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. Hedge fund advisors mark their positions up (down) following poor (good) performance of their equity holdings. Mismarking is more pronounced for advisors that are audited less frequently; are domiciled in offshore locations; self-report to a commercial database; and report more frequently to investors. Furthermore, equity mismarking is related to some of the reported return patterns documented in previous studies, such as a discontinuity in the distribution of returns around zero and smoothed returns.

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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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1. Introduction

The recent cases of hedge fund fraud prosecuted in the United States have made return smoothing and other forms of return manipulation by hedge funds a focal point of concern for regulators, investors, and legislators.[1] Echoing these concerns, several academic studies have provided indirect evidence of hedge fund manipulation by documenting suspicious patterns in self-reported hedge fund returns.[2] Although consistent with intentional manipulation by hedge funds, some of the documented patterns could simply arise from marking illiquid securities (see, e.g.,Getmansky, Lo, and Makarov (2004)). Thus, the previously documented return patterns alone do 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 to value illiquid "hard-to-value" securities.

Our paper provides direct evidence that hedge funds manipulate valuations of their individual portfolio positions. The direct evidence comes from analyzing a new dataset of individual stock positions' valuations reported by hedge fund advisors to the SEC in their 13F filings. Looking at stocks, presumably the most liquid securities, allows us to document manipulation while eliminating the possibility of unintentional mispricing inherent in pricing illiquid securities. Regulation dictates that hedge fund advisors should use closing market prices to value their stock positions. Only in rare circumstances, hedge fund advisors can use pricing discretion to value illiquid stocks that did not trade in a particular day or thinly-traded stocks trading at prices that did not reflect the most

[1] The most egregious case was that of Bernard L. Madoff Investment Securities LLC, which defrauded investors of billions of dollars in a massive Ponzi investment scheme.

[2] For evidence consistent with return smoothing see e.g., Bollen and Pool (2008), Getmansky, Lo, and Makarov (2004), and Asness, Krail, and Liew (2001). For evidence consistent with other forms of return manipulation see, e.g., Bollen and Pool (2009).

recent market conditions. We eliminate such rare occurrences and document mismarking even among the remaining most liquid stocks. By doing this, we are able to completely rule out illiquidity-related issues as the source of mismarking, but rather attribute the documented mismarking for these highly liquid stocks to intentional manipulation alone.

Our results are of importance to regulators, investors, and legislators. Intentional manipulation of hedge fund assets could result in wealth transfers across current, new, and redeeming hedge fund investors. Furthermore, manipulation intended to smooth reported returns could distort a hedge fund's risk-return profile, leading investors to make sub-optimal investment decisions. In this regard, against the backdrop of a public outcry for increased hedge fund disclosure, we show that hedge funds intentionally mismark even position valuations that they report to a regulatory agency.[3] Thus, mandated disclosure alone might not be enough to protect the interests of investors in deterring asset manipulation by hedge funds.

One reason for the manipulation of position valuations by hedge fund advisors is advancement of their own interests. Under this premise, we hypothesize that advisors could mismark to artificially enhance their performance metrics in order to maintain their current investor base and attract additional investment flows.[4] Consistent with this hypothesis, we show that hedge funds push their common stock valuations up following a

[3] 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 (2010) 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 the reported information. By way of illustration, they point to an example of a hedge fund manager who verbally reported assets under management over $300 million higher than the actual figure.

[4] 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. In another example, Bernard Madoff, chairman of Bernard L. Madoff Investment Securities LLC, received one of the most severe sentences in the history of hedge fund litigation, life imprisonment.

period of poor returns and push them down following a period of good returns in the equity part of their portfolio. Unlike previous research that focuses on indirect evidence from hedge fund reported returns, this pattern provides direct evidence on how actual marking behavior responds to portfolio returns.

Next, we hypothesize that if advisors are mismarking to further their own interests, we would expect hedge fund advisors to engage in more mismarking when the probability of them getting caught is lower. Evidence supporting this hypothesis shows that, indeed, mismarking by hedge fund advisors is more prevalent when the probability of them getting caught manipulating asset values is lower. Specifically, we show that hedge funds mismark to a greater extent when they are not regularly audited or when they are registered in less regulated offshore locations such as the Cayman Islands or the Bahamas.[5]

We extend the premise of mismarking in pursuit of advisors' self-interest a step further. The SEC Rule 502(c) of the Securities Act of 1933 prohibits hedge fund advisors from any form of general advertising.[6] We argue that, in an attempt to potentially bypass this regulation, some hedge fund advisors try to achieve more visibility by self-reporting to commercial databases or by reporting to their existing investors at a higher frequency.[7] We hypothesize that these advisors are more likely to take advantage of such visibility by using mismarking to generate better performance metrics in order to impress both future and current investors. Consistent with this view, we find that hedge fund advisors exhibit

[5] In a similar spirit, Cumming and Dai (2009) show that misreported returns are influenced by the country hedge funds are registered in, justified by regulatory differences among the countries.

[6] 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.

[7] For example, Ackermann, McEnally, and Ravenscraft (1999), Agarwal, Fos, and Jiang (2010), and Aiken, Clifford, and Ellis (2010) suggest an advertising rationale behind the decision of some hedge funds to self-report to commercial databases.

greater mismarking when their returns are more visible to current and potential fund investors. Perhaps aspiring to impress potential investors, advisors who self-report their hedge fund returns to CISDM mismark more than advisors who do not report to CISDM. Similarly, perhaps aspiring to impress current investors, advisors who report to their current investors at a higher frequency show more mismarking.

So far we have shown that the observed mismarking is caused by intentional manipulation that is consistent with advisors' incentives. However, it is not clear whether the impact of this mismarking behavior on reported returns is significant. For example, such an impact could be inconsequential for reported return, especially if mismarking of equity positions is overshadowed by other unobservable positions in the advisor's portfolio that are not reported in 13F filings. Our next set of tests examines the relation between patterns in hedge fund reported returns that are consistent with intentional manipulation and equity mismarking.

Advisors could potentially affect the reported returns of their hedge funds in two ways. First, advisors could use mismarking to alter 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 (see, e.g., Bollen and Pool (2009) and Waring and Siegel (2006)). Second, advisors could use mismarking to smooth reported returns to achieve attractive risk-return profiles for their hedge funds. We explore these two possibilities by comparing advisors that exhibit the greatest degree of mismarking with those that exhibit the least mismarking. Consistent with the first hypothesized return manipulation approach, advisors that exhibit the greatest degree of mismarking exhibit a greater discontinuity in their hedge funds' return distribution around zero. Consistent with the second hypothesized return manipulation approach, we show that advisors that exhibit the greatest degree of mismarking, report smoother hedge fund returns, characterized by a significant gap between the reported return and the economic return.

Taken altogether, our results suggest that hedge fund advisors are intentionally mismarking their equity positions. The mismarking behavior is both aligned to their incentives and is related to some of the suspicious reported return patterns documented in previous studies.

Our paper contributes to the growing literature that studies suspicious patterns in self-reported hedge fund returns. Most of the previously documented irregular patterns can be classified as: (1) disproportionally more small positive than small negative returns in the pooled distribution of returns around zero (see, e.g., Jylha (2010); Bollen and Pool (2009)) or (2) serial correlation in hedge fund's reported returns (see, e.g., Bollen and Pool (2008); Getmansky, Lo, and Makarov (2004); or Asness, Krail, and Liew (2001)). Another irregular pattern is a calendar effect in the form of higher reported hedge fund returns for the month of December (see, e.g., Agarwal, Daniel, and Naik (2009a)). Our research extends the insights of these papers by documenting a direct link between observable manipulation of hedge fund position valuations and the suspicious patterns of hedge fund returns mentioned above.

Our research is related to studies that analyze operational risks of hedge funds (see, e.g., Brown, Goetzmann, Liang, and Schwarz (2008); Brown, Goetzmann, Liang, and Schwarz (2010); and Cassar and Gerakos (2009)). For example, Brown, Goetzmann, Liang, and Schwarz (2010) show that hedge funds that have experienced legal and regulatory problems are more likely to have pricing problems. That is, such hedge funds are less likely to use independent pricing services firms and therefore more likely to apply pricing discretion, and they are likely to have switched their pricing service firm in the last year. Similarly, Cassar and Gerakos (2009) analysis of due diligence reports shows that hedge funds with less verifiable pricing sources and greater pricing discretion for their managers are more likely to exhibit smoothed returns. Unlike these studies, ours uses actual hedge fund position valuations for common stock securities and shows that hedge fund advisors mismark even highly liquid securities, a setting where hedge fund advisors should not apply pricing discretion.

Our paper is also related to Huang, Liechty, and Rossi (2009) who show that return smoothing causes serious biases in hedge fund performance and to other papers that analyze and evaluate performance of hedge funds.[8] Previous research has raised the possibility of performance evaluation biases from self-reported returns. By examining the marking behavior of hedge funds, we show that, perhaps trying to misguide investors, funds that self-report to CISDM show greater mismarking. As reported returns are a function of marking behavior, the greater mismarking tendency of self-reporting funds suggests that self-reported returns might not be a reliable measure of performance.

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 (2010) 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.

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

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 2 we discuss our data and present summary statistics on our sample. Section 3 provides an overview of mismarking at the position level. In Section 4 we relate mismarking to hedge fund advisors' incentives. Section 5 investigates the influence of mismarking on reported returns. Section 6 concludes.

2. Data

2.1. 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.[9] 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.[10] 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

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

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 CISDM hedge fund database and 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 1,025 hedge fund advisors that filed at least one 13F report during the 1999-2008 period was subjected to additional filters described below.

The second dataset that we used is from the Center for International Securities and Derivatives Markets (CISDM) hedge fund database. From this database we obtained information on monthly returns, reporting frequency, audit frequency, and domicile information for hedge funds that were managed by advisors in our sample.

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 the data using stock CUSIPs.

2.2. Data steps and mismarking measure

As we focus only on the valuation of equity positions, we excluded all positions corresponding to non-equity securities.[11] 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."[12]

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

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

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

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

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

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 mistakes possibly made when filling out the reports, such as scaling issues due to displaced decimal points or interchanged columns. Furthermore, we excluded 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 *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 all positions with an absolute *SM* value of more than 50%.[13]

2.3. Sample description

Our final sample consists of 885 hedge fund advisors and 15,243 quarterly reports. Sample summary statistics are reported in Table 1.

< Please insert Table 1 about here >

[13] The results of the paper are qualitatively similar if we either drop the filter related to the size of position mismarking or vary it to 40%, 30%, 20%, or 10%.

The number of hedge fund advisors that filed 13F reports increases from 194 in 1999 to 684 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 2,366 reports in 2008. Table 1 also shows the portfolio value and the number of distinct stocks in the portfolios of fund advisors. The mean portfolio size varies around the total sample mean of about 1,800 million USD.[14] 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.

3. Mismarking at the stock position level

3.1. A first look at stock 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 $|SM|>0$. Because 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 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 2 reports mean absolute mismarking, i.e., average of $|SM|$, computed across all positions for each year, as well as for the whole sample period. The fraction of positions with non-zero position mismarking is also reported.

< Please insert Table 2 about here >

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

The mean absolute mismarking over the whole sample period is 0.22%. It varies over time and reaches its maximum level of 0.43% in 2001. When looking at the fraction of mismarked positions, we observe that, on average, almost seven percent of the positions deviate from the CRSP valuation. 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 (11.76%) and the lowest in 2006 (4.55%). 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 0.6% percent of all positions.

3.2. Alternative explanations for the observed stock position mismarking

Although evidence from Panel A is consistent with intentional manipulation, advisors' legally allowed pricing discretion could also be responsible for the observed position mismarking. 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, hedge fund advisors are allowed to use their discretion to come up with a "fair value" estimate. In exercising their valuation discretion for non-traded stocks, 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 2 reports mean absolute mismarking and the fraction of positions that were mismarked, stratified by whether a stock traded or not during the report date. 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.

Consistent with hedge fund advisors using discretion to value non-traded stocks, the valuation deviation from CRSP is much larger for stocks that did not trade during the report date. Furthermore, the fraction of mismarked positions among non-traded stocks of 70.11% is much higher than the fraction of mismarked positions of 6.74% among traded stocks. A similar conclusion is reached when looking at the fraction of positions that are mismarked by at least 5% and 10%.

Nevertheless, for stocks that did trade on the report date, we still observe a substantial average deviation of 22 basis points from the CRSP valuation. Furthermore, the number of mismarked positions corresponding to stocks that did not trade is very small compared to the number of mismarked positions corresponding to stocks that did trade. They make up only 2.6%. Thus, legally-allowed discretion to value 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 such mismarking corresponds 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” 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 all 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. The most liquid stocks are placed in Decile 1 and the most illiquid stocks are placed in Decile 10.

Results from Panel C show that deviations from CRSP valuations are observed across all deciles regardless of the level of liquidity. Valuations deviate by 18 to 33 basis points from CRSP for Deciles 1 though 9. Importantly, a 22 basis points deviation is observed even for Decile 1, which includes the most liquid stocks. Only in Decile 10, which consists of the most illiquid stocks, the deviation is considerably larger with an average of 45 basis points. A similar conclusion is reached when comparing the fraction of mismarked positions across the deciles: The bottom decile shows a greater fraction of mismarked positions than the top decile. Recall that the bottom decile is likely to include very thinly-traded stocks, for the valuation of which managers are more likely to apply pricing discretion.

[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).

Despite the large 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, our findings from Panel C suggest that legally-allowed discretion to value thinly-traded stocks is not responsible for the vast majority of observed mismarked positions. Overall, the combined evidence from Panels B and C suggests that intentional manipulation is the most likely explanation for the observed mismarking.

3.3. Cross-sectional evidence

Next, we examine mismarking across hedge fund advisors. Mean absolute mismarking and fraction of mismarked positions are computed for each hedge fund advisor separately and then cross-sectional statistics are calculated.

< Please insert Table 3 about here >

Results from Table 3 show that, while the majority of hedge fund advisors show no or little mismarking, a non-trivial fraction of advisors, show a substantial degree of mismarking. For example, about 25 percent of advisors display a mean absolute mismarking that ranges from 0.25% (75^{th} percentile) to 5.76% (max). Furthermore, about ten percent of the hedge fund advisors have mean absolute mismarking that ranges from 0.69% (90^{th} percentile) to 5.76% (max). Similar conclusions are reached when looking at the fraction of mismarked positions. For example, 25 percent of the hedge fund advisors have a fraction of mismarked positions that ranges from 6.05% to 100%, whereas 10 percent of the hedge fund advisors have a fraction of mismarked positions that ranges from 14% to 100%.

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

4. Incentives and mismarking at the portfolio level

Having established that the majority of mismarked stock positions are consistent with intentional mismarking, we next relate advisors' mismarking (aggregated at the portfolio level) to their incentives to engage in manipulation. First, we examine whether mismarking is related to advisors' past performance in a way that is consistent with return smoothing. Second, we investigate whether advisors that are less likely to get caught show a stronger tendency to mismark. Our final investigation explores whether advisors that promote their hedge funds to current and potential investors by increasing visibility of their hedge funds' returns are more likely to mismark.

4.1. Past equity portfolio returns and mismarking

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 could enhance performance measures by smoothing reported returns of their hedge funds, which leads to reduced volatility of returns and improved performance statistics such as the Sharpe

Ratio. If mismarking is one of the tools used for return-smoothing, we would expect hedge fund advisors to overvalue their portfolios following low portfolio returns and to undervalue their portfolios following high portfolio returns.[17]

To test this hypothesis, we relate mismarking aggregated at the advisor's portfolio level to past portfolio returns using an OLS regression model. The dependent variable, *Portfolio Mismarking* (*PM*), is constructed for each advisor in each quarter. It 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:

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

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 based on the CRSP price.

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.

[17] 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 (2009a): 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 key independent variables in our regression are three return measures included in separate specifications. For each advisor, the first return measure is calculated as the buy-and-hold value-weighted return during quarter *t* on a portfolio comprised of 13F stock securities disclosed by the advisor at the end of quarter *t-1*. The portfolio return is calculated employing CRSP stock returns. The second measure captures performance of the 13F stock holdings portfolio by compounding the quarterly portfolio returns from the first measure over the last four quarters (including quarter t). Our last return measure captures the year-to-date (including quarter t) return by compounding the quarterly portfolio returns from the beginning of the current calendar year.

The idea behind this testing methodology 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. This suggests that the equity holdings returns that we use, although expected to be correlated with the real returns of the total portfolio, constitute a regressor that is measured with error. For this reason, the resulting coefficient estimates on the holdings returns will be biased towards zero (attenuation bias), which works against us finding a relation between mismarking and holdings returns.

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. We cluster standard errors by advisor. Estimation results and corresponding robust p-values are given in Table 4.

< Please insert Table 4 about here >

Results from Panel A of Table 4 show a negative and significant coefficient for *Return,* suggesting an inverse relationship between past portfolio returns and end-of-quarter net portfolio mismarking. This result is robust for each of the different return measures used as the main independent variable and is significant at the 1% significance level for all three specifications. Thus, consistent with return smoothing, lower returns cause an increase in the portfolio's net portfolio mismarking and vice versa. 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 4 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 significant at least at the 5% level. Our control variable remains insignificant.

Overall, our results suggest a pattern of intentional mismarking of equity position valuations in response to prior portfolio returns that is consistent with return smoothing.

4.2. Probability of getting caught and mismarking

Bollen and Pool (2008, 2009) show that suspicious patterns in hedge fund returns are less frequent among audited funds. Furthermore, Cumming and Dai (2009) document a higher incidence of misreported returns among offshore funds. Presumably more frequent audits and 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. More specifically, we run regressions of measures intended to capture general mismarking behavior at the advisor level on two key independent variables, *Infrequent Audit* and *Offshore,* indicating whether an advisor has at least one hedge fund operating in a setting with lax legal or reporting requirements. *Infrequent Audit* equals one for an advisor with at least one hedge fund that is audited less frequently than once a year and zero otherwise. *Offshore* equals one for an 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. Since these variables are constructed using data from CISDM, they are included in regressions specifications covering only advisors that report to CISDM and that we were able to match to our 13F data.[18] Furthermore, because the *Infrequent Audit* variable has a much higher incidence of missing values than *Offshore*, we include these variables in separate regression specifications.

To control for the illiquidity of stocks held by an advisor, we introduce an advisor-specific illiquidity measure, *SPI_AVG*. It is based on the quarterly stock portfolio illiquidity of an advisor (as described in Section 4.1) and calculated as the average across the advisor's quarterly observations.

Each of the three new mismarking measures that we employ as dependent variables is constructed by aggregating an advisor's quarterly mismarking measures across all of its

[18] We were able to match 1,520 hedge funds corresponding to 361 advisors to our 13F filing advisors.

quarters to come up with one advisor-specific measure. Recall that the measures introduced in the previous section (*PM, FRACDIF*) were intended to capture the direction of portfolio mismarking. The new measures introduced in this section and used in the rest of the paper are intended to detect general mismarking behavior of each advisor regardless of the direction of mismarking.

Our first mismarking measure, *ABS_PM*, is based on the notion that intentional mismarking potentially leads to a higher level of absolute deviation from the true portfolio value. *ABS_PM* is measured as the average of the absolute value of an advisor's quarterly *Portfolio Mismarking* (defined in Section 4.1). Our second mismarking measure, *STD_PM*, is the standard deviation computed from all the quarterly *Portfolio Mismarking* measures of a given advisor. Because hedge fund advisors engaging in active intentional mismarking are likely to show more variability in their mismarking behavior, such advisors ought to show a higher *STD_PM*. Our final mismarking measure, *FRAC*, captures the fraction of mismarked positions in an advisor's report. *FRAC* is computed as the fraction of mismarked positions for each report, averaged across all reports of each advisor. Again, under the presumption that the portfolios of actively mismarking managers contain a higher fraction of mismarked positions, *FRAC* ought to be higher for such advisors.

< Please insert Table 5 about here >

Results reported in Panel A of Table 5 show that advisors where at least one fund is subjected to infrequent audits show more mismarking. Although, this result is statistically significant for only two out of the three mismarking measures we employ, the coefficient signs are nevertheless consistent with the probability of getting caught inversely affecting mismarking behavior. Results from Panel B tell a similar story: Regardless of how we measure mismarking, advisors that are domiciled in countries with lax legal and reporting requirements are more likely to mismark.

The coefficient on the control variable *SPI_AVG* is positive when *ABS_PM* and *STD_PM,* but not *FRAC,* are used as dependent variables. This finding is consistent with previous results from Panel C of Table 2: illiquid positions are subject to a greater magnitude of mismarking but only make up a very small fraction in our sample and thus have no significant influence on the fraction of mismarking.

4.3. Visibility to investors and mismarking

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.[19] We examine whether this advertising rationale extends to the marking behavior of hedge fund advisors. We argue that some advisors generate a greater level of visibility either by self-reporting to commercial databases or by reporting to their investors more frequently. Taking advantage of the generated visibility, these advisors potentially mismark to generate attractive returns that they can advertise to current and potential investors.

To test for this hypothesized effect, we regress each of the three mismarking measures introduced above, *ABS_PM, STD_PM,* and *FRAC* on *CISDM Reporting* and *High Reporting Frequency*. *CISDM Reporting* equals one for an advisor that reports to CISDM and zero otherwise. This variable is included in regression specifications that include all advisors that file 13F reports. *High Reporting Frequency* is constructed from

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

CISDM data. It equals one for an advisor with at least one hedge fund that reports at least with monthly frequency to investors and zero otherwise. Since this variable is available only for advisors that report to CISDM, this variable is included in regressions specifications that include only advisors that report to CISDM.

< Please insert Table 6 about here >

Results from Panel A of Table 6 show that the coefficient on *CISDM Reporting* is positive and statistically significant. This result is consistent with the notion that, aspiring to impress potential investors, hedge fund advisors that report to CISDM employ mismarking as a tool of generating impressive performance metrics. Along the same vein, results from Panel B show a positive and significant coefficient on *High Reporting Frequency*. Thus, hedge fund advisors that inform their investors more frequently mismark their positions more. This result is consistent with hedge fund advisors employing mismarking to impress their current investors.[20]

5. Mismarking and reported returns

A presumed outcome from manipulation of asset valuations is altering reported returns so that more attractive performance metrics are generated. So far, we have shown that hedge fund advisors intentionally manipulate their equity valuations in a way that agrees with their incentives. However, the documented manipulation is only for a fraction of the advisors' portfolios and therefore might have little or no impact on the reported returns of the corresponding hedge funds managed by these advisors. In this section, we

[20] 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.

examine the extent to which the documented manipulation of equity valuations affects hedge fund reported returns. We focus on the two return patterns documented in the literature that are consistent with: (i) a discontinuous distribution of hedge fund returns around zero and (ii) smoothing of hedge fund reported returns.

5.1. Impact on distribution of returns around zero

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. We examine whether this pattern, which is consistent with a desire by hedge fund advisors to avoid losses at any cost, is related to equity mismarking at the advisor level.

5.1.1. A first look at mismarking and discontinuity of returns

We run regressions of our discontinuity metric on dummy variables reflecting the level of mismarking activity by advisors. To construct the discontinuity metric, we follow a two-step procedure. We first assign the CISDM 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 independent variables are constructed by dividing advisors into three equal-sized groups according to their mismarking. The benchmark group contains advisors with the lowest mismarking. 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 all advisors that belong to the group with the highest mismarking. This categorization is roughly based on cross-sectional patterns in mismarking documented in Table 3, where we observe extreme and moderate mismarkers along with advisors that show very little or no mismarking at all. Moreover, we use this dummy variable specification rather than a specification with a continuous mismarking variable to get a better economic sense of the differential impact that extreme or moderate mismarking has relative to no or very little mismarking. If advisors in the Medium and High Mismarking groups (compared against the Low Mismarking group) try 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*, (which is calculated as above) 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. The second control variable, *TPI_AVG,* is included to 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.

We include three different specifications, one for each of the mismarking variables, *ABS_PM, STD_PM,* and *FRAC,* which we use to construct the three mismarking groups. Table 7 reports results for each mismarking measure in separate columns. Panel A uses the subset of reported returns that are 100bps around zero to calculate the dependent variable, whereas Panels B and C use subsets of reported returns that are, respectively, 200bps and 300bps around zero.

< Please insert Table 7 about here >

Results from Table 7 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 the three panels and across all specifications that use different mismarking measures to classify the mismarking groups. The coefficient on *Medium Mismarking* is also positive in all specifications, but only in four out of nine cases significant at conventional levels. These results prove consistent with the highest mismarking advisors trying to avoid small losses at any cost.

5.1.2. Mismarking and the Kink fraud indicator

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 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 table. The regression results are presented in Table 8.

< Please insert Table 8 about here >

Results in Table 8 show that advisors who exhibit more mismarking manage a larger fraction of funds that are categorized as "Kink" funds, i.e., classified as 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 7 and 8 suggest that manipulating advisors show a discontinuity in the distribution of hedge fund reported returns around zero. Hedge fund

[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.

advisors seem to manipulate valuations such that returns, which are slightly below zero in reality, are reported as small positive returns.

5.2. Mismarking and return smoothing

Intentional return smoothing involves advisors' manipulation of position valuations on individual holdings to alter the reported hedge fund returns. The desired outcome of such a practice would be the artificial enhancement of performance statistics, with the ultimate goal of attracting additional investment inflows and/or affecting advisors' compensation. In this section, we examine whether the equity mismarking observed for our sample of hedge fund advisors is related to smoothing of reported returns.

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:

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

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 reported 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 run regressions of our return smoothing measure on the *Medium Mismarking* and *High Mismarking* and the two control variables *SPI_AVG* and *TPI_AVG* that control for the illiquidity of the underlying of assets. The dependent variable is the smoothing coefficient, θ_0, averaged across all funds managed by each advisor, with weights determined by each fund's average dollar value of assets under management.

Table 9 reports regression results. In Panel A, we restrict the subset of included risk factors in calculating θ_0 to a maximum of three factors. In Panel B we use an unrestricted model.

< Please insert Table 9 about here >

The coefficient values for *High Mismarking* range from -0.022 to -0.029. These coefficient values are significant both in an economic and statistical sense across all the different specifications, 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.

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 that are less than one. The reported intercept's p-values for the null hypothesis that the intercept is equal to one show a difference from one that is significant at the 1%-level in all specifications. The result suggests that advisors perhaps smooth returns by manipulating other types of assets that we do not observe in our 13F portfolio. These other assets might be highly illiquid, affording advisors greater opportunity for manipulation. In this regard, suggesting that hedge fund advisors hold highly illiquid assets in the unobservable non-equity part of their portfolios, the coefficient on the *TPI_AVG* is negative and significant for all specifications.

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 in this table are important for yet another reason: They show that mismarking in the equity part of the portfolio has a material impact on the hedge fund returns that advisors choose to report.

6. 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.[22]

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, presumably 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.

Our analysis showed that advisors mismark their stock positions in a way that is consistent with a pursuit of their own interest. Consistent with advisors trying to enhance their performance, we showed that hedge funds mark their common stock positions up following a period of poor returns and mark them down following a period of good

[22] 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.

returns. Consistent with taking advantage of a lower likelihood of getting caught, advisors that are audited less frequently and are domiciled in offshore locations show more mismarking. Furthermore, in an effort to perhaps impress potential investors and current investors, advisors that self-report to a commercial database or report to their current investors at a higher frequency exhibit relatively more mismarking.

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.

Taken altogether, our results suggest that hedge fund advisors intentionally mismarked their equity positions during the 1999-2008 period. The mismarking behavior appears to be aligned to advisors' incentives and is related to suspicious patterns in hedge fund reported returns documented in previous studies.

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 1
Sample characteristics

This table presents summary statistics for our sample of hedge fund advisors during the 1999 and 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	2,256	429	140	66
2000	241	699	1,969	408	126	63
2001	288	895	1,822	332	141	57
2002	330	1,056	1,442	215	128	55
2003	423	1,261	1,418	265	122	52
2004	532	1,603	1,842	337	134	54
2005	641	2,034	1,913	341	127	50
2006	731	2,313	1,960	335	123	45
2007	728	2,482	2,164	383	123	43
2008	684	2,366	1,602	254	109	35
Total sample	885	15,243	1,841	324	125	48

Table 2
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 mean absolute mismarking, i.e., average of |*SM*|, computed across all positions for each year as well as over the whole sample period. The fraction of positions with |*SM*|>0 and the fraction of positions deviating by at least 5% and 10%, respectively, are reported consecutively in the next three columns. 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 2 -- continued

Panel A: Stock position mismarking by year					
Year	Mean |*SM*|	% |*SM*|>0	% |*SM*| ≥ 5%	% |*SM*| ≥ 10%	Observations
1999	0.21%	8.05%	1.06%	0.65%	95,883
2000	0.21%	9.16%	0.91%	0.60%	108,615
2001	0.43%	10.08%	2.26%	1.33%	155,332
2002	0.22%	8.67%	1.01%	0.58%	163,629
2003	0.28%	11.76%	1.17%	0.74%	182,284
2004	0.30%	7.02%	1.10%	0.78%	258,278
2005	0.19%	5.71%	1.02%	0.60%	315,738
2006	0.14%	4.55%	0.71%	0.37%	330,388
2007	0.20%	6.07%	1.04%	0.55%	345,623
2008	0.17%	4.81%	0.82%	0.43%	296,025
Total sample	0.22%	6.90%	1.06%	0.62%	2,251,795

Panel B: Stock position mismarking stratified by whether a stock traded or not					
Trading Group	Mean |*SM*|	% |*SM*|>0	% |*SM*| ≥ 5%	% |*SM*| ≥ 10%	Observations
Traded	0.22%	6.74%	1.04%	0.61%	2,246,124
Not traded	1.76%	70.11%	7.49%	2.57%	5,671

Panel C: Stock position mismarking by stock illiquidity					
Illiquidity Decile	Mean |*SM*|	% |*SM*|>0	% |*SM*| ≥ 5%	% |*SM*| ≥ 10%	Observations
1 (most liquid)	0.22%	7.07%	1.05%	0.60%	789,341
2	0.20%	5.70%	0.96%	0.58%	402,000
3	0.20%	5.78%	0.97%	0.59%	272,562
4	0.18%	6.23%	0.89%	0.53%	202,699
5	0.19%	6.42%	0.90%	0.56%	160,628
6	0.21%	6.82%	1.01%	0.61%	130,783
7	0.23%	7.57%	1.06%	0.63%	103,483
8	0.28%	8.72%	1.24%	0.80%	80,558
9	0.33%	9.65%	1.48%	0.85%	61,704
10 (most illiquid)	0.45%	10.16%	2.33%	1.16%	42,009

Table 3
Cross-sectional distribution of mismarking

This table reports statistics on the cross-sectional distribution of mismarking measures. First, mean absolute mismarking and fraction of mismarked positions are computed for each hedge fund advisor. Next, the measures calculated at the advisor level are used to compute cross-sectional statistics.

Cross-sectional statistics	Mean $\lvert SM \rvert$	% $\lvert SM \rvert > 0$	% $\lvert SM \rvert \geq 5\%$	% $\lvert SM \rvert \geq 10\%$
mean	0.25%	5.69%	1.30%	0.79%
max	5.76%	100.00%	42.99%	22.12%
p90	0.69%	14.00%	3.52%	1.88%
p75	0.25%	6.05%	1.20%	0.67%
median	0.05%	1.91%	0.22%	0.09%
p25	0.01%	0.58%	0.00%	0.00%
p10	0.00%	0.00%	0.00%	0.00%
min	0.00%	0.00%	0.00%	0.00%

Table 4
Past returns and mismarking

This table presents results from pooled regressions of end-of-quarter mismarking measures on past returns. In Panel A, the dependent variable is *Portfolio Mismarking*. It 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 2. 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.* We measure *Return* for a given hedge fund advisor using three approaches and run separate regressions for each return measure. For each advisor, the first return measure is calculated as the buy-and-hold value-weighted return during quarter *t* on a portfolio comprised of 13F stock securities disclosed by the advisor at the end of quarter *t-1*. The portfolio return is calculated employing CRSP stock returns. The second measure captures performance of the 13F stock holdings portfolio by compounding the quarterly portfolio returns from the first measure over the last four quarters (including quarter t). Our last return measure captures the year-to-date (including quarter t) return by compounding the quarterly portfolio returns from the beginning of the current calendar year. Our key control variable in all panels 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.

Table 4 -- continued

Panel A: Past returns and portfolio mismarking (PM)			
Dependent variable: *PM*			
	Return based on		
Independent variables	*Last quarter*	*Last 4 quarters*	*Year-to-Date*
Intercept	-0.0008***	-0.0006***	-0.0007***
	(0.000)	(0.000)	(0.000)
Return	-0.0045***	-0.0026***	-0.0034***
	(0.001)	(0.000)	(0.001)
SPI	0.0004	0.0004	0.0004
	(0.345)	(0.349)	(0.349)
Observations	13,073	13,073	13,073
Clusters	882	882	882
R^2	0.92%	1.00%	0.98%

Panel B: Past returns and fractional difference between overstated and understated positions (FRACDIF)			
Dependent variable: *FRACDIF*			
	Return based on		
Independent variables	*Last quarter*	*Last 4 quarters*	*Year-to-Date*
Intercept	-0.0081***	-0.0078***	-0.0081***
	(0.000)	(0.000)	(0.000)
Return	-0.0201***	-0.0071**	-0.0097**
	(0.007)	(0.029)	(0.042)
SPI	0.0008	0.0008	0.0008
	(0.405)	(0.403)	(0.405)
Observations	13,073	13,073	13,073
Clusters	882	882	882
R^2	0.18%	0.13%	0.13%

Table 5
Probability of getting caught and mismarking

This table presents results from regressions of advisor-level general mismarking measures on advisor characteristics. Separate regressions are run for three dependent variables: *ABS_PM, STD_PM*, and *FRAC*. Each measure is first computed for each advisor and quarter and then averaged across all quarters to come up with one advisor-specific measure. Each advisor represents a unit of observation in all the regressions. For each advisor, *ABS_PM* is computed as the average of the absolute values of the quarterly *Portfolio Mismarking* measures. The *Portfolio Mismarking* measure is defined as in Table 4. *STD_PM* is the standard deviation computed from all the quarterly *Portfolio Mismarking* measures of a given advisor. To construct the last measure, *FRAC*, we calculate the fraction of mismarked positions for each report and take the mean by advisor. In Panel A, we analyze the influence of audit frequency on mismarking measures. The independent variables are listed in the first column. *Infrequent Audit* equals one for an advisor with at least one hedge fund that is audited less frequently than once a year and zero otherwise. The control variable, *SPI_AVG,* is calculated by taking the mean of *SPI* as defined in Table 4 over all of an advisor's reports. Panel B shows the impact of the advisor's funds' domicile on mismarking measures. *Offshore* equals one for an 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. 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.

Panel A: Influence of infrequent auditing on mismarking

	Dependent variables		
Independent variables	*ABS_PM*	*STD_PM*	*FRAC*
Intercept	0.0021***	0.0059***	0.0661***
	(0.000)	(0.000)	(0.000)
Infrequent Audit	0.0027*	0.0060*	0.0195
	(0.050)	(0.078)	(0.316)
SPI_AVG	0.0002***	0.0003***	-0.0003
	(0.000)	(0.000)	(0.123)
Observations	134	134	134
R^2	5.96%	3.66%	0.78%

Panel B: Influence of offshore domicile on mismarking

	Dependent variables		
Independent variables	*ABS_PM*	*STD_PM*	*FRAC*
Intercept	0.0018***	0.0048***	0.0553***
	(0.000)	(0.000)	(0.000)
Offshore	0.0014**	0.0036**	0.0201*
	(0.015)	(0.013)	(0.074)
SPI_AVG	0.0003***	0.0005***	0.0010
	(0.000)	(0.000)	(0.359)
Observations	356	356	356
R^2	5.49%	2.93%	0.90%

Table 6
Reporting and mismarking

This table presents results from regressions of advisor-level general mismarking measures on advisor characteristics. The dependent variables are the mismarking measures introduced in Table 5. Panel A compares the mismarking measures of advisors that report to those that do not report to CISDM. The independent variables include *CISDM Reporting* and *SPI_AVG*. *CISDM Reporting* equals one for an advisor that reports to CISDM and zero otherwise. The control variable, *SPI_AVG,* is defined in Table 5. Panel B shows the impact of reporting frequency on mismarking measures. *High Reporting Frequency* equals one for an advisor with at least one fund that reports at least with monthly frequency to investors and zero otherwise. 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.

Panel A: Influence of CISDM reporting on mismarking

	Dependent variables		
Independent variables	*ABS_PM*	*STD_PM*	*FRAC*
Intercept	0.0018***	0.0050***	0.0514***
	(0.000)	(0.000)	(0.000)
CISDM Reporting	0.0010**	0.0025**	0.0206***
	(0.017)	(0.019)	(0.008)
SPI_AVG	0.0003***	0.0005***	0.0011
	(0.000)	(0.001)	(0.380)
Observations	885	885	885
R^2	2.94%	1.76%	0.95%

Panel B: Influence of reporting frequency on mismarking

	Dependent variables		
Independent variables	*ABS_PM*	*STD_PM*	*FRAC*
Intercept	0.0009**	0.0025**	0.0435***
	(0.020)	(0.040)	(0.004)
High Reporting Frequency	0.0025***	0.0060***	0.0434**
	(0.005)	(0.007)	(0.039)
SPI_AVG	0.0017	0.0067	0.0125
	(0.341)	(0.387)	(0.676)
Observations	134	134	134
R^2	1.81%	2.71%	1.12%

Table 7
Mismarking and the distribution of reported returns around zero

This table relates 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 CISDM to its respective advisor. Next, for each advisor, we subtract the fraction of negative returns from the fraction of positive returns. To capture the influence of mismarking, we calculate independent variables based on the mismarking measures as defined in Table 5. Based on each mismarking measure we divide advisors into three equal-sized groups according to their mismarking. 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. The stock portfolio's illiquidity, *SPI_AVG,* is defined in Table 5. 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. Panel A uses the subset of reported returns that are 100bps around zero. In Panel B and C, we repeat the analysis described above based on interval widths of reported returns around zero of 200bps and 300bps, respectively. 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.

Panel A: Distribution of reported returns within 100bps around zero

Dependent variable: Fraction of positive minus fraction of negative reported returns

	Mismarking based on		
Independent variables	*ABS_PM*	*STD_PM*	*FRAC*
Intercept	0.0687***	0.0708***	0.0721***
	(0.000)	(0.000)	(0.000)
Medium Mismarking	0.0287**	0.0199	0.0104
	(0.032)	(0.118)	(0.409)
High Mismarking	0.0260*	0.0285*	0.0340**
	(0.070)	(0.055)	(0.023)
SPI_AVG	-0.0002	-0.0003	-0.0002
	(0.709)	(0.627)	(0.723)
TPI_AVG	-0.0366***	-0.0363***	-0.0380***
	(0.007)	(0.007)	(0.008)
Observations	354	354	354
R^2	3.10%	2.89%	3.39%

Table 7 -- continued

Panel B: Distribution of reported returns 200bps around zero			
Dependent variable: Fraction of positive minus fraction of negative reported returns			
	Mismarking based on		
Independent variables	*ABS_PM*	*STD_PM*	*FRAC*
Intercept	0.1458***	0.1495***	0.1513***
	(0.000)	(0.000)	(0.000)
Medium Mismarking	0.0478**	0.0352	0.0181
	(0.033)	(0.108)	(0.405)
High Mismarking	0.0478**	0.0493**	0.0607**
	(0.039)	(0.037)	(0.010)
SPI_AVG	-0.0011*	-0.0012*	-0.0010**
	(0.092)	(0.068)	(0.042)
TPI_AVG	-0.0256*	-0.0250*	-0.0280*
	(0.060)	(0.061)	(0.052)
Observations	354	354	354
R^2	1.95%	1.70%	2.39%

Panel C: Distribution of reported returns 300bps around zero			
Dependent variable: Fraction of positive minus fraction of negative reported returns			
	Mismarking based on		
Independent variables	*ABS_PM*	*STD_PM*	*FRAC*
Intercept	0.1880***	0.1901***	0.1925***
	(0.000)	(0.000)	(0.000)
Medium Mismarking	0.0625**	0.0559**	0.0328
	(0.014)	(0.026)	(0.182)
High Mismarking	0.0596**	0.0599**	0.0754***
	(0.022)	(0.024)	(0.005)
SPI_AVG	-0.0007	-0.0008	-0.0006
	(0.633)	(0.616)	(0.634)
TPI_AVG	0.0189*	0.0183*	0.0166
	(0.081)	(0.088)	(0.143)
Observations	354	354	354
R^2	2.12%	1.92%	2.43%

Table 8
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:

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

where X_k denotes the total number of observations that fall in bin k, n is the number of observations, and p_k is the probability that an observation falls in bin k. According to Bollen and Pool (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 Tables 5 and 7. 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		
Independent variables	*ABS_PM*	*STD_PM*	*FRAC*
Intercept	0.1200***	0.1302***	0.1456***
	(0.000)	(0.000)	(0.000)
Medium Mismarking	0.1494***	0.1180***	0.0816*
	(0.000)	(0.005)	(0.054)
High Mismarking	0.1132***	0.1146***	0.1046**
	(0.004)	(0.005)	(0.013)
SPI_AVG	0.0016	0.0014	0.0016
	(0.749)	(0.773)	(0.748)
TPI_AVG	0.0524	0.0457	0.0543
	(0.466)	(0.526)	(0.453)
Observations	343	343	343
R^2	3.84%	2.89%	2.00%

Table 9
Impact of mismarking on loss of economic return

This table presents results from regressions that relate return smoothing to mismarking activity. We quantify return smoothing using 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 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. In Panel A, we restrict the subset to a maximum of three factors whereas in Panel B we use an unrestricted model. The dependent variable is the smoothing coefficient, θ_0, which is the average of $\theta_{j,0}$ across all funds managed by each advisor, with weights determined by each funds' average assets under management. The independent variables are defined in Tables 5 and 7. 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 for which the null hypothesis *Intercept=1* is used. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Table 9 -- continued

Panel A: Calculation of fitted returns restricted to three factors			
Dependent variable: Advisor's smoothing coefficient θ_0			
	Mismarking based on		
Independent variables	*ABS_PM*	*STD_PM*	*FRAC*
Intercept	0.9027***	0.9054***	0.9036***
	(0.000)	(0.000)	(0.000)
Medium Mismarking	-0.0110	-0.0240**	-0.0137
	(0.351)	(0.044)	(0.246)
High Mismarking	-0.0288**	-0.0238*	-0.0284**
	(0.039)	(0.082)	(0.037)
SPI_AVG	-0.0017	-0.0019	-0.0019
	(0.462)	(0.435)	(0.413)
TPI_AVG	-0.0446**	-0.0422**	-0.0429**
	(0.013)	(0.017)	(0.015)
Observations	341	341	341
R^2	2.90%	2.77%	2.86%

Panel B: Unrestricted calculation of fitted returns			
Dependent variable: Advisor's smoothing coefficient θ_0			
	Mismarking based on		
Independent variables	*ABS_PM*	*STD_PM*	*FRAC*
Intercept	0.9143***	0.9175***	0.9195***
	(0.000)	(0.000)	(0.000)
Medium Mismarking	-0.0092	-0.0206*	-0.0212*
	(0.401)	(0.064)	(0.057)
High Mismarking	-0.0238*	-0.0216*	-0.0271**
	(0.064)	(0.087)	(0.030)
SPI_AVG	-0.0019	-0.0020	-0.0020
	(0.408)	(0.390)	(0.385)
TPI_AVG	-0.0431**	-0.0410**	-0.0416**
	(0.016)	(0.019)	(0.018)
Observations	341	341	341
R^2	2.93%	2.97%	3.38%

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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 all positions with an absolute valuation deviation of more than 50%.