CFR-Working Paper NO. 10-15

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G. Cici • A. Kempf • A. Puetz

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Gjergji Cici, Alexander Kempf, and Alexander Puetz*

May 2013

ABSTRACT

We provide evidence on the valuation of equity positions by hedge funds. Reported valuations deviate from standard valuations based on closing prices from CRSP for roughly seven percent of the positions. These equity valuation deviations are positively related to illiquidity and price volatility of the underlying stocks. They respond to past performance and intensify after an advisor starts reporting to a commercial database. Furthermore, advisors with more valuation deviations show a stronger discontinuity in their reported returns around zero, manage a higher fraction of potentially fraudulent funds, report smoother returns, and exhibit an upward spike in their December reported returns.

JEL classifications: G23, G28

Keywords: Hedge Funds, Return Management, Valuation Deviations

* Cici is from Mason School of Business, The College of William & Mary. Email: gjergji.cici@mason.wm.edu. Cici is also a Research Fellow at the Centre for Financial Research (CFR), University of Cologne. Kempf is from Department of Finance and Centre for Financial Research (CFR), University of Cologne. Email: kempf@wiso.uni-koeln.de. Puetz is from Department of Finance and Centre for Financial Research (CFR), University of Cologne. Email: puetz@wiso.uni-koeln.de.

✧ A previous version of this paper was titled "Caught in the Act: How Hedge Funds Manipulate their Equity Positions". The authors thank Luis Palacios and Rabih Moussawi from Wharton Research Data Services for providing them with the 13F positions valuation data. The authors thank Vikas Agarwal, Scott Gibson, Jim Hodge of Permal Asset Management, John Merrick, Harvey Westbrook, and Marco Rossi for their helpful comments. We also thank our discussants and other participants, including Nicolas Bollen, Patrice Fontaine, Mila Getmansky, Robert Kosowski, Jennifer Marietta-Westberg, Markus Glaser, and Jerry Parwada at our presentations at the 2012 AFA Annual Meeting in Chicago, 2012 EFA Annual Meeting in Copenhagen, 2012 EFM Symposium on Asset Management in Hamburg, 2011 Hedge Fund Conference at Vanderbilt University; 2011 Conference on Current Topics in Financial Regulation at University of Notre Dame; the 2011 Swiss Society for Financial Markets Research Conference in Zürich; the 2011 Annual Congress of the German Academic Association for Business Research (VHB) at the Technical University of Kaiserslautern; Karlsruhe Institute of Technology (KIT), Technical University of Dresden, University of Bonn, University of Duesseldorf, University of Frankfurt, University of Hannover, University of Lyon, University of Marburg, University of New South Wales, University of Sydney, University of Technology Sydney, University of Texas A&M, University of Zaragoza, and Vienna University of Economics and Business for their helpful comments.

I. Introduction

The recent cases of hedge fund fraud in the United States have made irregularities in the asset valuation practices of hedge fund advisors a point of concern for regulators, investors, and legislators. A key concern is that hedge funds strategically adjust their valuations, which can result in direct wealth losses for hedge fund investors; wealth transfers across current, new, and redeeming hedge fund investors; and sub-optimal investment decisions made by investors in response to distorted hedge fund risk-return profiles.[1]

The fundamental cause for these concerns is that, unlike mutual funds, hedge funds are exempt from the set of regulations comprising the Investment Company Act of 1940 (ICA).[2] As such, hedge funds do not have to follow the detailed valuation guidelines and rules provided by SEC under the framework of ICA, causing them to operate in an ambiguous legal environment.

Previous research has sought to shed light on the valuation practices of hedge funds, but, due to limited availability of position valuations data, the resulting analysis has produced only indirect evidence based on self-reported hedge fund returns. This paper provides direct evidence on the valuation of security positions for reporting purposes by hedge funds. Our direct evidence comes from analyzing a new dataset of individual stock position valuations reported by hedge fund advisors in 13F reports filed with the SEC.[3] A key advantage of using

[1] Under heightened pressure to take a more active role in detecting and combating hedge fund fraud, SEC recently launched the *Aberrational Performance Inquiry* initiative, under which SEC staff use proprietary models to detect abnormal performance that is indicative of hedge fund fraud (see U. S. Securities and Exchange Commission (2011)).
[2] Sections 3(C)(1) and 3(C)(7) of ICA exempt hedge fund advisors from the general regulatory requirements of ICA as long as they have a certain number of investors that are classified, respectively, as accredited investors or qualified purchasers.
[3] Positions in 13F reports represent the only detailed portfolio positions of hedge fund advisors that are publically available.

this dataset is that market prices of equity securities are readily available, which makes valuation irregularities fairly straightforward to detect.

We document that about seven percent of all equity positions—corresponding to about 150 thousand positions—are valued by hedge funds at prices that differ from closing prices as reported in CRSP. This is somewhat surprising since using closing prices to value positions is not only a widely-used practice for NAV calculations among institutions that are subject to ICA, but is also explicitly requested by the SEC when advisors file their 13F reports.

We show that valuation deviations are related to stock characteristics. Specifically, positions corresponding to highly illiquid stocks display more valuation deviations. A possible interpretation is that closing prices for illiquid stocks are less likely to be used in position valuations since they might be viewed as unreliable and unreflective of fair value based on the most recent market conditions. We also show that positions of stocks with higher intraday volatility display more valuation deviations. This is consistent with advisors relying on data feeds from vendors that use data collection and dissemination procedures that record prices at different point in times. Such arrangements would naturally lead to higher valuation deviations for stocks that experience high intraday price volatility.

We next explore whether strategic considerations on the part of advisors are also related with the valuation deviations that we document. Perhaps hedge fund advisors strategically manage their valuations to impress upon their potential or existing clients. Such a behavior is conceivable since the valuation practices of hedge fund advisors exist in a lax legal environment characterized by a high degree of ambiguity. Under the presumptions that hedge funds advisors use the same valuation practices for 13F reporting and net asset value calculations that get reported to investors we expect 13F valuations to reflect any strategic behavior by advisors.

We find support for the view that advisors strategically adjust their valuations based on two groups of tests. Results from the first group of tests show a negative relation between the direction of valuation deviations and past performance. Following weak past performance of hedge funds, we observe a tendency for positions to be marked up. Conversely, following strong past performance, we observe a tendency for positions to be marked down relative to standard valuations based on closing prices from CRSP. Digging deeper, we find that the negative relation between past performance and valuation deviations is confined only to those advisors that self-report to commercial databases. Such a pattern is consistent with advisors using valuation as a tool in trying to impress potential investors that are exposed to their self-reported returns.

Our second group of tests examines whether hedge fund advisors with more valuation deviations exhibit stronger irregularities in their reported returns identified in previous research. We show that advisors with more pronounced valuation deviations run more hedge funds that: have a stronger discontinuity in their reported returns around zero; are flagged by the "Kink" indicator of Bollen and Pool (2012) as potentially fraudulent; and report smoother returns. Furthermore, advisors that increase their tendency to overvalue or decrease their tendency to undervalue positions in the last calendar quarter exhibit a stronger upward spike in their December reported returns, where the return spike is modeled after Agarwal, Daniel, and Naik (2011).

Our paper is related to a growing literature that studies irregularities in self-reported hedge fund returns. The findings from this literature suggest that hedge funds report: (1)

smoothed returns (see, e.g., Bollen and Pool (2008) and Getmansky, Lo, and Makarov (2004)), (2) disproportionally more small positive than small negative returns in the pooled distribution of returns around zero (see, e.g., Jylha (2011) and Bollen and Pool (2009)), and (3) higher returns in December (see Agarwal, Daniel, and Naik (2011)).[4] We contribute to this literature by documenting a direct link between the valuation behavior of hedge fund advisors and irregularities in reported returns.

Our research is also related to studies that analyze the operational risks of hedge funds (see, e.g., Brown, Goetzmann, Liang, and Schwarz (2008); Brown, Goetzmann, Liang, and Schwarz (2012); Cassar and Gerakos (2011); and Liang (2003)). For example, Brown, Goetzmann, Liang, and Schwarz (2012) show that hedge funds that have experienced legal problems are less likely to use independent pricing agents, and they are more likely to have switched their pricing agent in the last year. Cassar and Gerakos (2011) show that hedge funds with less verifiable pricing sources and greater pricing discretion for their managers report smoother returns. Our paper acknowledges valuation irregularities as an operational risk and contributes to this literature by documenting new ways in which this type of operational risk manifests itself.

The remainder of the paper is organized as follows. Data and sample summary statistics are discussed in Section II. Section III provides an overview of valuation deviations and how they relate to stock characteristics. We explore strategic considerations related to the documented valuation deviations in Section IV. Section V investigates the relations between valuation deviations and irregularities in reported returns. Section VI concludes.

[4] See also Patton, Ramadorai, and Streatfield (2013) and Aragon and Nanda (2012) for evidence that hedge funds restate their initially reported returns in later data vintages.

II. Data

A. Data Sources and Identification of Hedge Fund Advisors

Our hedge fund 13F position valuations data came from Wharton Research Data Services (WRDS), which downloaded and parsed electronic 13F filings of our sample hedge fund advisors from the SEC EDGAR website. According to the Securities Exchange Act of 1934, all institutions with investment discretion over $100 million in certain pre-specified securities must report quarterly holdings to the SEC as part of their 13F filing requirement.[5] The securities for which institutions have to report their positions include equities, convertible bonds, options, and warrants; their names are periodically listed on the SEC website.[6] Our sample period begins in the first quarter of 1999 – the earliest period for which 13F reports are available in electronic format from EDGAR – and ends in the last quarter of 2008. Important for our study, WRDS' dataset differs from the 13F dataset provided by Thomson-Reuters, a 13F data source popular with academics, in one important way: Unlike Thomson-Reuters, WRDS provides valuations reported by each institution for each position.

To identify hedge fund advisors among all the 13F filing institutions, we relied on a proprietary list of hedge fund advisors provided by Thomson-Reuters. The list, which contained identification numbers (CIKs), assigned uniquely to each 13F filing institution by the SEC, was checked against various sources to make sure that the listed institutions were indeed hedge fund management companies. We checked the list against names of hedge fund management companies listed in the Center for International Securities and Derivatives Markets (CISDM), Lipper TASS, and Morningstar hedge fund databases and against advisor

[5] More information about the requirements of Form 13F pursuant to Section 13(f) of the Securities Exchange Act of 1934 can be found at: http://www.sec.gov/divisions/investment/13ffaq.htm.

[6] The official list of Section 13F securities can be found on the following SEC webpage: http://www.sec.gov/divisions/investment/13flists.htm.

names that were registered as investment advisors managing hedge funds on Form ADV filed with the SEC. The advisors' names were also checked using Lexis-Nexis searches and inspection of advisors' websites to ensure that they were involved in hedge fund management. Besides the intended checks, this procedure also generated additional hedge fund advisor names that we added to the original list. The resulting list of 978 hedge fund advisors that filed at least one 13F report during the 1999-2008 period was subjected to additional filters described below.

We employed the CISDM, Lipper TASS, and Morningstar hedge fund databases to obtain information on monthly returns, assets under management, and domicile for hedge funds that were managed by our sample advisors.

Our last dataset is the CRSP Monthly and Daily Stock Data Series. We used this dataset to supplement our holdings and position valuations data with historical prices, volume, and other information for individual stocks. This last dataset was linked with the rest of our data using stock CUSIPs.

B. Data Steps and Valuation Deviation Measure

Since we focus only on the valuation of equity positions, we excluded all positions corresponding to non-equity securities.[7] Key to our analysis is the valuation of each stock position reported by each hedge fund advisor along with the number of stock shares held in that position. Advisors are required to report position valuations in their 13F reports that are consistent with fair value principles. In accordance with this principle, the 13F filing

[7] Additional details on the procedure we used to clean our dataset from non-equities and data errors are provided in the appendix.

instructions request that *"In determining fair market value, [the advisor has to] use the value at the close of trading on the last trading day of the calendar year or quarter, as appropriate*."[8]

To assess the extent to which advisors conform with these valuation principles, we construct a valuation benchmark for each reported position that employs the stock prices reported in the CRSP daily stock files. CRSP files report for each stock on each date the last trading price from the exchange on which the stock last traded. For stocks that did not trade on a particular day, the price is reported as the average of ask and bid quotes at the close of the trading. We calculated how much the reported valuation of each stock position differs from a valuation that is based on stock prices reported in the CRSP database. We refer to this measure as *valuation deviation* (*VD*) and compute it as follows:

$$VD_{i,j,t} = \frac{reported\ valuation_{i,j,t} - CRSP\ valuation_{i,j,t}}{CRSP\ valuation_{i,j,t}} \tag{1}$$

where $reported\ valuation_{i,j,t}$ is the value reported by advisor i for a position of stock j in quarter t, and $CRSP\ valuation_{i,j,t}$ is the respective value based on the CRSP price. More specifically, $CRSP\ valuation_{i,j,t}$ is computed as

$$CRSP\ valuation_{i,j,t} = reported\ shares_{i,j,t} \times CRSP\ price_{j,t} \tag{2}$$

where $reported\ shares_{i,j,t}$ is the number of reported shares by advisor i for stock j in quarter t and $CRSP\ price_{j,t}$ is the stock price of stock j from the CRSP stock database as of the portfolio report day.

[8] See Special Instruction 9 at http://www.sec.gov/about/forms/form13f.pdf.

Our choice of CRSP-reported prices as a valuation benchmark is warranted by several considerations: First, CRSP prices are sourced from Interactive Data (ID), one of the major commercial providers of price data. ID sells price data to financial institutions directly or licenses it to other data vendors that in turn sell it to financial institutions. Thus, we expect the majority of institutions to use ID prices either directly or indirectly. For this reason, using the ID-sourced prices from CRSP helps minimize the presence of deviations due to advisors' data vendor choices. Second, the ID-sourced closing prices reported by CRSP represent composite or consolidated closing prices based on the last eligible trade made during regular trading hours across all market centers and exchanges. These composite closing prices, which in effect represent "official" closing prices, are prepared by an Exclusive Securities Information Process ("ESIP") center, which consolidates all trade and price data and disseminates the consolidated closing prices to all the data vendors.[9] Thus, regardless of whether an advisor uses a pricing feed from Bloomberg, Thomson-Reuters, or ID, the advisor will have access to the same official closing prices. Third, as a data provider to the academic community, CRSP employs extensive resources to ensure that historical stock prices of non-surviving companies are available, which minimizes survivorship-related biases that are likely to exist among data vendors serving primarily commercial clients.

To ensure that valuation deviations did not arise due to unintentional data entry errors or text-parsing errors, we performed corrections to address scaling issues due to displaced decimal points or interchanged columns. Furthermore, we excluded all stocks that had a stock

[9] Securities Industry Automation Corporation (SIAC) is the designated ESIP for all AMEX and NYSE listed securities while Nasdaq is the ESIP for all Nasdaq securities.

split in the last five days prior to the valuation date to eliminate the possibility of a non-zero *VD* caused by an accidental use of prices prior to the stock split.

As an additional screen, we included only 13F reports that were filed within forty-five days from the end of the calendar quarter, the legally required window within which the reports have to be filed. Furthermore, we excluded all advisors that filed less than four 13F reports. Finally, to eliminate remaining outliers (caused perhaps by filing or parsing errors that remained undetected by our data cleaning procedures) we excluded the most extreme 5% of the deviations.[10]

C. Sample Description

-- Please insert Table 1 approximately here --

Our final sample consists of 864 hedge fund advisors and 15,198 quarterly reports. Sample summary statistics are reported in Table 1. The number of hedge fund advisors that filed 13F reports increases from 194 in 1999 to 682 in 2008. Consistent with an increasing number of 13F filing advisors, the number of filed reports more than quadruples from 534 reports in 1999 to 2,360 reports in 2008. Table 1 also shows the portfolio value and the number of distinct stocks in the portfolios of fund advisors. The mean portfolio size varies around the total sample mean of about 1.8 billion USD.[11] Only in the years following the dot-com bubble (2002, 2003) and the subprime crisis (2008) the mean portfolio size is considerably smaller. On average, a hedge fund advisor's portfolio covers 125 distinct stocks, whereas the median number of stocks is 48. Both numbers declined between 1999 and 2008.

[10] We applied alternative filters related to the size of position valuation deviation that excluded positions deviating by more than 50%, 40%, 30%, 20%, or 10%, respectively. The results of the paper were qualitatively similar when these alternative filters were used.

[11] The 13F portfolio size is calculated based on CRSP prices and the reported number of shares.

III. Frequency and Magnitude of Valuation Deviations

A. Valuation Deviations over Time

We start by examining positions with reported valuations that differ from CRSP valuations. Since advisors are required to round reported valuations to the nearest one thousand dollars (as per Form 13F instructions), the valuation deviation of a position by less than $1,000 could be simply caused by rounding. Thus, to avoid deviations that arise due to rounding, for such positions we set *VD* equal to zero.

-- Please insert Table 2 approximately here --

Panel A of Table 2 reports the frequency of positions with: nonzero valuation deviations; positive valuation deviations; and negative valuation deviations. Focusing on all valuation deviations, we observe that, on average, about 7% of all positions, which translates into about 150 thousand out of roughly 2.3 million total positions, were valued at prices that deviated from CRSP prices. The fraction of positions with valuation deviations is higher in the first half than in the second half of the sample period. The largest value is reached in 2003 (11.56%) and the lowest in 2006 (4.50%). The marked decline in the fraction of valuation deviations from 2003 to 2004 by almost a half is consistent with Dimmock and Gerken (2013) who show a decline in return misreporting after hedge fund advisors were required in 2004 to register with the SEC. The fraction of positions that deviate from the CRSP valuation by at least five percent is much smaller, but still accounts for about one percent of all positions. The fraction of positions deviating by at least 10 percent makes up only 0.5 percent of all positions. [12]

Focusing on the signed deviations, we see an almost even split between positive and negative deviations, with negative deviations capturing a slightly higher fraction. For example, positive valuation deviations constitute 3.14% of all positions, while negative valuation deviations constitute 3.64%. A similar pattern exists even when we look at the fractions of positions that deviate by 5% or 10%. The presence of both positive and negative valuation deviations is consistent with a general low level of precision when valuing illiquid stock positions or other institutional arrangements, but could also be consistent with strategic valuation strategies, such as return smoothing whereby directional valuation is related to past performance.[13] We explore these possible explanations in what follows.

B. Valuation Deviations and Stock Illiquidity

It is possible that the positions with valuation deviations correspond to thinly-traded stocks trading at prices that do not reflect a fair value based on the most recent market conditions. For example, for stocks that traded early in the day but did not trade for the rest of the day, an advisor could choose to ignore the last trade price as a stale price and use discretion to come up with an alternative "fair value" estimate that reflects more recent

[12] In unreported results we compared valuations of our sample hedge fund advisors with those of top ten mutual fund advisors over the last five years of our sample period, for which we were able to download mutual fund 13F position valuation data from Morningstar Direct. Consistent with hedge fund advisors operating in an ambiguous legal environment, hedge fund advisors exhibit larger valuation deviations than mutual fund advisors. For example, positions with a deviation of at least 10% make up 0.40% of all hedge fund positions but only 0.17% of the mutual fund positions. These results are consistent with Schwarz and Potter (2013), who report that 0.20% of all mutual fund positions exhibit deviations of at least 10%. Furthermore, we also document that the average magnitude of hedge fund valuation deviations exceeds the average magnitude of mutual fund valuation deviations by almost a factor of three. We thank Nick Bollen for suggesting this comparison.

[13] For example, Cici, Gibson, and Merrick (2011) show that corporate bond mutual funds push their valuations up following poor fund performance and push them down following good performance.

developments.[14] Such a practice would lead to a deviation from the CRSP valuation, which is based on the last trading price for the day.

Panel B reports similar statistics as in Panel A for positions stratified into deciles by the underlying stock's illiquidity. As a measure of a stock's illiquidity we use the Amihud's ratio, defined as the ratio of a given stock's absolute return to its dollar volume.[15] For each stock and quarter, this ratio is averaged across all trading days of the quarter to come up with a quarterly measure. Stocks are ranked on illiquidity and sorted into deciles every quarter.

Here and in all subsequent analysis we dropped a small number of 5,657 positions corresponding to stocks that did not trade on the date of the report. In such instances, CRSP does not report a closing price but rather the average of the bid and ask closing quotes and advisors would be expected to conduct valuations based on prices provided by pricing services, quotes obtained from dealers, in-house valuation methodologies, or a combination of these approaches. This would naturally lead to a higher fraction of deviations that are of a mechanical nature, which is confirmed by the fact that 70 percent of the 5,657 positions were valued at prices that differed from CRSP prices.

Consistent with higher illiquidity affording advisors a higher level of valuation discretion, valuations deviations from Panel B show a nearly monotonic increase with the level of illiquidity. The fraction of positions with valuation deviations ranges from 5.57% to 9.99% across the different deciles. Thus, deviations from CRSP valuations are observed across all deciles regardless of the level of illiquidity. A significant fraction of deviations exists even among the highly liquid positions of Decile 1. This suggests that illiquidity alone

[14] According to regulation SFAS 157, as applied to Alternative Asset Management Companies, an advisor could make a case that a thinly traded stock represents a Level 2 asset, for which valuation discretion can be applied, rather than a Level 1 asset, for which valuation should be based on market prices only.
[15] See Amihud (2002).

cannot explain the observed valuation discrepancies among hedge fund advisors. That illiquidity is not the only factor is further supported by the fact that, despite the larger deviations observed in Decile 10, or even Decile 9, the number of deviations from these deciles is dwarfed by the number of deviations from the rest of the deciles. Thus, these findings suggest that discretion that is available when valuing thinly-traded stocks is not responsible for the vast majority of observed position valuation deviations. Similar patterns are observed for both positive and negative deviations.

C. Valuation Deviations and Stock Price Volatility

The observed valuation deviations could be the outcome of processes caused by institutional arrangements, of which we are not aware. For example, advisors or their external pricing services could rely on pricing feeds offering prices that differ from CRSP prices due to data collection and dissemination procedures that are specific to particular data vendors. Such practices could lead to use of prices recorded at different points in time, resulting in larger valuation deviations when intraday price volatility is higher for the underlying stocks. Thus, it is likely that the positions with nonzero valuation deviations correspond to stocks that experienced high intraday price volatility.

Panel C of Table 2 reports similar statistics as in Panels A and B for positions stratified into deciles by the underlying stocks' intraday price volatility. A stock's intraday volatility is measured as the spread between the highest and lowest trading price during the report day, divided by the average of highest and lowest trading price.

As expected, the relation between valuation deviations and intraday price volatility in Panel C is positive, suggesting that certain institution-specific valuation arrangements might play a role. Nonetheless, valuations deviations are observed across all deciles regardless of the level of intraday volatility. The fraction of positions with valuation deviations ranges from 5.82% to 7.44% across the different deciles. Importantly, a significant fraction of deviations exists even among the least volatile positions of Decile 1. The positions with valuation deviations represent 5.85% of all positions in Decile 1, suggesting that intraday volatility alone, as related to certain institutional arrangements, does not entirely explain the observed valuation discrepancies among hedge fund advisors. Similar patterns are observed for both positive and negative deviations.

In Panel D we report results from a multivariate logit regression, which models the probability of a non-zero, at least 5%, and at least 10% valuation deviation, respectively. Results from the logit regression generally confirm the qualitative nature of the univariate results presented in Panels B and C.

IV. Strategic Valuation Deviations

A. Past Performance and Directional Valuation Deviations

In this section we examine whether the valuation deviations that we documented are driven by strategic considerations. If some of these deviations are caused by strategic considerations, we would expect them to react to advisors' past performance.

To examine the relation between the marking behavior of advisors and performance of the hedge funds that they manage, we relate a directional valuation deviation measure at the advisor's portfolio level to past portfolio performance using a regression approach. The dependent variable, *Portfolio Valuation Deviation*, measures directional equity valuation deviations aggregated at the advisor's portfolio level. It is computed for each advisor in each quarter as the difference of the fraction of positions with positive valuation deviations and the fraction of positions with negative valuation deviations.

The key independent variables are two return measures, which reflect the advisor's past performance over the last twelve months. For each advisor, the first return measure, *Past Holding Return*, is calculated as the holdings-based return of a portfolio that mimics the holdings of the advisor's 13F portfolio. This holdings-based return is calculated by employing CRSP returns for the underlying portfolio stocks. The idea behind this measure is that an advisor looks at the true returns of the underlying assets in his portfolio at the end of quarter *t* and then strategically affects valuations. Ideally we would have used true returns of the total portfolio, but such returns are not available because only a fraction of the portfolio is reported in 13F reports. Thus, to capture the total performance of the advisor, we use an additional performance measure, *Past Reported Return*, which is the value-weighted average of the reported returns of all hedge funds managed by the advisor.

Another independent variable is *Database Reporting*, a dummy variable indicating whether an advisor reports to at least one of the three commercial databases, CISDM, Lipper TASS, and Morningstar, in a given quarter.[16]

The first control variable we include is the advisor's stock portfolio illiquidity, *Stock Illiquidity*. This variable is included to control for any effects that are related to valuation of thinly traded stocks, for which the manager can choose valuations that differ from what might be viewed as stale closing prices. For each advisor and quarter *Stock Illiquidity* is measured as the value-weighted mean of Amihud's ratio of all the stocks in portfolio. Similarly, the

[16] Some of the advisors that we classify as non-reporting could be reporting to some other databases. This, however, would work against us finding a difference in the valuation deviations between advisors we classify as reporting and those that we classify as non-reporting.

second control variable, *Stock Price Volatility*, is measured as the value-weighted mean of the intraday stock price volatility measure introduced in the previous section and is included to control for any valuation effects that are related to advisors holding more stocks with high intraday stock price volatility. Estimation results and corresponding p-values are reported in Table 3. Standard errors are clustered by advisor to account for correlation across the observations belonging to the same advisor.

-- Please insert Table 3 approximately here --

If the valuation behavior of hedge fund advisors is indeed driven by strategic considerations similar to those documented in Cici, Gibson, and Merrick (2011) for bond mutual funds, we would expect hedge fund advisors to strategically mark up their positions following low portfolio returns and strategically mark down positions following high portfolio returns. Results from the first three models show a negative coefficient on *Past Holding Return*, suggesting an inverse relationship between past portfolio returns and end-of-quarter *Portfolio Valuation Deviation*.[17] Thus, following lower past returns, an advisor tends to overvalue its portfolio. Alternatively, following higher past returns, an advisor tends to undervalue its portfolio. Such behavior suggests that a component of the valuation behavior of hedge fund advisors is directly driven by incentives related to performance considerations.

Our control variables, *Stock Illiquidity* and *Stock Price Volatility*, are insignificant. This is sensible since illiquidity or volatility by themselves should not predict the direction of valuation deviations. Furthermore, the inclusion of the control variables or year fixed effects does not affect our results.

[17] In unreported results we show that this finding qualitatively holds even when we use shorter intervals (defined over the last three, six months or from the beginning of the calendar year until the end of current quarter) to measure past performance.

B. Visibility and Strategic Deviations

In Models 4-6 we include the *Database Reporting* variable and also interact it with the *Past Holding Return*. Previous research that examines biases in self-reported hedge fund returns suggests an advertising rationale intended to generate more visibility behind the decision of some hedge funds to self-report to commercial databases.[18] We hypothesize that the negative relation between past performance and directional valuation deviations should be stronger among advisors that self-report to commercial databases, who can use valuation as a tool to generate attractive returns that they can advertise to potential investors.[19] Consistent with this hypothesis, the interaction term is negative and significant. Interestingly, for hedge fund advisors that do not self-report to commercial databases the relation between past performance and directional valuation deviations becomes insignificant, suggesting that only self-reporting advisors respond to past performance by adjusting their valuations strategically. Since reported returns are available only for self-reporting advisors, in Models 7-9 we replace the *Past Holding Return* with the *Past Reported Return* and we repeat the analysis only among the self-reporting advisors. Results from these models confirm that self-reporting hedge fund advisors adjust their valuations in response to past reported returns. Inclusion of the control variables or year fixed effects does not affect our key results.

[18] See, for example, Ackermann, McEnally, and Ravenscraft (1999), Agarwal, Fos, and Jiang (2011), and Aiken, Clifford, and Ellis (2012).

[19] The restriction imposed by SEC rule 502(c), which prohibits hedge fund advisors from engaging in any form of general advertising, actually makes reporting to commercial databases the best remaining advertising option for advisors.

C. Valuation Deviations Before and After Joining a Commercial Database

If reporting to commercial databases is a way for hedge fund advisors to advertise returns that have been affected by the valuation choices of advisors, we would expect hedge fund advisors to change their valuation behavior after joining the database. To test this effect, we focus on advisors with at least one holdings report before and after the first date of appearance in a commercial database. We are able to identify 38 such advisors.

Since we have shown that valuation deviations respond to past performance in either direction for the tests here and in subsequent sections we introduce a variable, *FRAC*, which reflects both positive and negative deviations. *FRAC* is measured as fraction of positions with nonzero valuation deviation for each advisor in each quarter

We use two approaches to compare the marking behavior before and after the first date of database reporting. The first one is in effect a difference in differences approach, whereby the *FRAC* of each advisor in each quarter is first benchmarked against the average *FRAC* of other advisors that never chose to report to a commercial database. Next, an average of the benchmarked measure is computed for each advisor before and after the first date of database reporting, and a paired t-test is used for the after-before comparison. The second approach compares the average advisors' rank based on their *FRAC* measure before and after, where ranks are normalized to be between 0 and 1.

-- Please insert Table 4 approximately here --

Table 4 shows that advisors show stronger equity valuation deviations after they start reporting to commercial databases. This result is statistically significant for both differences and is consistent with advisors changing their marking behavior after joining a commercial database. Our evidence that advisors tend to change their valuation behavior is interesting in that it raises doubts about the accuracy of self-reported returns for measuring hedge fund performance.

V. Valuation Deviations and Suspicious Return Patterns

In this section we explore whether hedge fund advisors that show more valuation deviations display stronger irregularities in their reported returns. We focus on three return patterns that are documented in the literature to be consistent with strategic return management: (1) a discontinuous distribution of hedge fund returns around zero, (2) smoothed hedge fund reported returns, and (3) upward biased reported returns in the month of December.

A. Discontinuity around Zero and Valuation Deviations

Bollen and Pool (2009) document a discontinuity in the distribution of pooled hedge fund reported returns whereby the number of small positive returns far outweighs the number of small negative returns. Such a pattern is consistent with hedge fund advisors trying to avoid reporting small negative returns by strategically marking up positions just enough to avoid negative returns. In a later extension, Bollen and Pool (2012) show that a particular discontinuity measure, which they refer to as the Kink measure, is the most significant measure for predicting hedge fund fraud. In what follows, we explore whether advisors that show more valuation deviations exhibit a stronger distribution discontinuity in their reported returns and manage a higher fraction of funds that are flagged as potentially fraudulent by the Kink measure.

A.1 Discontinuity Measure Based on Fixed Return Intervals

We run regressions of our discontinuity metric on dummy variables reflecting the level of equity valuation deviations by advisors. Our discontinuity metric is constructed by first pooling the reported returns of all hedge funds managed by each advisor and then computing the difference of the fraction of positive returns and negative returns within tight intervals around zero for each advisor.

The key independent variables are constructed by dividing advisors into three equal-sized groups according to their fraction of positions with nonzero valuation deviations, *FRAC*, as introduced in the previous section. Advisors with the lowest fraction of valuation deviations are in the benchmark group. We then define two dummy variables: *Medium Deviation* equals one for advisors belonging to the group with medium equity valuation deviations and zero otherwise. *High Deviation* equals one for advisors belonging to the group with the highest fraction of valuation deviations. The fraction of positions with nonzero valuation deviations is measured for each advisor in each quarter and then averaged across all quarterly observations of a given advisor to come up with one aggregated measure per advisor.

As control variables we include three variables, *Average Stock Illiquidity, Total Portfolio Illiquidity,* and *Average Stock Price Volatility*. The first control variable is included to control for any effects that are related to valuation of thinly traded stocks for which the manager has more valuation discretion. It is calculated as the average *Stock Illiquidity* across the advisor's quarterly observations. Since the return patterns of a hedge fund depend not only on the stocks held but also on other assets in the portfolio, we use the second variable to additionally control for any illiquidity-induced pricing issues related to assets other than equity securities, which we do not observe in our 13F portfolio data. *Total Portfolio Illiquidity* is measured as the beta exposure to Pástor and Stambaugh (2003)'s innovations in aggregate liquidity, aggregated at the advisor level by taking a value-weighted average across all funds managed by each advisor. *Average Stock Price Volatility* is calculated as the average *Stock Price Volatility* across the advisor's quarterly observations.

-- Please insert Table 5 approximately here --

Table 5 reports results.[20] We employ different specifications whereby the dependent variable, the fraction of positive minus fraction of negative reported returns, is constructed based on returns that fall within three intervals, i.e., +/-100, +/-200, and +/-300bps around zero.

Results show that the differential fraction of positive and negative reported returns is higher for advisors with the largest fraction of valuation deviations relative to advisors with the lowest fraction of valuation deviations. The coefficient on *High Deviation* is both economically and statistically significant across all specifications. For example, for the +/-100 bps interval, the differential fraction of positive and negative reported returns is about twice as high for the high deviating advisors than for the base group The coefficient on *Medium Deviation* is also positive in all specifications, but smaller in magnitude than the coefficient on *High Deviation.* Our results suggest that advisors strategically adjust their valuations in order to avoid reporting small losses, which causes a discontinuity in their reported returns around zero.

[20] For the sake of brevity, here and in the following analyses, we do not report coefficients for the control variables, but indicate the models where the controls are included.

A.2 Discontinuity Measure Based on the Kink Indicator

We next examine whether the observed valuation deviations are related to the Kink fraud indicator suggested by Bollen and Pool (2012). This measure is also based on the distribution of fund returns around zero. However, an advantage of this measure is that the size of the return interval is not set exogenously, but is determined optimally for each fund based on its return distribution. Moreover, Bollen and Pool (2012, p. 2694) show that the Kink fraud indicator is the most significant measure for detecting fraudulent behavior among hedge funds.

To calculate this measure, for each fund, we create a histogram of reported returns with the optimal bin size computed according to Silverman (1986).[21] Next, we count the number of return observations that fall in three adjacent bins, two to the left of zero and one to the right. If a fund shows no discontinuity and thus a smooth distribution, the number of observations in the middle bin should equal the average number of observations in the two surrounding bins. Thus, we test whether the number of observations in the middle bin is significantly lower than the average from the two adjacent bins. Following Bollen and Pool (2012), we categorize a fund as "Kink" fund when the number of observations in the middle bin is significantly less than expected at a 10% significance level. Next, for each advisor, the dependent variable is computed as the fraction of funds that are categorized as Kink funds. The independent variables are the same as in the previous section.

-- Please insert Table 6 approximately here --

[21] The optimal bin size for each fund is calculated as $\alpha \times 1.364 \times \sigma \times n^{-1/5}$, where σ is the monthly return standard deviation, n is the number of observations, and α is set equal to 0.776, corresponding to a normal distribution.

The regression results in Table 6 show that advisors who exhibit more valuation deviations manage a larger fraction of funds that are categorized as "Kink" funds, i.e., potentially fraudulent funds, than the base group. While "Kink" funds make up only about 8 to 12 percent of funds in the base group, their fraction is almost double among the high deviating advisors. For advisors with medium valuation deviations the respective coefficients are also positive, but significantly smaller than coefficients for advisors with high deviations (at a significance level of 10%). These results are also consistent with advisors that show more valuation deviations exhibiting a stronger discontinuity in their reported returns around zero relative to advisors in the benchmark group. Thus, evidence from Table 6 is consistent with the evidence presented in Table 5.

B. Smoothed Returns and Valuation Deviations

Previous studies document that hedge funds report remarkably smooth returns (see, e.g., Bollen and Pool (2008) and Getmansky, Lo, and Makarov (2004)). Return smoothing alters hedge fund reported returns and helps generate more attractive performance statistics. To measure return smoothing parameters, we use an approach that is similar to the approach used in Getmansky, Lo, and Makarov (2004). Hedge fund reported returns are modeled as a function of the underlying unobservable true economic returns. In the model, $R_{j,t}^{rep}$ represents the reported return of fund *j* for period *t* and $R_{j,t}$ stands for the unobserved economic return of fund *j* over the same period. The model specification includes concurrent and two lags of economic returns:

$$R_{j,t}^{rep} = a + \theta_{j,0} \cdot R_{j,t} + \theta_{j,1} \cdot R_{j,t-1} + \theta_{j,2} \cdot R_{j,t-2} + \varepsilon_{j,t}\,, \tag{3}$$

with constraints on coefficients such that $\theta_{j,k} \in [0,1]$, $k = 0,1,2$, and $1 = \theta_{j,0} + \theta_{j,1} + \theta_{j,2}$.

As the economic return is unobservable, we proxy for it with the predicted returns from a regression of reported excess fund returns on a subset of ten factors that are used to proxy for hedge fund trading strategies. The factors are: the three Fama and French (1993) factors; the five trend-following factors of Fung and Hsieh (2004); the change in the yield of a 10-year Treasury note; and the change in the credit spread.[22] We restrict the subset of included risk factors to a maximum of three factors by maximizing the R^2. Results using an unrestricted model are similar and not reported here in the interest of brevity.

Our first smoothing measure is the smoothing coefficient θ_0. It shows how much of the true economic return is reflected in the reported return. A θ_0 value equal to one means that, on average, a fund fully reported the true economic return. Return smoothing will lead to a less than one-for-one relation between reported returns and true economic returns, i.e., a θ_0 less than one, since reported returns do not fully incorporate all the available economic information. The second smoothing measure is the Herfindahl Index (ξ) suggested by Getmansky, Lo, and Makarov (2004) as a way to measure concentration of theta weights. This measure is constructed as the sum of the squared theta coefficients for each fund. Lower values for this measure are indicative of return smoothing. The last return smoothing measure is the first order serial correlation coefficient of reported returns (ρ), which will be higher in the presence of return smoothing. Unlike the first two measures, this third measure is simply computed from reported returns and is thus not dependent on a particular method used to model reported or economic returns. Each measure is first computed for each hedge fund and

[22] In robustness examinations we also use a subset of hedge fund strategy indices as factors to predict returns (see, e.g., Agarwal and Naik (2004)). Our results (not reported) remain the same.

then value-weighted across all funds managed by each advisor. The dependent variable is one of the three smoothing measures. The independent variables are the same as in the previous section.

-- Please insert Table 7 approximately here --

Table 7 reports regression results. The coefficient value for *High Deviation* is significantly smaller than zero when the θ_0 measure is the dependent variable. This is consistent with advisors that exhibit more valuation deviations reporting smoother returns than advisors that exhibit fewer valuation deviations. This conclusion is further supported by the sign and significance of coefficients on *High Deviation* when specifications with the other two dependent variables are used. As expected, advisors with high equity valuation deviations show a significantly lower Herfindahl Index and significantly higher serial correlation. For advisors with medium valuation deviations the respective coefficients are insignificant suggesting that valuation deviations of a more extreme nature might be needed to effectively smooth reported returns.

C. December Return Spike and Tendency to Change Directional Deviations

Agarwal, Daniel, and Naik (2011) show that hedge fund returns exhibit an upward spike in the month of December, which is related to hedge fund incentives. We examine whether the December spike is related to changes in the valuation behavior of hedge fund advisors.

The December spike is most likely to be driven by an increase in portfolio valuation which can result either from an increase in overvaluation or a decrease in undervaluation. Hence, we explore whether the December return spike metric is positively related to an increase in advisors' *Portfolio Valuation Deviation*, the directional valuation deviation measure introduced in Section IV.

The dependent variable, the advisor-specific December return spike, is constructed every year by first calculating the December return spike metric for each hedge fund. The December return spike metric is measured for each hedge fund each year as the difference between the December return and the average return of the 11 remaining months of the same year. Next, the December return spike metric is aggregated at the advisor level every year by taking a value-weighted average across all funds managed by the same advisor.

The key independent variables are constructed by dividing advisors into three equal-sized groups each year according to their increase in *Portfolio Valuation Deviation* over the last calendar quarter. Advisors with the lowest increase in *Portfolio Valuation Deviation* are in the benchmark group. We then define two dummy variables: *Medium Increase* equals one for advisors belonging to the group with medium increase in *Portfolio Valuation Deviation* and zero otherwise. *High Increase* equals one for advisors belonging to the group that increased the *Portfolio Valuation Deviation* the most.

Observations are at the advisor and year level and standard errors are clustered by advisor. In Model (2) and (3) we include the following control variables: *Stock Illiquidity* and *Stock Price Volatility*, calculated as in Section IV, and *Total Portfolio Illiquidity*, defined as in Section V.A and V.B.

-- Please insert Table 8 approximately here --

Regression results from Table 8 show that advisors who increased their tendency to overvalue positions in the last quarter the most show a significantly higher December spike metric. Specifically, advisors from this group show a December return that is more than 70 basis points higher than the December return of advisors with the lowest increase in *Portfolio Valuation Deviation*. This holds for all specifications regardless of whether control variables and year fixed effects are included. In summary, this result is consistent with the December spike being driven by hedge fund advisors increasing the tendency to overvalue or decreasing the tendency to undervalue their positions.[23]

Taken together, results from Tables 5-8 suggest that there is a strong relation between the advisors' valuation deviation patterns and irregularities in their reported returns.

VI. Conclusion

Hedge funds have enjoyed substantial leeway in how they value their assets for reporting and transaction purposes. However, recent egregious cases of manipulation by certain advisors have brought about increased criticism and scrutiny of hedge fund valuation practices. The recent developments and the growing size of the hedge fund industry have also given rise to calls for greater transparency and structure in the asset valuation process and more monitoring and enforcement efforts by regulators. As a step in this direction, the Statement of Financial Accounting Standards No. 157 (SFAS 157), also applicable to hedge fund advisory firms, was introduced to provide guidance on how to measure and report fair value of assets.[24]

[23] The specification that includes year fixed effects omits 1999. The large intercept from this regression is roughly consistent with the magnitude of the spike for 1999 reported in Agarwal, Daniel, and Naik (2011).
[24] Effective after November 15, 2007, SFAS 157 has introduced more structure in the valuation process. For example, when valuing positions, advisors are required to classify assets into three levels based on their liquidity. The most liquid assets from Level 1 should be valued using market prices and quotes. To value the least liquid assets from Level 3, advisors are required to come up with estimated fair values. Furthermore, careful documentation and justification is required as advisors decide to move a particular asset from one category to another.

Our research suggests that the calls for greater transparency and structure were well-justified. Using data from 1999 till 2008, a period roughly before SFAS 157 came into full effect, we documented a non-trivial number of valuation differences from standard valuations based on closing prices even though advisors were explicitly asked to use closing prices. The main conclusion of our paper is that the equity valuation deviations that we document are not driven only by difficulties associated with valuing illiquid securities or by other institutional arrangements, but also by strategic considerations. In light of the latter driver, one important aspect of our findings is that these discrepancies took place even for valuations that advisors reported to SEC in mandated 13F reports. This evidence is consistent with Brown, Goetzmann, Liang, and Schwarz (2012) who show that hedge fund managers misrepresent material information even when such information is likely to be verified.

Table 1
Sample Characteristics

This table presents summary statistics for our sample of hedge fund advisors during the 1999-2008 sample period. Statistics include: number of hedge fund advisors that filed 13F reports with the SEC, number of 13F reports filed by our sample advisors, the mean and median portfolio size as well as the mean and median number of distinct stocks in the 13F portfolios.

			13F portfolio size (in million $)		*Number of stocks in 13F portfolio*	
Year	*13F Advisors*	*13F Reports*	*Mean*	*Median*	*Mean*	*Median*
1999	194	534	2,250	429	140	66
2000	241	699	1,967	405	126	63
2001	288	895	1,820	331	140	56
2002	329	1,054	1,444	215	128	55
2003	420	1,254	1,427	265	124	52
2004	526	1,593	1,849	333	133	54
2005	635	2,027	1,919	338	127	50
2006	726	2,308	1,966	333	124	45
2007	724	2,474	2,169	386	123	43
2008	682	2,360	1,605	254	110	35
Total sample	864	15,198	1,845	323	125	48

Table 2
Stock Position Valuation Deviations, Illiquidity, and Intraday Volatility

This table reports descriptive statistics on the valuation deviations of the stock positions from 13F reports. We calculate how much the reported valuation of each stock position differs from a valuation that is based on prices from CRSP. We refer to this measure as *valuation deviation (VD)* and compute it as follows:

$$VD_{i,j,t} = \frac{reported\ valuation_{i,j,t} - CRSP\ valuation_{i,j,t}}{CRSP\ valuation_{i,j,t}}$$

where $reported\ valuation_{i,j,t}$ is the value reported by advisor *i* for a position of stock *j* in quarter *t*, and $CRSP\ valuation_{i,j,t}$ is the respective value based on the CRSP price. More specifically, $CRSP\ valuation_{i,j,t}$ is computed as $CRSP\ valuation_{i,j,t} = reported\ shares_{i,j,t} \times CRSP\ price_{j,t}$ where $reported\ shares_{i,j,t}$ is the number of reported shares by advisor *i* for stock *j* in quarter *t* and $CRSP\ price_{j,t}$ is the stock price of stock *j* from the CRSP stock database as of the portfolio report day. *VD* is set to zero if a position's reported value deviates from its CRSP valuation by less than $1,000. Panel A reports the fraction of positions with $|VD|>0$ and the fraction of positions deviating by at least 5% and 10%, respectively. For each deviation magnitude, also the fraction of positive and negative valuations is reported. The last column reports the number of observations. Panel B reports the same statistics as in Panel A, stratified by stock illiquidity, excluding the non-traded stocks. Positions are sorted into illiquidity deciles following a two-step approach: First, for each stock, illiquidity is measured by Amihud's ratio, defined as the ratio of a given stock's absolute return to its dollar volume. For each stock and quarter, this ratio is averaged across all trading days of the quarter to come up with a quarterly measure. The stock-quarter observations are ranked on illiquidity and sorted into deciles where the most liquid stocks are placed in Decile 1 and the most illiquid stocks are placed in Decile 10. Second, each position-quarter observation is sorted into the underlying stock's illiquidity decile. Panel C reports position valuation deviations stratified by a stock's intraday volatility, also excluding the non-traded stocks. Positions are sorted into volatility deciles following the two step approach in Panel B. A stock's intraday volatility is measured as the spread between the highest and lowest trading price during the report day, divided by the average of highest and lowest trading price. Panel D reports results from a multivariate logit regression, which models the probability of a non-zero, at least 5%, and at least 10% deviation, respectively.

Table 2 – continued

Panel A: Stock position valuation deviations by year										
	% |VD|>0			*% |VD| ≥ 5%*			*% |VD| ≥ 10%*			
Year	*All*	*Positive*	*Negative*	*All*	*Positive*	*Negative*	*All*	*Positive*	*Negative*	*Observations*
1999	7.95%	4.28%	3.68%	0.95%	0.59%	0.36%	0.54%	0.34%	0.20%	95,709
2000	9.06%	3.14%	5.92%	0.79%	0.32%	0.46%	0.48%	0.20%	0.28%	108,352
2001	9.89%	5.31%	4.58%	2.05%	1.13%	0.92%	1.12%	0.64%	0.48%	154,940
2002	8.59%	5.23%	3.36%	0.93%	0.46%	0.47%	0.49%	0.24%	0.25%	163,430
2003	11.56%	5.56%	6.00%	1.04%	0.48%	0.55%	0.60%	0.27%	0.33%	183,634
2004	6.68%	2.89%	3.79%	0.74%	0.32%	0.42%	0.42%	0.22%	0.20%	257,298
2005	5.60%	2.77%	2.84%	0.91%	0.40%	0.51%	0.48%	0.20%	0.28%	315,599
2006	4.50%	1.74%	2.76%	0.66%	0.28%	0.37%	0.31%	0.15%	0.16%	330,240
2007	6.02%	2.79%	3.23%	0.98%	0.43%	0.55%	0.49%	0.19%	0.30%	344,894
2008	4.76%	1.58%	3.18%	0.76%	0.26%	0.50%	0.37%	0.16%	0.21%	295,623
Total sample	6.78%	3.14%	3.64%	0.93%	0.43%	0.50%	0.49%	0.23%	0.26%	2,249,719

Panel B: Stock position valuation deviations stratified by stock illiquidity										
	% |VD|>0			*% |VD| ≥ 5%*			*% |VD| ≥ 10%*			
Illiquidity Decile	*All*	*Positive*	*Negative*	*All*	*Positive*	*Negative*	*All*	*Positive*	*Negative*	*Observations*
1 (most liquid)	6.94%	3.44%	3.50%	0.92%	0.44%	0.48%	0.47%	0.22%	0.25%	788,475
2	5.57%	2.72%	2.86%	0.83%	0.41%	0.43%	0.45%	0.23%	0.22%	401,606
3	5.67%	2.71%	2.96%	0.85%	0.42%	0.43%	0.47%	0.24%	0.23%	272,297
4	6.13%	2.87%	3.25%	0.78%	0.39%	0.39%	0.42%	0.23%	0.20%	202,530
5	6.32%	2.91%	3.41%	0.79%	0.36%	0.43%	0.45%	0.22%	0.23%	160,500
6	6.73%	3.08%	3.64%	0.93%	0.42%	0.51%	0.52%	0.25%	0.27%	130,846
7	7.46%	3.31%	4.15%	0.95%	0.41%	0.54%	0.52%	0.24%	0.28%	103,516
8	8.54%	3.60%	4.95%	1.07%	0.46%	0.61%	0.62%	0.28%	0.35%	80,574
9	9.50%	3.78%	5.72%	1.31%	0.46%	0.84%	0.68%	0.25%	0.43%	61,691
10 (most illiquid)	9.99%	3.71%	6.28%	2.15%	0.64%	1.51%	0.98%	0.29%	0.69%	42,027

Table 2 – continued

Panel C: Stock position valuation deviations stratified by stock's intraday volatility

Intraday volatility decile	*% |VD|>0*			*% |VD| ≥ 5%*			*% |VD| ≥ 10%*			
	All	*Positive*	*Negative*	*All*	*Positive*	*Negative*	*All*	*Positive*	*Negative*	*Observations*
1 (least volatile)	5.85%	2.74%	3.11%	0.75%	0.29%	0.45%	0.38%	0.15%	0.23%	159,319
2	5.82%	2.86%	2.97%	0.81%	0.34%	0.47%	0.41%	0.16%	0.25%	301,352
3	6.11%	2.98%	3.13%	0.84%	0.40%	0.44%	0.43%	0.19%	0.23%	320,863
4	6.43%	3.15%	3.29%	0.85%	0.43%	0.42%	0.45%	0.23%	0.23%	301,059
5	6.67%	3.23%	3.44%	0.82%	0.41%	0.41%	0.48%	0.25%	0.23%	276,325
6	6.99%	3.31%	3.67%	0.80%	0.43%	0.37%	0.46%	0.25%	0.21%	246,238
7	7.30%	3.42%	3.88%	0.89%	0.45%	0.45%	0.52%	0.28%	0.24%	208,965
8	7.44%	3.34%	4.10%	1.03%	0.51%	0.52%	0.55%	0.30%	0.26%	180,002
9	7.43%	3.28%	4.15%	1.26%	0.53%	0.73%	0.57%	0.29%	0.28%	149,120
10 (most volatile)	7.34%	3.00%	4.34%	1.79%	0.61%	1.17%	0.94%	0.33%	0.61%	100,819

Panel D: Multivariate logit regressions

Dependent variable:	*Probability of*		
	|VD|>0	*|VD| ≥ 5%*	*|VD| ≥ 10%*
Model:	*(1)*	*(2)*	*(3)*
Intercept	-2.5088***	-4.0909***	-4.7251***
	(0.000)	(0.000)	(0.000)
Amihud Illiquidity	0.0007*	0.0010**	0.0009
	(0.083)	(0.029)	(0.163)
Intraday Volatility	0.2671	3.2026***	3.1511***
	(0.741)	(0.000)	(0.000)
Observations	2,244,062	2,244,062	2,244,062
Pseudo R^2	3.4%	3.4%	3.4%

Table 3
Past Performance, Directional Valuation Deviations, and Visibility

This table presents results from advisor-quarter-level regressions of *Portfolio Valuation Deviation* on past returns. For each advisor in each quarter, *Portfolio Valuation Deviation* is computed as the difference of the fraction of positions with positive valuation deviations and the fraction of positions with negative valuation deviations. The key independent variables are two return measures, which reflect the advisor's past performance over the last twelve months: *Past Holding Return*, is calculated as the holdings-based return of a portfolio that mimics the holdings of the advisor's 13F portfolio. This holdings-based return is calculated by employing CRSP returns for the underlying portfolio stocks. *Past Reported Return* is the value-weighted average of the reported returns of all hedge funds managed by the advisor. Another independent variable is *Database Reporting*, a dummy variable indicating whether an advisor reports to at least one of the three commercial databases, CISDM, Lipper TASS, and Morningstar, in a given quarter. The first control variable is the advisor's stock portfolio illiquidity, *Stock Illiquidity*, which is measured as the value-weighted mean of Amihud's ratio of all the stocks in portfolio. The second control variable is *Stock Price Volatility*, which is measured as the value-weighted mean of the intraday stock price volatility measure introduced in Table 2. In Models (3), (6), and (9) yearly fixed effects are added as further controls. Robust p-values, presented in parentheses, are based on Rogers (1993) standard errors clustered by advisor. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Dependent variable:	*Portfolio Valuation Deviation*								
Model:	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
Intercept	-0.0065***	-0.0023	-0.0201**	-0.0049***	-0.0006	-0.0179*	-0.0089***	-0.0055	-0.0343***
	(0.000)	(0.398)	(0.033)	(0.001)	(0.827)	(0.061)	(0.000)	(0.255)	(0.009)
Past Holding Return	-0.0067**	-0.0100***	-0.0117***	-0.0010	-0.0044	-0.0064			
	(0.030)	(0.008)	(0.009)	(0.758)	(0.235)	(0.123)			
Database Reporting				-0.0038	-0.0039	-0.0040*			
				(0.111)	(0.103)	(0.098)			
*Past Holding Return*Database Reporting*				-0.0149**	-0.0148**	-0.0146**			
				(0.031)	(0.032)	(0.037)			
Past Reported Return							-0.0208**	-0.0219**	-0.0211**
							(0.012)	(0.012)	(0.025)
Stock Illiquidity		-0.0002	-0.0002		-0.0002	-0.0002		-0.0001	-0.0001
		(0.296)	(0.289)		(0.296)	(0.291)		(0.431)	(0.449)
Stock Price Volatility		-0.1159	-0.0817		-0.1170	-0.0847		-0.0991	-0.0460
		(0.129)	(0.405)		(0.123)	(0.387)		(0.457)	(0.801)
Yearly Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes
Observations	13,064	13,064	13,064	13,064	13,064	13,064	5,590	5,590	5,590
R^2	0.0%	0.1%	0.3%	0.2%	0.2%	0.4%	0.2%	0.2%	0.5%

Table 4
Equity Valuation Deviations Before and After Joining a Database

This table compares the equity valuation deviations of advisors before and after they join a commercial database. Valuation deviations are measured as the fraction of positions with nonzero valuation deviation for each advisor in each quarter (*FRAC*). The reported results are from a subsample of 38 advisors with at least one holdings report before and after the first date of appearance in a commercial database. Within this subsample, we use two ways to compare the marking behavior before and after the first date of database reporting. The first one (*DIFF-IN-DIFFS*) is in effect a difference in differences approach, whereby the *FRAC* for each advisor in each quarter is first benchmarked against the average *FRAC* of other advisors that never chose to report to a commercial database. Next, an average of the benchmarked measure is computed for each advisor before and after the first date of database reporting and a paired t-test is used for the comparison. The second approach (*RANK*) compares the average advisors' rank based on their *FRAC* measure before and after, where ranks are normalized to be between 0 and 1. P-values are presented in parentheses. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Deviation measure:	*FRAC*	
Approach:	*DIFF-IN-DIFFS*	*RANK*
Before	0.0256	0.6364
After	0.0898	0.7194
After-Before	0.0642*	0.0830***
	(0.055)	(0.002)

Table 5
Equity Valuation Deviations and the Distribution of Reported Returns around Zero

This table relates the distribution of reported returns around zero with equity valuation deviations. The dependent variable is the advisor's difference of the fractions of positive and negative reported returns within tight intervals around zero. To create this measure, we first assign hedge fund returns reported to commercial databases to its respective advisor. Next, for each advisor, we subtract the fraction of negative returns from the fraction of positive returns. We use subsets of reported returns that are within three intervals, i.e., +/-100, +/-200, and +/-300bps around zero, respectively. Results for each subset are reported in the respective columns. The key independent variables are constructed by dividing advisors into three equal-sized groups according to their equity valuation deviations. Advisors with the lowest valuation deviations are in the benchmark group. We then define two dummy variables: *Medium Deviation* equals one for advisors that belong to the group with medium equity valuation deviations and zero otherwise. *High Deviation* equals one for advisors that belong to the group with the highest valuation deviations. Equity valuation deviations are measured by the fraction of positions with nonzero valuation deviations, *FRAC*, as introduced in Table 4. *FRAC* is averaged across all quarterly observations of a given advisor to come up with one aggregated measure per advisor. In Models (2), (4), and (6), we include three control variables, *Average Stock Illiquidity*, *Total Portfolio Illiquidity*, and *Average Stock Price Volatility*. The first control variable is calculated as the average *Stock Illiquidity*, as introduced in Table 3, across the advisor's quarterly observations. *Total Portfolio Illiquidity* is measured as the beta exposure to Pástor and Stambaugh (2003)'s innovations in aggregate liquidity, aggregated at the advisor level by taking a value-weighted average across all funds managed by each advisor. *Average Stock Price Volatility* is calculated as the average *Stock Price Volatility*, as introduced in Table 3, across the advisor's quarterly observations. Each advisor represents a unit of observation in all the regressions. Robust p-values, presented in parentheses, are based on White (1980) standard errors. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Dependent variable:	*Fraction of positive minus fraction of negative reported returns*					
Interval around zero:	*+/-100bp*		*+/-200bp*		*+/-300bp*	
Model:	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Intercept	0.0614***	0.1129***	0.1443***	0.2743***	0.1864***	0.3386***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Medium Deviation	0.0157	0.0164	0.0098	0.0098	0.0282	0.0281
	(0.144)	(0.127)	(0.578)	(0.566)	(0.168)	(0.151)
High Deviation	0.0535***	0.0547***	0.0755***	0.0782***	0.0922***	0.0954***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Controls	No	Yes	No	Yes	No	Yes
Observations	432	432	432	432	432	432
R^2	3.7%	6.2%	3.4%	9.5%	3.7%	10.3%

Table 6
Equity Valuation Deviations and Fraction of Kink Funds

This table presents results from regressions that relate equity valuation deviations with the discontinuity around zero in hedge fund's return distribution. To identify a discontinuity in the distribution of hedge fund returns, we follow the approach of Bollen and Pool (2012). For each fund, we create a histogram of reported returns with the optimal bin size computed according to Silverman (1986). The optimal bin size is calculated as $\alpha \times 1.364 \times \sigma \times n^{-1/5}$, where σ is the monthly return standard deviation, n is the number of observations, and α is set equal to 0.776, corresponding to a normal distribution. Then, we count the number of return observations that fall in three adjacent bins, two to the left of zero and one to the right. If a fund shows no discontinuity and thus a smooth distribution, the number of observations in the middle bin should approximately equal the average number of observations in the two surrounding bins. Thus, we test whether the number of observations in the middle bin is significantly lower than the average from the two adjacent bins and divide the difference between the numbers of observations by its standard deviation. The test statistic is computed as:

$$t = \frac{X_2 - \frac{1}{2}\left(X_1 + X_3\right)}{\left[n(p_2 - p_2^2) + \frac{1}{4}n(p_1 - p_1^2 + p_3 - p_3^2) + np_2(p_1 + p_3) - \frac{1}{2}np_1p_3\right]^{1/2}}$$

where X_k denotes the total number of observations that fall in bin *k*, *n* is the number of observations, and p_k is the probability that an observation falls in bin *k*. According to Bollen and Pool (2012), a fund is categorized as "Kink" fund when the number of observations in the middle bin is significantly less than expected at a 10% significance level. For each advisor, the dependent variable is computed as the fraction of funds that are categorized as Kink funds. The key independent variables, *Medium Deviation* and *High Deviation*, and the control variables included in Model (2), *Average Stock Illiquidity*, *Total Portfolio Illiquidity*, and *Average Stock Price Volatility*, are defined as in Table 5. Robust p-values, presented in parentheses, are based on White (1980) standard errors. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Dependent variable:	*Fraction of Kink Funds*	
Model:	*(1)*	*(2)*
Intercept	0.1206***	0.0793
	(0.000)	(0.166)
Medium Deviation	0.0590*	0.0587*
	(0.087)	(0.090)
High Deviation	0.1159***	0.1160***
	(0.001)	(0.001)
Controls	No	Yes
Observations	426	426
R^2	2.3%	2.8%

Table 7
Equity Valuation Deviations and Return Smoothing

This table presents results from advisor-level regressions that relate return smoothing with equity valuation deviations. We quantify return smoothing using three different ways: First, we use the θ_0 from the model of Getmansky, Lo, and Makarov (2004). For each fund *j* in our sample we regress its reported return on its economic return using:

$$R_{j,t}^{rep} = a + \theta_{j,0} \cdot R_{j,t} + \theta_{j,1} \cdot R_{j,t-1} + \theta_{j,2} \cdot R_{j,t-2} + \varepsilon_{j,t}$$

with constraints on coefficients such that $\theta_{j,k} \in [0,1]$, $k = 0,1,2$ and $1 = \theta_{j,0} + \theta_{j,1} + \theta_{j,2}$. In this equation, $R_{j,t}^{rep}$ represents the reported return of fund *j* at date *t* and $R_{j,t}$ stands for the fund's economic return. As the economic return is unobservable, we proxy for it by using predicted returns from a regression of excess fund returns on a subset of factors that are used to proxy for hedge fund trading strategies. The factors we use include: the three Fama and French (1993) factors, five trend-following factors used by Fung and Hsieh (2004), the change in the yield of a 10-year Treasury note, and the change in the credit spread. We select the subset of factors by maximizing the adjusted R^2 and restrict the subset to a maximum of three factors. The first smoothing measure we use as dependent variable in our regressions is the smoothing coefficient θ_0. As the second smoothing measure, we use the Herfindahl Index which is constructed as the sum of the squared theta coefficients for each fund $\xi = \theta_0^2 + \theta_1^2 + \theta_2^2$. The last return smoothing measure we employ is the first order serial correlation coefficient of reported returns, ρ. Each measure is first computed for each hedge fund and then averaged across all funds managed by each advisor, with weights determined by each fund's average assets under management. The key independent variables, *Medium Deviation* and *High Deviation*, and the control variables included in Model (2), (4), and (6), *Average Stock Illiquidity*, *Total Portfolio Illiquidity*, and *Average Stock Price Volatility*, are defined as in Table 5. Each advisor represents a unit of observation in all the regressions. Robust p-values, presented in parentheses, are based on White (1980) standard errors. P-values are computed with respect to the null hypothesis that the coefficient is zero, except for the intercept in the θ_0 and ξ regressions for which the null hypothesis *Intercept=1* is used. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Dependent variable:	θ_0		ξ		ρ	
Model:	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Intercept	0.8977***	0.9331***	0.8333***	0.8610***	0.1694***	0.1923***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Medium Deviation	-0.0056	-0.0053	-0.0049	-0.0043	0.0037	0.0025
	(0.623)	(0.640)	(0.748)	(0.778)	(0.854)	(0.902)
High Deviation	-0.0345***	-0.0338***	-0.0409**	-0.0401**	0.0548**	0.0543**
	(0.006)	(0.006)	(0.010)	(0.012)	(0.011)	(0.011)
Controls	No	Yes	No	Yes	No	Yes
Observations	421	421	421	421	421	421
R^2	2.1%	4.3%	1.8%	3.1%	2.0%	3.0%

Table 8
Tendency to Change Directional Deviations and December Return Spike

This table presents results from advisor-level regressions that relate the December return spike with an increase in Portfolio Valuation Deviation. The dependent variable, the advisor-specific December return spike, is constructed every year by first calculating the December return spike metric for each hedge fund. The December return spike metric is measured for each hedge fund each year as the difference between the December return and the average return of the 11 remaining months of the same year. Next, the December return spike metric is aggregated at the advisor level every year by taking a value-weighted average across all funds managed by the same advisor. The key independent variables, *Medium Increase* and *High Increase*, are constructed by dividing advisors into three equal-sized groups each year according to their increase in *Portfolio Valuation Deviation* over the last calendar quarter. Advisors with the lowest increase in *Portfolio Valuation Deviation* are in the benchmark group. We then define two dummy variables: *Medium Increase* equals one for advisors belonging to the group with medium increase in *Portfolio Valuation Deviation* and zero otherwise. *High Increase* equals one for advisors belonging to the group that increased the *Portfolio Valuation Deviation* the most. *Portfolio Valuation Deviation*, as defined in Table 3, is the difference of the fraction of positions with positive valuation deviations and the fraction of positions with negative valuation deviations. In Model (2) and (3) we include the following control variables: *Stock Illiquidity* and *Stock Price Volatility*, calculated as in Table 3, and *Total Portfolio Illiquidity*, defined as in Table 5. In Model (3) yearly fixed effects are added as further controls. Robust p-values, presented in parentheses, are based on White (1980) standard errors. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Dependent variable:	*December return spike*		
Model:	*(1)*	*(2)*	*(3)*
Intercept	0.0067***	-0.0011	0.0672***
	(0.001)	(0.760)	(0.000)
Medium Increase	0.0013	0.0009	0.0021
	(0.626)	(0.718)	(0.419)
High Increase	0.0076**	0.0076**	0.0073**
	(0.027)	(0.022)	(0.021)
Controls	No	Yes	Yes
Yearly Fixed Effects	No	No	Yes
Observations	1,181	1,181	1,181
R^2	0.5%	2.5%	15.1%

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APPENDIX

Data Cleaning Procedure

This appendix describes the methodology we used to clean our dataset from securities other than common stocks and unintentional data errors. The data cleaning steps are presented below in sequential order.

Removing other types of securities

1. We drop each position for which we were not able to match the position's CUSIP to a stock from the CRSP monthly stock database.
2. We drop each position the name of which indicates that the respective security is not a common stock. Specifically, we drop those positions with names containing strings such as, e.g., 'BOND', 'CALL', 'CONVERTIBLE', 'DEBT', 'FRNT', 'PFD STOCK', 'PUT', 'WARRANT', et cetera. We also use several variations and abbreviations of these words to identify non-equities.
3. Furthermore, for each holding, we check Column 5 of Form 13F if that holding is identified as an option position. All option holdings identified in this manner are excluded. As some filings use different identifiers for options rather than the 'PUT' or 'CALL' designation, such as 'P' or 'C', we also make sure to identify and exclude such cases.
4. We conduct an additional check to identify options positions that were labeled as stock positions perhaps due to a filing error. We map the holdings positions to the Option Metrics database, which contains historical price data for the US equity options markets. We calculate the implied price for each holdings position as the reported value divided by the number of shares and compare this price to the prices of the options belonging to the respective security. If the implied price is between the option's best bid and best offer but the CRSP price is not, we drop the observation from the sample.

5. We exclude those observations for which the position size is given in terms of a principal amount instead of a number of shares, as denoted in Column 5 of Form 13F. The principal amount is only given in the case of convertible debt securities and therefore this designation indicates that the respective position is not an equity security.

Removing unintentional errors when filling out the report

6. We correct our dataset for scaling issues, e.g., due to a possibly displaced decimal point or due to reported position values that are not given in thousands of dollars as requested by Form 13F. In many cases such scaling issues apply to all the positions in a given report. Thus, we exclude the whole report from our sample if it contains at least one position for which its reported value divided by the CRSP value is close to 0.0001, 0.001, 0.01, 0.1, 10, 100, 1000, or 10000.
7. We exclude reports with position values and number of shares reported in interchanged columns. To identify these reports, we calculate the reciprocal of the implied price of each position by dividing the positions' reported number of shares by the reported value. If the reported number for a position's value is by mistake reported in the column designated for reporting the number of shares (and vice versa), the reciprocal of the implied price should equal the CRSP price.
8. We exclude all stocks that had a stock split within the last five days prior to the valuation date to eliminate the possibility of a non-zero valuation deviation caused by an accidental use of prices prior to the stock split.
9. Finally, to eliminate remaining outliers (caused perhaps by filing errors) we exclude the most extreme 5% of the deviating positions, measured by the absolute deviation from the CRSP price.

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centre for financial research
cfr/university of cologne
Albertus-Magnus-Platz
D-50923 cologne
fon +49(0)221-470-6995
fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de