fractional rank at the end of November is 0.5 (Table 1).

As discussed above, moneyness, delta, and fractional rank capture incentives that reward good performance. The next three measures belong to the group of returns management incentives that penalizes poor performance. The first two of these incentives are lockup period and restriction period. From Table 1, we observe that the mean lockup period (restriction period) is 0.16 (0.28) years.

[15] Coles, Daniel, and Naveen (2006) report the mean (median) delta of executive stock options for the top 1,500 firms in S&P from 1992 through 2002 to be \$600,000 (\$206,000).

The final measure is the dollar management fee at the end of November, which averages $2.34 million (Table 1).

3.5 Measures of opportunities to manage returns

Our first measure of opportunities for returns management is fund volatility. From Table 1, we observe that the mean (median) fund volatility is 4.20% (3.10%). Our second measure is the liquidity of each fund, which we capture by its exposure to Pastor and Stambaugh's (2003) liquidity risk factor. For this purpose, we estimate fund-level time-series regressions of excess returns on the seven factors of Fung and Hsieh (2004) augmented with the liquidity risk factor.[16] A higher beta on the liquidity risk factor implies that the fund has greater exposure to illiquidity and is, therefore, more illiquid.[17] From Table 1, we observe that the mean (median) of the liquidity beta is 0.05 (0.01). The interquartile range of the liquidity beta is 0.18 (i.e., $0.11 - (-0.07)$), which suggests that there is considerable cross-sectional variation in the liquidity risk exposure across different hedge funds.

3.6 Measures of reserves

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

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

4. December Spike

To test our hypotheses, we must first estimate the December spike in a multivariate setting that controls for risk in both the time-series and cross-sectional settings. Before conducting a multivariate analysis, we provide a univariate comparison of gross returns and residual returns for the hedge funds in our sample for December, and the monthly average for the rest of the year (Table 2). Results from t-tests suggest that the average gross returns in December are significantly greater than those for the rest of the year—the December return spike is 1.26%. This spike could be partly due to factor premiums being higher in December (see Table 2). After controlling for this possibility, we find

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

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

Table 2
December spike in fund returns and risk factors

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

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

that the December residual spike is 0.44%. This finding suggests that higher factor premiums in December do not completely explain the December spike pattern.

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

4.1 Multivariate analysis using gross-of-fee returns and residuals

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

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

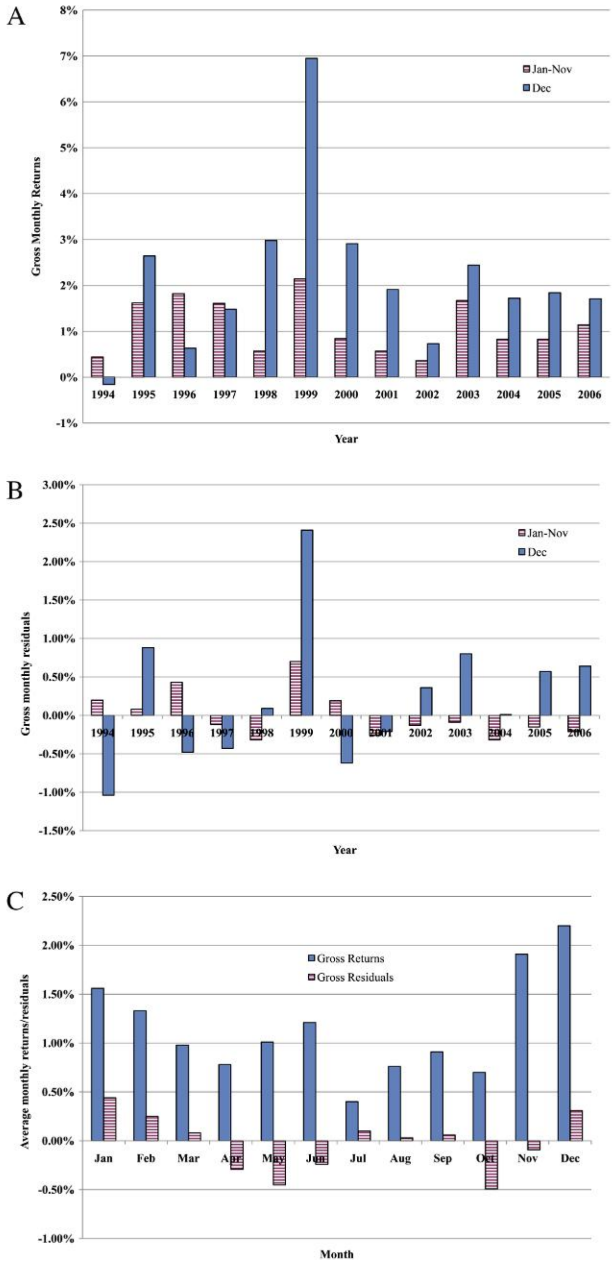

Figure 2
Average returns and residuals
The average return (Panel A) and the average residual (Panel B) for both the January to November period and the month of December are presented on an annual basis. Panel C presents the average return and average residual for each month. Returns are the monthly gross fund returns. Residuals are the residuals from the time-series regressions of funds' gross returns using the seven-factor model of Fung and Hsieh (2004).

$$\begin{aligned}\text{Return}_{i,m} = {} & \lambda_0 + \lambda_1 I(\text{December}) + \lambda_2 I(\text{Non-Dec Quarter-End}) \\ & + \lambda_3(\text{CSVol})_m + \lambda_4\text{Delta}_{i,m-1} + \lambda_5\text{Moneyness}_{i,m-1} \\ & + \lambda_6\text{Lockup}_i + \lambda_7\text{Restrict}_i + \lambda_8\text{Size}_{i,m-1} + \lambda_9\sigma_i + \lambda_{10}\text{Age}_i \\ & + \lambda_{11}\text{MFee}_i + \lambda_{12}\text{Return}_{i,m-1} + \lambda_{13}\text{Return}_{i,m-2} \\ & + \sum_{s=1}^{3}\lambda_{14}^{s} I(\text{Strategy}_{i,s}) + \sum_{k=1995}^{2006}\lambda_{15}^{k} I(\text{Year}_{t,k}) + \xi_{i,m}, \end{aligned} \tag{1}$$

where $\text{Return}_{i,m}$ is the gross-of-fee return of fund i in month m; $I(\text{December})$ is an indicator variable that takes the value of 1 if "m" is December, and 0 otherwise; $I(\text{Non-Dec Quarter-End})$ is an indicator variable that takes the value of 1 if the month corresponds to a quarter-end other than December (i.e., March, June, or September) and 0 otherwise; CSVol_m is the cross-sectional volatility during month m; $\text{Delta}_{i,m-1}$ is the sensitivity of the managers' wealth to a 1% change in NAV for fund i at the end of month $m-1$; $\text{Moneyness}_{i,m-1}$ represents the returns necessary to reach the threshold NAV before incentive fees are paid for fund i at the end of month $m-1$; Lockup_i and Restrict_i are the lockup and restriction periods, respectively, for fund i; $\text{Size}_{i,m-1}$ is the size of the fund measured as the natural logarithm of the assets under management (AUM) for fund i for month $m-1$; σ_i is the standard deviation of the prior year's monthly returns of fund i; Age_i is the age in years of fund i at the end of the prior year; MFee_i is the management fee rate charged by fund I; $I\left(\text{Strategy}_{i,s}\right)$ are strategy dummies that take the value of 1 if fund i belongs to strategy s and 0 otherwise; $I\left(\text{Year}_{t,k}\right)$ are year dummies; and $\xi_{i,m}$ is the error term.[19]

We report our findings in Table 3.[20] Our results for Model 1 show that the slope coefficient on the December dummy is positive ($\lambda_1 = 1.067$) and highly significant at the 1% level. This *December return spike* of 1.067% is economically significant given that the average returns are 1.15% per month.

As discussed above, part of the December returns could result from hedge funds trading in the same securities as mutual funds that engage in year-end return manipulation. In the absence of high-frequency holdings data, it is impossible to precisely quantify the magnitude of active and passive portfolio

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

[20] We winsorize the extreme 1% of all of the variables in order to minimize the influence of outliers. Here and throughout the article, we report the p-values after adjusting for heteroskedasticity, clustering at the fund level, and including year dummies. Petersen (2009) shows through simulations that estimating standard errors clustered on one dimension and including dummies for the other yields results similar to clustering on two dimensions. Following Petersen (2009), we cluster standard errors on more frequent fund clusters than the time clusters that are less frequent in our sample (11,305 funds compared to 156 months).

Table 3
December spike: Multivariate results

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

This table reports OLS regressions of monthly gross returns (Returns_m) and residual returns (Residuals_m), where the residuals are estimated from fund-level time-series regressions of excess gross returns on the seven factors of Fung and Hsieh (2004). The December dummy equals 1 if the month is December, and 0 otherwise. The Non-December Quarter-End dummy equals 1 if the month corresponds to a quarter-end (other than December), and 0 otherwise. CS-Volatility_m is the cross-sectional volatility of fund returns during month m. Returns_{m-1}, Residuals_{m-1}, Delta_{m-1}, Moneyness_{m-1}, Size_{m-1}, and Age_{m-1} are as of the prior month, $m-1$. Moneyness is the returns necessary to reach the threshold NAV before incentive fees are paid. Returns_{m-2} and Residuals_{m-2} are gross returns and residual returns, respectively, during month $m-2$. Volatility is the standard deviation of monthly returns during the year. Remaining variables are as defined in Table 1. 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.

pumping in December. However, we can estimate the fraction of the December returns that could be attributed to hedge funds taking advantage of mutual fund behavior. This is possible because, unlike mutual funds, hedge funds are unlikely to have an active interest in managing returns at quarter-ends, as they are not subject to portfolio disclosure requirements. Thus, a finding of higher quarter-end returns for hedge funds would suggest that hedge funds might be beneficiaries of returns management by mutual funds. For this purpose, we included a non-December quarter-end dummy.

The results in Model 1 of Table 3 show that the non-December quarter-end dummy is positive (coefficient = 0.009) but not statistically significant, which suggests that hedge fund returns at quarter-ends are only marginally influenced by the inflation of mutual fund returns. In a study by Carhart et al. (2002), the ratios of the coefficients on the year-end dummy to the coefficients on the quarter-end dummy (b_1/b_3) are 3.26 (i.e., 53.01 ÷ 16.27) and 2.57 (29.6 ÷ 11.54) for *all* funds in the two specifications in Panels A and B of Table 2 of Carhart et al. (2002; see page 671). If hedge funds passively benefit from the gaming behavior of mutual funds when they hold the same securities, then one would expect a similar ratio of coefficients on year-end and quarter-end dummies (as a rough approximation) in Model 1 of Table 3. However, in our case, this ratio is substantially higher, 118.56 (i.e., 1.067 ÷ 0.009), indicating that the hedge fund returns exhibit a considerably greater December return spike even after allowing for the possibility that they could be passively benefiting from the portfolio pumping activity of mutual funds. Taking the ratio of 3.26 for mutual funds and the coefficient on the quarter-end dummy of 0.009 for hedge funds, we estimate that mutual funds' portfolio pumping at year-end contributes, at best, 0.03% (0.009 × 3.26) to the December return spike observed in hedge funds of 1.067%. The balance of the December return spike could, therefore, be due to active returns management by hedge funds driven by incentives and opportunities.

To allow for the possibility that managers might increase their risk exposure in December, we include the cross-sectional volatility measure, CS Volatility$_m$. We find that the coefficient on cross-sectional volatility is positive (coefficient = 0.009) and significant at the 1% level. This implies that higher cross-sectional volatility is associated with higher returns.

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

In Model 2, we re-estimate Model 1 but with residual returns (or the 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 are a result of higher risk premiums in December. We find that the slope coefficient for the December dummy is significantly positive. This December residual spike of 0.437% is economically significant given that the average monthly return is 1.15%.[21]

[21] We undertake several robustness tests. First, to better control for changes in risk in the current year, we replace prior-year volatility with volatility estimated over the twelve months ending with November of the current year. Our December spikes remain unaffected. Second, it is conceivable that managers gradually adjust their returns and do not limit their manipulations to the month of December. Hence, we include a November dummy in addition to the December dummy. We find a November return spike of 1.089% ($p < 0.01$) and a residual spike of 0.033% ($p = 0.28$), while the magnitude of the December spikes remains virtually unaffected. Thus, it appears that returns management is primarily a December phenomenon. Third, we include six lags of residuals. Only

Overall, this section has shown how we estimate the December return spike and the December residual spike for the overall sample. This sets the stage for our investigation of our first two hypotheses.

5. Do Funds with Higher Incentives and Greater Opportunities Exhibit Bigger December Spikes?

We hypothesize that funds with higher incentives (funds that are in the money and near the money, funds that have higher deltas, funds that have better relative performance, funds that have shorter lockup and restriction periods, and funds that earn significant dollar management fees) should exhibit December spikes. We also posit that funds with greater opportunities (funds with higher volatility and funds with more exposure to the liquidity risk factor) should display December spikes. Secondly, we hypothesize that funds that have higher incentives (opportunities) should exhibit greater December spikes than those with low incentives (opportunities).

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

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

Table 4 shows that the December residual spike is significantly positive (0.700%) for in-the-money funds, which is consistent with hypothesis 1. Moreover, we find that this spike for in-the-money funds is significantly greater than for out-of-the-money funds (difference = 0.700 − (–0.263) = 0.963%), which is consistent with hypothesis 2. We find similar results for near-the-money funds. The December return spike for near-the-money funds is also significantly positive (= 0.537%), and this spike is significantly greater (0.800%) than for out-of-the-money funds. The spikes and differential spikes are economically large, as the average monthly return (residual) is 1.15% (−0.03%). These results are intuitive given the fact that the benefits of returns management are highest for in-the-money funds and, to a somewhat lesser extent, for near-the-money funds.[22]

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the first three lags are statistically significant, but our December dummy coefficient remains virtually the same. Finally, we estimate p-values using Newey-West corrected standard errors with 6 lags and 11 lags. In both cases, we continue to find a significant coefficient for the December dummy.

[22] We use two robustness tests. First, we reclassify funds as in-the-money, near-the-money, and out-of-the-money using strategy-level μ and σ (instead of fund-level μ and σ). Second, we ignore μ and σ, and sort firms into

We repeat our analysis using the second measure of incentives—delta. We find that funds with a high delta exhibit a significantly positive December residual spike of 0.562%. In addition, this spike is significantly greater (0.241%) than for funds with a low delta.[23]

Third, we use the fractional rank at the end of November. We form three groups: top 20%, bottom 20%, and middle 60%. Consistent with our expectations, we find that the December residual spike is significantly positive for the top 20% and the middle 60%. However, the difference in December residual spike between the top 20% and the bottom 20% is not significantly positive,

Table 4
Do funds with higher incentives and greater opportunities manage their reported returns?

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

(*continued*)

three groups based on moneyness with respect to zero: (i) those that are positive as of the end of November (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). In both cases, our inferences remain unchanged.

23 Higher deltas could occur, from higher percentage incentive fees, among other things. We therefore sort funds into three groups based on the percentage incentive fee: those above 20%, those that charge exactly 20% (80% of our sample), and those that charge below 20%. We find that funds with a higher percentage incentive fee have a higher December residual spike and that this spike is significantly greater than that exhibited by low-incentive-fee funds.

Table 4
Continued

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

The table reports the slope coefficients for the December dummy for Models 1 and 2 in Table 3 for the various subsamples listed in the first column. Funds are classified into three groups based on their moneyness as of the end of November, where moneyness is the returns necessary to reach the threshold NAV before incentive fees are paid. Out-of-the-money funds are those for which moneyness is less than $-(\mu + \sigma)$. Near-the-money funds are those for which moneyness is between $-(\mu + \sigma)$ and $-(\mu - \sigma)$. In-the-money funds are those for which moneyness is greater than $-(\mu - \sigma)$. μ is the average monthly fund return, and σ is the standard deviation of monthly fund returns using the entire return history for each fund. Fractional rank is the rank (between 0 and 1) of the fund at the end of November each year based on its performance from January to November, relative to all funds using a specific 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 the end of November. Dollar Management Fee at the end of November is the management fee rate multiplied by the fund size at the end of November. For characteristics other than moneyness, we utilize independent sorts based on Delta at the end of November, Lockup, Restriction Period, Dollar Management Fee at the end of November, Volatility, and Liquidity. The High (Low) groups consist of funds for which the characteristic is greater than or equal to (less than) the median value that year. Similarly the Long (Short) groups consist of funds for which the characteristic is greater than or equal to (less than) the median value that year. The difference in the December spike is between the first group and the second group. For moneyness, the difference is with respect to the out-of-the-money group. For fractional rank, the difference is with respect to the bottom 20% 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 percentages, e.g., a coefficient of 1.483 is equal to 1.483%. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively. Standard errors are corrected for heteroskedasticity and fund-level clustering with p-values reported in parentheses.

although the difference in the spike between the funds in the middle 60% and the bottom 20% is significantly positive (difference = 0.196%; p-value = 0.024).

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

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

We next examine the role of opportunities in returns management behavior. We use two distinct proxies for opportunities: volatility and liquidity. The results in Table 4 indicate that funds with high volatility exhibit a significantly positive residual spike of 0.662%, which is significantly more pronounced than for funds with low volatility (0.211%).[25,26]

Next, we classify the funds into different groups based on their exposure to illiquidity. From Table 4, we find that the December residual spike for low-liquidity funds is significantly positive (0.562%) and that it is significantly higher (0.232%) than for high-liquidity funds.[27,28]

Overall, we find convincing evidence that the funds that have higher incentives and greater opportunities are the ones that manage their reported returns.

6. Robustness

In this section, we document the robustness of our primary finding that funds with higher incentives and greater opportunities manage their reported returns. Table 5 reports the results for each of the tests we perform. For brevity, we report the overall December residual spike from Model 2 of Table 3, the December residual spike for the higher incentives and opportunities subsamples from Column 3 of Table 4 (test of hypothesis 1), and the difference in December residual spikes between the higher incentives and opportunities groups,

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24 Both size (assets under management) and the percentage management fee contribute to higher dollar management fees. We therefore undertake two independent sorts based on November-end fund size and the percentage management fee. We find that both subsamples—funds that are larger and funds that charge a higher rate—exhibit a December spike. However, while the larger funds exhibit a significantly bigger December residual spike than the smaller funds, the higher-fee funds exhibit significantly smaller December residual spikes than the lower-fee funds. Thus, it appears that dollar management fees are an important driver of returns management.

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

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

27 Hedge funds trading in illiquid assets sometimes keeps 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 of the fund performance. If this occurs 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 a bigger December spike, we believe that this might capture the side-pocket effect.

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

Table 5
Do funds with higher incentives and greater opportunities manage their reported returns? Robustness

		Base Case: Gross Residual	Additional factors: BM + Momentum	Additional factors: DVIX + OTM Put	Including Vega	Time -varying Risk Exposure	Fund Fixed Effects	Adjustment for Backfilling Bias	Net Residual	Adjustment for Seasonality
		1	2	3	4	5	6	7	8	9
1	December spike: In the Money	0.700***	1.397***	1.878***	0.694***	0.619***	0.797***	0.708***	0.568***	0.459***
2	Differential Dec spike: In the Money Less Out of the Money	0.963***	1.926***	1.770***	0.960***	0.899***	0.920***	0.969***	0.814***	0.600***
3	December spike: Near the Money	0.537***	0.967***	1.472***	0.543***	0.475***	0.889***	0.530***	0.483***	0.356***
4	Differential Dec spike: Near the Money Less Out of the Money	0.800***	1.495***	1.364***	0.809***	0.755***	0.848***	0.791***	0.729***	0.497***
5	December spike: High Delta	0.562***	1.005***	1.544***	0.565***	0.496***	0.714***	0.564***	0.478***	0.329***
6	Differential Dec spike: High Delta Less Low Delta	0.241***	0.235***	0.316***	0.312***	0.231***	0.224***	0.233***	0.209***	0.115***
7	December spike: Top 20%	0.335***	1.193***	1.715***	0.345***	0.200**	0.326***	0.322***	0.307***	0.088
8	Differential Dec spike: Top 20% Less Bottom 20%	−0.168	0.017	0.190	−0.149	−0.269**	−0.024	−0.187	−0.197*	−0.354***
9	December spike: Mid 60%	0.699***	1.200***	1.716***	0.693***	0.637***	0.759***	0.698***	0.572***	0.477***
10	Differential Dec spike: Mid 60% Less Bottom 20%	0.196**	0.024	0.191*	0.198**	0.169**	0.340**	0.188**	0.068	0.035
11	December spike: Short Lockup Period	0.556***	0.967***	1.388***	0.551***	0.513***	0.721***	0.561***	0.480***	0.352***
12	Differential Dec spike: Short Lockup Period Less Long Lockup Period	0.117	−0.004	0.565	0.116	0.118	0.128	0.122	0.116	0.087
13	December spike: Short Restriction Period	0.587***	1.061***	1.539***	0.589***	0.524***	0.733***	0.590***	0.511***	0.353***
14	Differential Dec spike: Short Restriction Period Less Long Restriction Period	0.258***	0.243***	0.247***	0.265***	0.256***	0.272***	0.258***	0.244***	0.184***
15	December spike: High $ Management Fee	0.551***	0.994***	1.516***	0.556***	0.493***	0.681***	0.554***	0.466***	0.327***
16	Differential Dec spike: High $ Management Fee Less Low $ Management Fee	0.237***	0.229***	0.278***	0.242***	0.243***	0.211***	0.236***	0.202***	0.133***

(*continued*)

Table 5
Continued

		Base Case: Gross Residual	Additional factors: BM + Momentum	Additional factors: DVIX + OTM Put	Including Vega	Time -varying Risk Exposure	Fund Fixed Effects	Adjustment for Backfilling Bias	Net Residual	Adjustment for Seasonality
		1	2	3	4	5	6	7	8	9
17	December spike: High Volatility	0.662***	1.567***	2.052***	0.665***	0.555***	0.891***	0.665***	0.567***	0.422***
18	Differential Dec spike: High Volatility Less Low Volatility	0.451***	1.432***	1.390***	0.455***	0.359***	0.479***	0.447***	0.393***	0.316***
19	December spike: Low Liquidity	0.562***	1.231***	1.699***	0.566***	0.471***	0.847***	0.561***	0.476***	0.240***
20	Differential Dec spike: Low Liquidity Less High Liquidity	0.232***	0.775**	0.687***	0.241***	0.146**	0.400***	0.220***	0.198***	0.085

For various robustness tests, the table reports the residual spike for the overall sample (Model 2 of Table 3), the residual spike for the various subsamples (Column 3 of Table 4), and the difference in December residual spike between various subsamples (Column 4 of Table 4). The "Base Case" reported in Column 1 corresponds to the numbers reported in Tables 3 and 4 using residuals estimated from gross returns. "Additional factors: BM + Momentum," reported in Column 2, uses the residual obtained using the seven factors of Fung and Hsieh (2004), and two additional factors: book-to-market and momentum. "Additional factors: DVIX + OTM Put," reported in Column 3, uses the residual obtained using the seven factors of Fung and Hsieh (2004) and two additional factors: the first difference in the VIX factor of Hasanhodzic and Lo (2007), and the out-of-the-money put option factor of Agarwal and Naik (2004). "Including Vega," reported in Column 4, uses the residuals obtained from Model 2 of Table 3 but augmented with the inclusion of vega as an additional control variable. "Time-varying Risk Exposure," reported in Column 5, uses the residuals obtained by allowing the monthly market beta in the seven-factor model of Fung and Hsieh (2004) to vary with the relative year-to-prior month performance of the fund with respect to its peer group. "Fund Fixed Effects," reported in Column 6, are based on an estimation of Model 2 of Table 3 for the overall sample and for various subsamples using fund fixed effects. "Adjustment for Backfilling Bias," reported in Column 7, is based on results excluding the first two years for data of each fund. "Net Residual," reported in Column 8, is based on the use of net returns instead of gross returns to estimate the residuals. "Adjustment for Seasonality," reported in Column 9, uses the residuals obtained using the seven factors of Fung and Hsieh (2004) and six additional factors: book-to-market, municipal bond closed-end fund, high yield, momentum, lookback straddle on stocks, and lookback straddle on interest rates. Funds are classified into three groups based on their moneyness at the end of November, where moneyness is the returns necessary to reach the threshold NAV before incentive fees are paid. Out-of-the-money funds are those for which moneyness is less than $-(\mu+\sigma)$. Near-the-money funds are those for which moneyness is between $-(\mu+\sigma)$ and $-(\mu-\sigma)$. In-the-money funds are those for which moneyness is greater than $-(\mu-\sigma)$. μ is the average monthly fund return, and σ is the standard deviation of monthly fund returns using the entire return history for each fund. Fractional rank is the rank (between 0 and 1) of the fund at the end of November each year based on its performance from January to November relative to all funds following a particular strategy, i.e., fractional relative rank. Following Sirri and Tufano (1998), we divide the funds into top 20%, middle 60%, and bottom 20% groups based on their fractional relative rank at the end of November. Dollar Management Fee at the end of November is the management fee rate multiplied by the fund size at the end of November. For characteristics other than moneyness, we undertake independent sorts based on Delta as of November-end, Lockup, Restriction Period, Dollar Management Fee as of the end of November, Volatility, and Liquidity. The High (Low) groups consist of funds for which the characteristic is greater than or equal to (less than) the median value that year. Similarly, the Long (Short) groups consist of funds for which the characteristic is greater than or equal to (less than) the median value that year. 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 percentages, e.g., a coefficient of 0.437 is equal to 0.437%. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively. Standard errors are corrected for heteroskedasticity and fund-level clustering with p-values reported in parentheses.

and their corresponding lower incentives and opportunities counterparts from Column 4 of Table 4 (test of hypothesis 2). For ease of comparison, Column 1 reports the base case numbers from Tables 3 and 4. As per hypotheses 1 and 2, we expect rows 1 through 20 to be significantly positive. In the rest of this section, we describe the findings as they relate to a battery of questions asked to confirm that the returns management we observe is a genuine phenomenon.

6.1 Can an omitted factor explain returns management?

An (omitted) factor with December seasonality might have the power to explain hedge fund returns. For this omitted factor to be the main driver of returns management, it must be the case that (i) high-incentive, high-opportunity funds should load on this omitted factor (which would result in a December spike for these subsamples, consistent with the first hypothesis; and (ii) this loading must be greater than the loading for low-incentive, low-opportunity funds (which would result in the high-incentive, high-opportunity funds having a greater December spike than their low-incentive, low-opportunity counterparts, consistent with the second hypothesis. As this seems difficult to argue, we do not expect an omitted factor to fully explain the returns management documented in this article. Nevertheless, we allow for the possibility that an omitted factor might give rise to evidence that could be interpreted as returns management. We therefore perform additional tests (described below), the results of which suggest that an omitted factor could not be responsible for the returns management that we document.

If there is an omitted factor, it is likely to be relevant for funds belonging to strategies for which the seven factors do a poor job of explaining fund returns. In this regard, we first estimate the time series of monthly returns for each strategy by taking a simple average of returns of the funds belonging to that strategy, and then regress the excess strategy return on the seven factors of Fung and Hsieh (2004) to obtain the adjusted R-squared.[29] We then sort the strategies into two categories based on adjusted R^2 and re-estimate Model 2 of Table 3 for these two groups. We find that the subsample of funds belonging to strategies that exhibit low adjusted R^2 has a December residual spike of 0.294%, which is significantly lower than for the subsample of funds belonging to strategies that exhibit high adjusted R^2 (0.357%). This result does not support the suggestion that an omitted factor is responsible for our results.

However, given that equity long-short strategies constitute one-third of our sample, we concentrate on including more equity-oriented factors in the seven-factor Fung and Hsieh (2004) model. In this regard, we augment the seven-factor model with the book-to-market and momentum factors, and repeat our analysis with the residuals from the nine-factor model. Column 2 of Table 5 reports the results. We continue to find a significant December spike for funds

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

with high incentives and opportunities, and this spike is significantly greater than for funds with low incentives and opportunities.

We also augment the seven-factor model with the out-of-the-money put option factor of Agarwal and Naik (2004), and the VIX factor found in Hasanhodzic and Lo (2007). We repeat our analysis using residuals obtained after including these two factors. Column 3 of Table 5 reports the results, which indicate that all of our inferences continue to hold.

6.2 Can inadequate controls for excessive risk taking in December explain the returns management?

If our controls for risk taking in December are inadequate, one might observe a December spike. However, to document returns management, the omitted controls must lead to a greater spike for high-incentive, high-opportunity funds. We believe that this is hard to argue.

If funds take more risk in December, the cross-sectional distributions of fund residuals are likely to have fatter tails. Specifically, the excess kurtosis of December residuals should be positive and significantly greater than the excess kurtosis of residuals from January to November, which does not appear to be the case. The excess kurtosis of December residuals is 138.5 (p-value $= 0.20$), which is not significantly different (p-value $= 0.91$) from the excess kurtosis of residuals in the other months (kurtosis $= 128.4$). Nevertheless, we take two additional steps to control for risk taking—one in the cross-sectional setting and the other in the time-series setting.

First, we include the prior month's vega—the sensitivity of the manager's compensation for a 1% point change in volatility—as an additional control in Model 2 of Table 3. Vega has been used as a proxy for risk-taking incentives (Guay 1999; Coles, Daniel, and Naveen 2006). By including vega, we allow performance to vary with risk-taking incentives. We then perform all of our subsample analysis (Table 4) using this enhanced Model 2 regression. As the results reported in Column 4 of Table 5 show, all of our results hold.

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

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

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

$$\beta_{i,t} = \kappa_{i,1} + \kappa_{i,2}\, Frank_{i,t-1}, \tag{3}$$

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

$$\beta_{i,December} = \kappa_{i,1} + \kappa_{i,2} Frank_{i,November}. \tag{4}$$

Similarly, one can compute the betas for the other months of the year. We find that the December beta is significantly higher than the average beta for the rest of the year (0.32 and 0.24, respectively; $p = 0.02$). To document returns management, we then re-estimate cross-sectional regressions of the residuals obtained using the above method for the full sample (Model 2 of Table 3) and for various subsamples (Table 4). Column 5 of Table 5 reports the results. We continue to find support for returns management.

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

6.3 Do managers work so much harder in December that their work drives our conclusions on returns management?

In this subsection, we control for the possibility that all managers work especially hard in December. We do not believe this to be the case, because incentive fees depend not only on whether a manager surpasses a threshold but also on the magnitude by which he/she exceeds expectations. Therefore, the manager has an incentive to work hard all of the time and not just in December, as fees are increasing in the profits he/she makes for investors. However, if we assume that all managers work harder in December than in other months, then those managers with higher incentives are likely to work harder than those with lower incentives and this, in turn, could potentially explain a *subset* of our results—those results indicating that managers with high incentives exhibit a positive December spike (hypothesis 1) and that these managers exhibit a greater December spike than managers with low incentives (hypothesis 2). It is hard, however, to argue why high-opportunity managers would work harder in December than low-opportunity managers. Therefore, the "working hard" story cannot explain all of our results.

One way of testing whether hard work plays a role is to examine skewness. We find that skewness of residuals in December is not significantly

[30] Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997), among others, document tournament behavior in mutual funds, while Brown, Goetzmann, and Park (2001) document a similar behavior in hedge funds.

positive (skew = 2.7; p-value = 0.32), and it is not significantly different (p-value = 0.52) from the skewness of residuals for the January to November period (skew = 1.1). Therefore, managers do not appear to work relatively harder in December. Nevertheless, we attempt to control for any unobserved hard work that managers might be putting in December as follows:

$$Residual_{it} = Function\{December,\ Controls\} + \varepsilon_{it} \text{ and} \tag{5}$$

$$\varepsilon_{it} = Hard\,Work_i + \eta_{it}. \tag{6}$$

$Hard\ Work_i$ represents the fund-specific time-invariant unobserved hard work of manager i. As we do not have a good proxy for hard work, the effect of hard work on performance is reflected in the error term. If managers work harder in December, then this would imply that the error term would be correlated with the December dummy and, hence, the OLS regressions would be invalid. A simple econometric solution to this correlated omitted variable problem is to estimate fund fixed effects. We therefore estimate Model 2 of Table 3 using fund fixed effects and then replicate Table 4 using this model. Column 6 of Table 5 reports the results. All of our inferences remain unchanged.

6.4 Does controlling for backfilling bias change the results?

In this subsection, we try to control for backfilling bias. As mentioned before, our sample includes the performance history of defunct funds (36% of fund-year observations), which leads us to believe that survivorship bias is not a major concern. To tackle backfilling bias, we follow Ackermann, McEnally, and Ravenscraft (1999), and exclude the first two years' data for each fund from the analysis. We report the results in Column 7 of Table 5 and find that all of our inferences continue to hold.

6.5 Are the results similar if net-of-fee returns are used?

We utilize net returns, which are important to investors, instead of gross returns to estimate the residuals using Fung and Hsieh (2004) regressions. We then estimate Model 2 of Table 3 for the overall sample and for various subsamples using these residuals. Column 8 of Table 5 reports the results. In 19 out of the 20 cases, the findings are consistent with our hypotheses.

6.6 Can seasonality in the underlying assets of hedge funds explain our results?

To ensure that our results are not driven by seasonality in the underlying assets of hedge funds, we include additional factors to estimate the residuals. Specifically, we augment our base case model (seven-factor model of Fung and Hsieh 2004) with three factors that are known to exhibit turn-of-the-year effects. First, we add Fama and French's (1993) book-to-market (HML) factor. Ritter and Chopra (1989) and Loughran (1997) document seasonality in the book-to-market effect with value firms showing higher January returns than growth firms. Second, we add the municipal bond closed-end fund factor found in Starks, Yong, and Zheng (2006), who document a turn-of-the-year or January effect for municipal bond closed-end funds. Third, we include Chang and Pinegar's (1986) high-yield bond factor. Chang and Pinegar (1986) find evidence of a January effect in non-investment-grade bonds but no evidence of a January effect in investment-grade bonds or Treasury bonds.[31] For the sake of completeness, we also include three more factors: the momentum factor suggested by Jegadeesh and Titman (1993); lookback straddle on stocks, which is found in Fung and Hsieh (2004); and lookback straddle on interest rates, as suggested in Fung and Hsieh (2004). This gives us a comprehensive 13-factor model to investigate whether our results are driven by seasonality arising from the underlying assets held by hedge funds. The results are reported in Column 9. All of our results continue to hold.

6.7 Do other months exhibit similar patterns, i.e., are the December results spurious?

A finding of similar patterns in the residual spike for months other than December would raise doubts about our returns management story. To rule out the possibility that our results are spurious, we take two steps. First, using the 13-factor residual as the dependent variable in Model 2 of Table 3, we estimate the January spike by replacing the December dummy with a January dummy, and we estimate the February spike by replacing the December dummy with a February dummy. We continue this exercise for all of the monthly spikes from January to November. Second, we repeat these regressions for each of the subsamples based on incentives to effectively replicate Table 4 using January–November spikes.[32] Here, we are careful to use incentives for the prior month to form the subsamples. For example, when we are examining the February spike, we use incentives as of the end of January. In unreported results, we find that the December residual spikes for different high-incentive subsamples are positive and significant in five of eight cases. In contrast, we do not find any systematic patterns in the residual spikes for the different incentive subsamples for any of the months from January to November.[33] These results indicate that the returns management we document is not spurious.

In summary, our inference that funds with higher incentives and greater opportunities manage returns is robust to several alternative interpretations.

[31] Their finding is supported by Maxwell (1998), who concludes that window dressing is a significant factor behind the January effect in non-investment-grade bonds.

[32] One might observe a spike in any given month as long as opportunities are there. We therefore focus on incentives to ensure that the returns management we document is not spurious.

[33] There are some sporadic or spurious cases of significance for some subsamples for February, April, June, October, and November.

7. What Are the Modus Operandi That Funds Use for Returns Management?

Given the evidence of returns management, we investigate the mechanism employed by funds to accomplish such management. Toward that end, we test hypotheses 3 and 4 (*savings* and *borrowing* hypotheses). Recall that the *savings hypothesis* posits that funds underreport positive returns up to November to create reserves that can be added to months with negative returns. Unused reserves are then added back in December. We test this by adding two explanatory variables to Model 1 of Table 3: (a) $\text{Reserves}_{i,m-1}$, the cumulative return from January up to month m, which takes a value of 1 if positive and 0 otherwise; and (b) the interaction of this variable with the December dummy. If the fund manager is adding reserves accumulated in previous months in December, then this interaction term should be positive. Our results, shown for Model 1 in Panel A of Table 6, confirm that the coefficient on the interaction is positive (coefficient = 0.074) and significant at the 1% level. This result is also economically significant. A one-standard-deviation change in the reserves variable results in an increase in December returns of 0.97%.

An alternative method of computing 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 an MA(2) process in true returns. Following their insights, we also construct an alternative measure of reserves—the cumulative difference between the unobserved true returns and the observed returns up to month m, which takes a value of 1 if positive and 0 otherwise. In untabulated results, we find that the interaction of this alternative measure of reserves with the December dummy is significantly positive for Model 1 (coefficient = 0.667; significant at the 1% level). These findings again lend strong support to the savings hypothesis.

Next, we test the *borrowing hypothesis,* which suggests that portfolio pumping by funds causes December returns to be higher at the expense of January returns. In this scenario, one would expect lower returns in January of the year following a high December return. To test this hypothesis, we add two variables to Model 1 of Table 3: (a) a January dummy that takes a value 1 if the month is January of next year and 0 otherwise; and (b) the interaction of the January dummy with returns during the previous month. As per the borrowing hypothesis, one would expect to observe a negative coefficient for the interaction term. Results reported in Model 2 of Panel A of Table 6 indicate that the coefficient on the interaction of the January dummy and the lagged monthly return is negative (coefficient = –0.014) but not statistically significant.[34] Thus, we do not find support for the borrowing hypothesis.

[34] We find that the slope coefficient on the January dummy itself is positive (coefficient = 0.518) and significant at the 1% level in Model 2 of Table 6. This is consistent with the well-documented January effect in stock returns.

Finally, we test both the *savings* and *borrowing* hypotheses by including the corresponding variables in Model 3 of Panel A of Table 6. We continue to find support for the savings hypothesis but not for the borrowing hypothesis.

Panel B of Table 6 reports the two coefficients from Model 3, Panel A, Table 6, that test the savings and borrowing hypotheses for the high-incentive

Table 6
How do funds manage returns? Tests of the savings and borrowing hypotheses

Panel A

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

(*continued*)

Table 6
Continued

Panel B

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

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

and high-opportunity subsamples.[35] We find consistent support for the savings hypothesis across all subsamples, but the evidence in favor of the borrowing hypothesis is weak at best.

7.1 An additional test of the borrowing hypothesis based on portfolio holdings

We undertake additional tests of the borrowing hypothesis using equity holdings data for hedge funds. In particular, we follow the approach used 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, the SEC requires that all funds with assets in 13(f) securities exceeding \$100 million and with large positions in stocks (more than 10,000 shares or \$200,000) need to submit 13f filings on a quarterly basis. This enables us to obtain equity holdings data for 206 hedge funds in our sample.[36]

35 If saving and borrowing were the only mechanisms by which funds could manage their returns, then we should find that either the borrowing effect or the saving effect is significantly greater for the high-incentive, high-opportunity groups relative to their low-incentive, low-opportunity counterparts. As other mechanisms might also result in returns management, we have no hypothesis concerning the strength of the borrowing and saving effects in the high groups compared to the low groups. Therefore, we only report the borrowing coefficient and the saving coefficient for the high groups.

36 We follow a procedure similar to Brunnermeier and Nagel (2004), who identify the equity holdings of 52 hedge funds. Recently, Griffin and Xu (2009) used holdings data for hedge funds to determine the presence of skill.

We report the average year-end inflation of stocks held by hedge funds in Table 7. Our analysis follows that found in Table 7 of Carhart et al. (2002). Each year, we sort stocks into five quintiles based on six-month returns up to the second-last day of the year. We then sort these stocks into five quintiles based on market capitalization on the second-last day of the year. This provides us with 25 return-size portfolios.

Next, we determine the year-end inflation in those 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 characteristics such as moneyness, delta, fractional rank, and dollar management fees at the end of November. We also use other attributes, such as lockup periods, restriction periods, the volatility of fund returns, and fund exposure to illiquidity, to segregate funds into different subsamples. For example, using November-end moneyness, 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 of the 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 those that are in-the-money and near-the-money, have high deltas, have high fractional ranks (top 20% and middle 60%), have short lockup and restriction periods, and have high dollar management fees. Similarly, funds with greater opportunities to inflate returns are those with high volatility and high exposure to illiquidity.

Following Carhart et al. (2002), we compute return inflation as the return on each of the 25 long-short stock portfolios on the last day of the year net of its return on the first day of the next year. To examine whether this inflation is significantly different from zero, we first compute the return inflation for every non-overlapping two-day period in the year. We then compute a z-statistic for return inflation for each of the 25 portfolios for each year as the return inflation net of the average of all possible two-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 the average end-of-year inflation across 25 return-size portfolios over the nine-year period (Table 7). The z-statistic for this overall average is the sum of the z-statistics over the 325 portfolio-year combinations divided by the square root of 325. The reported p-value is the probability of obtaining a z-statistic greater than this overall z-statistic.

In addition, Agarwal, Fos, and Jiang (2010) use holdings data to estimate the reporting-related biases, and Agarwal et al. (2010) study the determinants and abnormal performance of hedge fund holdings that are not immediately disclosed.

Table 7
Tests of borrowing hypothesis based on stock holdings data

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

This table reports the average year-end inflation of stocks held by hedge funds. The analysis follows that in Table 7 of Carhart et al. (2002). Each year, stocks are sorted into five quintiles based on six-month returns up to the second-last day of the year. Stocks are also sorted into five quintiles based on market capitalization as of the second-last day of the year. This yields $13 \times 5 \times 5 = 325$ portfolio-year combinations. Within each portfolio, we perform independent sorts based on various fund characteristics, such as end-of-November moneyness, end-of-November delta, lockup periods, restriction periods, fractional relative rank, end-of-November dollar management fees, volatility of fund returns, and liquidity betas. Funds are classified into three groups based on their moneyness at the end of November, where moneyness is the returns necessary to reach the threshold NAV before incentive fees are paid. Out-of-the-money (OTM) funds are those for which moneyness is less than $-(\mu + \sigma)$. Near-the-money (NTM) funds are those for which moneyness is between $-(\mu + \sigma)$ and $-(\mu - \sigma)$. In-the-money (ITM) funds are those for which moneyness is greater than $-(\mu - \sigma)$. μ is the average monthly fund return, and σ is the standard deviation of monthly fund returns using the entire return history for each fund. Following Sirri and Tufano (1998), funds are classified into three groups based on their fractional relative rank at the end of November—top 20%, middle 60%, and bottom 20%. The High (Low) groups consist of funds for which the characteristic is greater than or equal to (less than) the median value that year. In each of the 25 portfolios, we go long on stocks in the hedge fund with higher incentives (ITM and NTM, high delta, low lockup and restriction periods, top 20% and middle 60% relative rank, and high dollar management fee) and higher opportunities (high volatility and low liquidity beta), and short on stocks in hedge funds with lower incentives (OTM, low delta, high lockup and restriction periods, bottom 20% relative rank, and low dollar management fee) and lower opportunities (low volatility and high liquidity beta) to manage returns. Year-end Return Inflation is calculated as the return on this long-short portfolio on the last day of the year minus the portfolio return on the first day of the next year. To compute the z-statistic, we first compute the return inflation for every non-overlapping two-day period in that year for each portfolio. The z-statistic for each portfolio is given by: (Year-end Return Inflation minus the mean of all possible two-day returns for that portfolio) divided by the standard deviation of the two-day returns for that portfolio. For the sake of brevity, we report only the average year-end inflation across the 325 portfolio-year combinations. The z-statistic for this overall average is the sum of the z-statistics of the 325 portfolio-years divided by the square root of 325. The reported p-value is the probability of obtaining a z-statistic greater than this overall z-statistic assuming a standard normal distribution. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

The results in Table 7 indicate that funds with higher moneyness, greater deltas, superior relative performance, and larger dollar management fees exhibit abnormally high year-end return inflation, which is followed by a reversal on the first day of January. We do not find that illiquid funds engage in borrowing from the future. While, on the surface, this may seem surprising, it must be noted that the funds that are forced to report their equity holdings are large, equity-oriented funds and their typical holdings are not invested in illiquid securities. Overall, these findings suggest a subgroup of hedge funds facing stronger incentives to inflate year-end returns by borrowing from January returns.

However, some caveats are in order. First, this holdings-based test sheds light only on the borrowing hypothesis and does not preclude the possibility of funds also saving for rainy days, which could 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, which are likely to be liquid. Arguably, if one had access to the non-equity holdings of hedge funds, some of which are likely to be more illiquid, one might find even stronger evidence of borrowing from January returns.

8. Concluding Remarks

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

We also provide evidence on two mechanisms that might be employed by hedge funds to manage returns. The 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 a rainy day). If some of these reserves are left unutilized, they are added to the December returns, which results in a spike. The second mechanism involves funds borrowing from their January returns of the subsequent year to improve their December returns in the current year. This can be achieved by funds pushing up the security prices at the end of December through last-minute buying, which is followed by price reversals in January.

Our findings have important implications for regulators and investors. Regulatory bodies in the US, such as the SEC, have recently expressed concern about accurate security valuation in hedge funds. Our findings have important implications for investor welfare as well. 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 the timing of their entry into and exit from those funds. Our results can help regulators and investors better understand the potential returns management phenomenon in the hedge fund industry.

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

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

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

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