Do institutional investors have an ace up their sleeves? Evidence from confidential filings of portfolio holdings

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Executive Summary

This paper is the first study to examine the confidential holdings of institutional investors that are filed separately from their original/regular 13F holdings. Unlike the original holdings that are promptly disclosed on a quarterly basis, the confidential holdings are not revealed for up to one year. The Securities and Exchange Commission allows institutions to delay disclosure if they can provide justifications showing that instant disclosure could reveal their proprietary trading strategies and thereby hurt their competitive positions. Hence, the confidential holdings of institutions should better reflect their private information. The extant literature that uses portfolio holdings to evaluate stock-selection skills has relied on standard databases such as Thomson CDA/Spectrum, which only report original holdings. Thus, the prior literature may have underestimated the ability of institutional investors and ignored the cross-sectional differences in the ability of different types of institutional investors.

We contribute to this literature by studying a hand-collected comprehensive dataset of confidential holdings filed through the 13F amendments. Our preliminary results are consistent with certain types of institutional investors possessing superior information as evidenced by their confidential portfolios exhibiting superior risk-adjusted performance. Specifically, we find that asset-management firms (such as hedge funds, investment companies/advisors, and pension funds) that follow more active investment strategies are more likely to seek confidentiality compared to relatively passive investors such as banks and insurance companies. In addition, compared to original holdings, we observe that confidential holdings are more likely to contain private information as they include stocks associated with information-sensitive events such as mergers and acquisitions, and those having greater information asymmetry. Finally, we show that confidential holdings of asset-management firms exhibit superior risk-adjusted performance.

Taken together, our findings provide useful insights into the economics of portfolio disclosure and thus have important implications for investment professionals, policy makers, and regulators. For practitioners, we provide new evidence on the stock-picking skill of institutional investors. For policy makers and regulators, our results inform the debate on the portfolio disclosure in the investment management industry.

I. Research Objectives and Literature Review

A number of papers have examined the performance of institutional investors using their quarterly portfolio holdings reported to the Securities and Exchange Commission (SEC). For example, Grinblatt and Titman (1989, 1993), Grinblatt, Titman, and Wermers (1995), Daniel, Grinblatt, Titman, and Wermers (1997), Chen, Jegadeesh, and Wermers (2000), Wermers (2000), Frank, Poterba, Shackelford, and Shoven (2004), Kacperczyk, Sialm, and Zheng (2005), Wermers, Yao, and Zhao (2007), among others, analyze whether mutual funds outperform their benchmarks. Griffin and Xu (2008) and Aragon and Martin (2009) conduct a similar analysis with another class of active managers — hedge funds. For an excellent survey of the literature on performance evaluation using information on portfolio holdings, see Wermers (2006). Although all the institutions that have investment discretion over $100 million or more in Section 13(f) securities are required to disclose their portfolio on a quarterly basis by filing 13F forms, the Securities and Exchange Commission (SEC) allows for the confidential treatment of certain portfolio holdings of institutions for which they can file 13F amendments. With adequate written factual support from the manager, this provision allows the institutions to delay the disclosure of their holdings up to one year from the date the manager is required to file the original 13F form.[1]

All papers in the current academic literature use only the data reported in original 13F filings, usually from the Thomson CDA/Spectrum database, and therefore ignore the confidential filings of institutions in the 13F amendments filed with the SEC but not included in the Thomson database.[2] Our paper fills this gap in the literature by being the first study that examines the existence of private information in the confidential filings of institutional investors and whether such filings are associated with superior risk-adjusted performance compared to the original filings.

If the portfolio managers possess private information, they have incentives to not disclose their positions before they have reaped the benefits. For example, Perry Corp, a well-known hedge fund, attempted to keep secret its building of position in Mylan Inc. in 2004 when the company was contemplating a merger with King Pharmaceuticals Inc. The deal ultimately fell

[1] This one-year period can be extended further if an instruction with additional factual support is filed by the manager 14 days in advance of the expiration date.

[2] Aragon and Martin (2009) is one among the very few papers that use the original 13F filings. They examine the original filings of a random sample of 300 hedge funds from the SEC EDGAR database but not their confidential filings that are available in the 13F amendments filed separately.

through, mainly due to the opposition of another hedge fund and billionaire investors Carl Icahn. But Perry was under investigation by the SEC on the allegation of improperly withholding details about a large investment in an effort to profit. Though the two parties settled in July 2009, the case highlights continuing tension between the desire of some investors to withhold information that could reveal their investment strategy, and the demand of the public and regulators for transparency.

As a matter of fact, in the past, several hedge funds and successful investors such as Warren Buffett have appealed to the SEC for an exemption from revealing their positions in the 13F forms but have been unsuccessful in convincing the SEC. Philip Goldstein, an activist hedge fund manager at Bulldog Investors likens his stock holdings "trade secrets" like the protected formula used to make Coke, and contends that complying with the 13F rule "constitute[s] a 'taking' of [the fund's] property without just compensation in violation of the Fifth Amendment to the Constitution."[3]

Consistent with the contention regarding this subject and the importance of the 13F disclosure, beginning in 1998, the SEC tightened the conditions for accepting the 13F amendments that allow the managers confidential treatment for their portfolio holdings (Beckett, 1998).[4] Hence, there are significant costs associated with filing 13F amendments as the managers are required to describe the investment strategy, e.g., risk arbitrage, associated with the securities for which they are seeking confidentiality. Furthermore, the managers are required to demonstrate that revelation of these holdings can hurt their competitive position. If the managers choose to file 13F amendments for those securities where they have superior private information, prior literature would have underestimated the managerial ability.

In this paper, we examine if there is indeed any evidence of superior information in the confidential filings of institutions. Specifically, our research objectives are to address the following three questions:

1. Are confidential filings more likely to be made by certain institutions that are often believed to possess private information such as hedge funds, investment advisors, and investment companies?

[3] For a more detailed discussion, see Philip Goldstein's interview in September 12, 2006 issue of Businessweek: http://www.businessweek.com/print/investor/content/sep2006/pi20060913_356291.htm

[4] Cauchi (2005) also discusses the increased stringency in the filing requirements.

2. Do the stocks included in the confidential filings support the motives of these filings, e.g., are these stocks associated with certain corporate events such as mergers and acquisitions and/or these stocks likely to have greater information asymmetry?
3. Do confidential filings show higher abnormal returns than the original 13F filings as evidence of superior information being embedded in the confidential filings?

II. Research Outline: Data, Hypotheses, and Methodology

II.A Data

One of the main challenges in this study has been to collect and process the 13 filings of institutions that are reported to the SEC EDGAR database. We retrieve original and amendment 13F filings from EDGAR database over the sample period from March 1999 to June 2007. Even though we have filings available after June 2007, we stop at that date to allow us to examine the performance one year after the end of our sample period. As the reporting styles vary significantly across different institutions, obtaining holdings data from these documents is a very time-consuming task. In our preliminary analysis, we were able to extract the stock holdings in a sample of over 60% of all the original and amendment filings reported to the SEC over the sample period. As required by the SEC, all 13F amendment documents should specify whether they are restatements or pertain to new holdings that are excluded from the original filings. Our analysis focuses only on the latter case and identifies confidential stock holdings as those in an amendment filing that are unreported in the corresponding original filing, or constitute at least a 100% increase from the positions in the original filing. We focus on only common stock holdings for which risk-adjusted performance measures are well-defined in the extant literature and also allow us to compare our results with the prior literature. Finally, we filter about 1% of all the filings that show extremely long delays from the holdings date, possibly as a result of data errors.

Based on the above selection criteria, we are able to identify 941 confidential 13F filings by 131 institutions and 38,219 original 13F filings by 2,917 institutions. The dollar value of the stock positions included in the confidential filings is substantial, with an average of $323 million per filing, representing on average, about 13% of the dollar value of the revealed stock positions in the original filings.

We use this novel dataset to address the three research questions by first modeling the determinants of confidential filings and then examining the abnormal performance of these filings relative to that of the original 13F filings that are disclosed on quarterly basis.

II.B Hypotheses Development and Methodology

Asset-management companies are perhaps most likely to be engaged in proprietary trading strategies where private information allows them to deliver superior returns for their investors. Of course, the degree to which they possess information and their ability to benefit from it will vary with hedge funds being at one end of the spectrum for being the most aggressive and active managers and pension funds being at the other end, and investment companies/advisors falling somewhere in between. In contrast, the primary business of banks and insurance companies is different from asset management firms. Hence, they are less likely to be involved in gathering private information and stock picking. This suggests that compared to banks and insurance companies, asset-management firms are more likely to strategically disclose their holdings and seek confidential treatment for their 13F filings.

Thus, our first hypothesis is as follows:

HYPOTHESIS 1: *Institutions that apply more active investment strategies are more likely to have confidential holdings.*

Our second hypothesis is about the type of stocks that are included in the confidential filings. Since the primary motivation of seeking confidentiality is to preserve the value of private information, confidential filings should reflect such information. An explicit case identified by the SEC where managers are allowed confidentiality relates to open risk arbitrage positions. Hence, an important determinant of a stock being included in the confidential filings should be whether the firm is involved in M&A speculation.

In addition, another factor that would determine if a stock is incorporated in the confidential portfolios of institutions is the degree of information asymmetry. Greater information asymmetry provides more opportunities for profitable private information acquisition activities.[5] This incentivizes the institutions to conceal their information by including such stocks in their confidential filings. We use several proxies for firm-specific drivers of information asymmetry. These include firm size, book-to-market, sales growth, liquidity, and analyst following. Extant literature indicates that greater information asymmetry is associated with smaller stocks (Chari, Jagannathan, and Ofer (1988), Llorente, Michaely, Saar, and Wang (2002)), lower book-to-market stocks (McLaughlin, Safieddine, and Vausdevan (1998)), illiquid

[5] In fact, some investors having private information can lead to greater information asymmetry. Since we do examine the determinants of information asymmetry, we are not concerned about the direction of causality and only care about the type of stocks associated with greater information asymmetry.

stocks (Glosten and Milgrom (1985), Merton (1987), Diamond and Verrecchia (1991), and Kim and Verrecchia (1994)), and lesser analyst following (Brennan and Subrahmanyam (1995), Hong, Lim, and Stein (2000), Chang, Dasgupta, and Hilary (2006)).

Since the primary motivation for institutions to file their holdings confidentially is driven by information, stocks involved in M&A speculation and those associated with greater information asymmetry are more likely to be included in the confidential portfolios. If M&A speculations are positively correlated with ex post M&A announcement, then stocks of firms that are targets of M&A transactions should appear disproportionately among the confidential holdings. This provides us with the following empirical hypothesis:

HYPOTHESIS 2: *Stocks associated with greater likelihood of private information (i.e., those involved in mergers and acquisitions and those with higher information asymmetry (i.e., stocks with smaller market capitalization, lower book-to-market ratio, higher illiquidity, and lower analyst following)) are more likely to be included in the confidential filings.*

We test the above Hypotheses 1 and 2 by estimating the following logistic regression:

$$Prob\left(S_{i,t}\right) = f\left(Institution\ Type, Stock\text{-}related\ Information\ variables\right) + Controls + Industry\ Dummies + Quarter\ Dummies$$

where $S_{i,t}$ is an indicator variable that equals one if the stock S is included in the confidential filings of institution i during quarter t, *Institution Type* includes indicator variables for three of the four types of institutions in our sample, namely hedge funds (HF), investment companies/advisors (MF), and pension funds (PF) with the excluded category being banks and insurance companies, and $Stock-related\ Information\ variables$ include an indicator variable IND_MA that takes a value of one if the stock is of a firm involved in merger and acquisition (M&A), natural logarithm of the market capitalization of the firm (LOGSIZE), industry-adjusted book-to-market value of the firm (BM_ADJ)[6], stock illiquidity (ILLIQ), and the extent of analyst following (ANALYST). Control variables include past twelve-month stock returns for momentum effect, sales growth of the firm, and distance-to-default measure as computed in Vassalou and Xing (2004). Finally, we include dummies for industries and quarters

[6] Following Daniel et al. (1997), the book-to-market (B/M) ratio is the ratio of the book-value at the end of the firm's fiscal year during the calendar year preceding the formation date to the market value at the end of the preceding December. We then "industry-adjust" the B/M ratios by subtracting the long-term industry average book-to-market ratio from each individual firm's ratio, following Cohen and Polk (1998). The B/M ratios are adjusted for industries using the 48 industry classifications as in Fama and French (1997).

to control for industry and variation over time. Following the insights in Petersen (2009), we correct the standard errors through clustering by institution.

In terms of expected form of results, for evidence in support of Hypotheses 1 and 2, we expect a (a) positive sign on the indicator variables: HF, MF, and PF, (b) positive sign on the indicator variable, IND_MA, negative signs on LOGSIZE, BM_ADJ, and ANALYST, and positive sign on ILLIQ.

If the private information embedded in the confidential filings is superior, one would expect that the abnormal performance of these filings should be greater than that of the original 13F filings that are publicly disclosed. This provides us with our last hypothesis:

HYPOTHESIS 3: *Abnormal performance of the confidential filings for each type of institution should be greater than that of its corresponding original filings.*

We test the above hypothesis by estimating the following regression:

$$DGTW\_adj\ Returns = f(Institution\ \&\ Filing\ Type) + Controls + Quarter\ Dummies$$

where $DGTW\_adj\ Returns$ are the returns of the equally-weighted portfolio of original or confidential filings of institutional investors after adjusting for the benchmark returns as in Daniel, Grinblatt, Titman, and Wermers (1997), commonly referred to as DGTW holdings-based measure [7], $Institution\ \&\ Filing\ Type$ are indicator variables for each of the original and confidential filings of the four types of institutions in our sample: (a) hedge funds (HFORIG and HFCONF), (b) investment companies/advisors (MFORIG and MFCONF), (c) pension funds (PFORIG and PFCONF), (d) banks and insurance companies (BKORIG and BKCONF), with the excluded category being the original filings of banks and insurance companies (BKORIG). Control variables include the natural logarithm of the total number of stocks in both the filings (original and confidential), natural logarithm of the frequency of confidential filings, and the natural logarithm of the dollar value of both the filings. We include dummies for quarters to control for variation over time and correct the standard errors through clustering by institution.

In terms of expected form of results, for evidence in support of Hypothesis 3, we expect the equally-weighted DGTW benchmark-adjusted returns to be higher for the confidential filings

[7] Following their methodology, in June of each year, we form 125 portfolios using all the common stocks listed on NYSE, AMEX and NASDAQ based on the size (NYSE size-quintile), book-market ratio and momentum using monthly CRSP data. After getting the quintile for each stock, we match with the daily CRSP data. The daily DGTW benchmark return for each fractile is the value-weighted daily return of all the stocks in that fractile.

compared to the original filings of each type of asset-management firms and for all the asset-management firms (HF, MF, and PF) together, i.e., (a) $DGTW_{HFCONF} > DGTW_{HFORIG}$ (b) $DGTW_{MFCONF} > DGTW_{MFORIG}$, (c) $DGTW_{PFCONF} > DGTW_{PFORIG}$, and (d) $DGTW_{HFCONF} > DGTW_{HFORIG}$ & $DGTW_{MFCONF} > DGTW_{MFORIG}$ & $DGTW_{PFCONF} > DGTW_{PFORIG}$.

Our preliminary results support all three hypotheses. First, we find that asset-management firms such as hedge funds, investment companies and investment advisors, and pension funds are more likely to seek confidentiality compared to banks and insurance companies. Second, we observe that compared to original filings, confidential filings are more likely to include stocks associated with information-sensitive events such as mergers and acquisitions, and stocks with greater information asymmetry as measured by firm size, trading liquidity, and analyst coverage. Finally, we notice that confidential filings exhibit superior risk-adjusted performance compared to the original filings and this is especially true for asset-management firms that are more likely to invest in gathering private information.

III. Potential Implications and Conclusions

Our research has important implications for researchers and regulators concerned with the transparency of securities markets in general, and the role of mandatory disclosure of investments by institutions in particular. Currently, views are split especially on to what extent lightly-regulated financial institutions (such as hedge funds) should be monitored by the regulators or other market participants. A thorough study based on a complete collection of institutional investors' quarterly holdings could certainly help settle the controversy regarding the value and effect of "non-transparent" holdings and identify key factors that cause cross-sectional variation in the confidential filing activities.

Our findings will provide useful references for law and policy makers on how far they should go in regulating the investment management industry and in tightening up disclosure rules; and for institutional investors on the best practice of disclosing investment positions. Finally, our research also helps researchers better understand the potential bias from conducting analyses based on the conventional data sources on institutional investors' portfolio holdings.

IV. Timetable

We plan to complete the project in one year's time, progressing in three stages.

- Stage One: data collection and preliminary data analysis. We have currently finished preliminary data collection. We expect to complete this stage in another two to three months.
- Stage Two: formal analyses and possible data expansion/refinement. This state will take about six month during which we will write up the results into academic research paper(s).
- Stage Three: polish and dissemination of our research work. This state could be relatively open-ended. We plan to submit the resulting paper(s) to a wide range of professional conferences, both for academicians and practitioners, including those sponsored by the Q-Group. We will target both general-interest conferences (such as the American Finance Association Annual Conference) as well as special topic conferences on investment management. The target print outlet of our research work will be a leading finance journal.

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RESEARCH

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1. Do Institutional Investors Have an Ace Up Their Sleeves? Evidence from Confidential Filings of Portfolio Holdings (with Wei Jiang, Yuehua Tang, and Baozhong Yang)

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1. Research Grant from BNP Paribas Hedge Fund Centre at HEC Paris (10,000 Euros) in 2009 (with Costanza Meneghetti)

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4. Foundation for Managed Derivatives Research (FMDR) Grant (US $15,000) in 2005 (with Nicole Boyson and Narayan Y. Naik)

5. BSI Gamma Foundation Research Grant (US $12,000) in 2004 (with Naveen D. Daniel and Narayan Y. Naik)

6. BSI Gamma Foundation Research Grant (US $12,000) in 2002 (with Narayan Y. Naik)

7. INQUIRE Europe Research Grant (CHF15, 000) in 2002 (with Naveen D. Daniel and N.Y. Naik)

8. INQUIRE UK Research Grant (£10,000) in 1998 (with Narayan Y. Naik)

SCHOLASTIC AWARDS AND HONORS

1. Faculty Recognition Award for Excellence in Research, Robinson College of Business, 2008.
2. Summer Research Grant, Robinson College of Business — 2002, 2003, 2004, 2005, 2006, 2007, 2008, and 2009
3. First prize for best paper in hedge funds at European Finance Association (EFA) 2006 conference
4. First prize for best paper in hedge funds at European Finance Association (EFA) 2003 conference
5. 2001 INQUIRE Europe, Third Prize (2002)
6. Dimitris N. Chorafas Foundation Prize for Economics and Computational Finance (2000)
7. Fauchier Partners' Ph.D. Scholarship at London Business School (1999-2001)
8. Edward Jones Fellowship at London Business School (1998-99)
9. Frank Russell International Ph.D. Scholarship in Investment Management at LBS (1997-98)
10. Investment Management Program Prize at London Business School (1997-98)
11. London Business School Ph.D. Program Financial Award (1996-2001)
12. British Council Chevening Scholarship for Ph.D. Program (1996-99)
13. Awarded for securing first rank in Master of Management Studies (1994)
14. Chairman, Board of Governors, Gold Medal for securing highest marks among all the disciplines (1992)
15. Vice-Chancellor’s Gold Medal for securing highest marks in Mechanical Engineering (1992)
16. Silver Medal for securing highest marks in Machine Design in Engineering (1992)
17. National Merit Scholarship in Engineering (1988-92)

FELLOWSHIPS

1. Research Fellow, Centre for Financial Research (CFR), University of Cologne, Germany
2. Research Associate, EDHEC Risk and Asset Management Research Center

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INVITED PRESENTATIONS TO INDUSTRY

1. UK Society of Investment Professionals (UKSIP), London, February 2007

2. Riskinvest 2004 – Optimal risk management techniques and investment strategies for pension funds, hedge funds, and investment managers, November 2004

3. International Conference on Hedge Funds by Ecole des sciences de la gestion and the Institut de Finance Mathématique de Montéal, October 2004 (keynote address)

4. Quantitative Trading and Investment Strategies for Global Derivatives, Quant 2003 Congress, Risk Waters Group, New York, November 2003

5. Schroder Charity Investment Forum, November 2001 (keynote address)

OTHER PRESENTATIONS

1. London School of Economics Alternative Investments Conference – Hedge Fund Clones, April 2007

TEACHING

Georgia State University

1. PhD Seminar in Empirical Asset Pricing and Investments – Fall 2008, Fall 2006, Fall 2004

   Average Teaching Evaluation: 4.4 (Scale 1=Very Poor; 5=Very Good)

2. The Financial System (MBA Elective) – Fall 2008, Summer 2008, Fall 2007, Fall 2005, Spring 2004, Spring 2003, Spring 2002

   Average Teaching Evaluation: 4.0 (Scale 1=Very Poor; 5=Very Good)

3. The Financial System (Undergraduate Elective) – Summer 2009, Spring 2009, Summer 2008, Spring 2008, Fall 2007, Summer 2007, Summer 2006, Fall 2005, Summer 2005, Spring 2005, Fall 2004, Spring 2004, Fall 2003, Spring 2003, Fall 2002, Spring 2002 (2 sections)

   Average Teaching Evaluation: 4.4 (Scale 1=Very Poor; 5=Very Good)

INDUSTRIAL EXPERIENCE

Larsen & Toubro Limited, India (1994-96)

1. Executive, Chemical Plants & Systems Division, Projects Group

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PERSONAL INFORMATION

Immigration Status: India (citizen) USA (Permanent Resident)

Marital Status: Married (two children)

Wei Jiang

Columbia Business School, Uris Hall 803
New York, NY 10027
Tel: (212) 854 9002
E-mail: wj2006@columbia.edu

EDUCATION

University of Chicago

Ph.D. in Economics, June 2001.
M.A. in Economics, July 1997.
Prelims: Financial Economics, Econometrics, July 1998.

Fudan University, China

M.A. in International Economics, July 1992.
B.A. in Economics, July 1989.
Fast-Track College Preparatory Program for Talented Students (replacing high-school), February – July 1985.

EMPLOYMENT AND WORK EXPERIENCE

Columbia Business School

Associate Professor of Finance and Economics, with tenure, July 2009 – present.
Sidney Taurel Associate Professor of Finance and Economics, July 2006 – June 2009.
Associate Professor of Finance and Economics, July 2005 – June 2006.
Assistant Professor of Finance and Economics, July 2001 – June 2005.
Courses taught: Corporate Finance (MBA), Business Finance (Executive MBA), Global Immersion—China (MBA), Doctoral Seminar in Corporate Finance (Ph.D.).

The Wharton School of the University of Pennsylvania

Visiting Associate Professor of Finance, July 2006-June 2007.
Course taught: Advanced Corporate Finance (MBA).

University of Chicago

Department of Economics

Lecturer, September 1998-June 2000. Courses taught: Introduction to Econometrics, Introduction to Finance.

Financial Mathematics Master Program, Department of Mathematics

Lecturer, March 2000-June 2001. Courses taught: Financial Econometrics.

Prudential Securities (New York Office)

Consultant, international division, October 1997-June 1998.

Prudential Securities (Shanghai Office)

Associate, December 1994-August 1996.

Fudan University, School of Economics

Lecturer, September 1992-December 1994. Courses taught: Microeconomics, Macroeconomics, Investments.

FELLOWSHIP, GRANTS, AND AWARDS

Research

National Science Foundation (NSF) Grant, "A Micro View of the Mortgage Crisis: Evidence from Loan-Level Data from a Large Bank," Principal Investigator, with Ashlyn Nelson and Edward Vytlacil, 2009-2012.

Journal of Finance Brattle Award, finalist ("Hedge Fund Activism, Corporate Governance, and Firm Performance"), co-recipient with Alon Brav, Frank Partnoy, and Randall Thomas, 2008.

Federal Deposit Insurance Corporation (FDIC) Financial Research Grant, "Simultaneous Holding of Debt and Equity by Institutional Investors," Co-Investigator with Kai Li and Pei Shao, 2008-2009.

The Roger F. Murray Best Paper Award by the Q Group, 2nd Place, co-recipient with Alon Brav, 2007.

The Institute for Quantitative Investment Research (INQUIRE UK) Annual Best Paper Prize, co-recipient with Alon Brav, 2007.

Chicago Quantitative Alliance (CQA) Annual Academic Competition Best Paper Award, 2nd Place, co-recipient with Alon Brav, 2007.

"Shareholders and Corporate Governance Research Agenda and Conference" grant, the Millstein Center for Corporate Governance and Performance, Yale School of Management, Co-Investigator with Alon Brav, 2007.

Journal of Finance Smith-Breeden Distinguished Paper Prize ("Offering versus Choice in 401(k) Plans: Equity Exposure and Number of Funds"), co-recipient with Gur Huberman, 2006.

The Q-Group Research Grant, "Hedge Fund Activism," Co-Investigator with Alon Brav, 2006-2007.

Federal Deposit Insurance Corporation (FDIC) Financial Research Grant, "Hedge Fund Activism," Co-Investigator with Alon Brav, 2006-2007.

Chazen Fellowship, 2006.

Whitebox Scholar, Yale International Center of Finance, summer 2005.

TIAA-CREF Institute Research Grant, "Director Ownership of Mutual Funds," Co-Investigator with Qi Chen, 2004-2005.

PER Seed Grant for economics, 2004.

Chazen Fellowship, 2004.

INQUIRE grant on quantitative investment research, "Market Timing by Mutual Funds," 2004.

Eugene Lang Fellowship, 2003.

Chazen Fellowship, 2002.

Francis Yuen Dissertation Scholarship, September 2000-June 2001.

Francis Yuen Fellowship, September 1997-June 2000.

University of Chicago Graduate Scholarship, September 1996-June 1997.

Teaching

Executive MBA Award for Commitment to Excellence, graduating class of 2009.

Executive MBA Award for Commitment to Excellence, graduating class of 2007.

Dean's Award for Teaching Excellence in a Core Course, 2006.

Executive MBA Award for Commitment to Excellence, graduating class of 2005.

Best Instructor, voted by the class, Financial Mathematics Master Program, University of

Chicago, 2000.

Faculty Teaching Award, Fudan University, 1994.

Other

"Outstanding Woman in Finance," nominated by China Futures Association, 1995.

"Best Graduate of the Year" (equivalent *summa cum laude*), Fudan University, 1989.

First Prize, National Competition on Chinese Language and Literature for junior middle school students, 1984.

PUBLISHED AND ACCEPTED PAPERS

- In Refereed Journals:

[12] "Activist Arbitrage: A Study of Open-Ending Attempts of Closed-End Funds" with Michael Bradley, Alon Brav, and Itay Goldstein, *Journal of Financial Economics*, forthcoming.

[11] "Returns to Hedge Fund Activism," with Alon Brav, Frank Partnoy, and Randall Thomas, *Financial Analyst Journal*, 2008, vol 64, 45-61.

[10] "Directors' Ownership in the U.S. Mutual Fund Industry," with Qi Chen and Itay Goldstein, *Journal of Finance*, 2008, vol 63(5), 2629-2677.

[9] "Hedge Fund Activism, Corporate Governance, and Firm Performance," with Alon Brav, Frank Partnoy, and Randall Thomas, *Journal of Finance*, 2008, vol. 63 (4), 1729-1775, finalist for the Brattle Award.

[8] "Defined Contribution Pension Plans: Determinants of Participation and Contribution Rates," with Gur Huberman and Sheena Iyengar, *Journal of Financial Services Research*, 2007, vol. 31(1), 1-32.

[7] "Price Informativeness and Investment Sensitivity to Stock Prices," with Qi Chen and Itay Goldstein, *Review of Financial Studies*, 2007, vol. 20 (3), 619-650.

[6] "Offering vs. Choices in 401(k) Plans: Equity Exposure and Number of Funds," with Gur Huberman, *Journal of Finance*, 2006, vol. XLI(2), 763-801, winner of the Smith-Breeden Distinguished Paper Prize.

[5] "Analysts' Weighting of Private and Public Information," with Qi Chen, *Review of Financial Studies,* 2006, vol. 19(1), 319-355.

[4] "A Nonparametric Approach to Measuring and Testing Curvature," with Jason Abrevaya, *Journal of Business and Economic Statistics*, 2005, vol. 23(1), 1-19.

[3] "Investor Learning about Analyst Ability," with Qi Chen and Jennifer Francis, *Journal of Accounting and Economics*, 2005, vol. 39(1), 3-24.

[2] "Positive Hurdle Rates without Asymmetric Information," with Qi Chen, *Financial Research Letters,* March 2004, 1(2), 106-112.

[1] "A Nonparametric Test of Market Timing," *Journal of Empirical Finance*, 2003, vol. 10(4), pp 399 – 425.

- Other Publications:

[3] "How Much Choice Is Too Much?: Contributions to 401(k) Retirement Plans," with Gur Huberman and Sheena Iyengar, chapter in *Pension Design and Structure: New Lessons from Behavioral Finance*, edited by Olivia Mitchell and Stephen Utkus, Oxford University Press, 2004,

pp 83-96.

[2] "How Do Analysts Weight Private Information and Why?" with Qi Chen, in *Corporate Governance: Implications for Financial Services Firms*, Proceedings of the 39th Chicago Federal Reserve Bank of Chicago Conference on Bank Structure and Competition, 2004, pp 336-353.

[1] "Commodity Futures Market in China," with David Wall, *The Futures and Derivatives Law Review,* Volume 2 Issue 1, Cavendish Publishing Limited, London, January 1995, pp 13-42. Reprinted in *Financing China Trade and Investment*, ed. Kui-Wai Li, Praeger, Westport & London, 1997, pp183 – 214.

WORKING PAPERS

"Payoff Complementarities and Financial Fragility: Evidence from Mutual Fund Outflows," with Qi Chen and Itay Goldstein, revise and resubmit, *Journal of Financial Economics*.

"When Creditors are Shareholders: Effects of Simultaneous Holding of Debt and Equity by Institutional Investors," with Kai Li, and Pei Shao, revise and resubmit, *Review of Financial Studies*.

"Takeover Activities and Target Valuations: Feedback Loops in Financial Markets," with Alex Edmans and Itay Goldstein.

"Liar's loan?—Effects of Origination Channel and Information Falsification on Mortgage Delinquency," with Ashlyn Nelson and Edward Vytlacil.

WORK IN PROGRESS

"Mortgage Securitization and Loan Performance: A Contrast of Ex Ante and Ex Post Relations," with Ashlyn Nelson and Edward Vytlacil.

"Wolf-Packing in Hedge Fund Activism," with Alon Brav.

"Hedge Funds and the Changing Nature of Chapter 11," with Kai Li and Wei Wang.

"Do Institutional Investors Have an Ace Up Their Sleeves? Evidence from Confidential Filings of Portfolio Holdings," with Vikas Agarwal, Yuehua Tang, and Baozhong Yang.

"Inferring Reporting Bias in Hedge Fund Databases from Hedge Fund Equity Holdings," with Vikas Agarwal and Vyacheslav Fos.

INVITED PRESENTATIONS AND PROFESSIONAL ACTIVITIES (including scheduled)

- Conferences
  - American Finance Association Annual Meeting, January 2002*.
  - Eastern Finance Association Annual Meeting, April 2002.
  - The 13th Financial Economics and Accounting Conference (at the University of Maryland), November 2002.
  - Midwestern Finance Association Annual Meeting, April 2003*.
  - Wharton PRC Annual Conference, April 2003.
  - Chicago Federal Reserve Bank 2003 Bank Structure Conference, May 2003*.
  - Western Finance Association Annual Meeting, June 2003*.
  - The 14th Financial Economics and Accounting Conference (at Indiana University), November 2003.

- Wharton Workshop on Household Financial Decision-Making and Portfolio Choice, March 2004.
- The 6th Texas Finance Festival, April 2004*.
- The Financial Intermediation Research Society (FIRS) Conference on Banking, Insurance and Intermediation, May 2004*.
- European Finance Association Annual Meeting, August 2004*.
- The Swedish Institute of Financial Research (SIFR) Conference on Portfolio Choice and Investor Behavior, September 2004.
- NBER Behavioral Finance Meeting, October 2004.
- Mitsui Life Symposium "Institutional Investors: Issues in Asset Management and Governance", University of Michigan Business School, invited participation, June 2005.
- Columbia Law School Center on Corporate Governance and the UCLA-Sloan Research Program on Business Organizations conference "Shareholder Democracy: Its Promises and Perils," invited participation, December 2005.
- Financial Research Association Conference, December 2005.
- Columbia Business School Chazen Institute conference "China at the Crossroads: FX and Capital Markets Policy for the Next Decade", Session Chair, February 2006.
- The Second FIRS Conference on Banking, Corporate Finance and Intermediation, June 2006. (Two papers and discussant)*.
- Western Finance Association Annual Meeting, June 2006 (paper and discussant)*.
- NBER Summer Institute Corporate Governance Workshop, July 2006.
- The Swedish Institute of Financial Research (SIFR) Conference on Institutions, Liquidity, and Asset Prices, August 2006.
- UNC-Duke Corporate Finance Conference, September 2006 (discussant).
- Conference on Investor Activism, Vanderbilt, October 2006*.
- New York Fed/NYU Joint Conference on Financial Intermediation, November 2006 (discussant).
- Five-Star Conference, December 2006 (discussant).
- American Finance Association Annual Meeting, January 2007.
- Association of American Law Schools Annual Meeting, January 2007.
- Conference on Activist Investors, Hedge Funds, and Corporate Governance, Vanderbilt University Law School's Law and Business Program and the University of Amsterdam, Amsterdam, March 2007.
- Wharton Workshop on Household Financial Decision-Making and Portfolio Choice, March 2007 (discussant).
- American Law and Economics Association Annual Meeting, May 2007*.
- The Fourth Annual Conference of the Caesarea Center at the Arison School of Business, IDC, May 2007 (discussant).
- European Financial Management Association Meetings, June 2007.
- IESE Conference on Complementarities and Information, Barcelona, June 2007.
- Western Finance Association Annual Meeting, June 2007 (two papers and session chair)*.
- NBER Summer Institute Capital Markets and the Economy Workshop, July 2007.*
- The 18th International Conference on Game Theory, Workshop on Global Games, Center for Game Theory in Economics in SUNY Stony Brook, July 2007.
- Chicago Quantitative Alliance (CQA) Annual Conference, September 2007.*
- FDIC/JFSR 7th Annual Bank Research Conference, September 2007.
- Shareholders and Corporate Governance Research Agenda and Conference, Yale School of Management and Oxford University, October 2007. *
- University of Texas (Austin) Annual Institutional Investors Conference, November 2007 (discussant).

- UNICREDIT Group Conference on the Span and Scope of Banks, Stability and Regulation, December 2007.
- Utah Winter Finance Conference, February 2008.
- NYU/Penn Law and Finance Conference, February 2008 (discussant).
- The Chinese Finance Association Annual Conference, July 2008 (session chair and discussant).
- NBER Summer Institute Corporate Finance Meeting, July 2008*.
- University of Oregon Conference on Institutional Investors and the asset management industry, July 2008.
- NBER China Conference, October 2008 (discussant).
- The 5th Annual Conference on Corporate Finance at Washington University in St. Louis, October 31, 2008.*
- The UNC-Duke Corporate Finance Conference, October 31, 2008.*
- American Finance Association Annual Meeting, January 2009 (paper presentation and discussant).
- NYU/Penn Law and Finance Conference, February 2009.*
- The Financial Intermediation Research Society (FIRS) Conference on Banking, Insurance and Intermediation, May 2009.
- NBER Summer Institute Market Institutions and Financial Market Risk Meeting, July 2009*.
- UBC Finance Summer Conference, July 2009.
- European Finance Association Annual Meeting, August 2009.
- The Philadelphia Fed's Conference on Recent Developments in Consumer Credit and Payments, September 2009.
- Association for Public Policy Analysis and Management (APPAM) 31st Annual Research Conference, November 2009.
- American Economic Association Annual Meeting, January 2010.

*: Presenting author.

- <u>Seminars and Workshops (including scheduled)</u>

  Chicago Department of Economic (2001)
  Chicago Graduate School of Business (2001)
  Cornell Johnson School of Management (2001)
  UIUC Department of Finance (2001)
  UNC Kenan-Flagler Business School (2001)
  UC Davis Graduate School of Business (2001)
  Columbia Business School (2001)
  Columbia Law School (2003)
  New York Federal Reserve Bank (2003)
  New York University Stern School of Business (2003)
  Federal Reserve Board of Governors (2004)
  Duke Fuqua School of Business (2004)
  Fudan University School of Economics (2004)
  Peking University Guanghua School of Management (2004)
  CEIBS Department of Finance (2004)
  NYU-Columbia Joint Seminar (2004)
  Hong Kong University of Science and Technology School of Business (2004)
  UC Berkeley Department of Economics (2004)
  UC Davis Graduate School of Business (2004)

London Business School (2004)
Cheung Kong School of Business (2005)
Yale School of Management (2005)
UC Berkeley Haas School of Business (2005)
Rice University Graduate School of Management (2005)
SUNY Binghamton School of Management (2006)
Stockholm School of Economics (2006)
Tsinghua School of Economics and Management (2006)
Federal Deposit Insurance Corporation Corporate Finance Research Workshop (2006)
Drexel University College of Business (2006)
Wharton School (2007)
University of Florida College of Business Administration (2007)
Columbia Law School (2007)
Inquire (U.K.) Seminar (2007)
Goldman Sachs Asset Management Seminar (2007)
University of Massachusetts School of Management (2007)
Tuck School of Business at Dartmouth (2007)
University of Minnesota Carlson School of Management (2007)
Kellogg School of Management (2007)
UNC Kenan-Flagler Business School (2007)
UBC Sauder School of Business (2007)
Penn State Smeal College of Business (2007)
Boston College Carroll School of Management (2008)
Hong Kong University of Science and Technology School of Business (2008)
Yale University School of Management (2008)
University of Texas at Dallas School of Management (2008)
Harvard Business School (2008)
Federal Deposit Insurance Corporation Corporate Finance Research Workshop (2008)
Queens University School of Business (2009)
Georgia State University (2009)
Federal Reserve Bank of Kansas City (2009)
George Mason University School of Management (2010)

- Other Talks and Speeches
  - "Corporate Governance and Limits to Arbitrage," China National Accounting Institute (Shanghai) Incubator Program Conference on Corporate Governance, Distinguished Speaker, November 2005.
  - "Do Activist Hedge Funds Create Value?" Ivy Asset Management Corporation/Columbia Business School "Thought Leadership" Hedge Fund Research Forum, speaker, June 2007 and December 2007.

- Professional Services

- Ad hoc reviewer for *Journal of Finance, Review of Financial Studies*, *Quarterly Journal of Economics, Journal of Business, Review of Economics and Statistics, Journal of Banking and Finance, Journal of Empirical Finance, Journal of Applied Econometrics*, *American Economic Review*, *Review of Economic Studies, Management Science, National Science Foundation, Journal of Financial Markets, Journal of Financial and Quantitative Analysis, Journal of Public Economics, Journal of Financial Intermediation, Financial Management, Journal of Business and Economic Statistics.*
- Program Committee:
  - Western Finance Association Annual Meeting, since 2007.
  - The Chinese Finance Association Annual Conference, since 2008.
  - The Corporate Finance Conference at Washington University in St. Louis, since 2009.

DOCTORAL STUDENTS

- Jose Martinez, sponsor and main advisor, 2006. Oxford University Said School of Business. First placement: Swedish Institute for Financial Research (SIFR).
- George Murillo, sponsor and main advisor, graduate with distinction, 2008. First placement: Goldman Sachs & Co.
- Linying Zhao (Department of Economics), sponsor and main advisor, 2009. First placement: Shanghai University of Finance and Economics.
- Huidan Lin (Department of Economics), committee member, 2009. First placement: IMF.
- Xiaozheng Wang, committee member, 2009. First placement: Criterion Economics Consulting.
- Yael Eisenthal, sponsor and main advisor, graduate with distinction, 2009. First placement: Goldman Sachs Asset Management.
- Vyacheslav Fos, supervisor, on-going.

MEDIA MENTION

- "A Nonparametric Test of Market Timing"
  - "12-Step Program to Index Funds," Index Funds Advisors, 2003
- "Defined Contribution Pension Plans: Determinants of Participation and Contribution Rates"
  - Wall Street Journal, May 1st, 2003, February 11, 2005
  - The Philadelphia Inquirer, May 2nd, 2003
  - Reuters, November 12, 2003
  - New York Times, January 5, 2005
  - The Wall Street Journal, Money, May 2005
  - Fortune, December 23, 2005
  - CFO Magazine, May 1, 2007
  - Institutional Investor, April 2004
  - FRBSF Economic Letter, June 6, 2008
- "Directors' Ownership in the Mutual Fund Industry"
  - Money Management Executive, February 14, 2005
- "Hedge Fund Activism, Corporate Governance, and Firm Performance"
  - Economist, September 30, 2006; June 2, 2007

- New Zealand Herald, October 2, 2006
- Business Week, October 16, 2006
- Investor Dealers Digest, October 30, 2006
- New York Times, February 18, 2007; August 26, 2007
- Financial Times, February 19 and April 27, 2007
- HedgeWorld News, February 20, 2007
- Financial Post, March 6, 2007
- Merger & Acquisition, May 1, 2007
- CFO Magazine, June 1, 2007
- Alternative Universe, June 11, 2007
- Nikkei Financial News, August 24, 2007

- "Returns to Hedge Fund Activism"
  - The Wall Street Journal, August 1, 2008
- "Liar's loan?"
  - Seeking Alpha, July 23, 2009
- Other media quote
  - "Not so Choice," *Institutional Investor*, July 2005
  - "How Activists Attack Bigger Game," *The Wall Street Journal,* July 11, 2007
  - "Activists Make More News," *Investment Dealers Digest*, February 4, 2008
  - "Ask a Professor: Hedge Funds," *NPR*, December 16, 2008
  - "Is Google Doing the Right Thing?" *Financial Times*, February 3, 2009

OTHER PROFESSIONAL AFFILIATION AND SERVICES

- School and University
  - Member, finance recruiting committee, 2003, 2008.
  - Co-organizer, finance seminars, July 2002-June 2003; July 2007-June 2008.
  - Finance Core Course Coordinator, July 2007-June 2009.
  - Member, MBA Committee, July 2007-June 2008.
  - Member, Crisis and the Curriculum Committee, 2009.
  - Alternate, University Institutional Review Bureau (IRB), July 2009 – present.
- Outside University
  - TIAA-CREF Institute
    Fellow, July 2005 - present.
  - New York Civil Liberties Union (NYCLU)
    Leading member, NYCLU Investment Committee, July 2009 - present

Yuehua Tang

Department of Finance
J. Mack Robinson College of Business
Georgia State University
35 Broad Street, Suite 1221
Atlanta, GA 30303

Office: (404) 413-7313
Home: (678) 662-5129
Email: fncyttx@langate.gsu.edu

AREARS OF INTERESTS

Empirical Asset Pricing and Investment, including Portfolio Management, Institutional Investors and Capital Markets; Corporate Finance; International Finance

EDUCATION

- **Georgia State University**, Robinson College of Business, August 2008-Present
  Ph.D in Finance (expected 2013)
- **EU Erasmus Mundus M.A. Program "International Trade and European Integration"**, Staffordshire University (UK); University of Antwerp (Belgium); Prague University of Economics (Czech Republic), 2007-2008
  M.A. in Economics (with Distinction)
- **Renmin University of China** (Beijing, China), Major in International Finance, 2006-2008
  M.A. in Economics
- **Nankai university** (Tianjin, China), Major in International Economics and Trade, 2002-2006
  B.A. in Economics

RESEARCH

Publications in Refereed Journals

- "Determinants of Official Development Assistance in the Post-Cold War Period", with Fan He, *The Chinese Journal of International Politics* (Oxford University Press), 2008 (02). pp: 205-227.

Other Publications and Book Reviews

- "An Empirical Study on the Determinations of Official Development Assistances (ODA) in the Post-Cold War Era", with Fan He, *Quarterly Journal of International Politics*, 2007 (04). pp: 64-80. (In Chinese)
- "An Empirical Analysis of China's Saving and Investment in Three Sectors". with Fan He, *Research on Financial and Economic Issues*, 2007 (11). pp: 3-10. (In Chinese)
- "The Challenges to the Hegemony Position of United States", with Fan He, *Study Monthly*, 2007 (04). (In Chinese)
- "Will Trade Surplus of China Keeps on Increasing?" with Fan He, *China Securities Journal*, 2006

(12). (In Chinese)

- Book reviews respectively on *"Confessions of an Economic Hit Man"*, *"Hedgehogging"*, *"Currency Wars" and "A Thread Across the Ocean"* published in *Shanghai Securities News* in 2006 and 2007. (In Chinese)

Working in Progress

- "Do Institutional Investors Have an Ace Up Their Sleeves? Evidence from Confidential Filings of Portfolio Holdings," with Vikas Agarwal, Wei Jiang, and Baozhong Yang.

ACADEMIC EXPERICENES

- Graduate Research Assistant for Prof. Baozhong Yang, Dept. of Finance, Robinson College of Business, Georgia State University, August 2008 – Present
- Research Assistant for Professor Fan He, Institute of World Economics and Politics, Chinese Academy of Social Sciences, September 2006- May 2008

INDUSTRY EXPERIENCES

- Research Assistant (Intern), Dept. of International Affairs, Ministry of Finance P.R. China, 2007
- Trade Consultant (Intern), Corporate and Investment Banking, Citibank N.A., Beijing, 2006
- Financial Analyst (Intern), Motorola Accounting Service Center, I/C Team, Tianjin, 2006
- Customer Manager Assistant (Intern), Shanghai Pudong Development Bank, Tianjin, 2005

HONORS AND AWARDS

- Ph.D Fellowships, Georgia State University, 2008 –present
- Erasmus Mundus Scholarship, European Union, 2007-2008
- National Graduate Student Scholarship, Renmin University of China, 2006-2008
- First-Class scholarship of Outstanding Student, Nankai University, 2005
- National Scholarship of Outstanding Student, Nankai University, 2005
- "Tri-A Outstanding Student" Scholarship, Nankai University, 2005
- Second-class Prize in "Xiqing Bei" Paper Competition of School of Economics, Nankai University, 2005
- Monomial Scholarship of Outstanding Student, Nankai University, 2004
- Second-class Scholarship of Outstanding Student, Nankai University, 2002

ADDITIONAL INFORAMTION

- Candidate of Chartered Financial Analyst (CFA), Level I (London, Dec. 2007)
- Certificate of China National Computer Rank Examination (NCRE): Rank II in Visual Foxpro and Rank III in Internet Technology
- Software: SAS, STATA, Matlab, Eviews, FoxPro, Microsoft Office, Oracle.

PROFESSIONAL AFFILIATIONS

- American Finance Association
- Financial Management Association

(Updated August 2009)

BAOZHONG YANG

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Robinson College of Business
Georgia State University
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Email: bzyang@gsu.edu

Education

Ph.D., Finance, Stanford Graduate School of Business, 2003-2008
Ph.D., Mathematics, Massachusetts Institute of Technology, 1996-2000
B.S., Mathematics, Peking University (Beijing, China), 1992-1996

Research Interests

Theoretical and Empirical Corporate Finance, Market Microstructure, Behavioral Finance, Asset Pricing

Working Papers

1. A Dynamic Model of Corporate Financing with Market Timing, 2008
2. Repeated Correlated Updating, Excess Comovement, and Low-Dimensional Factor Structures, 2008
3. The Mystery of Zero-Leverage Firms (with Ilya A. Strebulaev), 2006

Publications in Refereed Journals

4. Compactification of the moduli spaces of vortices and coupled vortices (with Gang Tian), 553, 2002, *Journal für die reine und angewandte Mathematik*, 17-41.
5. Removable singularities of Yang-Mills connections in higher dimensions, 209, 2003, *Pacific Journal of Mathematics*, 381-398.
6. The uniqueness of tangent cones for Yang-Mills connections with isolated singularities, 180, 2003, *Advances in Mathematics*, 648-691.

Work in Progress

7. Do Institutional Investors Have an Ace Up Their Sleeves? Evidence from Confidential Filings of Portfolio Holdings (with Vikas Agarwal, Wei Jiang, and Yuehua Tang)
8. Dynamic Capital Structure with Heterogeneous Agents in a General Equilibrium (with Ajay Subramanian)

Employment History

- Assistant Professor of Finance, Georgia State University, 2008-present

- George Polya Postdoctoral Fellow and Lecturer, Department of Mathematics, Stanford University, 2000-2003

Research Experiences

- Research Assistant for Prof. Kenneth Singleton, Prof. Ilya A. Strebulaev, and Prof. Jeff Zwiebel, Graduate School of Business, Stanford University, 2004-present
- George Polya Postdoctoral Fellow, Department of Mathematics, Stanford University, 2000-2003
- Research Assistant, Department of Mathematics, MIT, 2000

Teaching Experiences

- Instructor, *Financial Markets and Institutions,* Georgia State University, 2008-present
- Teaching Assistant, *Corporate Finance I*, Prof. Paul Pfleiderer, Stanford University, 2006
- Teaching Assistant, *PhD Econometrics II*, Prof. Kenneth Singleton, Stanford GSB, 2006
- Teaching Assistant, *Corporate Valuation, Governance, and Behavior*, Prof. Jeff Zwiebel, Stanford GSB, 2004-2005
- Instructor, Department of Mathematics, Stanford University, 2000-2003
  - Undergraduate Courses: *Linear Algebra, Differential Equations, Functional Analysis*
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Invited Presentations and Conferences

2006	WFA Annual Meeting, Keystone, CO
2008	University of Minnesota, University of Maryland, University of California at Los Angeles, University of Houston, University of Wisconsin-Madison, University of Toronto, Georgia State University, University of Hong Kong (scheduled), Hong Kong Science and Technology University (scheduled), Nanyang Technology University (scheduled)
2009	All Georgia Conference

Referee Activities

American Economic Review, Review of Financial Economics

Honors and Awards

- Stanford Graduate School of Business PhD Fellowships, 2003-present
- NSF Research Grant: DMS-0104163, 2001-2003
- George Polya Postdoctoral Fellowship, Dept. of Mathematics, Stanford University, 2000-2003
- Sigma Xi, 2002
- MIT Department of Mathematics PhD Fellowships, 1996 - 2000
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Do hedge funds manage their reported returns?

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Abstract

We find that hedge fund returns during December are significantly higher than those during the rest of the year even after controlling for funds' risk exposures and factor risk premiums in December. More importantly, we find that this *December spike* is higher for funds with greater incentives and greater opportunities to inflate returns. These results suggest that hedge funds manage their returns upwards in an opportunistic fashion in order to earn higher fees. Finally, we provide evidence that funds inflate December returns by under-reporting returns earlier in the year and/or by borrowing from January returns in the following year.

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Do hedge funds manage their reported returns?

Abstract

We find that hedge fund returns during December are significantly higher than those during the rest of the year even after controlling for funds' risk exposures and factor risk premiums in December. More importantly, we find that this *December spike* is higher for funds with greater incentives and greater opportunities to inflate returns. These results suggest that hedge funds manage their returns upwards in an opportunistic fashion in order to earn higher fees. Finally, we provide evidence that funds inflate December returns by under-reporting returns earlier in the year and/or by borrowing from January returns in the following year.

Do hedge funds manage their reported returns?

Hedge funds are compensated by incentive fees based on annual performance exceeding prespecified thresholds, which in turn are determined by the hurdle rate and high-water mark provisions. Additionally, better annual performance results in more investor inflows into the fund. Hence, there exist strong incentives for managers to improve performance as the year comes to a close.[8] Using a comprehensive database of hedge funds, we, for the first time, show that hedge funds inflate 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.

Our claim of hedge funds managing returns upwards is based on two findings. First, we observe that December returns of hedge funds are significantly higher than their average returns from January to November. This result holds even after we control for funds' risk exposures in December, the possibility that the factor risk premiums happen to be higher during December in our sample, and several fund characteristics that could affect returns. We refer to this as the *December residual-spike*, which equals 0.36% per month and is economically significant given the average monthly return of 1.06% in our sample.

Second, 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. First one relates to the promise of rewards for good performance. Second one relates to the threat of penalties in the form of capital withdrawal by investors following poor performance. These incentives motivate funds to report better performance.

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

To capture the first set of incentives that reward good performance, we recognize that the performance-based compensation contract provides asymmetric call-option-like payoff. We proxy these incentives by the moneyness and delta (pay-performance sensitivity) of the incentive-fee call option as of November-end. Additionally, incentives arise from the flow-performance sensitivity, as investors direct more money into hedge funds that perform better relative to their peer group (see, e.g., Agarwal, Daniel, and Naik (2004)). We proxy these incentives by the performance rank for each fund based on January–November returns relative to its peer group.

To capture the second set of incentives related to penalties for poor performance, we first consider lockup and restriction periods, which determine the severity of threat of capital withdrawals.[9] Shorter lockup and restriction periods imply that investors could withdraw their capital quickly in response to poor performance. Therefore, they act as a disciplining mechanism, which can lead to managers paying excessive attention to short-term performance, thereby providing incentives for returns management. Furthermore, given the flow-performance relation, larger funds that charge higher percentage management fee stand to lose the most from capital withdrawals. We proxy such an incentive by the November-end dollar management fee (= Management Fee Rate × Assets as of November-end). Therefore, taken together, the second set of incentives includes lockup and restriction periods, and the November-end dollar management fee.

In addition to the two types of incentives, arguably funds must also have opportunities to manage returns. For example, funds with higher volatility may be able to hide returns management with greater ease, and therefore may display bigger December spike. Similarly,

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

funds with higher exposure to liquidity risk can more easily influence the prices of securities they own to inflate the December returns. In light of this, we proxy the opportunities to manage returns by a fund's volatility and a fund's exposure to liquidity risk.

Consistent with the above line of reasoning, we find that funds with higher incentives and greater opportunities exhibit bigger December spike. In particular, we find that the December spike is positively associated with the moneyness of the incentive-fee call option as of November-end. We observe highest December residual-spike for in-the-money funds (0.57%) followed by near-the-money funds (0.49%). These numbers are significantly different from that for out-of-the-money funds, which exhibit no December residual-spike. We also find that funds with higher delta at November-end display significantly greater December residual-spike compared to the low delta funds (0.41% vs. 0.26%). These results are consistent with our hypothesis that the incentives that reward good performance drive the December spike.

Further, we find that funds with shorter lockup periods exhibit a December residual-spike of 0.41%. This is significantly greater than that for funds with longer lockup period, which exhibit virtually no spike in December returns. We also find that funds with higher November-end dollar management fee exhibit significantly greater December residual-spike compared to the lower management fee counterparts (0.44% vs. 0.27%). These findings support the idea that incentives that penalize poor performance also affect the December spike.

Finally, we observe that funds with more opportunities to mask return management, i.e., higher volatility and higher liquidity risk, show a significantly bigger December residual-spike compared to funds with lower volatility and lower liquidity risk. The difference in December residual-spike between the high- and low-volatility groups is 0.38%. We find mixed evidence that liquidity risk impacts the December spike.

Although we observe significant December residual-spike in hedge fund returns, we acknowledge that its magnitude depends on the choice of risk-adjustment model. However, regardless of the exact magnitude of spike, the fact that it is correlated with proxies for incentives and opportunities provides strong evidence that hedge funds may be managing their reported returns.

The evidence of returns management begs the following question: What are the mechanisms by which hedge funds manage their returns? We focus on two mechanisms. All else equal, investors direct more money into funds that report a greater fraction of monthly returns that are positive.[10] This provides incentives for the manager to engage in intra-year smoothing of returns so as to maximize the present value of fees. Specifically, the first mechanism would involve funds underreporting positive returns realized during the early part of the year to create reserves which can be added to future returns if they happen to be negative ("saving for the rainy day"). Any unused reserves get added to the December returns when financial audit takes place at the end of the year. This can potentially give rise to a December spike.[11] The second mechanism relates to funds "borrowing" from their future performance to report higher returns in December in order to earn their incentive fees in the current year itself.[12] Funds can push up the security prices at December-end by last-minute buying. This is followed by price reversals in January, which effectively amounts to borrowing from January returns. Our results are consistent with funds managing their returns through both saving and borrowing mechanisms.

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

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

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

Our findings contribute to the literature that explores the effect of managerial incentives for earnings management (Healy, 1985; Bergstresser and Phillipon, 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. Recently, the Securities and Exchange Commission (SEC) has been especially concerned about issues related to accurate valuation of securities in hedge fund portfolios.[13] Return management behavior in hedge funds is important from the point of view of investor welfare, too. If some hedge funds inflate returns in December, investors cashing out at year-end benefit at the cost of those entering and remaining in those funds. Further, if funds save for the rainy day by underreporting in the earlier part of the year, investors cashing out earlier may lose to other investors. Hence, investors entering and leaving the fund at different points in time may get systematically rewarded or penalized as a result of returns management by hedge funds. Our findings can help regulators and investors spend their limited resources to pay particular attention to funds with higher incentives and greater opportunities to manage returns.

The remainder of the paper is organized as follows. Section II shows how our investigation contributes to the existing literature. Section III presents testable hypotheses. Section IV describes the data and construction of variables. Section V investigates our hypothesis related to the existence of December spike, while Section VI examines the types of funds that exhibit greater December spike. Section VII sheds light on the modus operandi of returns management. Section VIII offers concluding remarks.

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

II. Related Literature

Our study contributes to the literature on earnings management and executive compensation by documenting returns management in hedge funds and its relation to economic incentives and opportunities available to the manager to engage in such an activity.

There exists a large literature on earnings management in corporations.[14] It shows that firms manage earnings toward specific earnings thresholds (see, e.g., Burgstahler and Dichev (1997), DeGeorge, Patel, and Zeckhauser (1999), and Daniel, Denis, and Naveen (2008)). In particular, it shows that firms, *inter alia,* manage earnings to avoid reporting losses, avoid earnings decline, or meet dividend thresholds. In case of hedge funds, the threshold to earn incentive fees is the strike price of the option-like incentive fee contract, and the returns necessary to meet that threshold represents the moneyness of the option. Our investigation shows that the magnitude of December spike in hedge funds is larger for funds with in-the-money and near-the-money options relative to those with out-of-the-money options. This is similar to the results of Efendi, Srivastava, and Swanson (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 examining the relation between earnings management and incentives from compensation.[15] Healy (1985) and Gaver, Gaver, and Austin (1995) relate managers' accrual policies with incentives arising from their bonus contracts. Goldman and Sleazak (2006) provide theoretical underpinnings for why stock-based compensation can induce earnings management. Although stock-based compensation motivates the managers to exert more effort, it can also tempt them to exaggerate

[14] See Healy and Wahlen (1999), Dechow and Skinner (2000), Fields, Lys, and Vincent (2001), and Stolowy and Breton (2004) for surveys on this literature.
[15] See Murphy (1999) and Core, Guay, and Larcker (2003) for surveys of the literature on executive compensation.

their performance. Burns and Kedia (2006) find that the delta of CEO's option portfolio is positively related to the propensity of misreporting. We contribute to this strand of literature by establishing a link between incentives and returns management in a different setting. Specifically, we show that hedge funds with higher delta of their call-option-like incentive fee contracts exhibit a larger December spike.

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

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

Finally, our paper complements the literature on return smoothing by hedge funds. Getmansky, Lo, and Makarov (2004) show positive autocorrelations in monthly returns and attribute it to hedge funds' exposure to illiquidity and potential smoothing of returns. Bollen and

Krepely (2007) demonstrate that it is difficult to detect intentional smoothing of returns by looking at autocorrelations. In this paper, we uncover one of the effects of return smoothing on hedge fund return distribution. We argue that hedge funds can intentionally smooth returns during the earlier part of the year by underreporting their positive returns (saving for the rainy day). This, in turn, can potentially result in December spike when the underreported returns get added back at year-end when financial performance is audited.

III. Hypotheses Development

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

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

Typically, incentive fees are paid once a year based on annual performance. As the year draws to a close, the manager is better able to judge whether the fund's performance will be sufficiently greater in the remaining periods such that the year-end NAV will be greater than the

threshold NAV. This suggests that if the manager is close to the threshold NAV or above it, he is likely to engage in returns management to benefit from additional incentive fees. Such returns management is more likely to get reflected in December, the last month of the year, which we test through the following hypothesis:

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

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

While finding support for Hypothesis 1 is a *necessary* condition for documenting returns management behavior, a *sufficient* condition would be to show that the December spike is related systematically to the costs and benefits of returns management. We develop these hypotheses here. As discussed in Section II, we know from the earnings management literature that incentives can arise from thresholds in case of corporations. We also know that incentives arise from the pay-for-performance sensitivity (delta) of the executive compensation contract. Drawing from these insights, we use the distance from the threshold (moneyness) and delta of the call-option-like incentive fee contract to proxy for the explicit incentives faced by hedge funds. For example, if by November-end, the call option of a fund is deep out of the money, inflating returns in December might not help to earn any incentive fee for the year. Hence, one would expect the in-the-money and near-the-money funds to exhibit greater December spike compared to the out-of-the-money funds. Further, we also expect funds with greater pay-performance sensitivity (or higher delta) to exhibit greater December spike 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 that funds with superior relative performance should have higher incentives to inflate year-end returns.

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

In addition to the incentives to inflate returns, funds must also have the *opportunities* to engage in this behavior. Arguably, hedge funds with more volatile trading strategies have greater opportunities to inflate returns, because it may be more difficult to detect such an activity in more volatile funds. Furthermore, hedge funds that trade in relatively illiquid securities have better opportunities to influence the prices of securities they own, sometimes for the purpose of inflating returns.[16] These arguments provide us with our second hypothesis:

[16] 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 in their *Wall Street Journal*

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

If we find evidence in support of Hypotheses 1 and 2, we could then say that hedge funds engage in returns management. It would then be natural to explore the mechanisms they employ to manage their returns. It is conceivable that hedge funds "*save for the rainy day*" and create reserves by underreporting positive returns earlier in the year and use them during bad months to avoid reporting losses. In the case of hedge funds, the tendency to create reserves could be driven by investors' preference for funds with fewer loss-making months. While saving for the rainy day does not lead to higher reported annual returns and hence higher incentive fees in the current year, it could lead to higher fees in the future. In Addendum A, we provide empirical evidence that, all else equal, higher the number of months within a calendar year in which the fund reports positive returns, greater is the capital that investors put into the fund. The resulting increase in assets under management will lead to higher fees in the future, and hence funds have an incentive to engage in such behavior. In case some reserves remain unutilized by the end of the year, the manager is forced to include them in December due to auditing reasons, thus leading to the December spike. This leads us to our third hypothesis.

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

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article and how this can provide incentives to "inflate marks." Their article also mentions the three levels of precision set by the Financial Accounting Standards Board (FASB) ranging from the most precise method of "marking to market", followed by "marking to matrix", to the least precise method of "marking to model" to value securities.

It is well-documented that mutual funds push up the prices of securities they hold at December-end by creating a short-term price pressure through purchases during the last few minutes of trading on the last day of the year (see e.g., Carhart et al. (2002), Bernhardt and Davies (2005)). This is followed by price reversals in January, which effectively amounts to *borrowing* from January returns. It is plausible that hedge funds borrow from January returns in a similar fashion.[17] By doing so, funds can earn their incentive fees earlier. 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.

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

IV. Data and Variable Construction

IV.A. Data Description

In this paper, we construct a comprehensive hedge fund database that is a union of four large databases, namely, Center for International Securities and Derivative Markets (CISDM), Hedge Fund Research (HFR), Morgan Stanley Capital International (MSCI), and Tremont Advisory Shareholder Services (TASS) (now Lipper). This database reports net-of-fee monthly returns, assets under management, and fund characteristics, such as hurdle rate and high-water mark provisions, lockup, notice, and redemption periods, incentive fee rate, management fee rate, inception date, and fund strategy.[18] This enables us to resolve occasional discrepancies

[17] Another way that the hedge fund manager could borrow from future returns is by selling deep out-of-the-money put options on the index and delta-hedging them in December. Selling the puts generates income up front, while the cost of replication through dynamically delta-hedging is incurred over a period that can extend beyond December. However, this argument assumes that the computation of NAV does not account simultaneously for both the short position in the option and the delta-hedge component.

[18] The database provides information on contractual features as of the last date for which the fund's data is available. Following previous researchers, we assume that these contract features hold throughout the life of the fund.

among different databases as well as to create a sample that is more representative of the hedge fund industry. Our sample period extends from January 1994 to December 2002. We focus on post-1994 period to mitigate potential survivorship bias, as most of the databases start reporting information on "defunct" funds only after 1994.[19] After merging the four databases, we find that there are 7,535 hedge funds: 3,924 remained live as of December, 2002 while 3,611 became defunct during our sample period. In Figure 2, we report the overlap among the four databases with a Venn diagram. It highlights the fact that there are a large number of hedge funds that are unique to each of the four databases. Merging them, therefore, helps to capture a more representative sample of the hedge fund universe.

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

IV.B. Measures of Performance

We consider two performance measures for our study. Our first measure is gross return of fund *i* in month *m*, $\text{Returns}_{i,m}$, where *m* runs from January 1994 to December 2002. We compute the gross-of-fee returns from net-of-fee returns following the methodology of Agarwal, Daniel, and Naik (2006) (see Appendix B for details). The reason for using gross-of-fees returns instead

Discussions with industry experts suggest that this is a reasonable assumption, as it is easier for a manager to start a new fund with different contract terms instead of going through the legal complications of changing existing contracts with numerous investors.

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

of net-of-fee returns is to mitigate any problems created by the path dependency in the computation of incentive fees, which can induce smoothing in net-of-fee monthly returns (see Getmansky, Lo and Makarov (2004)). Gross returns do not suffer from this problem. In the rest of the paper, for brevity, we simply refer to gross returns as returns. For robustness, we repeat our analysis using net-of-fee returns and obtain similar inferences (we report these results in Section V.B).

To test for December spike, we need to control for the systematic risks of hedge funds. Hence we employ a second measure, $Residual_{i,m,}$ 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).[20] This is in the spirit of Bollen and Krepely (2007), who estimate the predicted returns from Fung and Hsieh's (2004) seven-factor model and define it as the nondiscretionary component of hedge fund returns. Thus, the residuals can be thought of as the discretionary component of returns over which the manager may be able to exercise influence. The motivation behind this measure is analogous to that for the discretionary accruals in earnings management literature, which are defined as the residuals from a regression of accruals on explanatory variables (such as change in sales etc.) that are predicted to be related to accruals (see Jones (1991) and Ball and Shivakumar (2006)).

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

IV.C. Measures of Risk Exposures

As hedge fund returns are available only on a monthly basis, it is difficult to use a time-series approach to estimate the month-to-month risk exposures using a multifactor model.

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

Therefore, we use a cross-sectional approach to determine the variation in risk exposures over time. In particular, each month, we compute CS Volatility$_m$, the cross-sectional dispersion in returns of N hedge funds during month m, as $\sqrt{\sum_{i=1}^{N}(r_{i,m}-\bar{r}_m)^2}$ where $r_{i,m}$ is the return of fund i in month m, and $\bar{r}_m$ is the cross-sectional average of fund returns in month m.[21] If funds increase their risk exposures, then CS Volatility$_m$ will increase. Hence, we use CS Volatility$_m$ to proxy for the risk exposures. From Table I, we observe that the mean (median) cross-sectional volatility of funds' monthly returns is 6.02% (5.83%). As an alternative to cross-sectional volatility, in Section V.B, we allow funds to vary their risk exposures to market factor on a monthly basis. Our results reported later with this control are qualitatively similar.

IV.D. Measures of Incentives to Manage Returns

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

Our first measure of returns management incentives is related to the moneyness of the

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

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

Our *Hypothesis 2* states that funds that are in the money and near the money are more likely to engage in returns management compared to funds that are out of the money. For this purpose, we categorize funds into three groups based on the moneyness at the end of November. We first compute the mean (μ) and standard deviation (σ) of a fund's returns using the entire data in our sample. We provide an example to illustrate our classification algorithm. Suppose a fund has μ and σ of 1% and 5%. This fund is deemed to be *near the money* if its moneyness lies between –6% [–(μ + σ)] and +4% [–(μ – σ)]. Following this example further, if the fund's moneyness is greater than +4%, we define it to be *in the money,* and if the fund's moneyness is less than –6%, we define it to be *out of the money*. It is important to note that the use of 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, on average, 31% of the funds are near the money, 38% are in the money, and remaining 31% are out of the money, suggesting that the return distribution is far from normal. Furthermore, in Section VI.A, we use alternative procedures to classify funds based on their moneyness and demonstrate that our results are robust to different classification criteria.

Our second measure of returns management incentives is the delta of the portfolio of call options endowed to the fund by the incentive fee contract. The delta of each of the call options depends on the current NAV (S), the threshold NAV that must be reached before the manager can claim an incentive fee (X), and other fund characteristics, such as the fund size and fund volatility. We compute the delta as of the end of each month, which equals the expected dollar change in the manager's compensation for a one-percent change in the fund's month-end NAV (see Appendix B for details). From Table I, we find that the mean (median) monthly delta equals \$170,000 (\$20,000).[22]

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

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

IV.E. Measures of Opportunities to Manage Returns

Our first measure of opportunities for returns management is fund volatility. From Table I, we observe that the mean (median) fund volatility is 4.82% (3.83%). Our second measure of opportunities is the liquidity of each fund, which we capture by its exposure to the liquidity risk

[22] Coles, Daniel, and Naveen (2006) report the mean (median) delta of executive stock options for the top 1500 firms in S&P during 1992–2002 to be \$600,000 (\$206,000).

factor of Pastor and Stambaugh (2003). For this purpose, we estimate fund-level time-series regression of returns on the seven factors of Fung and Hsieh (2004), augmented with the liquidity risk factor.[23] A higher beta on the liquidity risk factor implies that the fund has greater exposure to illiquidity and therefore is more illiquid.[24] From Table I, we observe that the mean (median) of the liquidity beta is 0.02 (0.00). The interquartile range of liquidity beta is 0.15 (i.e., 0.09 – (–0.06)) suggests that there is considerable cross-sectional variation in the liquidity risk exposure across different hedge funds.

IV.F. Measures of Reserves

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

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

V. Is There Evidence of a December Spike?

Before conducting multivariate analysis, we provide in Table II, a univariate comparison of gross returns and residual returns of hedge funds in our sample for December and the monthly average during the rest of the year (January–November). Results from *t*-tests suggest that the average gross returns and residuals in December are significantly greater than those for the rest of the year. The December return is higher by 1.55% in terms of gross returns and the risk-

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

[24] 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.

adjusted return is higher by 0.25%.[25] We also compare the factor premiums between December and rest of the year. Although the factor premiums are higher in December, our findings of a December spike in residual returns suggest that higher factor premiums in December cannot completely explain this pattern.

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

In this section, we extend our analysis to a multivariate setting after controlling for fund characteristics, strategy and year effects. In particular, we estimate the following regression[26]:

$$\begin{aligned}\text{Return}_{i,m} = {} & \lambda_0 + \lambda_1 I(\text{December}) + \lambda_2 I(\text{Non-Dec Quarter-End}) + \lambda_3 (\text{CSVol})_m \\ & + \lambda_4 \text{Return}_{i,m-1} + \lambda_5 \text{Return}_{i,m-2} + \lambda_6 \text{Delta}_{i,m-1} + \lambda_7 \text{Moneyness}_{i,m-1} \\ & + \lambda_8 \text{Lockup}_i + \lambda_9 \text{Restrict}_i + \lambda_{10} \text{Size}_{i,m-1} + \lambda_{11} \sigma_i + \lambda_{12} \text{Age}_i + \lambda_{13} \text{MFee}_i \\ & + \sum_{s=1}^{3} \lambda_{14}^s I(\text{Strategy}_{i,s}) + \sum_{k=1994}^{2002} \lambda_{15}^k I(\text{Year}_{t,k}) + \xi_{i,m}\end{aligned} \qquad \textbf{(1)}$$

where $\text{Return}_{i,m}$ is the gross-of-fee return of fund *i* in month *m*, $I(\text{December})$ is an indicator variable that takes the value 1 if '*m*' is December, and 0 otherwise, $I(\text{Non-Dec Quarter-End})$ is an indicator variable takes a value of 1 if the month corresponds to a quarter-end other than December, (i.e., March, June, or September), and equals 0 otherwise, 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* as of end of month *m-1*, $\text{Moneyness}_{i,m-1}$ of fund *i* at the end of month *m-1*, Lockup_i and Restrict_i are the lockup and restriction periods for fund *i*, $\text{Size}_{i,m-1}$ is the size of the fund measured as the natural logarithm of the assets under management (AUM) for fund *i* for

[25] We also compare each month's gross return to the gross return in December. We find the December gross return to be higher in each of the 11 pair-wise comparisons and the differences to be statistically significant.

[26] We winsorize extreme 1% of all the variables in order to minimize the influence of outliers. Here and throughout the paper, we report the p-values after adjusting for heteroskedasticity, clustering at the fund-level, and including year dummies. Petersen (2006) shows through simulations that estimating standard errors clustered on one dimension and including dummies for the other yield results similar to clustering on two dimensions. Following Petersen (2006), we cluster standard errors on more frequent fund clusters than the time clusters that are less frequent in our sample (7,535 funds compared to 108 months).

month *m-1*, σ_i is the standard deviation of prior year's monthly returns of fund *i*, Age_i is the age in years of fund *i* at the end of prior year, MFee_i is the management fee rate charged by fund *i*, $I\left(\text{Strategy}_{i,s}\right)$ are strategy dummies that take the value 1 if fund *i* belongs to strategy *s*, and 0 otherwise, $I\left(\text{Year}_{t,k}\right)$ are year dummies, and $\xi_{i,m}$ is the error term.[27]

We report our findings in Table III. Our results for Model 1 show that the slope coefficient on December dummy is positive (λ_1 = 1.511) and highly significant at 1% level. We term this the *December return-spike*. The coefficient estimate implies that December returns are higher by 1.5%. This result is economically significant given that the average returns are 1.06% per month.

As discussed earlier, it is possible that a part of the December returns could result if hedge funds trade in the same securities as mutual funds that engage in year-end return manipulation. In the absence of high-frequency holdings data, it is not possible to precisely quantify the magnitude of active and passive portfolio pumping during December. However, we can estimate the fraction of the December return that could be due to hedge funds taking advantage of mutual fund behavior. This is possible because, unlike mutual funds, hedge funds are unlikely to have an active interest in managing returns at quarter-ends, since they are not subject to portfolio disclosure requirements. Thus, if we find higher quarter-end returns for hedge funds, it 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 III show that the non-December quarter-end dummy is positive (coeff. = 0.082) and significant at the 1% level, suggesting that hedge fund returns at quarter-ends could be influenced by the inflation of mutual fund returns. In the study by Carhart

[27] We also conduct our analysis at the substrategy level using the original strategy classification in the four databases and find qualitatively similar results.

et al. (2002), the ratio of coefficient on the year-end dummy to the coefficient on the quarter-end dummy (b_1/b_3) is 3.26 (i.e., 53.01÷16.27) and 2.57 (29.6÷11.54) for *all* funds (see Table II, Panels A and B, of Carhart et al. (2002): page 671). If hedge funds were passively benefiting from the gaming behavior of mutual funds by holding the same securities, then one would expect a similar ratio of coefficients on year-end and quarter-end dummies (as a rough approximation) in Model 1 of Table III. However, in our case, this ratio is substantially higher, 18.4 (i.e., 1.511÷0.082), indicating that the hedge fund returns exhibit a considerably bigger December return-spike even after allowing for the possibility that they could be passively benefiting from portfolio pumping activity of mutual funds. Taking the higher ratio of 3.26 and the coefficient on Quarter-end dummy of 0.082, we estimate that portfolio pumping at year-ends by mutual funds contributes at best 0.3% (0.082 × 3.26) to the December return-spike of 1.511% observed in hedge fund returns. The balance of the December return-spike could be due to active returns management by hedge funds driven by incentives and opportunities, as we examine in the next section.

To allow for the possibility that managers could increase their risk exposures in December, we also included the cross-sectional volatility measure, CS Volatility$_m$. We find the coefficient on cross-sectional volatility is positive (coeff. = 0.066) and significant at the 1% level. This implies that higher cross-sectional volatility is associated with higher returns.

Consistent with the findings of Agarwal, Daniel, and Naik (2006), who estimate cross-sectional regressions of annual returns, we observe that delta, lockup period, and restriction period are positively related to returns. Consistent with the evidence of serial correlation in hedge fund returns documented in the literature, we find that the coefficient on the first lag of returns is positive and significant. The coefficient on the second lag is positive but not significant.

In Model 2, we re-estimate Model 1 but with the residual returns (or discretionary component of returns) as the dependent variable. In addition, we replace the two lags of returns with those of residuals. Residuals strip out the effect of higher returns in December that will result if risk premiums are higher in December. We find that the slope coefficient on December dummy is significantly positive. We term this the *December residual-spike*. Based on coefficient estimates, we find the December residual-spike is 0.362%, which is economically significant given that the average monthly return is 1.06%. Overall, the results in Table III show support for our Hypothesis 1.

V. B. Robustness

In this section, we demonstrate that our results are robust to several alternative specifications. Appendix C, Panel A reports only the December return-spike and residual-spike based on Models 1 and 2 of Table III. For brevity, we do not report the coefficients on control variables.

First, we use net returns instead of gross returns. Row 1 reports the results. Second, to better control for changes in risk in the current year, we replace prior year volatility with volatility estimated over the twelve months ending November of the current year. Row 2 reports the results. Third, we repeat our analysis in Model 2 by replacing the residual with the sum of residual and the intercept from the Fung and Hsieh (2004) model. Row 3 reports the results. Fourth, we add the book-to-market and momentum factors to the Fung and Hsieh (2004) seven-factor model and use the residuals from this nine-factor model as the dependent variable. Row 4 reports the results.

Fifth, we allow for time-varying risk loadings in estimating residuals. Specifically, to allow for the incentives to increase risk (embedded in the flow-performance relation), we allow the monthly loading on the market factor to be a function of the performance of the fund relative

to its peers. We hypothesize this relation to be of the following functional form.

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

where β_t is the loading on the market factor in month t and $Frank_{t-1}$ is the fractional rank based on fund's returns from January to month $t-1$ relative to other funds following the same strategy within a given year. For January, *Frank* is assumed to be zero for all funds because there are no tournament-related incentives at the start of the year.[28] Empirical implementation effectively amounts to re-estimating residuals by augmenting Fung and Hsieh (2004) model with the interaction of $Frank_{t-1}$ and $R_{mt} - R_{ft}$. Row 5 reports the results.[29]

Finally, it is conceivable that managers gradually adjust their returns and do not limit their manipulations to the month of December. Hence, we replace the December dummy with a November–December dummy, which takes the value 1 if month equals November or December. Row 6 reports the results.

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

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

In Section III, we hypothesized that funds that have higher incentives (funds that are in the money and near the money, funds that have higher delta, funds that have better relative performance, funds that have shorter lockup and restriction periods, and funds that earn

[28] A number of papers (Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997) among others) document tournament behavior in mutual funds.

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

significant dollar management fees) should exhibit greater December returns. We also posited that funds with greater opportunities (funds with higher volatility and funds with more exposure to liquidity risk factor) should display greater December returns. To test this notion (Hypothesis 2), we first create subsamples based on these key variables. Specifically, each year, we divide the funds into *high* and *low* categories based on the median of these variables at the end of each November. 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 III for these subsamples of funds. Table IV reports the results for the subsamples. For brevity, we report only the slope coefficients for the December dummy (the return-spike and 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 (based on Chow-test).

From Table IV, we find the December return-spike to be higher for in-the-money and near-the-money funds compared to out-of-the-money funds. The coefficient estimates from Column 1 imply that the December returns are greater for in-the-money funds by 1.910% (i.e., 2.281 – 0.371) when compared to out-of-the-money funds. The December return-spike is also greater for near-the-money funds by 1.457% (1.828 – 0.371) relative to out-of-the-money funds. These results also indicate that the December return-spike is greater for the in-the-money funds relative to near-the-money funds (2.281% versus 1.828%), a difference that is significant at the 1% level and is intuitive, given the fact that benefits of returns management are highest for in-the-money funds.

Results are similar when we look at the December residual-spike. Columns 4-6 report the results. Compared to out-of-the-money funds, the December residual-spike is significantly greater for in-the-money funds by 0.597% and near-the-money funds by 0.517%. Once again, in-

the-money funds exhibit a significantly greater December residual-spike relative to near-the-money funds. These figures are economically large, as the average monthly return (residual) is 1.06% (–0.02%).

Next, we repeat our analysis using the second measure of incentives—delta. We find that funds with high delta exhibit greater December return-spike compared to funds with low delta. The December return-spike is significantly higher for the high-delta funds by 0.355% (i.e., 1.642% – 1.287%). We find similar results with the December residual-spike. High-delta funds exhibit a significantly higher residual-spike of 0.158% (0.414% – 0.256%).

Third, we use the November-end fractional rank. We form three groups, with the top 20% in one group, the bottom 20% in the second group, and the middle 60% in the third group.[30] Consistent with our expectations, we find that the December return-spike is highest for the top 20%, followed by the funds in the middle 60%, with the bottom 20% having the lowest return-spike. The results based on December residual-spike are similar, but with one exception – the top 20% funds do not exhibit the highest December residual-spike.

Fourth, we use lockup period and restriction period. Since only 19% of the funds have lockup period, the low-lockup period group effectively consists of firms that impose no lockup provisions. Results in Column (1) show that funds with shorter lockup periods exhibit significantly higher December return-spike compared to the funds with longer lockup periods (1.559% versus 1.164%). Similarly, we find that funds with shorter restriction periods exhibit higher December returns compared to the funds with longer restriction periods (1.555% versus 1.488%), though the difference is not statistically significant. Results are qualitatively similar when we examine the December residual-spike. Again, funds with shorter lockup periods show

[30] We have followed Sirri and Tufano (1998) breakpoints here. We get similar results to those reported below if we form 3 groups based on top 25%, middle 50%, and bottom 25%.

significantly higher residual-spike than the funds with longer lockup periods (0.409% versus 0.008%). Further, funds with shorter restriction periods also exhibit bigger December residual-spike compared to the funds with longer restriction periods (0.421% versus 0.322%).[31]

Finally, we sort funds into two groups based on dollar management fee as of November-end. We find that the funds that earn larger fees show a December return-spike of 1.599%, which is significantly higher than the December return-spike of 1.425% for the low-fee funds. Similarly, the December residual-spike for high-fee funds is significantly higher than that for low-fee funds (0.442% vs. 0.267%).

We next examine the role of opportunities in the returns management behavior. We use two distinct proxies for opportunities, namely volatility and liquidity. From results in Table IV, we find that funds with high volatility exhibit more pronounced December return-spike than do funds with low volatility (2.468% vs. 0.546%). Similarly, the December residual-spike for the high-volatility funds is significantly higher than the low-volatility funds (0.545% versus 0.165%).[32]

Next, we classify funds into different groups based on exposure to illiquidity. From the results in Table IV, we find that the December return-spike is higher for low-liquidity funds by 0.499% (1.791% – 1.292%). This suggests that more illiquid funds that have greater opportunities to engage in returns management exhibit higher December return-spike.[33]

[31] Although the difference is of expected sign, the difference is not statistically significant.

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

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

However, this result does not hold for residual-spike, where we find that low-liquidity funds exhibit lower December residual-spike relative to high-liquidity funds.

VI. A. Robustness

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

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

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

Earlier, we showed that funds that earn higher dollar management fees exhibit a greater December spike. Both size (assets under management) and percentage management fee rate contributes to higher dollar management fee. We therefore do two independent sorts based on November-end fund size and percentage management fee. Row 4 reports the results for subsamples based on fund size, while Row 5 reports the results for groups based on percentage management fee. We find that neither size nor the percentage management fee by itself has an

impact on December spike, thus confirming that the incentives captured by the dollar management fee are driving the December spike.[34]

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

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

Given the evidence of returns management, we next investigate the mechanism employed by funds to accomplish such management. Toward that end, we test Hypotheses 3 and 4 (*savings* and *borrowing* hypotheses) developed in Section III. To recall, the *savings hypothesis* posits that funds underreport positive returns up to November to create reserves to add to months with negative returns. The unused reserves are then added back in December. We test this by including two additional explanatory variables to Model 1 of Table III: (a) $\text{Reserves}_{i,m\text{-}1}$, the cumulative return from January up to month $m-1$ if positive, and 0 otherwise, and (b) the interaction of this variable with the December dummy. If the fund manager is adding those reserves from previous months in December, then one would expect to see this interaction term to be positive. Our results for Model 1 in Table V confirm that this is indeed the case, with the coefficient on the interaction being positive (coeff. = 0.112) and significant at the 1% level. This result is also economically significant. One standard deviation change in the Reserves variable results in an increase of 1.46% in December returns.

An alternative way to compute reserves is to determine the difference between true

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

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

Next, we test our *borrowing hypothesis*, which addresses the possibility that portfolio pumping by funds causes December returns to be higher at the expense of January returns. In this scenario, one would expect to see a lower January return in the next year following a high December return in the current year. To test this hypothesis, we include two additional variables to Model 1 of Table III: (a) a January dummy that takes the value 1 if the month is January of next year, and 0 otherwise, and (b) the interaction of the January dummy with returns during the previous month. As per the borrowing hypothesis, one would expect to observe a negative coefficient for the interaction term. Results reported in Model 2 of Table V indicate that the coefficient on the interaction of the January dummy and the lagged monthly return is negative (coeff. = –0.040) and significant at the 1% level.[35] This result is also economically significant. A one standard deviation increase in the December returns is associated with a borrowing of 0.39% returns from January of the following year. As before, our results for the other variables remain unchanged. This provides evidence in support of the borrowing hypothesis.

Finally, we test for both *savings* as well as *borrowing* hypotheses together by including the corresponding variables together in Model 3 of Table V. We find that both the interaction

[35] We find that the slope coefficient on January dummy itself is positive (coeff.=0.612) and significant at the 1% level in Model 2 of Table V. This is consistent with the well-documented January effect in stock returns.

terms (i.e., December dummy with reserves up to the previous month-end, and January dummy with previous month's return) are significant at the 1% level. This suggests that funds employ *both* savings and borrowing mechanisms to boost December returns. Overall, the results from this section strongly support Hypotheses 3 and 4.

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

In this subsection, we provide additional tests of the borrowing hypothesis using the equity holdings data of hedge funds. In particular, we follow the approach in Carhart et al. (2002), who examine year-end inflation in equities held by mutual funds. Unlike mutual funds, hedge funds do not need to disclose their portfolio holdings on a quarterly basis. However, SEC requires that all funds with assets exceeding $100 million and holding large positions in stocks (more than 10,000 shares or $200,000) need to submit 13f filings. This enables us to obtain equity holdings data of 161 hedge funds from our sample.[36]

We report the average year-end inflation of stocks held by hedge funds in Table VI. Our analysis follows that in Table VII of Carhart et al. (2002). Each year, we sort stocks into five quintiles based on 6-month returns up to the second-last day of the year. We then sort these stocks into five quintiles based on market capitalization on the second-last day of the year. This provides us 25 return-size portfolios.

Next, we determine the year-end inflation in these stocks held by hedge funds that have higher incentives and greater opportunities to inflate December returns. For this purpose, we form groups of funds based on their characteristics such as moneyness, delta, fractional rank, and dollar management fees at the end of November. We also use other attributes such as lockup period, restriction period, volatility of fund returns, and fund's exposure to illiquidity to segregate funds into different sub-samples. For example, using November-end moneyness, as

[36] We follow a procedure similar to Brunnermeier and Nagel (2004) who identify equity holdings of 52 hedge funds. Recently, Griffin and Xu (2008) have also used holdings data of hedge funds to determine presence of skill.

before, we divide the funds into three groups: in the money, near the money, and out of the money. Using November-end fractional rank, as in Sirri and Tufano (1998), we divide funds into three groups: top 20%, middle 60%, and bottom 20%. For all remaining characteristics, we form two groups (High and Low) using the median value each year as the cutoff.

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

Following Carhart et al. (2002), we compute return inflation as the return on each of the 25 long-short stock portfolios on the last day of the year net of its return on the first day of next year. To examine whether this inflation is significantly different from zero, we first compute this return inflation for every non-overlapping 2-day period in the year. We then compute a z-statistic for return inflation for each of the 25 portfolios for each year as the return inflation net of the average of all possible 2-day returns during that year, divided by the standard deviation of the two-day returns over that year. For the sake of brevity, we report in Table VI, the average end-of-year inflation across 25 return-size portfolios over the 9-year period. The z-statistic for this overall average is the sum of the z-statistic over the 225 portfolio-year combinations divided by square root of 225. The reported p-value is the probability of obtaining a z-statistic greater than this overall z-statistic.

Results in Table VI indicate that funds with higher moneyness, greater delta, superior relative performance, larger dollar management fee, and lower restriction periods exhibit

abnormally high year-end return followed by a reversal on the first day in January. These findings suggest that a subgroup of hedge funds facing stronger incentives inflate year-end returns by borrowing from January returns.

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

VIII. Concluding Remarks

In this paper, we provide strong evidence of hedge funds inflating their returns in an opportunistic fashion to increase their compensation. Specifically, we find that hedge funds exhibit a December residual-spike of 36 basis points, even after controlling for potential increase in December factor premium and various fund characteristics including their risk-taking behavior at year-ends. More importantly, we show that the cross-sectional variation in the December spike is positively related to the incentives of the fund manager to maximize fees and the opportunities available for the fund manager to engage in return inflation.

We also provide evidence on two potential mechanisms employed by hedge funds to manage returns. First method involves funds underreporting their returns in the early part of the year in order to create reserves for possible poor performance later in the year (saving for the rainy day). In case some of these reserves are left unutilized, they get added to the December returns resulting in the spike. Second mechanism involves funds borrowing from their January

returns of the subsequent year to improve their December returns. This can be achieved by funds pushing up the security prices at December-end by last-minute buying, which is followed by price reversals in January.

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

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Figure 1: Distribution of Hedge Funds by Data Sources

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

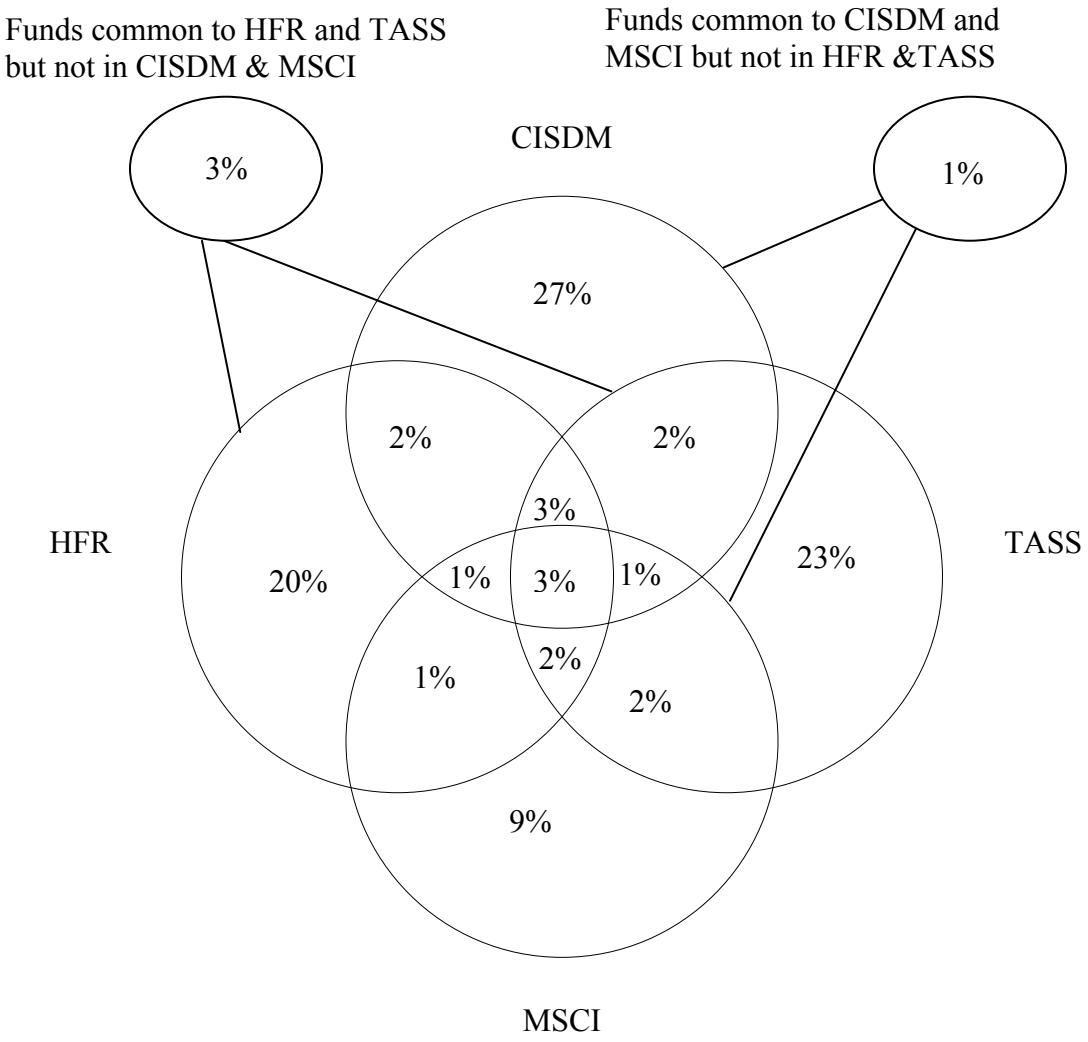

Table I. Summary Statistics

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

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

Table II. Do Funds Exhibit a December Spike? Univariate Results

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

	Dec Average	Jan-Nov Average	Dec Average − Jan–Nov Average (*p*-value)
Gross hedge fund returns	2.51%	0.96%	1.55%*** (0.000)
Residual hedge fund returns	0.23%	−0.02%	0.25%*** (0.000)
SP	0.76%	0.46%	0.30% (0.852)
SCLC	2.51%	–0.32%	2.83%** (0.023)
10Y	0.35%	0.25%	0.10% (0.880)
CS	0.36%	0.06%	0.30% (0.483)
BdOpt	3.09%	1.15%	1.94% (0.741)
FXOpt	3.91%	–1.52%	5.43% (0.434)
ComOpt	2.10%	–2.00%	4.10% (0.358)

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

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

Independent Variables	Expected Sign	Model 1 $Returns_m$	Model 2 $Residuals_m$
December Dummy (λ_1)	+	1.511^{***}	0.362^{***}
		(0.000)	(0.000)
Non-December Quarter-End Dummy		0.082^{***}	0.019
		(0.005)	(0.402)
$CS\text{-}Volatility_m$		0.066^{***}	0.068^{***}
		(0.000)	(0.000)
$Returns_{m-1}$ ($Residuals_{m-1}$ for Model 5)		0.101^{***}	0.079^{***}
		(0.000)	(0.000)
$Returns_{m-2}$ ($Residuals_{m-2}$ for Model 5)		0.002	0.038^{***}
		(0.534)	(0.000)
$Delta_{m-1}$		0.120^{***}	0.080^{***}
		(0.000)	(0.000)
$Moneyness_{m-1}$		0.001	-0.005^{***}
		(0.482)	(0.000)
Lockup Period		0.127^{***}	0.001
		(0.001)	(0.974)
Restriction Period		0.192^{***}	0.029
		(0.000)	(0.130)
$Size_{m-1}$		-0.092^{***}	-0.105^{***}
		(0.000)	(0.000)
Prior Year Volatility		0.002	-0.039^{***}
		(0.761)	(0.000)
Age_{m-1}		-0.029^{***}	0.001
		(0.000)	(0.718)
Management Fee Rate		2.601	0.828
		(0.148)	(0.331)
Intercept, Strategy Dummies, and Year Dummies		Yes	Yes
Observations		195717	195717
Adjusted R^2		3.4%	1.9%

Table IV. Do funds manage their reported returns? Evidence from cross-sectional variation in December spike

The table reports the slope coefficients for the December dummy for Models 1 and 2 in Table III for the various subsamples listed in the first column. Funds are classified into three groups based on their moneyness as of November end, where moneyness is computed as the difference between spot and exercise price divided by the exercise price. Out-of-the-money funds are those whose moneyness is less than $-(\mu + \sigma)$. Near-the-money funds are those whose moneyness is between $-(\mu + \sigma)$ and $-(\mu - \sigma)$. In-the-money funds are those moneyness is greater than $-(\mu - \sigma)$. μ is the average monthly fund return, and σ is the standard deviation of monthly fund returns using the entire return history for each fund. Fractional rank is the rank (between 0 and 1) of the fund at November-end each year based on its performance from January to November, relative to all funds within a strategy, i.e., fractional relative rank. Following Sirri and Tufano (1998), we divide the funds into top 20%, middle 60%, and bottom 20% based on their fractional relative rank as of November-end. Dollar management fee at the end of November is the management fee rate multiplied by the fund size at November-end. For characteristics other than moneyness, we do independent sorts based on Delta as of November end, Lockup, Restriction Period, Dollar Management Fee as of November end, Volatility, and Liquidity. The High (Low) groups consist of funds whose characteristic is greater than or equal to (less than) the median value that year; similarly for Long (Short) periods in all instances. The difference in the December spike is between the High and Low groups. In the case of moneyness, the difference is with respect to out-of-the-money group. The *p*-values given in parentheses adjacent to the difference values are based on Chow-tests that examine whether this difference is significantly different from zero. The "expected sign" is the hypothesized sign for the difference in December spikes. All figures are in percentage, e.g., a coefficient of 2.281 is equal to 2.281%. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively. Standard errors are corrected for heteroskedasticity and fund-level clustering with *p*-values reported in parentheses.

	Dec return-spike as per Model 1, Table III	Expected Sign	Difference (*p*-value)	Dec residual-spike as per Model 2, Table III	Expected Sign	Difference (*p*-value)
Subsample	**1**	**2**	**3**	**4**	**5**	**6**
INCENTIVES TO MANAGE RETURNS						
In the Money	2.281***			0.566***		
	(0.000)	+	1.910*** (0.000)	(0.000)	+	0.597*** (0.000)
Near the Money	1.828***			0.486***		
	(0.000)	+	1.457*** (0.000)	(0.000)	+	0.517*** (0.000)
Out of the Money	0.371***			-0.031		
	(0.000)			(0.680)		
High Delta	1.642***			0.414***		
	(0.000)	+	0.355*** (0.000)	(0.000)	+	0.158* (0.055)
Low Delta	1.287***			0.256***		
	(0.000)			(0.000)		
Top 20% Fractional rank	2.129***			0.071		
	(0.000)	+	0.820*** (0.000)	(0.485)	+	–0.234 (0.105)
Mid 60% Fractional rank	1.677***			0.605***		
	(0.000)	+	0.368*** (0.003)	(0.000)	+	0.300*** (0.000)
Bottom 20% Fractional rank	1.309***			0.305***		
	(0.000)			(0.003)		
Long Lockup	1.164***			0.008		
	(0.000)	–	–0.395*** (0.006)	(0.945)	–	–0.401*** (0.001)
Short Lockup	1.559***			0.409***		
	(0.000)			(0.000)		
Long Restriction Period	1.488***			0.322***		
	(0.000)	–	–0.067 (0.517)	(0.000)	–	–0.099 (0.238)
Short Restriction Period	1.555***			0.421***		
	(0.000)			(0.000)		
High $ Management Fee	1.599***			0.442***		
	(0.000)	+	0.174* (0.076)	(0.000)	+	0.175** (0.027)
Low $ Management Fee	1.425***			0.267***		
	(0.000)			(0.003)		

Table IV. (contd.) Do funds manage their reported returns? Evidence from cross-sectional variation in December spike

	Dec return-spike as per Model 1, Table III	Expected Sign	Difference (*p*-value)	Dec residual-spike as per Model 2, Table III	Expected Sign	Difference (*p*-value)
Subsample	**1**	**2**	**3**	**4**	**5**	**6**
OPPORTUNITIES TO MANAGE RETURNS						
High Volatility	2.468*** (0.000)	+	1.922*** (0.000)	0.545*** (0.000)	+	0.380*** (0.000)
Low Volatility	0.546*** (0.000)			0.165*** (0.000)		
High Liquidity	1.292*** (0.000)	–	–0.499*** (0.000)	0.584*** (0.000)	–	0.482*** (0.000)
Low Liquidity	1.791*** (0.000)			0.102 (0.104)		

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

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

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

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

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

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

Appendix A: Classification of Hedge Fund Strategies

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

I = incentive fee rate (expressed as a fraction)

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

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

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

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

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

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

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

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

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

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

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

Appendix C. Robustness Tests

Panel A reports the coefficient of December dummy from Table III for various alternative specifications. See Section V.B for the description of various robustness tests. Panel B reports the coefficient of December dummy of Table III for various subsamples. See Section V1.A for the description of various robustness tests. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Panel A: Replicating Table III

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

Appendix C. (contd.) Robustness Tests

Panel B: Replicating Table IV for various subsamples

Row	Subsample	Dec return-spike as per Model 1, Table III	Difference (*p*-value)	Dec residual-spike as per Model 2, Table III	Difference (*p*-value)
1. Strategy level μ and σ	**In the Money**	2.456*** (0.000)	2.015*** (0.000)	0.597*** (0.000)	0.628*** (0.000)
	Near the Money	1.446*** (0.000)	1.005*** (0.000)	0.465*** (0.000)	0.496*** (0.000)
	Out of the Money	0.441*** (0.000)		–0.031 (0.700)	
2. Moneyness with respect to zero	**In the Money (Moneyness ≥ 0)**	2.322*** (0.000)	2.130*** (0.000)	0.594*** (0.000)	0.822*** (0.000)
	Near the Money (Moneyness < 0, Top half)	1.248*** (0.000)	1.056*** (0.000)	0.525*** (0.000)	0.753*** (0.000)
	Out of the Money (Moneyness < 0, Bottom half)	0.192 (0.127)		–0.228** (0.026)	
3. Incentive fee rate	**Incentive fee rate > 20%**	1.731*** (0.000)	0.186 (0.458)	0.594*** (0.002)	0.176 (0.381)
	Incentive fee rate = 20%	1.478*** (0.000)	–0.067 (0.539)	0.318*** (0.000)	–0.100 (0.266)
	Incentive fee rate < 20%	1.545*** (0.000)		0.418*** (0.000)	
4. Fund size	**High Fund Size**	1.514*** (0.000)	–0.008 (0.936)	0.412*** (0.000)	0.112 (0.165)
	Low Fund Size	1.522*** (0.000)		0.300*** (0.000)	
5. Management fee rate	**High Management Fee**	1.529*** (0.000)	0.091 (0.437)	0.348*** (0.000)	–0.077 (0.426)
	Low Management Fee	1.438*** (0.000)		0.425*** (0.000)	

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

This table reports OLS estimates using $Flow_t$ as the dependent variable. Sample period is from 1994 to 2002. Flow is the annual investors' dollar flow scaled by assets. The independent variables include 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 ($Return_t$), 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% respectively. p-values corrected for heteroskedasticity and fund-level clustering are reported in parentheses.

	Expected Sign	Dependent variable: $Flow_t$	
NPM_{t-1}	+	0.023^{***} (0.000)	
NPM_t	+		0.056^{***} (0.000)
$Rank_{t-1}$ - Bottom Quintile		0.134 (0.584)	0.259 (0.283)
$Rank_{t-1}$ - 4th Quintile		0.626^{***} (0.002)	0.661^{***} (0.001)
$Rank_{t-1}$ - 3rd Quintile		1.028^{***} (0.000)	1.047^{***} (0.000)
$Rank_{t-1}$ - 2nd Quintile		0.465^{**} (0.045)	0.578^{**} (0.012)
$Rank_{t-1}$ - Top Quintile		0.867^{**} (0.015)	0.971^{***} (0.007)
$Delta_{t-1}$		0.155^{***} (0.000)	0.156^{***} (0.000)
Hurdle Rate		0.034 (0.115)	0.031 (0.139)
High-Water Mark		0.073^{***} (0.002)	0.069^{***} (0.004)
Lockup Period		–0.032 (0.312)	–0.027 (0.388)
Restriction Period		-0.086^{***} (0.009)	-0.096^{***} (0.004)
$Size_{t-1}$		-0.191^{***} (0.000)	-0.192^{***} (0.000)
$Flow_{t-1}$		0.064^{***} (0.000)	0.065^{***} (0.000)
$Volatility_{t-1}$		-3.097^{***} (0.000)	-2.421^{***} (0.000)
Age_{t-1}		-0.015^{***} (0.000)	-0.014^{***} (0.000)
Management Fee Rate		1.664 (0.284)	1.834 (0.236)
$Return_t$		0.620^{***} (0.000)	0.378^{***} (0.000)
Intercept		0.472^{***} (0.000)	0.220^{***} (0.003)
Strategy dummies		Yes	Yes
Year dummies		Yes	Yes
Adjusted R^2		12.8%	13.2%
Observations		16,901	16,901