Caught in the Act:

How Hedge Funds Manipulate their Equity Positions[✧]

Gjergji Cici, Alexander Kempf, and Alexander Puetz*

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ABSTRACT

Using 13F position valuations, we show that hedge fund advisors intentionally mismark their stock positions. We document manipulation even after eliminating issues inherent in the pricing of illiquid securities. The documented mismarking is related to hedge fund incentives. Mismarking is more pronounced for advisors that self-report to commercial hedge fund databases and increases after advisors start reporting. Significantly stronger mismarking is also documented among advisors that report more frequently to their current investors and are domiciled in offshore locations. Our analysis shows that advisors employ mismarking strategically to smooth their reported returns and push otherwise small negative returns above zero.

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* 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.

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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 manipulation of asset valuations by hedge funds 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.

Echoing these concerns, several academic studies that focused on self-reported hedge fund returns have documented patterns that are consistent with manipulation of asset valuations and returns. Specifically, the evidence is consistent with hedge funds: (1) smoothing reported returns (see, e.g., Bollen and Pool (2008) and Getmansky, Lo, and Makarov (2004)), (2) pushing otherwise small negative returns above zero (see, e.g., Jylha (2011) and Bollen and Pool (2009)), and (3) manipulating reported returns upward in December (see Agarwal, Daniel, and Naik (2010)).

Although suggestive of intentional manipulation, some of these patterns could simply arise from issues related to pricing of illiquid securities (see Getmansky, Lo, and Makarov (2004)). For example, when hedge funds value illiquid securities using stale prices, this practice can give rise to smooth reported returns. Furthermore, when hedge fund advisors value securities that have not traded, they might use their legally allowed pricing discretion to move otherwise small negative returns slightly above zero. Thus, analysis of reported returns alone does not provide a definitive answer as to whether hedge funds intentionally manipulate their position valuations, simply use stale prices, or use legally allowed pricing discretion.

This paper analyses the valuations of common stock positions reported by hedge fund advisors. In doing so, it makes a contribution to the previous literature that provides indirect evidence from reported returns. Focusing on the position valuations of common stocks, presumably the most liquid securities, allows us to document direct evidence of manipulation while eliminating the possibility of unintentional mispricing due to stale prices or pricing discretion.

Our direct evidence comes from analyzing a new dataset of individual stock position valuations reported by hedge fund advisors in 13F reports that they file with the SEC. These positions represent the only detailed portfolio positions of hedge fund advisors that are publically available. Most important, the reported valuations for these positions provide a unique opportunity to look at the valuation practices used by hedge fund advisors for NAV calculations since such practices should be consistently applied across the different reporting requirements of an advisor.[1]

Using a mismarking measure that reflects how much reported position valuations differ from alternative valuations based on stock prices reported in the CRSP database, we document that about 150 thousand positions (roughly seven percent) out of about 2.3 million positions are mismarked. To get a sense for the economic magnitude of mismarking, we show that the reported valuations for these 150 thousand positions deviate from CRSP-based valuations by roughly 2.5 percent in absolute terms. Such a level of mismarking, although not

[1] One exception to the uniform application of valuation practices would be informal valuations prepared for internal reporting, such as those used for internal risk assessment and risk management purposes (Alternative Investment Management Association (2007)). Also, the notion that valuation methods used to value 13F positions should reflect those used for NAV calculations was supported by conversations with SEC staff members and employees of investment management companies. This is indeed supported by evidence presented later in the paper showing that the marking behavior of hedge fund advisors is related to their reported returns, which in turn are a function of NAVs.

extreme, is not trivial in an economic sense and leads to the natural question: What causes these positions to be valued at prices that differ from CRSP prices?

Regulation dictates that hedge fund advisors use closing market prices to value their stock positions. Only in rare circumstances can hedge fund advisors use pricing discretion to value illiquid stocks that did not trade at all or thinly-traded stocks trading at prices that did not reflect the most recent market conditions. Thus, one possible explanation is that the mismarked positions correspond to illiquid securities that advisors valued by applying their valuation discretion resulting in the use of prices that differed from CRSP prices. Exploring this possibility, we eliminate the rarely occurring positions corresponding to illiquid stocks and document mismarking even among the remaining most liquid stocks. By doing so, we are able to completely rule out illiquidity-related issues as the source of mismarking.

Previous research suggests that the majority of hedge fund advisors rely on independent pricing committees or external parties to compute their NAVs, and among these advisors fewer pricing irregularities are to be found (see, Cassar and Gerakos (2011)). Our results from the cross-section of hedge fund advisors are consistent with this previous finding, as we show that the majority of hedge fund advisors show little or no mismarking. However, a non-trivial fraction of roughly 25 percent of our sample advisors shows mismarking of an economically significant magnitude.

It is still possible that the mismarking we observe could be of a random nature, perhaps caused by institutional details of which we are not aware. If that was the case, mismarking should not be related to hedge fund advisors' incentives. Our findings from a battery of tests show that the documented mismarking is strongly related to hedge fund incentives, and therefore is not the byproduct of some unknown random process.

To explore whether advisors engage in mismarking in pursuit of their self-interest, we first explore whether advisors that more aggressively promote their funds to potential investors use mismarking as a tool to achieve their marketing goals. Previous studies suggest that advisors choose to self- report to commercial databases in order to increase the visibility of their funds and attract new clients (see, e.g., Ackermann, McEnally, and Ravenscraft (1999), Agarwal, Fos, and Jiang (2010), and Aiken, Clifford, and Ellis (2011)). The reason why reporting to commercial databases might be an attractive marketing tool for hedge fund advisors is that SEC Rule 502(c) of the Securities Act of 1933 prohibits hedge fund advisors from any form of general advertising.[2]

We hypothesize that these self-reporting advisors are more likely to take advantage of their created visibility by using mismarking to generate better performance metrics in order to impress future investors. Consistent with this view, we find that hedge fund advisors that choose to report their returns to at least one of the three hedge fund databases used in our study exhibit greater general mismarking than those advisors that do not report their returns. Further supporting the advertising rationale behind the decision to self-report returns, we find that general mismarking is greater after a hedge fund advisor appears in a commercial database than before. Additional tests show that, perhaps aspiring to impress current investors, advisors who report to their current investors at a higher frequency show more mismarking. Taken altogether, these findings make an important contribution, in particular, to the literature that questions the accuracy of hedge fund reported returns[3] and, in general, to

[2] SEC Rule 502(c) of the Securities Act of 1933 bars hedge fund advisors from general advertising that includes any form of communication published in newspapers and magazines or broadcasted over television or radio.

[3] Previous research has raised the possibility of performance evaluation biases from self-reported returns (see, e.g., Agarwal, Fos, and Jiang (2010), Huang, Liechty, and Rossi (2009); Agarwal, Daniel, and Naik (2010); Aiken, Clifford, and Ellis (2011); Bollen and Pool (2009)).

the literature that studies hedge fund performance using self-reported returns[4] by providing new evidence questioning the accuracy of self-reported returns for measuring hedge fund performance.

Next, we hypothesize that if hedge fund advisors are mismarking in pursuit of self-interest, we would expect them to mismark more when the probability of them getting caught is lower. Our findings show that, indeed, general mismarking is more prevalent among advisors that face a lower probability of getting caught. Specifically, we show that hedge fund advisors mismark to a greater extent when they are registered in less-regulated offshore locations such as the Cayman Islands or the Bahamas.[5]

We turn next to specific forms of mismarking that hedge fund advisors could use to promote their self interests. The first specialized form of mismarking we analyze is mismarking intended to smooth reported returns. We employ two testing techniques. The first one, which is based on the Getmansky, Lo, and Makarov (2004) methodology applied to hedge fund self-reported returns, shows that advisors who exhibit more general mismarking also report smoother returns. The second testing technique, which makes use of our equity position valuations, shows that advisors push their equity valuations up following a period of poor performance and push them down following a period of good performance.[6] Unlike previous research that focuses on indirect evidence from hedge fund reported returns, this

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[4] See, e.g., Brown, Kang, In, and Lee (2010); Agarwal, Daniel, and Naik (2009); Fung, Hsieh, Naik, and Ramadorai (2008); Ingersoll, Spiegel, Goetzmann, and Welch (2007); Kosowski, Naik, and Teo (2007); and Ackermann, McEnally, and Ravenscraft (1999).

[5] In a similar spirit, Cumming and Dai (2010) show that misreported returns are influenced by the country hedge funds are registered in, justified by regulatory differences among the countries.

[6] Hedge fund advisors that manipulate their position valuations clearly face costs that could be related to litigation or loss of reputation. The resulting costs from litigation could be in the form of long prison sentences or severe fines. For example, James Nicholson, founder or Westgate Capital Management LLC was sentenced to 40 year in prison for misrepresenting performance of his hedge funds to investors in what appeared to be a Ponzi scheme.

pattern provides direct evidence on how actual hedge fund valuations respond to portfolio returns.

Another form of specialized mismarking that we explore is related to hedge fund advisors altering the return distribution of their hedge funds. Given that a zero return is a powerful quantitative anchor that investors desire to surpass, advisors might manipulate valuations to avoid small negative returns by causing a discontinuity in reported returns whereby the number of small positive returns significantly exceeds the number of small negative returns (see, e.g., Bollen and Pool (2009) and Waring and Siegel (2006)). Consistent with this hypothesized return manipulation approach, advisors that show more mismarking exhibit a stronger discontinuity in their hedge funds' return distribution around zero than advisors with little mismarking.

Besides being related to studies that examine the suspicious patterns of hedge fund reported returns[7], 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 (2011); Cassar and Gerakos (2011); and Liang (2003)). For example, Brown, Goetzmann, Liang, and Schwarz (2011) show that hedge funds that have experienced legal problems are less likely to use independent pricing agents, which affords them greater pricing discretion, 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. Unlike these studies, ours uses actual hedge fund position valuations for common stock securities and

[7] See, e.g., Agarwal, Daniel, and Naik (2010); Bollen and Pool (2008); Bollen and Pool (2009); Getmansky, Lo, and Makarov (2004); and Jylha (2011).

shows that hedge fund advisors mismark even highly liquid securities, a setting where hedge fund advisors should not apply pricing discretion.

There is also empirical work focusing on the pricing of funds' corporate bond holdings and its influence on return smoothing. Studies by Aiken (2009) and Cici, Gibson, and Merrick (2011) document marking patterns, respectively, for hedge funds and mutual funds that are consistent with return smoothing. In contrast, we focus on the pricing of hedge funds' stock holdings for which market prices are readily available. Since we document mismarking for these highly liquid securities, we can rule out illiquidity as the source of mismarking and attribute the documented mismarking to intentional manipulation.

The remainder of the paper is organized as follows. In Section I we discuss data and sample summary statistics. Section II provides an overview of mismarking at the position level. Section III relates mismarking to hedge fund advisors' incentives. Sections IV and V investigate the influence of mismarking on reported returns. Section VI discusses the remaining puzzle and Section VII concludes.

I. 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 all electronic 13F filings available on 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.[8] 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.[9] 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 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

[8] 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.

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

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, reporting frequency, and domicile information 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 Mismarking Measure

Since we focus only on the valuation of equity positions, we excluded all positions corresponding to non-equity securities.[10] 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. For example, one of the instructions for 13F filers says 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."[11]

Using stock prices from the CRSP daily stock database, we calculated how much the reported valuation of each stock position differs from a valuation that is based on stock prices

[10] Additional details on the procedure we used to clean our dataset from non-equities and data errors are provided in the appendix.
[11] See Special Instruction 9 at http://www.sec.gov/about/forms/form13f.pdf.

reported from the CRSP database. We refer to this mismarking measure as *stock position mismarking* (*SM*) and compute it as follows:

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

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. While $CRSP\ price_{j,t}$ equals an exchange-determined closing price for stocks that traded, it represents an average of the bid and ask quotes for stocks that did not trade on a particular day.

To ensure that mismarking did not arise due to unintentional errors, we performed corrections for possible data entry errors, such as scaling issues due to displaced decimal points or interchanged columns. Furthermore, we excluded all stocks that had a stock split in the last five days prior to the valuation date to eliminate the possibility of a non-zero *SM* 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 of 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 errors) we excluded the most extreme 5% of the mismarked positions, measured by the absolute deviation from the CRSP price.[12]

C. Sample Description

Our final sample consists of 864 hedge fund advisors and 15,198 quarterly reports. Sample summary statistics are reported in Table I. 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 I 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.[13] 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.

II. Mismarking at the Stock Position Level

A. Frequency and Magnitude of Position Mismarking

We assess the mismarking behavior of hedge fund advisors by examining positions with reported valuations that differ from CRSP valuations, i.e., positions with $|SM|>0$. Since advisors are required to round reported valuations to the nearest one thousand dollars (as per Form 13F instructions), mismarking of a position by less than $1,000 could be simply caused

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

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

by rounding. Thus, to avoid position valuations deviations that arise due to rounding, for such positions we set *SM* equal to zero.

Panel A of Table II reports the frequency of positions that are classified as mismarked based on our *SM* measure. The first column shows that, on average, about 7% of all positions were valued at prices that deviated from CRSP prices, suggesting that about 150 thousand positions were mismarked out of roughly 2.3 million total positions. The fraction of mismarked positions 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 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.

To get a sense for the economic magnitude of mismarking, the fourth column reports the mean absolute mismarking, i.e., average of |*SM*|, computed across all positions that were mismarked. The average mismarking among these positions is 2.49%, suggesting a degree of mismarking that, although not extreme, is economically significant.

B. Is Illiquidity Responsible for the Documented Mismarking?

Although the observed position mismarking documented in Panel A is consistent with intentional manipulation, it is also consistent with advisors using legally allowed pricing discretion. One possibility is that the observed deviations apply only to stocks that did not trade on the report date. If an exchange-determined price for a given stock did not exist because the stock did not trade that day, advisors are allowed to use their discretion to come up with a “fair value” estimate. In doing so, hedge fund advisors can use prices provided by pricing services, quotes obtained from dealers, in-house valuation methodologies, or a combination of these approaches. Thus, we would expect position valuations for non-trading stocks to differ from CRSP valuations, which in such cases are based on the average of the bid and ask quotes.

Panel B of Table II reports results stratified by whether a stock traded or not during the report date.[14] Consistent with hedge fund advisors using discretion to value non-traded stocks, the majority of positions among non-traded stocks (about 70%) are valued at prices that deviated from CRSP prices. Nevertheless, the mismarked positions continue to make up a non-trivial fraction of roughly 7% among the positions of traded stocks, and continue to display an economically significant mismarking of about 2.49%. This evidence, combined with the fact that the number of positions corresponding to stocks that did not trade is very small (only 5,657 positions out of roughly 2.3 million positions) suggest that legally-allowed discretion applied to the valuation of non-traded stocks is not responsible for the vast majority of observed valuation deviations.

Another possible explanation for the observed stock position mismarking is that the mismarked positions 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, the advisor could choose to ignore the last trade price as a stale price and use discretion to come up with an alternative "fair value"

[14] A caveat applies to the interpretation of our mismarking measure for non-traded stocks. A position of a stock that did not trade on a particular date and has $|SM|>0$ is not necessarily mismarked as long as its valuation falls within the range of values determined by the stock bid and ask quotes. We simply refer to this position as "mismarked" relative to the CRSP valuation.

estimate that reflects more recent developments.[15] Although this is still within the legal confines, such a practice would lead to a deviation from the CRSP valuation, which is based on the last trade price for the day.

Panel C excludes non-traded stocks and reports similar statistics as in Panel B for the remaining positions stratified by stock 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.[16] 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.

Results from Panel C show that deviations from CRSP valuations are observed across all deciles regardless of the level of illiquidity. The fraction of mismarked positions ranges from 5.57% to 9.99%. Importantly, a significant fraction of mismarked positions exists even among the highly liquid positions that fall in Decile 1. The mismarked positions represent 6.94% of all positions in Decile 1 and they are mismarked by 2.34%, suggesting that illiquidity alone cannot explain the mismarking behavior of hedge fund advisors. That illiquidity plays a minor role is further supported by the fact that, despite the larger mismarking observed for Decile 10, or even Decile 9, the number of mismarked positions from these deciles is dwarfed by the number of mismarked positions from the rest of the deciles. Thus, these findings suggest that legally-allowed discretion to value thinly-traded stocks is not responsible for the vast majority of observed mismarked positions. Overall, the

[15] 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.
[16] See Amihud (2002).

combined evidence from Panels B and C rules out illiquidity as the main driver for the observed mismarking.

C. Stock Position Mismarking Across Advisors

Next, we examine how widespread mismarking is across hedge fund advisors. Cassar and Gerakos (2011) document that the majority of hedge fund advisors rely on independent pricing committees or external parties to compute their NAVs, and for this reason, these advisors exhibit fewer pricing irregularities. Applied to our setting, the Cassar and Gerakos (2011) evidence would suggest that the equity position mismarking we document should be confined to a small subset of advisors.

In Table III, the fraction of mismarked positions and the magnitude of mismarking among each advisor's mismarked positions are first computed for each hedge fund advisor separately over the entire sample period and then cross-sectional statistics are calculated.

Consistent with the majority of advisors using independent parties for NAV pricing, most advisors show little or no mismarking. However, a non-trivial fraction of advisors, show a substantial degree of mismarking. For example, 25 percent of the hedge fund advisors have a fraction of mismarked positions that ranges from 6% to 100%. The magnitude of mismarking tells a similar story, as the mismarked positions for 25 percent of advisors are mismarked by 4.8% to 26%. In sum, mismarking is confined to a sizable subset of hedge fund advisors, the majority of hedge fund advisors display little or no mismarking, and the differences in mismarking between the former and latter group are of a severe magnitude.

Taken together, the findings of Section II point to intentional manipulation as the most likely explanation for the high degree of mismarking observed among a subset of our sample of hedge fund advisors.

III. Incentives and Mismarking at the Portfolio Level

The previous section ruled out illiquidity of the underlying stocks as an explanation for the mismarking we document. However, it is possible that the observed mismarking is the outcome of random processes caused by unknown institutional details, such as unintentional data entry errors, defective data feeds, programming errors, or other institutional and reporting practices that we are not aware of. If randomness is responsible, mismarking should not be related to hedge fund advisors' incentives. Therefore, we next explore whether the equity mismarking we document is related to hedge fund advisors' incentives.

Since there are different ways in which advisors could mismark, we start by employing general measures of mismarking intended to capture all forms of mismarking. As part of this analysis, we first examine whether advisors that promote their hedge funds to potential and current investors by increasing visibility of their hedge funds' returns are more likely to mismark. Then, we investigate whether advisors that are less likely to get caught show a stronger tendency to mismark.

A. Mismarking as a Marketing Tool Targeting New Investors

Previous research that examines biases in self-reported hedge fund returns suggests an advertising rationale behind the decision of some hedge funds to self-report to commercial databases.[17] We examine whether this advertising rationale extends to the valuation practices of hedge fund advisors. We hypothesize that some advisors generate more visibility by self-reporting to commercial databases. Taking advantage of the generated visibility, these advisors potentially mismark to generate attractive returns that they can advertise to potential investors. In the analysis that follows we examine whether mismarking is related to the choice of advisors to join a commercial databases and whether their marking behavior changes before and after the first date of appearance in a commercial database.

A.1. The Choice to Report to a Database and Mismarking

To examine whether advisors that report to commercial databases exhibit more mismarking, we regress each of our general measures of mismarking on *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 measures of mismarking are intended to capture all forms of mismarking in which an advisor might potentially engage. We use two measures. The first one, *ABS_PM*, is based on the notion that, regardless of the type of mismarking, a high mismarking advisor should exhibit a higher level of absolute deviation from the true portfolio value. Thus, *ABS_PM* is measured as the absolute value of an advisor's quarterly *Portfolio Mismarking* (*PM*), which in turn is measured as the net dollar value of a stock portfolio's total mismarking at the end of a given quarter t, divided by the portfolio value determined by CRSP prices:

[17] See, for example, Ackermann, McEnally, and Ravenscraft (1999), Agarwal, Fos, and Jiang (2010), and Aiken, Clifford, and Ellis (2011) .

$$PM_{i,t} = \frac{\sum_j \left(reported\ valuation_{i,j,t} - CRSP\ valuation_{i,j,t} \right)}{\sum_j CRSP\ valuation_{i,j,t}}, \tag{3}$$

Our second general mismarking measure, *FRAC*, captures the fraction of mismarked stock positions for each advisor in each quarter.

To account for any of the rare occurrences of valuation deviations for thinly traded stocks that are within the confines of legally allowed pricing discretion, in all specifications we include a variable that controls for the illiquidity of the stocks in each portfolio. Stock portfolio's illiquidity, *SPI*, is measured as the value-weighted mean of Amihud's ratio of all the stocks in the portfolio.

All analysis is done at the advisor and quarter level. Table IV shows results using two different specifications. The first specification is a pooled regression. The second specification includes time-fixed effects to control for any unobservable time effects that could equally affect the mismarking behavior of all advisors. Thus, the second specification is better suited for analyzing the explanatory power of the cross-section. In both specifications, standard errors are clustered by advisor.

There are 462 advisors out of the 864 advisors in our sample that report to at least one of the commercial databases. Results show that, regardless of the specification or the mismarking measure used, the coefficient on *Database Reporting* is positive and statistically significant. Said in a different way, advisors that choose to report to commercial databases exhibit more mismarking. This result is consistent with the notion that, aspiring to impress potential investors, these hedge fund advisors employ mismarking as a tool for generating impressive performance metrics.[18] The control variable *SPI* has no significant impact on mismarking.

A.2. Mismarking Behavior Before and After Joining a Database.

If reporting to commercial databases is a way for hedge fund advisors to advertise returns that have been shaped by mismarking to potential investors, we would expect hedge fund advisors to show higher mismarking after joining the database. Thus, we next explore whether the mismarking behavior of advisors changes after they join a commercial database.

Focusing on advisors with at least one holdings report before and after the first date of appearance in a commercial database generates a list of 38 advisors. We use two ways to compare the mismarking behavior before and after the first date of database reporting. The first one is in effect a difference in differences approach, whereby the mismarking measure (*ABS_PM* and *FRAC*) for each advisor in each quarter is first benchmarked against the average mismarking measure 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. In a similar spirit, the second approach compares the average advisors' rank based on their mismarking variable before and after, where ranks are normalized to be between 0 and 1.

Results from Table V show that advisors that choose to report to commercial databases show more mismarking after they start reporting to commercial databases. This result is

[18] One could argue that returns reported to a commercial hedge fund database could potentially help investors figure out that an advisor is manipulating its valuations. However, the fact that Bernard Madoff reported grossly fabricated returns to one of the hedge fund databases for 11 years and got away with it for such a long time illustrates that investors have no ability to detect fraud simply based on reported returns.

statistically significant for all four differences computed. In sum, the combined evidence from Tables IV and V make an important contribution by providing new evidence that questions the accuracy of self-reported returns for measuring hedge fund performance.

B. Mismarking as a Marketing Tool to Impress Existing Investors

Besides trying to impress new investors, advisors could also try to impress their existing investors. Similar to the advertizing rationale associated with the choice to self-report to commercial databases, we argue that some advisors generate a greater level of visibility among their existing investors by reporting to them at a higher frequency. Taking advantage of the generated visibility, these advisors potentially mismark to generate attractive returns that they can continue to advertise to existing investors.

To test for this hypothesized effect, we regress each of our general mismarking measures on dummy variables indicating the frequency of reporting to existing investors. The frequency with which advisors report to their existing investors is available only in the CISDM database for only 133 advisors, which restricts this section's tests to this subgroup. The analysis is conducted at the advisor and quarter level.

We employ two different specifications. In Panel A of Table VI, the key independent variable, *Monthly Reporting,* equals one for each advisor with at least one hedge fund that reports at least with monthly frequency to investors and zero otherwise. In Panel B, we further separate the advisors identified by the *Monthly Reporting* variable into two groups and, therefore, define two new variables, *Monthly Reporting All* and *Monthly Reporting Not All*. The former variable equals one for each advisor managing only hedge funds that report to existing investors on at least a monthly frequency. The latter variable equals one for each advisor managing at least one fund, but not all funds, that report to investors on at least a monthly frequency.

Results from Panel A suggest that high frequency of reporting to existing investors is associated with more mismarking. This is consistent with the notion that, aspiring to impress current investors, advisors who report to their current investors at a higher frequency show more mismarking. As shown in Panel B, this result is entirely driven by advisors who choose frequent reporting for all their funds. In both approaches the control variable *SPI* remains insignificant.

C. Probability of Getting Caught and Mismarking

Cumming and Dai (2010) document a higher incidence of misreported returns among offshore funds. Presumably being domiciled in a country with strict regulations preclude hedge funds from manipulating their asset valuations as they face a greater probability of getting caught.

To test this hypothesis, we examine the relation between general mismarking behavior and measures indicating whether the advisor operates in a setting with lax legal requirements. We include two specifications. In Panel A of Table VII, the key independent variable, *One Fund Offshore,* indicates whether an advisor has at least one hedge fund that is domiciled in the Bahamas, Barbados, Belize, Bermuda, Cayman Islands, Curacao, or Virgin Islands, and zero otherwise. In Panel B, we introduce two new independent variables, *Offshore All* and *Offshore Not All*. The former variable equals one for each advisor managing only hedge funds that are domiciled offshore. The latter variable equals one for each advisor managing at least one, but not all, funds that are domiciled offshore.

Results reported in Panel A of Table VII show that advisors managing at least one fund that is domiciled offshore show more mismarking. Results from Panel B tell a similar story, but they appear to emphasize that this effect is confined primarily to advisors that manage only funds that are domiciled in offshore locations. These results are consistent with the view that advisors that face lax regulatory requirements are more likely to mismark because they face a lower probability of getting caught. The coefficient on the control variable *SPI* remains insignificant.

IV. Do Hedge Fund Advisors Strategically Mismark to Smooth Returns?

One presumed goal of mismarking position valuations by hedge fund advisors is artificial enhancement of performance measures to maintain the current base of investors and attract additional investment flows. In particular, advisors can enhance performance measures by smoothing reported returns of their hedge funds.

The return smoothing hypothesis makes two testable predictions. Return smoothing alters the hedge fund reported returns. When its hedge fund's assets exhibit weak performance, the advisor mismarks positions to boost reported returns. Conversely, when the hedge fund's assets exhibit strong performance, the advisor mismarks positions to hold back on the reported returns.[19] Return smoothing thus causes information to not be fully incorporated into reported returns, giving rise to a less than one-for-one relation between the underlying assets' true economic returns and reported returns. Our first set of tests examines whether mismarking is related to this specific pattern for the reported returns.

[19] This form of manipulation consists of underreporting both gains and losses and is consistent with the notion of returns management discussed in Agarwal, Daniel, and Naik (2010): Fund managers might overvalue their portfolio to avoid reporting negative returns and undervalue their portfolio to create reserves which can be added to future returns if they happen to be negative ("saving for the rainy day").

The second prediction links mismarking behavior directly with past performance. When its hedge fund shows weak performance, the advisor ought to respond by overstating the valuations of the portfolio. Conversely, when its fund shows strong performance, the advisor ought to respond by understating the valuations of the portfolio. Our second set of tests examines whether we observe this pattern in the valuations of advisors' portfolios.

A. Reported Returns

A.1. Methodology

Getmansky, Lo, and Makarov (2004) model hedge fund reported returns as a finite moving average of the underlying true economic returns that are unobservable. 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 economic return is a function of information that determines the equilibrium value of the fund's securities.

The following nonlinear regression is a model specification that, as in Getmansky, Lo, and Makarov (2004), includes two lags of economic returns:

$$R_{j,t}^{rep} = a + \theta_{j,0} \cdot R_{j,t} + \theta_{j,1} \cdot R_{j,t-1} + \theta_{j,2} \cdot R_{j,t-2} + \varepsilon_{j,t}, \tag{4}$$

with constraints on coefficients such that $\theta_{j,k} \in [0,1]$, $k = 0,1,2$, and $1 = \theta_{j,0} + \theta_{j,1} + \theta_{j,2}$. The key coefficient, θ_0, 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, fund *j* 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 calculation of θ_0 for each fund involves several steps. As the economic return is unobservable, we proxy for it by using 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 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.

To examine whether the equity mismarking observed for our sample of hedge fund advisors is related to return smoothing, we employ regressions at the advisor level where the dependent variable is one of our three smoothing measures. Our first smoothing measure is the smoothing coefficient θ_0. 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 we employ is the first order serial correlation coefficient of reported returns (ρ), which, as suggested in Getmansky, Lo, and Makarov (2004), will be higher in the presence of return smoothing. Each measure is first computed for each hedge fund and then value-weighted across all funds managed by each advisor. Thus, for each measure we have one observation per advisor.

The key independent variables are constructed by dividing advisors into three equal-sized groups according to their mismarking. Advisors with the lowest mismarking are in the benchmark group. We then define two dummy variables: *Medium Mismarking* equals one for advisors that belong to the medium mismarking group and zero otherwise. *High Mismarking* equals one for advisors that belong to the group with the highest mismarking. This categorization is roughly based on cross-sectional patterns in mismarking documented in Table III, where we observe extreme and moderate mismarkers along with advisors that show very little or no mismarking at all. If advisors in the medium and high mismarking groups (compared against the low mismarking group) use mismarking to smooth reported returns, the coefficients on the dummy variables should be positive.

As control variables we include the advisor's stock portfolio illiquidity, *SPI_AVG*, and the advisor's total portfolio illiquidity, *TPI_AVG*. The first control variable, *SPI_AVG,* is included to control for any effects that are related to valuation of thinly traded stocks for which the manager has some valuation discretion. It is based on the quarterly stock portfolio illiquidity of an advisor and calculated as the average 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 *TPI_AVG* 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. *TPI_AVG* 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.

A.2. Results

Table VIII reports regression results. We restrict the subset of included risk factors in calculating θ_0 to a maximum of three factors. Results using an unrestricted model are similar and not reported here in the interest of brevity.

The coefficient values for *High Mismarking* range from -0.0324 to -0.0337 when the θ_0 measure is used as the dependent variable. These coefficient values are significant both in an economic and statistical sense, proving that advisors with the highest equity portfolio mismarking have a significantly lower θ_0 than advisors with the lowest equity portfolio mismarking. This result is consistent with advisors with the highest equity mismarking smoothing reported returns to an even greater extent than advisors with the least equity mismarking. That high mismarking advisors smooth reported returns more than the low mismarking advisors is further supported by the sign and significance of coefficients on *High Mismarking* when specifications with the other two dependent variables are used. As expected, high mismarking advisors show a lower Herfindahl Index and higher serial correlation. The fact that high mismarking but not medium advisors show behavior consistent with return smoothing relative to the benchmark group is not that surprising given the evidence from Table III, where we see that only a fraction (roughly 25%) of advisors show abnormal mismarking.

Notably, the intercepts show that advisors from the benchmark group who are presumably least likely to engage in manipulation of their stock positions, have θ_0 coefficients and Herfindahl Indexes that are less than one and serial correlation coefficients that are significantly different from zero. The reported intercept's p-values for the null hypothesis that the intercept is equal to one or greater than zero in the case of the serial correlation coefficient specification show a difference that is significant at the 1%-level in all specifications. The result suggests that advisors perhaps conduct additional return smoothing by manipulating other types of assets that are not observed in 13F portfolios.

Since we control for illiquidity-related pricing issues, we conclude that the evidence presented in this table is consistent with all advisors smoothing returns and advisors with the highest equity mismarking smoothing even more. Furthermore, the results reported here are important for yet another reason: They show that mismarking in the equity part of the portfolio has a material impact on the reported hedge fund returns.

B. Portfolio Valuation Patterns

B.1. Methodology

To examine the relation between the marking behavior of advisors and performance of the hedge funds that they manage, we relate directional mismarking at the advisor's portfolio level to past portfolio returns using a regression approach. The dependent variable, *Portfolio Mismarking* (*PM*), is constructed for each advisor in each quarter as shown in Section III.A. Specifically, *PM* is measured as the net dollar value of a portfolio's total mismarking at the end of a given quarter, divided by the portfolio value as determined by CRSP prices. In addition, we use an alternative measure of mismarking, *FRACDIF*. For each advisor in each quarter, *FRACDIF* is computed as the difference of the fraction of positively mismarked positions and the fraction of negatively mismarked positions. Although, both portfolio mismarking measures are highly correlated, they capture somewhat different patterns of mismarking at the portfolio level. The *PM* measure is more sensitive to severe mismarking that could be limited to a small number of large positions. On the other hand, the *FRACDIF* measure is better positioned to capture relatively small mismarking spread across a large number of the portfolio positions.

The key independent variables in our regression are two return measures, which reflect the advisor's past performance over the last twelve months. For each advisor, the first return measure 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 using this measure is that an advisor looks at the real returns of the underlying assets in his portfolio at the end of quarter *t* and then decides whether and how much to mismark. Ideally we would have used real 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, which is the value-weighted average of the reported returns of all hedge funds managed by each advisor.

B.2. Results

Estimation results and corresponding p-values are given in Table IX. Standard errors are clustered by advisor. *PM* and *FRACDIF* are the dependent variables, respectively, in Panels A and B. Results from Panel A show a negative coefficient on the past performance variables for all four specifications, suggesting an inverse relationship between past portfolio returns and end-of-quarter net portfolio mismarking.[20] Thus, consistent with return smoothing, lower returns lead to an increase in the portfolio's net portfolio mismarking and vice versa. Statistical significance of the result holds for three out the four specifications. Although the sign of the coefficient is as expected, it is not significant when the PM measure is used in the specification with time fixed effects. Our control variable, *SPI,* is insignificant in each regression. This is sensible since illiquidity by itself should not predict the direction of mismarking.

Panel B of Table IX also supports the view that advisors mismark to smooth returns: Following a low (high) portfolio return, an advisor tends to increase (decrease) the difference between the fraction of overvalued stocks and the fraction of undervalued stocks in her portfolio. The respective coefficients are negative and statistically significant in all four specifications. Our control variable remains insignificant.

V. Do Hedge Fund Advisors Strategically Mismark to Alter Return Distributions?

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. The return discontinuity hypothesis generates a testable prediction: Advisors that mismark more ought to exhibit a stronger distribution discontinuity in their reported returns. In the analysis that follows, we employ two tests to measure whether mismarking is related to the discontinuity in reported returns.

[20] 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.

A. Discontinuity Measure Based on Fixed Return Intervals

A.1. Methodology

We run regressions of our discontinuity metric on dummy variables reflecting the level of mismarking activity by advisors. To construct our first discontinuity metric, we follow a two-step procedure. We first assign the reported returns of all hedge funds to each respective advisor. Next, for each advisor, the discontinuity metric is computed as the difference of the fraction of positive returns and the fraction of negative returns within tight intervals around zero.

The key independent variables are *Medium Mismarking* and *High Mismarking* that were introduced in the previous section. If advisors in the medium and high mismarking groups (compared against the low mismarking group) mark strategically to avoid reporting small negative returns, we would expect the coefficients on the dummy variables to be positive. As control variables we include the advisor's stock portfolio illiquidity, *SPI_AVG,* and the advisor's total portfolio illiquidity, *TPI_AVG,* also defined in the previous section.

A.2. Results

Table X reports results. 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 highest mismarking relative to advisors with the lowest mismarking. The coefficient on *High Mismarking* is both economically and statistically significant across all specifications that use different mismarking measures to classify the mismarking groups and different intervals to construct the dependent variable. The coefficient on *Medium Mismarking* is also positive in all specifications, but significant at conventional levels in only five out of the six specifications. These results are consistent with the highest mismarking advisors trying to avoid small losses at any cost, which is consistent with the return discontinuity hypothesis.

B. Discontinuity Measure Based on Optimal Return Intervals

B.1. Methodology

We complement the analysis of the return distribution around zero by examining whether the observed mismarking is related to the Kink fraud indicator suggested by Bollen and Pool (2010). 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 (2010, p. 26) 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 approximately equal the average number of observations in the two surrounding bins. Thus, we test whether the number of observations

[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.

in the middle bin is significantly lower than the average from the two adjacent bins. According to Bollen and Pool (2010), 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. 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.

B.2. Results

The regression results in Table XI show that advisors who exhibit more mismarking manage a larger fraction of funds that are categorized as "Kink" funds, i.e., potentially fraudulent funds. These results are also consistent with advisors that mismark more showing fewer small negative reported returns in the hedge funds they manage relative to advisors in the benchmark group.

Taken together, the results of Table X and XI suggest that high mismarking advisors show a discontinuity in the distribution of hedge fund reported returns around zero. Hedge fund advisors seem to manipulate valuations such that otherwise small negative returns are slightly pushed above zero.

VI. The Remaining Puzzle

Given our evidence of mismarking and its relation to hedge fund incentives, the mere fact that hedge fund advisors choose to mismark when their 13F valuations are available to the public remains puzzling. The notion that hedge fund advisors misrepresent material information even when such information is likely to be verified has found support in the concurrent literature. Brown, Goetzmann, Liang, and Schwarz (2011) show that over 15 percent of their sample hedge funds misstated material facts to due diligence firms even when they knew that these firms were hired to verify that reported information. In an illustrative example, they point to a hedge fund manager who verbally reported assets under management over $300 million higher than the actual figure.

Perhaps hedge fund advisors are over-confident in their ability to avoid getting caught. A combination of several factors might contribute to this over-confidence. While most of the cases that the SEC has brought against hedge fund advisors that misstated their assets have been for extreme, hard-to-justify cases of manipulation, the mismarking of equity positions we document is not that extreme. Perhaps advisors believe that they can get away with a certain amount of mismarking, which, if done in moderation, would keep the SEC from building strong cases of manipulation against them.

Another factor that might contribute to this over-confidence is that Regulation 13(f) is limited in its effectiveness. This was exposed in a recent review of the Section 13(f) reporting requirements prepared by the SEC's Office of Inspector General.[22] Specifically, one key finding of the report was that "No SEC division or office has been delegated authority to review the Section 13(f) reports, and no regular or systematic review or analysis of this information is conducted." Another finding was that "There is no periodic monitoring of the Section 13(f) reporting process, including no review of the Form 13F filing for accuracy and completeness." Since these findings state that no SEC office has the authority to monitor 13F filings, enforcement actions by the SEC in response to reporting irregularities should be non-existent or minimal, at best. This means that mismarking should largely go unnoticed since

[22] See U. S. Securities and Exchange Commission (2010).

there seems to be a lack of verification of 13F reports, and even if it is recognized, the real consequences from misreporting in 13F filings are currently rather limited.

That hedge fund advisors face limited consequences from misreporting in 13F forms is supported by additional evidence cited in the report prepared by SEC's Office of Inspector General. Namely, the report states that there is not even one staff member wholly allocated to examining the Form 13F filings. Rather, there is one paralegal specialist from the SEC's Division of Investment Management who is partially allocated to this task, and does so informally at that. She primarily collects e-mails and logs calls from the public related to issues with certain Form 13F filings. Even when this SEC staff member contacts 13F filers to notify them of deficiencies or errors, all that is requested from these filers is that they address the identified issues. This correction process might take months to resolve but will not result in any sanctions.

VII. Conclusion and Further Research

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 approaches. 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.[23]

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 showed that hedge fund advisors intentionally manipulate position valuations of common stocks, some of the most liquid securities in the financial markets. One important aspect of this finding is that manipulation took place even for valuations that advisors reported to SEC in mandated 13F reports. Thus reporting alone was not enough to preclude advisors from asset manipulation. This latter finding is important in light of the recent review of the Section 13(f) reporting requirements prepared by the SEC's Office of Inspector General. The reporting irregularities we document support the recommendations raised in this review both for a greater involvement by the SEC in the implementation of Section 13(f) and for changes to Section 13(f) that would increase the oversight over its implementation.

Our analysis showed that advisors mismark their stock positions in a way that is consistent with a pursuit of their own interest. In an effort to perhaps impress potential investors and current investors, advisors that self-report to a commercial databases or report to their current investors at a higher frequency exhibit relatively more mismarking. Consistent with taking advantage of a lower likelihood of getting caught, advisors that are domiciled in offshore locations show more mismarking. Consistent with advisors trying to enhance their performance, we showed that hedge funds mark their common stock positions

[23] Effective after November 15, 2007, SFAS 157 has introduced more structure in the asset valuation process. For example, when valuing positions, hedge fund advisors are required to classify their 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.

up following a period of poor returns and mark them down following a period of good returns.

Our finding of a significant relation between mismarking of common stock positions by advisors and manipulation of the reported returns of their hedge funds suggests that mismarking is consequential. Specifically, a comparison of advisors that exhibit the greatest degree of mismarking to those that exhibit the least mismarking shows that the former group of advisors exhibits a greater discontinuity in their hedge funds' return distribution around zero and smoother reported returns.

The litigation costs associated with mismarking are much larger for the mismarking of equity positions than for the mismarking of positions of illiquid securities that are not reported to the public, such as over-the-counter derivative securities. That is, it is easier to make a case for manipulation of a common stock position, for which market prices are readily available, than for an exotic derivative security the value of which is difficult to assess. Therefore, we would expect to see more manipulation among non-stock positions. Further research is warranted to examine how manipulation of equity positions relates to the manipulation of other less liquid positions, perhaps when better data for non-equity positions becomes available.

Table I
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 II
Stock Position Mismarking

This table reports descriptive statistics on the valuation deviation 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 *stock position mismarking (SM)* and compute it as follows:

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

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. *SM* 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 |*SM*|>0 and the fraction of positions deviating by at least 5% and 10%, respectively. The next column reports the mean absolute mismarking, i.e., average of |*SM*|, computed conditionally only across the mismarked positions for each year as well as over the whole sample period. The last column reports the number of observations. Panel B shows position valuation deviation, stratified by whether a stock traded or not during the report day. Reported statistics are the same as in Panel A. Panel C reports position valuation deviations 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. Reported statistics are the same as in Panel B.

Table II -- continued

Panel A: Stock position mismarking by year					
Year	% |*SM*|>0	% |*SM*| ≥ 5%	% |*SM*| ≥ 10%	Conditional mean |*SM*|	Observations
1999	7.95%	0.95%	0.54%	2.08%	95,709
2000	9.06%	0.79%	0.48%	1.82%	108,352
2001	9.89%	2.05%	1.12%	3.50%	154,940
2002	8.59%	0.93%	0.49%	2.10%	163,430
2003	11.56%	1.04%	0.60%	1.92%	183,634
2004	6.68%	0.74%	0.42%	2.18%	257,298
2005	5.60%	0.91%	0.48%	2.64%	315,599
2006	4.50%	0.66%	0.31%	2.53%	330,240
2007	6.02%	0.98%	0.49%	2.85%	344,894
2008	4.76%	0.76%	0.37%	2.95%	295,623
Total sample	6.78%	0.93%	0.49%	2.49%	2,249,719

Panel B: Stock position mismarking stratified by whether a stock traded or not					
Trading Group	% |*SM*|>0	% |*SM*| ≥ 5%	% |*SM*| ≥ 10%	Conditional mean |*SM*|	Observations
Traded	6.62%	0.91%	0.49%	2.49%	2,244,062
Not traded	70.04%	7.19%	2.26%	2.34%	5,657

Panel C: Stock position mismarking stratified by stock illiquidity					
Illiquidity Decile	% |*SM*|>0	% |*SM*| ≥ 5%	% |*SM*| ≥ 10%	Conditional mean |*SM*|	Observations
1 (most liquid)	6.94%	0.92%	0.47%	2.34%	788,475
2	5.57%	0.83%	0.45%	2.61%	401,606
3	5.67%	0.85%	0.47%	2.63%	272,297
4	6.13%	0.78%	0.42%	2.30%	202,530
5	6.32%	0.79%	0.45%	2.38%	160,500
6	6.73%	0.93%	0.52%	2.55%	130,846
7	7.46%	0.95%	0.52%	2.43%	103,516
8	8.54%	1.07%	0.62%	2.53%	80,574
9	9.50%	1.31%	0.68%	2.77%	61,691
10 (most illiquid)	9.99%	2.15%	0.98%	3.80%	42,027

Table III
Cross-sectional Distribution of Mismarking

This table reports statistics on the cross-sectional distribution of mismarking measures. First, fraction of mismarked positions and conditional mean absolute mismarking are computed for each hedge fund advisor over the entire sample period. If a hedge fund advisor does not report mismarked positions, her conditional mean absolute mismarking is set to zero. Next, the measures calculated at the advisor level are used to compute cross-sectional statistics.

Cross-sectional statistics	% $\|SM\|>0$	% $\|SM\| \geq 5\%$	% $\|SM\| \geq 10\%$	Conditional mean $\|SM\|$
Mean	5.65%	1.18%	0.65%	3.25%
Max	100.00%	42.57%	21.56%	25.57%
p90	13.96%	3.17%	1.69%	8.19%
p75	6.00%	0.96%	0.51%	4.80%
Median	1.88%	0.17%	0.04%	1.81%
p25	0.54%	0.00%	0.00%	0.57%
p10	0.00%	0.00%	0.00%	0.00%
Min	0.00%	0.00%	0.00%	0.00%

Table IV
Choice to Report to a Database and Mismarking

This table compares the general mismarking measures of advisors that report to those that do not report to at least one of the three commercial databases, CISDM, Lipper TASS, and Morningstar. Results are from regressions of advisor-quarter-level general mismarking measures on *Database Reporting*, a dummy variable indicating whether an advisor reports to at least one of the three databases in the respective quarter. Each advisor's quarterly report is a unit of observation in the following regressions. Separate regressions are run for each of the two mismarking measures that are used as dependent variables: *ABS_PM* and *FRAC*. A*BS_PM* is computed as the absolute value of an advisor's quarterly *Portfolio Mismarking (PM)*, which is defined as the net dollar value of a stock portfolio's total mismarking at the end of a given quarter, divided by the stock portfolio value as determined by CRSP prices. *Portfolio Mismarking* (*PM*) is constructed for each advisor *i* in each quarter *t* at the report day as:

$$PM_{i,t} = \frac{\sum_j \left(reported\ valuation_{i,j,t} - CRSP\ valuation_{i,j,t} \right)}{\sum_j CRSP\ valuation_{i,j,t}},$$

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 computed using the CRSP price as shown in Table II. *FRAC* is computed as the fraction of mismarked positions in an advisor's report. All regressions are run using two different specifications. The first specification, *OLS*, is a pooled regression. The second specification, *TIME_FE*, includes time-fixed effects to control for any unobservable time effects that could equally affect the mismarking behavior of all advisors. Our key control variable in all specifications is the stock portfolio's illiquidity measure, *SPI*, measured as the value-weighted mean of Amihud's ratio of all the stocks in the portfolio. Amihud's ratio is computed 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. 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.

Influence of Commercial Database Reporting on Mismarking				
Dependent variable:	*ABS_PM*		*FRAC*	
Regression method:	*OLS*	*TIME_FE*	*OLS*	*TIME_FE*
Intercept	0.0013***	0.0015***	0.0489***	0.1112***
	<(0.001)	(0.007)	<(0.001)	<(0.001)
Database Reporting	0.0008***	0.0007***	0.0118**	0.0108*
	(0.004)	(0.006)	(0.041)	(0.066)
SPI	0.0001	0.0001	0.0011	0.0010
	(0.320)	(0.340)	(0.260)	(0.260)
Observations	15,198	15,198	15,198	15,198
Clusters	864	864	864	864
R^2	0.20%	0.55%	0.18%	1.53%

Table V
Mismarking Behavior Before and After Joining a Database

This table compares the mismarking behavior of advisors before and after they join a commercial database. 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 mismarking 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 mismarking measure (*ABS_PM* and *FRAC*) for each advisor in each quarter is first benchmarked against the average mismarking measure of other advisors that never chose to report to a commercial database. Next, an average of the benchmarked mismarking 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 mismarking variables 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.

Mismarking Before and After Reporting to a Commercial Database

Mismarking based on:	*ABS_PM*		*FRAC*	
Approach:	*DIFF-IN-DIFFS*	*RANK*	*DIFF-IN-DIFFS*	*RANK*
Before	-0.0008	0.6075	0.0241	0.6153
After	0.0021	0.7066	0.0899	0.7058
After-Before	0.0029**	0.0990***	0.0658*	0.0905***
	(0.017)	<(0.001)	(0.050)	(0.002)

Table VI
Mismarking as a Marketing Tool to Impress Existing Investors

This table presents results from regressions of advisor-quarter-level general mismarking measures on the frequency with which an advisor's hedge funds report to their investors. Each advisor's quarterly report is a unit of observation in the following regressions. The dependent variables are the mismarking measures introduced in Table IV. In Panel A, the key independent variable, *Monthly Reporting*, equals one for each advisor-quarter with at least one hedge fund that reports at least with monthly frequency to existing investors and zero otherwise. In Panel B, *Monthly Reporting Not All* equals one for each advisor-quarter for which at least one, but not all, of the advisor's funds report to their existing investors on at least a monthly frequency. *Monthly Reporting All* equals one for each advisor-quarter for which all funds report to their existing investors on at least a monthly frequency. All regressions are run using two different specifications, *OLS* and *TIME*_FE as defined in Table IV. Our key control variable in all specifications is the stock portfolio's illiquidity measure, *SPI*, as defined in Table IV. 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.

Panel A: Influence of at Least Monthly Reporting on Mismarking

Dependent variable:	*ABS_PM*		*FRAC*	
Regression method:	*OLS*	*TIME_FE*	*OLS*	*TIME_FE*
Intercept	0.0008**	-0.0010**	0.0296***	-0.0170*
	(0.022)	(0.014)	(0.009)	(0.080)
Monthly Reporting	0.0017***	0.0015***	0.0354**	0.0319**
	(0.006)	(0.009)	(0.015)	(0.024)
SPI	0.0002	0.0003	0.0079	0.0087
	(0.638)	(0.501)	(0.369)	(0.318)
Observations	1,787	1,787	1,787	1,787
Clusters	133	133	133	133
R^2	0.22%	1.60%	0.66%	2.92%

Panel B: Influence of Fraction of Funds with at Least Monthly Reporting on Mismarking

Dependent variable:	*ABS_PM*		*FRAC*	
Regression method:	*OLS*	*TIME_FE*	*OLS*	*TIME_FE*
Intercept	0.0008**	-0.0010**	0.0296***	-0.0171*
	(0.022)	(0.013)	(0.009)	(0.079)
Monthly Reporting Not All	-0.0005	-0.0006	0.0279	0.0262
	(0.251)	(0.222)	(0.396)	(0.422)
Monthly Reporting All	0.0018***	0.0015***	0.0355**	0.0320**
	(0.005)	(0.008)	(0.015)	(0.024)
SPI	0.0002	0.0003	0.0080	0.0088
	(0.587)	(0.464)	(0.367)	(0.318)
Observations	1,787	1,787	1,787	1,787
Clusters	133	133	133	133
R^2	0.30%	1.60%	0.70%	2.90%

Table VII
Probability of Getting Caught and Mismarking

This table compares the general mismarking measures of advisors that manage offshore funds to those that do not manage offshore funds. Each advisor's quarterly report is a unit of observation in the following regressions. The dependent variables are the mismarking measures introduced in Table IV. In Panel A, the key independent variable, *One Fund Offshore,* equals one for each advisor with at least one hedge fund that is domiciled in the Bahamas, Barbados, Belize, Bermuda, Cayman Islands, Curacao, or Virgin Islands and zero otherwise. In Panel B, *Offshore Not All* equals one or each advisor managing at least one, but not all, funds that are domiciled offshore in a given quarter. *Offshore All* equals one for each advisor-quarter for which all funds are domiciled offshore. All regressions are run using two different specifications, *OLS* and *TIME*_FE as defined in Table IV. Our key control variable in all specifications is the stock portfolio's illiquidity measure, *SPI*, as defined in Table IV. 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.

Panel A: Influence of Offshore Domicile on Mismarking				
Dependent variable:	*ABS_PM*		*FRAC*	
Regression method:	*OLS*	*TIME_FE*	*OLS*	*TIME_FE*
Intercept	0.0015***	0.0009	0.0492***	0.0851***
	<(0.001)	(0.158)	<(0.001)	<(0.001)
One Fund Offshore	0.0008**	0.0009**	0.0177*	0.0187**
	(0.040)	(0.033)	(0.056)	(0.046)
SPI	0.0000	-0.0000	0.0003	0.0002
	(0.485)	(0.836)	(0.511)	(0.539)
Observations	6,151	6,151	6,151	6,151
Clusters	427	427	427	427
R^2	0.10%	0.80%	0.30%	1.40%

Panel B: Influence of Fraction of Funds with Offshore Domicile on Mismarking				
Dependent variable:	*ABS_PM*		*FRAC*	
Regression method:	*OLS*	*TIME_FE*	*OLS*	*TIME_FE*
Intercept	0.0015***	0.0009	0.0492***	0.0857***
	<(0.001)	(0.153)	<(0.001)	<(0.001)
Offshore Not All	0.0007	0.0007	0.0116	0.0125
	(0.133)	(0.108)	(0.214)	(0.185)
Offshore All	0.0014*	0.0014*	0.0376**	0.0387**
	(0.055)	(0.053)	(0.035)	(0.030)
SPI	0.0000	-0.0000	0.0003	0.0002
	(0.481)	(0.833)	(0.504)	(0.526)
Observations	6,151	6,151	6,151	6,151
Clusters	427	427	427	427
R^2	0.10%	0.80%	0.60%	1.70%

Table VIII

Impact of Mismarking on Return Smoothing and Loss of Economic Return

This table presents results from advisor-level regressions that relate return smoothing to mismarking activity. 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 nonlinear OLS regressions:

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

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 funds' average assets under management. Our key independent variables are based on the mismarking measures introduced in Table IV: For each advisor, the quarterly measures *ABS_PM* and *FRAC* are averaged across all quarters to come up with one advisor-specific measure. Based on each mismarking measure we divide advisors into three equal-sized groups. Our basic group contains the advisors with the lowest mismarking measures. We then define two dummy variables. *Medium Mismarking* takes the value one if an advisor belongs to the medium mismarking group and zero otherwise. *High Mismarking* equals one if an advisor belongs to the group with highest mismarking measures. The results for each mismarking measure are presented in the respective column. Our control variables are defined as follows: The stock portfolio's illiquidity, *SPI_AVG,* is calculated by taking the mean of *SPI* as defined in Table IV over all of an advisor's reports. The total portfolio's illiquidity, *TPI_AVG,* is the beta exposure to Pástor and Stambaugh (2003)'s innovations in aggregate liquidity, averaged across all funds managed by each advisor, with weights determined by each funds' average assets under management. 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.

Table VIII -- continued

Mismarking based on:	*ABS_PM*			*FRAC*		
Dependent variable:	θ_0	ξ	ρ	θ_0	ξ	ρ
Intercept	0.9013***	0.8391***	0.1553***	0.9001***	0.8372***	0.1576***
	<(0.001)	<(0.001)	<(0.001)	<(0.001)	<(0.001)	<(0.001)
Medium Mismarking	-0.0157	-0.0235	0.0384*	-0.0107	-0.0137	0.0293
	(0.158)	(0.128)	(0.060)	(0.351)	(0.369)	(0.144)
High Mismarking	-0.0324**	-0.0362**	0.0586***	-0.0337***	-0.0402**	0.0603***
	(0.012)	(0.023)	(0.006)	(0.007)	(0.012)	(0.005)
SPI_AVG	-0.0016	-0.0018	0.0018**	-0.0018	-0.0019	0.0020**
	(0.412)	(0.369)	(0.014)	(0.343)	(0.302)	(0.011)
TPI_AVG	-0.0516	-0.0692	0.1081	-0.0553	-0.0733	0.1129
	(0.214)	(0.228)	(0.169)	(0.159)	(0.184)	(0.141)
Observations	421	421	421	421	421	421
R^2	2.61%	2.06%	2.72%	2.82%	2.37%	2.78%

Table IX
Past Returns and Mismarking

This table presents results from advisor-quarter-level regressions of mismarking measures on past returns. In Panel A, the dependent variable is *Portfolio Mismarking* (*PM*) as defined in Table IV. In Panel B, *FRACDIF* is the dependent variable. For each advisor in each quarter, *FRACDIF* is computed as the difference of the fraction of positively mismarked positions and the fraction of negatively mismarked positions. In both panels, the key independent variable is *Return*, which reflects the advisor's past performance over the last twelve months. *Return* is measured in two ways: For each advisor, the first return measure 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 second measure for *Return* is the value-weighted average of the reported returns of all hedge funds managed by each advisor. Both regressions are run using two different specifications, *OLS* and *TIME*_FE as defined in Table IV. Our key control variable in both specifications is the stock portfolio's illiquidity measure, *SPI*, as defined in Table IV. 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.

Panel A: Past returns and portfolio mismarking (PM)				
Dependent variable:	*PM*			
Return based on:	*Holdings Return*		*Reported Return*	
Regression method:	*OLS*	*TIME_FE*	*OLS*	*TIME_FE*
Intercept	-0.0004***	-0.0005	-0.0007***	-0.0015*
	<(0.001)	(0.408)	<(0.001)	(0.055)
Return	-0.0021***	-0.0028***	-0.0017**	-0.0014
	<(0.001)	(0.002)	(0.047)	(0.155)
SPI	0.0001	0.0001	-0.0000	-0.0000
	(0.542)	(0.498)	(0.175)	(0.787)
Observations	13,066	13,066	5,590	5,590
Clusters	861	861	392	392
R^2	0.40%	0.70%	0.10%	1.20%

Table IX -- continued

Panel B: Past returns and fractional difference between overstated and understated positions (FRACDIF)				
Dependent variable:	*FRACDIF*			
Return based on:	*Holdings Return*		*Reported Return*	
Regression method:	*OLS*	*TIME_FE*	*OLS*	*TIME_FE*
Intercept	-0.0078***	-0.0380***	-0.0102***	-0.0494***
	<(0.001)	<(0.001)	<(0.001)	(0.005)
Return	-0.0064**	-0.0096*	-0.0211**	-0.0203**
	(0.041)	(0.091)	(0.011)	(0.049)
SPI	0.0001	0.0002	-0.0003	-0.0003
	(0.839)	(0.761)	(0.244)	(0.382)
Observations	13,066	13,066	5,590	5,590
Clusters	861	861	392	392
R^2	0.00%	0.80%	0.20%	1.20%

Table X
Mismarking and the Distribution of Reported Returns around Zero

This table relates the distribution of reported returns around zero to mismarking. 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 100bps, 200bps, and 300bps around zero, respectively. Results for each subset are reported in the respective columns. The key independent variables, *Medium Mismarking* and *High Mismarking,* and our control variables, the stock portfolio's illiquidity, *SPI_AVG,* and the total portfolio's illiquidity, are defined in Table VIII. 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:	*100bps*		*200bps*		*300bps*	
Dependent variable:	*ABS_PM*	*FRAC*	*ABS_PM*	*FRAC*	*ABS_PM*	*FRAC*
Intercept	0.0574***	0.0597***	0.1299***	0.1356***	0.1693***	0.1763***
	<(0.001)	<(0.001)	<(0.001)	<(0.001)	<(0.001)	<(0.001)
Medium Mismarking	0.0343***	0.0185*	0.0583***	0.0236	0.0821***	0.0443**
	(0.005)	(0.092)	(0.002)	(0.186)	<(0.001)	(0.031)
High Mismarking	0.0462***	0.0549***	0.0699***	0.0873***	0.0886***	0.1053***
	<(0.001)	<(0.001)	<(0.001)	<(0.001)	<(0.001)	<(0.001)
SPI_AVG	-0.0004	-0.0003	-0.0014**	-0.0012***	-0.0011	-0.0009
	(0.488)	(0.571)	(0.029)	(0.004)	(0.478)	(0.474)
TPI_AVG	-0.0319	-0.0338	0.0038	0.0017	0.0327	0.0287
	(0.367)	(0.317)	(0.948)	(0.975)	(0.642)	(0.669)
Observations	432	432	432	432	432	432
R^2	2.98%	4.05%	2.87%	4.24%	4.01%	4.66%

Table XI
Mismarking and Fraction of Kink funds

This table presents results from regressions that relate mismarking 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 (2010). 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:

$$t = \frac{X_2 - \frac{1}{2}(X_1 + X_3)}{\left[n(p_2 - p_2^2) + \frac{1}{4} n(p_1 - p_1^2 + p_3 - p_3^2) + np_2(p_1 + p_3) - \frac{1}{2} np_1 p_3 \right]^{1/2}}$$

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 (2010), 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 independent variables are defined in Table VIII. 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: Frequency of Kink funds per advisor		
Mismarking based on:	*ABS_PM*	*FRAC*
Intercept	0.1211***	0.1269***
	<(0.001)	<(0.001)
Medium Mismarking	0.0821**	0.0450
	(0.022)	(0.190)
High Mismarking	0.0891**	0.1086***
	(0.012)	(0.004)
SPI_AVG	0.0020	0.0021
	(0.709)	(0.669)
TPI_AVG	0.0824	0.0922*
	(0.144)	(0.098)
Observations	426	426
R^2	1.94%	2.29%

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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 mismarking 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 mismarked positions, measured by the absolute deviation from the CRSP price.