The Reliability of Voluntary Disclosures: Evidence from Hedge Funds*

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Abstract

We analyze the reliability of voluntary disclosures of financial information, focusing on widely-employed hedge fund performance reports to publicly available databases. In snapshots of these databases captured at different points in time, we detect that historical returns are routinely revised. These revisions are not random or mere corrections of earlier mistakes; they are partly forecastable by fund characteristics. Moreover, funds that revise their performance histories significantly and predictably underperform those that have never revised, suggesting that unreliable disclosures constitute a valuable source of information for current and potential investors. These results speak to current debates about mandatory disclosures by financial institutions to market regulators.

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I. Introduction

In January 2011 the Securities and Exchange Commission proposed a rule requiring U.S.-based hedge funds to provide regular reports on their performance, trading positions, and counterparties to a new financial stability panel established under the Dodd-Frank Act. For the 200 or so "large" hedge funds (managing over $1 billion), which collectively manage over 80% of total assets under management, detailed quarterly reports would be required, while for smaller hedge funds, these reports would be less detailed and required only annually. Unsurprisingly, hedge funds argued against this proposal, citing concerns that the government regulator responsible for collecting the reports could not guarantee that their contents would not eventually be made public.[1]

The economic theory literature almost uniformly predicts that providing more information to consumers is welfare enhancing (an early example is Stigler (1961), also see Jin and Leslie (2003, 2009) and references therein). Hedge funds, however, are notoriously protective of their proprietary trading models and positions, and generally disclose only limited information, even to their own investors. One important piece of information that many hedge funds do offer to a wider audience is their monthly investment performance. This information (as well as information on fund characteristics and assets under management),[2] is self-reported by thousands of individual hedge funds to one or more publicly available databases. These databases are widely used by researchers, current and prospective investors, and the media. As SEC rules preclude advertising by hedge funds, disclosing past performance and fund size to these publicly available databases is thought to be one of the few channels that hedge funds can use to market themselves to potential new investors (see Jorion and Schwarz (2010) for example).

In this paper, we examine the reliability of these voluntary disclosures by hedge funds. We do so by tracking snapshots of the publicly available hedge fund databases captured at different points in time between 2007 and 2011. In each "vintage" of these databases[3],

[1] See SEC press release 2011-23, available at www.sec.gov/news/press.shtml. For response from the hedge fund industry, see "Hedge Funds Gird to Fight Proposals on Disclosure", *Wall Street Journal*, February 3 2011.

[2] Note that the information provided does not include the holdings or trading strategies of the fund.

[3] This has links with the "real time data" literature in macroeconomics, see Croushore (2011) for a recent

hedge funds provide information on their performance from the time they began reporting to the database until the most recent period. We find evidence that in successive vintages of these databases, *older* performance records (pertaining to periods as far back as fifteen years) of hedge funds are routinely revised. This behavior is widespread: we document that nearly 40% of the 18,382 hedge funds in our sample have revised their previous returns by at least 0.01% at least once, and over 20% of funds have revised a previous monthly return by at least 0.5%. These revisions across database vintages are not random, indeed, they are partly predictable using information on the characteristics and past performance of hedge funds. For example, funds in the Emerging Markets style are significantly more likely to have revised their histories of returns than Fixed Income funds, and larger funds (i.e., those with greater assets under management) and less liquid funds are also more likely to revise.

Are these revisions innocuous despite being systematically associated with particular fund characteristics? One possibility is that these are mere corrections of earlier mistakes. Another possibility is that these revisions are manifestations of the asymmetric information problem embedded in voluntary disclosures of financial information. To better understand whether these revisions constitute negative signals about particular hedge funds, at each vintage of data, we categorize hedge funds into those that have revised their return histories at least once (revisers) and the remainder (non-revisers). We find that far from being innocuous, this classification is very helpful in predicting funds' future performance. On average, revising funds significantly underperform non-revising funds. Moreover, we find there is a far greater risk of experiencing a large negative return when investing in a revising fund rather than in a non-revising fund. In short, this method reveals in *real time* that funds with unreliable reported returns are likely to underperform in the future, and is robust to risk-adjustment using various models, changes in our threshold for detecting significant revisions, and various other changes in parameter values.

To provide a concrete example of the sort of episode that we refer to, consider the following (anonymized but true) case of Hedge Fund X, which was incorporated on August 1993. In January 1994 the fund began reporting to a database, and a year after inception it reported assets under management (AUM) of US$ 75 MM. In mid 2000, the fund experienced

survey.

a troubled quarter and saw its AUM halve in value. It then ceased reporting AUM figures. The fund's performance recovered, and in October 2008 it reported a particularly good double digit return, putting it in the top decile of funds. However on January 2009 the October 2008 return was revised downward significantly, into a large *negative* return. A similar pattern emerged later that year, when a previously reported high December 2008 return was adjusted downward in the June 2009 vintage, along with two other past returns altered. A further sequence of poor returns was then revealed, and the fund was finally reported as closed in the month of July 2009.

Our analysis suggests that mandatory, audited disclosures by hedge funds, such as those proposed by the SEC earlier this year, would be beneficial to investors and help to prevent such negative outcomes. Two links with the issue of information disclosure in health economics are noteworthy. Jin and Leslie (2003) use the 1998 implementation of a rule that restaurants in Los Angeles prominently display standardized hygiene "grade" cards to study this issue. Using data on revenues for individual restaurants in Los Angeles and data on the number of people admitted to hospitals with food-related illnesses, they find that the increase in the information provided to consumers made them more sensitive to hygiene scores, and caused them to substitute away from low to high hygiene establishments, thus raising overall hygiene levels across all restaurants. To draw a parallel with our hedge fund application, the mandatory provision of accurate performance data at each point in time might enable investors to better distinguish between high and low skill funds, thus generating significant welfare improvements by raising quality standards for investment management.

An alternative perspective on disclosure considers an important aspect of the problem, namely the appropriate *form* of the mandated disclosure. Dranove, *et al.* (2003) analyze the use of publicly available "report cards" (which measure not only health outcomes, but also the initial health of patients) on individual doctors and hospitals in New York and Pennsylvania in the early 1990s. These were introduced with the aim of enabling patients to identify the best heathcare providers, and to provide an incentive for these heathcare providers to improve the quality of care offered. However, the authors find that report cards lead to more surgeries for healthier patients, where the gains are lower and the costs the same, and the substitution of less invasive procedures in place of surgeries for sicker patients, leading to worse health outcomes. The evidence suggests that health care providers acquire "inside information" on the patient's initial health after having seen them, and may decline to treat patients that are riskier in person than on paper, as this would lead to a low report card score. This evidence raises some questions about the potential impacts of mandatory hedge fund disclosures. Consider a situation in which hedge funds are more highly skilled at valuing illiquid assets than regulators, who establish standardized valuation methods for mandatory disclosures. This standardization may lead to funds avoiding certain assets that they deem to be under-valued relative to the standardized valuation method, even if these are in reality worthwhile investments. This substitution away from such illiquid assets could in turn lead to lower liquidity and efficiency of these asset markets.

One solution might be to design a disclosure system that allows funds some flexibility in the choice of valuation method used to report performance, despite the presence of a standard method. The presence of a standardized, transparent method for valuing illiquid assets in hedge fund portfolios may make investors more sensitive to the use of other valuation methods, and may increase the overall quality of pricing such assets, but with exemptions provided if requested and justified. For example, a hedge fund may have a good reason to decide to price an illiquid asset using a non-standard method, and if the standard method is well-known and understood, then the reasons for using a different approach would need to be made clear to investors. Thus a standard approach may provide a lower bound on the quality of method for pricing an illiquid asset.

The remainder of the paper is structured as follows. In Section II we review the related literature. In Section III, we describe the data and introduce how we determine revisions. Section IV outlines our methodology. In Section V, we present our empirical results. Section VI concludes.

II. Related Literature

Several previous authors have noted problems with self-reported hedge fund returns. The fact that hedge fund managers voluntarily disclose returns to hedge fund databases means that they get to choose if and when to start reporting, and when to stop reporting. This leads to substantial data biases not seen in traditional data sets, such as listed equities or registered mutual funds. Ackermann, McEnally and Ravenscraft (1999), Fung and Hsieh (2000), Fung and Hsieh (2009) and Liang (2000) provide an overview of these biases such as survivorship, self-selection and backfill. Self-reporting also leads to the possibility of using different models to value assets, as well as the possibility of earnings smoothing. For example, Getmansky, Lo and Makarov (2004) document high serial correlation in reported hedge fund returns relative to other financial asset returns, and consider various reasons such as underlying asset illiquidity to explain this. Asness, Krail and Liew (2001) note that the presence of serial correlation leads reported returns to appear less risky and less correlated with other assets than they truly are, thus providing an incentive for hedge fund managers to intentionally "smooth" their reported returns, a form of earnings management for the hedge fund industry. Bollen and Pool (2008) extend Getmansky, Lo and Makarov (2004) to consider autocorrelation patterns that change with the *sign* of the return on the fund, with the hypothesis being that hedge fund managers have a greater incentive to smooth losses than gains, and they find evidence of this in their analysis. This finding is reinforced using a different approach in Bollen and Pool (2009), who document that there are substantially fewer reported monthly returns that are small and negative than one might expect. When aggregating to bimonthly returns no such problem arises, suggesting that the relative lack of small negative returns in the data is caused by temporarily overstated returns. Agarwal, Daniel and Naik (2011) find evidence that hedge funds tend to underreport returns during the calendar year, leading to a spike in reported returns in December that cannot be explained using risk-based factors. The motivation for doing so is that hedge funds are paid incentive fees once a year based on annual performance. This finding echoes a similar result for quarter-end returns for mutual funds, see Carhart *et al.* (2002). While our paper is related to this stream of research, the empirical phenomenon we document might be better labeled "history management" rather than earnings management.

The literature has also considered the role of mandatory disclosures for hedge funds. For a unique, and brief, period in 2006 before the rule was vacated, the SEC required hedge funds to disclose a variety of information such as potential conflicts of interest, and past legal and regulatory problems. These Form ADV disclosures were designed to deter fraud, or control operational risk more generally. Brown, Goetzmann, Liang and Schwarz (2008) report evidence that these mandatory disclosures of information related to operational risk were beneficial to investors. The authors find that the information in these disclosures enabled investors to select managers that went on to have better performance, and that conflicts identified in the Form ADV filings were correlated with other flags for operational risks.

Our analysis of changes in the reported histories of hedge fund returns is also related to Ljungqvist, Malloy and Marston (2009), who study changes in the I/B/E/S database of analysts' stock recommendations. These authors document that up to 20% of matched observations are altered from one database to the next, using annual vintages of the IBES database from 2001-2007. Like us, they find that these revisions are not random: recommendations that were further from the consensus, or from "all star" analysts, were more likely to be revised than others, and undoing these changes reduces the persistence in the performance of analyst recommendations. While the focus of these authors was primarily to illuminate problems of replicability in academic research, our concerns run deeper on account of the environment of limited disclosure for hedge funds. This environment generates a greater reliance on self-reported hedge fund data. We demonstrate that hedge fund return revisions could skew allocations by investors reliant on the initial return presented. Moreover, the significantly lower future returns and greater downside risks in troubled times of funds with unreliable (revised) disclosures suggests that the issue that we identify represents a source of risk to hedge fund investors, and quite possibly a broader systemic risk.

Our paper also contributes to a growing list of examples highlighting the benefits of an independent auditor or regulator for financial institutions. In related work on banking supervision, Daníelsson, *et al.* (2001) note that under Basel II European banks were given the choice of using a standardized model to measure their risk exposures, which were used in setting their capital requirements, or using their own in-house models. These in-house models were subject to audit by the banking regulator, but due to the complexity of each bank's models it is questionable whether it was possible or feasible for the regulator to properly monitor their effectiveness. After the financial crisis, it was noted in the press and in the finance literature that these models appear to have under-estimated the true risk of many banks' positions. Most recently, researchers and regulators have called into question the market for corporate bond ratings (see Griffin and Tang (2011) and Bolton, *et al.* (2011), for example). Before their bonds can be purchased by portfolio managers and other large investors, corporations usually need to get a credit rating from one of the three big ratings agencies: Standard & Poors, Moodys or Fitch. These ratings agencies are all notionally independent of the corporates requesting the rating, but the way that ratings agencies are compensated and the repeated nature of the interactions between the corporates and the agencies have lead some, e.g. Bolton, *et al.* (2011), to question whether they should be considered truly independent. In the wake of the recent financial crisis, when certain bond products that had been given the highest possible rating turned out to be worthless, more discussions have taken place about reforming the credit rating industry.

Finally, it is worth noting here that in addition to issues of financial stability, information on the trading strategies and positions of hedge funds also has implications for how they are compensated. Foster and Young (2010) show theoretically the difficulty of devising a performance-based compensation contract for hedge fund managers that rewards skilled managers but not unskilled managers. With only returns histories made available for performance evaluation, unskilled managers can mimic skilled managers arbitrarily well simply by taking on an investment with a small probability of a large crash. Foster and Young (2010) argue that transparency of positions, not just performance, is needed to separate skilled managers from unskilled managers.

III. Data

III.A. Consolidated Hedge Fund and Fund-of-Fund Data

We employ a large cross-section of hedge funds and funds-of-funds over the period from January 1994 to May 2011, which is consolidated from data in the TASS, HFR, CISDM, Morningstar, and BarclayHedge databases. Appendix A contains details of the process followed to consolidate these data. The funds in the combined database come from a broad range of vendor-classified strategies, which are consolidated into ten main strategy groups: Security Selection, Macro, Relative Value, Directional Traders, Funds-of-Funds, Multi-Process, Emerging Markets, Fixed Income, Managed Futures, and Other (a catch-all category for the remaining funds).[4] The set contains both live and dead funds. Returns and assets under management (AUM) are reported monthly, and returns are net of management and incentive fees.

III.B. Hedge Fund Database Vintages

Hedge fund data providers publish new versions of their databases from time to time. These updates not only include the incremental changes since the previously published version, but also the entire history of returns for each fund including incremental changes. This allows us to compare reported histories across vintages of these databases at various points in time. We store a total of 40 vintages of the different databases between July 2007 and May 2011.[5] At each of these vintages $v \in \{1, 2, \ldots 40\}$, we capture return and asset under management (AUM) information for all available databases. Not every database is updated as frequently as we collected these vintages, and in those cases the newer vintage is simply identical to the previous one.

We apply some standard filters to the data before analysis. First, we remove 82 funds with very large or small returns to eliminate a possible source of error (truncating between monthly return limits of -90%, and +200%).[6] Second, we remove 186 funds that report data only quarterly. Third, we remove funds with insufficient return histories (less than 12 months) and missing fund level data (such as no "Strategy" or "Offshore" indicators recorded). Fourth, as less than one-third of Morningstar funds passed these quality filters, we remove the remaining 832 Morningstar funds to ensure sufficient depth by database. The final cleaned dataset contains 18,382 unique hedge funds.

Table I shows some characteristics of the sample. Sample funds exist on average for five years, have US $104 MM in assets, and average returns of approximately 7.7% per annum. Slightly over a quarter of them are Funds-of-Funds, with Security Selection and Managed

[4] The mapping between these broad strategies and the detailed strategies provided in the databases is reported in the appendix.

[5] Vintages were collected in July 2007, and then monthly from January 2008 to May 2011, with February and November 2009 omitted due to data download errors.

[6] Although -100 would be the natural choice, we used -90 to specifically remove cases in which data providers use large negative returns as placeholders for missing observations.

Futures being the predominant hedge fund strategies represented in the data. Approximately one-third of the funds are from the TASS database, with the CISDM database accounting for the smallest share of the four databases represented in our final sample, at just under 10% of the funds.

[*Insert Table I here*]

III.C. Changes: Revisions, Deletions and Additions

We compare return histories across successive vintages,[7] and, group changes into three categories, in a similar fashion to Ljungqvist, Malloy and Marston (2009). The first category is "Revisions": has a fund changed return observations between successive vintages? We ensure that these are significant revisions by only considering those above 1 basis point in size, so that we do not count rounding errors as revisions (a possibility if a fund moves, say, from reporting returns with 4 decimal point precision to 2 decimal point precision). The second category is "Additions": are returns added for funds, in successive vintages? This is an attempt to capture extensions of the past history of funds. The third category is "Deletions": are returns deleted that have been reported and present in prior vintages?

Table II shows the prevalence of these three different types of changes to funds' return histories. Over 40% of funds have one of the three types of changes described above ("Any Change"). Of these, revisions of pre-existing data are the most frequent, at 38%, followed by deletions at 6% and additions at 2%. (Some funds have multiple types of changes, and so the sum of the individual categories is greater than the any change proportion.) This large percentage of funds with revisions demonstrates that this is a widespread problem: funds that have had at least one change in their reported history manage around 46% of the average total assets under management, and with this total peaking at $1.8 trillion in June 2008 this constitutes an important issue.

To provide a concrete example, consider Ret_v, the return at vintage v (normally we would index this by fund i for month t but we disregard this for ease of exposition). Let

[7] We restrict ourselves to looking at differences between vintages v and $v-1$ for each fund. A different approach, which would potentially pick up more changes, would be to compare v and all prior vintages. In this sense, our evaluation of changes is likely to provide a conservative estimate of the total number of changes.

$v-1$ indicate the previously available vintage for the database in which the fund's data was reported (this may not necessarily be immediately one vintage prior as not all databases update simultaneously). A deletion implies that a return goes missing between vintages, e.g., Ret_{v-1} was reported but Ret_v was not. An addition implies that a 'new' return appears in a later vintage, i.e., Ret_{v-1} was not in the database, but Ret_v is present. Clearly there are legitimate circumstances in which this would happen, such when a new fund launches or when new return updates are provided for months between the dates at which the two vintages were captured. In order to rule these cases out, in our compilation of return additions, we exclude all fund launches (in which there is no return for the entire fund in the preceding vintage), as well as excluding return months within 12 months from the vintage $v-1$ date to prevent picking up late reporting.[8]

Turning to revisions, we consider cases in which both Ret_{v-1} and Ret_v are available but are not equal to each other. As mentioned above, we filter out small changes (less than 1 basis point) that may occur on account of rounding errors. As a robustness check, we redefine a significant revision as one that is at least 10 basis points, with minimal changes to our results.

[*Insert Table II here*]

III.D. Hedge Fund Return Factors

To make appropriate risk adjustments in analyzing portfolio performance for the revising and non-revising funds, we calculate alphas via the widely-used Fung and Hsieh seven-factor model for hedge fund returns (Fung and Hsieh (2001)). The Fung-Hsieh factors have been shown to have considerable explanatory power for hedge fund and fund-of-funds returns. They comprise four market related factors: an equity market factor (S&P 500); equity size factor (Russell 2000 less S&P 500); bond market factor using a constant-maturity adjusted

[8] For example, consider the case in which vintage $v-1$ for a fund was captured in June 2009, and this vintage shows fund histories up to February 2009. The next vintage v is captured in August 2009 and this vintage shows fund histories up to July 2009. We would disregard any additions of data occurring after the month of June 2008 when computing the additions for this fund. So for example, if March 2009 and April 2009 returns are missing in $v-1$ but present in v, these months would not be counted as additions, to ensure that we do not capture late updates of returns by the fund's manager to the database provider. Our focus for additions is backfilling of past history rather than short-term lags in fund reporting.

ten-year Treasury bond yield; bond credit spread factor, using change in Moody's BAA credit spread over a constant-maturity adjusted ten-year Treasury bond yield; and three trend-following strategy factors formed from excess returns on portfolios of lookback straddle options for bonds (PTFSBD), currencies (PTFSFX), and commodities (PTFSCOM)[9]. In robustness checks, we also include an eighth factor for emerging markets, namely MSCI Emerging Market index returns.

IV. Methodology

We begin by documenting the characteristics of funds that are prone to changing their return histories. The main part of the analysis focuses on the most prevalent category of changes, namely revisions. We first check whether revisions are biased in a particular direction. We then form portfolios of reviser and non-reviser funds to ascertain the information content of revisions for future performance and shortfalls. Finally, we document the differences between initially perceived and final histories (first in versus last shown) to better understand how an investor using the database would see different pictures of hedge fund performance at different vintages of the data.

IV.A. The Determinants of History Changes

Our first step is to combine all three types of changes to fund histories, and assign a '1' to any fund which experiences one of these changes across any two vintages of data. Assigning a '0' to all other funds, we then estimate a cross-sectional fund level probit regression, conditioning this variable (which we label $Change_i$ for fund i) on various fund characteristics (described in the next section, constructed using data from the last available vintage for the fund, and denoted by the vector X_i below):

$$Change_i = \alpha + X_i'\beta + u_i \tag{IV.1}$$

[9] Data for the trend following factors can be found on David Hsieh's website (http://faculty.fuqua.duke.edu/∼dah7/HFRFData.htm). Datastream and the Federal Reserve website are sources for the equity and bond factors respectively.

We estimate this equation using probit models separately for the three different change types, namely additions, deletions and revisions. In this specification, the right-hand side comprises pure cross-sectional variables, but we consider factors that vary across both funds and time, such as prior fund performance, in the specification described below which explains changes at each vintage.

In the vintage level specification outlined in equation (IV.2), we focus only on explaining revisions. The right-hand-side variables are computed at vintage $v-1$ to explain revisions occurring between vintages $v-1$ and v, to ensure that we are capturing the conditions prevailing prior to revisions.[10]

$$Rev_{i,v} = \alpha + X'_{i,v-1}\beta + u_{i,v} \tag{IV.2}$$

IV.A.1. Performance and Characteristics

The variables that we employ as determinants of hedge fund return changes can be broadly categorized into performance and fund characteristics. This subsection briefly explains the variables employed in each category.

Performance We employ four performance measures to explain changes in hedge fund return histories. First, we use assets under management (AUM) to study whether changes are more likely to occur for larger or smaller hedge funds. We rank funds by their lifetime average AUM (computed using data at the final vintage available for the fund). Second, we use the average of lifetime returns for each fund (computed using data at the final vintage available for the fund). This is to capture the possibility that weaker performing funds might resort to changes to recast their histories. Third, we use the standard deviation of lifetime returns (computed using data at the final vintage available for the fund). Funds with more volatile returns might experience pressure to delete or recast disappointing performance. Finally, we use a measure of return smoothing suggested by Getmansky, Lo and Makarov

[10]Standard errors are clustered by database in equation (IV.1) and by vintage in equation (IV.2). The former is to control for the possibility that errors across funds are correlated according to the database since some databases may be systematically worse than others at permitting revisions.The latter is to control for the possibility that there are certain periods in which unexplained revisions are more likely to be correlated, such as during the crisis.

(2004), namely the first-order autocorrelation coefficient of lifetime returns. In all cases the ranks of the funds are standardized between 0 and 1.

Characteristics We also consider a variety of fund characteristics as explanatory variables. We include dummies for the ten hedge fund strategies into which the funds are grouped. Differences in volatility and liquidity occasioned by the use of these different strategies, as well as differential access to information about these strategies (for example, Emerging Markets) might lead to differences in the propensity to alter data. We also consider an indicator for whether the fund is offshore or onshore, as funds in offshore jurisdictions may be subject to less scrutiny. We include a variable that captures the lockup restrictions imposed by the fund on its investors. These restrictions provide liquidity safeguards for the fund manager but also may allow managers to hide from the reputational consequences of changing data within the period of the lockup. Finally, we include an indicator for whether the fund has any audit information available in the database.[11]

Other Variables Finally, we include two other variables that may influence the likelihood of revisions. We employ dummies for each of the four databases in the study, as the controls (such as verification of returns pre-loading) implemented by each database vendor may differ, and influence the propensity for changes. We also include a variable which computes the maximum number of returns in fund i's lifetime history. If there is a small fixed chance of data capture error, then a longer return history provides more exposure to return revisions. Of course, this is also a measure of the age of a fund, so this variable has multiple interpretations.

The appendix contains descriptive statistics for several of these variables.

IV.B. Explaining the Direction of Revisions

Having examined the broad determinants of history changes and revisions, we next investigate whether there is a bias in the direction of revisions. To do so, we determine the net number of positive versus negative revisions for each fund over the sample, and use this

[11] Underlying databases differ in the types and level of information they provide, with some providing the date of last audit, other providing annual audit flags, and yet others providing auditor names. Our indicator takes the value '1' if *any* audit information is available for the fund, and zero otherwise.

information to create a indicator variable for revision direction. This indicator, $REVDIR_i$, is assigned +1 if fund i had more positive than negative revisions, and -1 if the opposite occurs. Funds with no revisions have the indicator set as zero. A small portion of funds have exactly equal positive and negative number of revisions and these funds were dropped for this exercise (860 funds or 4.6% of the sample).

We model the characteristics of revising funds, relative to no change at all, using a multinomial logistic regression with a similar structure to equation (IV.1). Namely, with no revisions as the base outcome:

$$\ln\left(\frac{\Pr[REVDIR_i = j \mid X]}{\Pr[REVDIR_i = 0 \mid X]}\right) = \alpha_{j|0} + X'\beta_{j|0}, \quad j \in \{-1, +1\} \tag{IV.3}$$

IV.C. Are Revisions Informative About Future Performance?

We next analyze whether identifying revisions in performance histories is useful for forecasting future performance. The null hypothesis is that these revisions are innocuous and provide no information about future returns. One alternative is that they are an indicator of either poor operational controls or of dishonesty, both of which provide negative information about revising funds. (See Brown *et al.* (2008) on operational risk and hedge fund returns.) A third possibility is that revisions are a sign of honesty, in the sense that revisers 'fess up' to past mistakes. In this case, we might expect performance to be higher for revisers than non-revisers.

To consider these hypotheses rigorously, we employ two methods to determine the performance differentials between revising and non-revising funds. Our first approach is to form portfolios of the returns of funds based on their revision behaviour. We consider two groups, "reviser" funds that have revised at least once, and "non-reviser" funds that have had no revisions up until a given vintage. At each vintage, beginning at the second, we classify funds into these two groups, note the date of the vintage, and track all subsequent returns in the reviser and non-reviser portfolios. Note that this is a real-time strategy: consider the example of a revision occurring in August 2008, when compared with the previous August 2007 vintage – we would add the revising fund to the reviser portfolio and track its returns from September 2008 onwards. Thus, the non-reviser portfolio contains funds that *never* revise across all vintages that we consider, as well as funds that have *not yet* been identified as revisers. That is, if fund i revises for the *first* time at vintage v, its performance *prior* to the date of capture of this vintage will be included in the non-reviser portfolio. However, once the fund joins the reviser portfolio it permanently drops out of the non-reviser portfolio. Within each portfolio, we weight all monthly returns of funds equally, computing a time-series of portfolio returns.

The second approach that we adopt is to understand the impact of falsely provided history by undoing the impact of revisions. We do so by comparing the initially reported return for fund i in month t with that return in the last vintage of the database. This analysis attempts to answer the following question: if an investor only looked at a return expressed by the fund's portfolio manager the first time it was made public, how does this differ from what a researcher sees in the database at the last available vintage?

V. Results

V.A. The Determinants of History Changes

Tables III to VI show the results of estimating the probit regression equation IV.1 for the different change types. These regressions present the marginal effects of each continuous right hand side variable, that is, the change in probability that results from an infinitesimal change in each of these variables. For dummy variables, such as offshore, the effect is captured for the discrete change of the variable from 0 to 1.

Table III looks at whether a fund made any changes (revisions, additions, deletions). We find that asset size and return autocorrelation are positive and significant determinants of a fund's propensity to report a change in history.[12] The number of returns present for a fund has a significant effect on the propensity to make a change, although this could be simply a mechanical effect as described above. Turning to the strategy indicators Funds-of-Funds show the highest chance of reporting changes. This is perhaps unsurprising: Fund-of-Fund performance numbers are a function of underlying hedge fund performance numbers,

[12] Although these marginal effects are focused on the median rank, we confirm in the appendix that these effects are present when considering other quantiles.

suggesting that their revisions may simply be a function of revisions in their underlying hedge fund holdings. Furthermore, an increase in the restrictions on removing capital from the fund has a positive and significant effect on the propensity to report changes in histories. This may be correlated with greater asset illiquidity, as suggested by Aragon (2007), or constitute evidence that having a "longer period in which to hide" prior to withdrawals by investors shields funds from the adverse consequences of revisions. Finally, fund performance rank is negatively correlated with the propensity to make any changes at the 10% significance level, suggesting that poorer performing funds are associated with revisions. The direction of causality is unclear from this analysis and we investigate it in greater detail below.

[*Insert Tables III and IV here.*]

Table IV focuses solely on revisions, and generates similar results to those in the previous table. As revisions are the largest component of fund changes as seen in Table II, this is perhaps unsurprising. The presence of audit information, reflected in the audit flag, has a large positive and marginally significant coefficient. At first glance this seems counter-intuitive, as one might expect that funds not subject to audits would have more latitude to change returns. However, it may be the case that auditing could trigger corrections in returns – alternatively frequent changes in returns might prompt investors to press for funds to undergo audits.

For the return additions in Table V, the drivers are not as clear cut. The coefficient on AUM rank is now negative and although significant at 1% level, the coefficient is economically very small (close to zero). Return variability has no bearing on the propensity to add returns.

[*Insert Tables V and VI here.*]

Table VI, for deletions, shows that larger funds are more likely to delete returns from one vintage to the next. Furthermore, more volatile funds are prone to deletions as expected.

V.B. The Determinants of the Direction of Revisions

We have shown that larger funds with smoother returns and weaker performance histories tend to revise more. We now analyze whether these revisions are biased in a specific direction.

Table VII shows the drivers of negative or positive net counts of revisions relative to the base comparison group of funds that did not revise at all.

[*Insert Table VII here.*]

In Table VIII Panel A, the presence of an audit flag significantly raises the chance of having a revision (the probability of the base category falls by 16.3%). The impact is greater for more negative revisions as can be seen from the greater change of 9.5% relative to the 6.7% seen for more positive revisions.

For the continuous variables in Panel B, we consider the impact of moving from the 25^{th} to the 75^{th} quartile of the lifetime variables. The AUM and return autocorrelation variables confirm the results in Table IV, namely that larger funds and funds with smoother returns make more revisions, but for neither variable does this appear to affect the direction of revisions.

The impact of average returns on revision direction is significant, though with a differing sign depending on whether we measure the average return over the entire life of the fund or only over the period until the date of the previous vintage. In the former case, poor performance is associated with more negative revisions, (18.4% for the 0.25 rank compared with 13.1% for the 0.75 rank). In the latter case, considered in Table IX, we find that average returns are estimated with a positive coefficient, suggesting that funds with better past performance are more likely to revise returns. Taking these findings together, this foreshadows a result from the next section: funds that revise their returns tend to perform poorly in periods subsequent to revisions.

Using information from the previous vintage enables us to include an indicator variable for whether the fund reported a revision in the previous vintage. We report results from that specification in Table IX Panel B. We find that the coefficient on this indicator variable is highly significant, revealing that some funds are regular revisers of their returns.

[*Insert Tables VIII and IX here.*]

V.C. Differences between revisers and non-revisers

Figure I plots the cumulative performance of the reviser and non-reviser portfolios constructed as described in section IV.C. Panel A shows that the returns of the revisers are clearly substantially lower than those of non-revisers. This difference is economically substantial with a difference of 11.2% emerging after just over three years. As we found earlier that reviser and non-reviser funds have different characteristics, we check that the return differentials between these groups are not simply manifestations of these different characteristics. In order to do so, we compute the cross-sectional median of two of these characteristics, namely (one-month lagged) AUM and lockup period across all funds reporting in each period, and re-plot the figures for reviser and non-reviser funds that fall above and below these breakpoints. We find that the revisers continue to consistently underperform the non-revisers within each of these double-sorted portfolios. These additional charts are displayed in the appendix.

[*Insert Figure I here.*]

Figure I Panel B shows that the reviser portfolio experiences very significant outflows beginning in August-September 2008, during the Lehman collapse. The impact of big outflows and subsequent fire sales of fund assets might be one potential reason for the poor performance of the reviser portfolio (see Coval and Stafford (2007) and Jotikasthira *et al.* (2011) for evidence of the importance of this mechanism). The flows may also simply be responding to poor performance, a la DeLong *et al.* (1990).

We check whether these performance differentials are statistically significant, and whether they merely represent differences in exposures to risk factors of the reviser and non-reviser portfolios. Table X shows that the return difference between these portfolios is highly significant and robust to the use of different risk-adjustment models. The alpha on the Fung-Hsieh seven factor model of the non-reviser-reviser difference is 0.23% per month, or 2.8% per annum net of all fees and costs. We plot the cumulative alpha from the Fung-Hsieh seven factor model in Figure II, and find that it resembles the plot of raw returns: the non-revisers consistently out-perform the revisers. We also risk-adjusted using the Fama-French three factor model, as well as augmented variants including momentum and liquidity factors. The results remain robust to these alternative risk-adjustment methods as can be seen in Panel B of Table X.

[*Insert Table X here.*]

[*Insert Figure II here.*]

If revisions are a signal of unreliable information and operational risk in the fund, we might also expect to see differences in the tail risk of revisers relative to non-revisers. The dramatic outflows from the reviser portfolio suggest that these differences may be stark. To confirm this, we employ the historical simulation method, in which we estimate the bottom decile of performance from all returns seen from the beginning of the reviser portfolio up until each date, moving through time (this is done at the individual fund level within each of the portfolios). We also average the returns falling below these empirically computed decile thresholds to arrive at an expected shortfall measure. Figure III Panels A and B plots these measures for the cross section of underlying funds of the respective portfolios.

[*Insert Figure III here.*]

The figures show that the empirical bottom decile and the expected shortfall of the reviser portfolio is virtually always below the non-reviser portfolio over the entire period for both portfolio and cross-sectional measures. There is a dramatic divergence during the crisis with the empirical percentile and the expected shortfall collapsing in the months of October and November 2008. While the tail risk of the revisers at the fund level recovers and seems quite similar to that of the non-revisers in the more recent periods, this could be attributed to the weakest funds having been eliminated from the portfolio during the period of the crisis. Overall, it appears from this analysis that investors are at greater downside risk when investing in funds that revise their returns. We also checked the results using lower percentile thresholds, and the conclusions are similar.

We now take a different approach and compare the 'initial' perceived and 'final' histories for all fund across the entire time horizon. Figure IV shows that while the first vintage appears in July 2007, revisions occur across the entire possible range of return history from 1994 to 2011. The bars show the average positive and negative differences between initial and final histories pertaining to each month of the return data, averaged across all revising funds. A positive (negative) difference indicates that the final return is higher than the initial return, i.e., returns have been revised up (down). It appears (from the pink dashed lines, which plot periods when average hedge fund returns across all 18,382 funds are lower than two standard deviations away from the mean) that there is a greater tendency to revise past reported returns during periods of extremely negative average returns.

[*Insert Figure IV here.*]

Figure V shows clearly that the cumulative difference between final and initial returns has a significant negative trend. Fund performance histories appear initially good, but in periods of stress the true, more sobering, performance is revealed. This suggests the danger of prospective investors being wooed into making decisions based on initially reported histories which are then subsequently revised.

[*Insert Figure V here.*]

VI. Conclusions

This study examines the reliability of voluntary disclosures of performance information by hedge funds. We do so by tracking "vintages" of publicly available hedge fund databases captured at different points in time. Each database vintage contains entire histories of performance for individual funds, and we find evidence that in successive vintages of these databases, *older* performance records (pertaining to periods as far back as ten years) of hedge funds are routinely revised. These revisions are widespread, with nearly 40% of the 18,382 hedge funds in our sample (managing around 45% of average total assets) having revised their historical returns at least once. These revisions are not merely random reporting errors: they are partly predictable using information on the characteristics and past performance of hedge funds, with larger and less liquid funds being more likely to revise their returns. Most interestingly, detecting that a fund has revised one of its past returns helps us to predict that it will subsequently underperform funds that have never revised their returns.

Recent policy debates on the pros and cons of imposing stricter reporting requirements on hedge funds have raised various arguments. The benefits of disclosures include market regulators having a better view on the systemic risks in financial markets, and investors and regulators being able to better determine the true, risk-adjusted, performance of the fund. The costs include the administrative burden of preparing such reports, and the risk of leakage of valuable proprietary information, in the form of trading strategies and portfolio holdings. Our analysis suggests that mandatory, audited disclosures by hedge funds, such as those proposed by the SEC earlier this year, would be beneficial to investors and regulators.

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Table I
Descriptive Statistics

This table shows the breakdown of the eligible funds as at May 2011. AUM refers to assets under management.

Panel A: Fund Breakdown

	Fund Count	**Vintage count**	**Avg AUM US$ MM**	**Avg Return**	**Avg months of returns**
	18,382	40	104.19	0.640	66.42

Panel B: Strategy Breakdown

	Fund Count	**Count%**
Security Selection	3,009	16.37%
Macro	1,201	6.53%
Relative Value	250	1.36%
Directional Traders	2,358	12.83%
Funds of Funds	4,846	26.36%
Multi-Process	1,877	10.21%
Emerging	821	4.47%
Fixed Income	957	5.21%
Other	174	0.95%
Managed Futures	2,889	15.72%
	18,382	100.00%

Panel C: Database Breakdown

	Fund Count	**Count%**
TASS	6,604	35.93%
HFR	4,742	25.80%
CISDM	1,698	9.24%
BarclayHedge	5,338	29.04%
	-	-
	18,382	100.00%

Table II
Summary Statistics of Return Changes

This table shows the breakdown of the changes in returns between successive vintages where data is available for that database. Let Ret v be the return at vintage v. Deletion (Del) means a return goes missing between vintages: Ret v-1 was available but Ret v is not available. Addition (Add) means a return appears in a later vintage: Ret v-1 was missing but Ret v is available not missing (NaN). (Add excludes fund launches, first time a return appears for that fund, and funds entering within 12 months from vintage v-1 date to not pick up late reporting.) Revision (Rev) means return has changed: both Ret v-1 and Ret v are available but are not equal to each other. (Rev excludes absolute revisions <= 0.01 to avoid spurious changes in significant digits in reporting e.g. from 2 to 4 decimal places.) Any Change means the fund experienced at least one of the change types (Del, Add, Rev) in the period of analysis.

Panel A: Changes Breakdown at Fund Level

	Fund Count	**Any Change Count**	**Deletions Count**	**Additions Count**	**Revisions Count**
Funds	18,382	7,421	1,078	370	6,906
% of Total Funds		40.4%	5.9%	2.0%	37.6%

Panel B: Size of Revisions

		Revisions Count		
	Fund Count	**at least 0.01%**	**at least 0.1%**	**at least 0.5%**
Funds	18,382	6,906	5,803	3,972
% of Total Funds		37.6%	31.6%	21.6%

Table III
Probit Regression for Any Changes

The table shows the marginal effects from a probit regression. The dependent variable is the dummy reflecting whether a fund had any change (Deletion, Revision or Addition) over the period of all the vintages. This is explained by the rank of lifetime variables of average assets under management, average return, return standard deviation, return first auto correlation (rho1) and the number of returns the fund reported (lifen). Other relevant fund variables are an offshore dummy, total restrictions variable (measured as the sum of the reported lockup periods) and an audit information flag. Relevant control dummies of fund strategy and database of fund are included. Regressors are described in the text. dF/dx is for discrete change of dummy variable from 0 to 1, and the slope at the mean for continuous variables. Standard errors estimated by clustering by database. The number of stars * denote significance at 10%, 5% and 1% respectively.

Change	**dF/dx**	**Mean**	**Robust SE**	**z**	
lifeaumavgrank	0.236	0.500	0.051	4.640	***
liferetavgrank	-0.090	0.500	0.054	-1.650	*
liferetstdrank	0.066	0.500	0.041	1.600	
rho1rank	0.117	0.500	0.015	7.870	***
lifen	0.002	66.422	0.000	4.750	***
offshore	-0.007	0.501	0.006	-1.180	
lockup	0.000	164.623	0.000	5.050	***
audit	0.174	0.712	0.089	1.840	*
DB HFR	-0.015	0.258	0.009	-1.730	*
DB CISDM	-0.065	0.092	0.073	-0.870	
DB BarclayHedge	0.104	0.290	0.011	9.430	***
Macro	0.084	0.065	0.007	11.930	***
Relative Value	0.185	0.014	0.058	3.160	***
Directional Traders	-0.005	0.128	0.014	-0.380	
Fund-of-Funds	0.218	0.264	0.016	13.390	***
Multi-Process	0.057	0.102	0.017	3.500	***
Emerging	0.118	0.045	0.010	12.120	***
Fixed Income	0.031	0.052	0.034	0.940	
Other	0.128	0.009	0.117	1.110	
Managed Futures	0.118	0.157	0.042	2.830	***
Number observations			18,382		
Log pseudolikelihood			-10,965.23		
Pseudo R2			11.56%		

Table IV
Probit Regression for Revisions

The table shows the marginal effects from a probit regression. The dependent variable is the dummy reflecting whether a fund had a Revision over the period of all the vintages. This is explained by the rank of lifetime variables of average assets under management, average return, return standard deviation, return first auto correlation (rho1) and the number of returns the fund reported (lifen). Other relevant fund variables are an offshore dummy, total restrictions variable (measured as the sum of the reported lockup periods) and an audit information flag. Relevant control dummies of fund strategy and database of fund are included. Regressors are described in the text. dF/dx is for discrete change of dummy variable from 0 to 1, and the slope at the mean for continuous variables. Standard errors estimated by clustering by database. The number of stars * denote significance at 10%, 5% and 1% respectively.

Revisions	**dF/dx**	**Mean**	**Robust SE**	**z**	
lifeaumavgrank	0.247	0.500	0.055	4.480	***
liferetavgrank	-0.081	0.500	0.044	-1.840	*
liferetstdrank	0.073	0.500	0.041	1.770	*
rho1rank	0.119	0.500	0.017	6.900	***
lifen	0.002	66.422	0.000	4.360	***
offshore	-0.021	0.501	0.005	-4.040	***
lockup	0.000	164.623	0.000	7.130	***
audit	0.172	0.712	0.097	1.660	*
DB HFR	-0.015	0.258	0.007	-2.020	**
DB CISDM	-0.043	0.092	0.081	-0.520	
DB BarclayHedge	0.118	0.290	0.011	10.760	***
Macro	0.080	0.065	0.007	12.050	***
Relative Value	0.179	0.014	0.057	3.180	***
Directional Traders	-0.006	0.128	0.011	-0.540	
Fund-of-Funds	0.209	0.264	0.011	19.690	***
Multi-Process	0.066	0.102	0.018	3.680	***
Emerging	0.112	0.045	0.006	19.820	***
Fixed Income	0.018	0.052	0.040	0.470	
Other	0.113	0.009	0.108	1.070	
Managed Futures	0.124	0.157	0.045	2.810	***
Number observations			18,382		
Log pseudolikelihood			-10,755.84		
Pseudo R2			11.60%		

Table V
Probit Regression for Additions

The table shows the marginal effects from a probit regression. The dependent variable is the dummy reflecting whether a fund had an Addition over the period of all the vintages. This is explained by the rank of lifetime variables of average assets under management, average return, return standard deviation, return first auto correlation (rho1) and the number of returns the fund reported (lifen). Other relevant fund variables are an offshore dummy, total restrictions variable (measured as the sum of the reported lockup periods) and an audit information flag. Relevant control dummies of fund strategy and database of fund are included. Regressors are described in the text. dF/dx is for discrete change of dummy variable from 0 to 1, and the slope at the mean for continuous variables. Standard errors estimated by clustering by database. The number of stars * denote significance at 10%, 5% and 1% respectively.

Additions	**dF/dx**	**Mean**	**Robust SE**	**z**	
lifeaumavgrank	-0.002	0.500	0.001	-1.760	*
liferetavgrank	-0.004	0.500	0.006	-0.670	
liferetstdrank	0.006	0.500	0.004	1.450	
rho1rank	0.003	0.500	0.004	0.740	
lifen	0.000	66.422	0.000	6.020	***
offshore	0.001	0.501	0.002	0.380	
lockup	0.000	164.623	0.000	0.580	
audit	0.010	0.712	0.004	1.980	**
DB HFR	-0.006	0.258	0.001	-4.700	***
DB CISDM	-0.013	0.092	0.001	-5.430	***
DB BarclayHedge	-0.003	0.290	0.001	-3.710	***
Macro	-0.004	0.065	0.003	-1.060	
Relative Value	0.003	0.014	0.008	0.430	
Directional Traders	-0.004	0.128	0.004	-0.990	
Fund of Funds	0.007	0.264	0.002	3.840	***
Multi-Process	-0.004	0.102	0.001	-2.390	**
Emerging	0.002	0.045	0.002	1.390	
Fixed Income	0.005	0.052	0.009	0.650	
Other	0.043	0.009	0.007	11.040	***
Managed Futures	0.004	0.157	0.004	1.030	
Number observations			18,382		
Log pseudolikelihood			-1,647.63		
Pseudo R2			9.04%		

Table VI
Probit Regression for Deletions

The table shows the marginal effects from a probit regression. The dependent variable is the dummy reflecting whether a fund had a Deletion over the period of all the vintages. This is explained by the rank of lifetime variables of average assets under management, average return, return standard deviation, return first auto correlation (rho1) and the number of returns the fund reported (lifen). Other relevant fund variables are an offshore dummy, total restrictions variable (measured as the sum of the reported lockup periods) and an audit information flag. Relevant control dummies of fund strategy and database of fund are included. Regressors are described in the text. dF/dx is for discrete change of dummy variable from 0 to 1, and the slope at the mean for continuous variables. Standard errors estimated by clustering by database. The number of stars * denote significance at 10%, 5% and 1% respectively.

Deletions	**dF/dx**	**Mean**	**Robust SE**	**z**	
lifeaumavgrank	0.013	0.500	0.005	2.430	**
liferetavgrank	-0.030	0.500	0.025	-1.170	
liferetstdrank	0.009	0.500	0.005	1.730	*
rho1rank	-0.005	0.500	0.012	-0.460	
lifen	0.000	66.422	0.000	19.050	***
offshore	0.019	0.501	0.007	2.850	***
lockup	0.000	164.623	0.000	-0.620	
audit	0.018	0.712	0.003	6.170	***
DB HFR	-0.007	0.258	0.002	-3.880	***
DB CISDM	-0.031	0.092	0.002	-16.320	***
DB BarclayHedge	-0.021	0.290	0.002	-10.230	***
Macro	0.004	0.065	0.006	0.810	
Relative Value	0.050	0.014	0.015	4.070	***
Directional Traders	0.006	0.128	0.004	1.390	
Fund-of-Funds	0.022	0.264	0.003	7.090	***
Multi-Process	-0.011	0.102	0.004	-2.400	**
Emerging	0.019	0.045	0.008	2.650	***
Fixed Income	0.015	0.052	0.015	1.080	
Other	0.017	0.009	0.021	0.900	
Managed Futures	0.008	0.157	0.006	1.410	
Number observations			18,382		
Log pseudolikelihood			-3,931.17		
Pseudo R2			4.19%		

Table VII
Multinomial Logistic Regression on Revision Direction

These are coefficients from a multinomial logit regression on revision direction relative to no change at all. Revision Direction is the net number of positive or negative revisions experienced by a fund. The base case of zeros refers to funds having no revisions at all. Funds with exactly equal positive and negative revisions were dropped (4.6% of funds). Regressors are as in Table IV. Standard errors estimated by clustering by database.

Panel A. More negative revisions				
-1 to 0	**Coeff**	**Robust SE**	**z**	
lifeaumavgrank	1.079	0.194	5.550	***
liferetavgrank	-0.788	0.299	-2.640	***
liferetstdrank	0.510	0.125	4.070	***
rho1rank	0.555	0.065	8.590	***
lifen	0.009	0.002	4.160	***
offshore	-0.095	0.047	-2.030	**
lockup	0.001	0.000	4.190	***
audit	0.934	0.539	1.730	*
DB HFR	0.100	0.031	3.270	***
DB CISDM	-0.027	0.418	-0.060	
DB BarclayHedge	0.768	0.032	24.340	***
Macro	0.326	0.061	5.390	***
Relative Value	0.668	0.158	4.240	***
Directional Traders	-0.161	0.079	-2.040	**
Fund-of-Funds	0.884	0.093	9.470	***
Multi-Process	0.136	0.093	1.460	
Emerging	0.429	0.064	6.740	***
Fixed Income	-0.084	0.187	-0.450	
Other	0.295	0.311	0.950	
Managed Futures	0.548	0.258	2.120	**
constant	-4.073	0.444	-9.170	***

Panel B. More positive revisions				
-1 to 0	**Coeff**	**Robust SE**	**z**	
lifeaumavgrank	1.100	0.326	3.380	***
liferetavgrank	0.071	0.124	0.570	
liferetstdrank	0.065	0.240	0.270	
rho1rank	0.587	0.089	6.600	***
lifen	0.008	0.002	4.890	***
offshore	-0.167	0.038	-4.340	***
lockup	0.001	0.000	5.040	***
audit	0.690	0.483	1.430	
DB HFR	-0.201	0.027	-7.590	***
DB CISDM	-0.467	0.389	-1.200	
DB BarclayHedge	0.262	0.059	4.430	***
Macro	0.415	0.028	15.030	***
Relative Value	0.882	0.394	2.240	**
Directional Traders	0.088	0.038	2.340	**
Fund-of-Funds	0.946	0.062	15.150	***
Multi-Process	0.359	0.126	2.850	***
Emerging	0.651	0.071	9.220	***
Fixed Income	0.160	0.185	0.870	
Other	0.663	0.502	1.320	
Managed Futures	0.519	0.177	2.930	***
constant	-3.832	0.308	-12.430	***
Panel C. Regression statistics				
Number observations		17,587		
Log pseudolikelihood		-14,089.61		
Pseudo R2		9.23%		

Table VIII
Change in Predictions for Revision Direction

The panels below show changes in predicted probabilities in the revision direction multinomial logit regression, where -1 indicates more negative revisions, 1 for more positive revisions in the fund and 0 for no revisions at all. Panel A shows impact of the Audit flag dummy and Panel B shows a change from 1st to 3rd quartile in lifetime ranks. Confidence intervals are estimated by the delta method.

Panel A: Audit

Audit flag					
	Audit	**No Audit**	**Diff**	**95% CI for**	**Diff**
Pr(y=-1|x):	0.189	0.093	0.095	[0.0810,	0.1098]
Pr(y=1|x):	0.182	0.115	0.067	[0.0518,	0.0824]
Pr(y=0|x):	0.630	0.792	-0.163	[-0.1821,	-0.1428]

Panel B: Change in quartiles

Lifetime Average AUM					
	AUM 0.75	**AUM 0.25**	**Diff**	**95% CI for**	**Diff**
Pr(y=-1|x):	0.186	0.129	0.057	[0.0462,	0.0679]
Pr(y=1|x):	0.194	0.133	0.061	[0.0496,	0.0719]
Pr(y=0|x):	0.620	0.738	-0.118	[-0.1323,	-0.1032]

Lifetime Return Average					
	Ret 0.75	**Ret 0.25**	**Diff**	**95% CI for**	**Diff**
Pr(y=-1|x):	0.131	0.184	-0.053	[-0.0636,	-0.0421]
Pr(y=1|x):	0.168	0.154	0.015	[0.0036,	0.0258]
Pr(y=0|x):	0.700	0.662	0.038	[0.0238,	0.0524]

Lifetime Return Standard Deviation					
	Std 0.75	**Std 0.25**	**Diff**	**95% CI for**	**Diff**
Pr(y=-1|x):	0.173	0.140	0.033	[0.0217,	0.0438]
Pr(y=1|x):	0.160	0.162	-0.002	[-0.0133,	0.0092]
Pr(y=0|x):	0.667	0.698	-0.031	[-0.0455,	-0.0159]

Lifetime Return First Autocorrelation					
	Rho 0.75	**Rho 0.25**	**Diff**	**95% CI for**	**Diff**
Pr(y=-1|x):	0.171	0.142	0.029	[0.0184,	0.0397]
Pr(y=1|x):	0.178	0.146	0.033	[0.0219,	0.0435]
Pr(y=0|x):	0.651	0.713	-0.062	[-0.0759,	-0.0477]

Table IX
Probit Regression for Revisions at Vintage Level

The table extends Table V, showing the marginal effects from a probit regression of Revisions, by now indexing data at a vintage level. The dependent variable is the dummy reflecting whether a fund had a Revision between the last available vintage (indicated by v-1) and the current vintage v. This is explained by the rank of lifetime variables up to v-1 of average assets under management, average return, return standard deviation, return first auto correlation (rho1) and the number of returns the fund reported. Other relevant fund variables are an offshore dummy, total restrictions variable (measured as sum of reported lockup periods) and an audit information flag. Relevant control dummies of fund strategy and database of fund are included. Regressors are described in the text. dF/dx is for discrete change of dummy variable from 0 to 1, and the slope at the mean for continuous variables. Standard errors estimated by clustering by vintage. The number of stars * denote significance at 10%, 5% and 1% respectively. Panel B is similar to Panel A but adds a dummy if the fund had a Revision in the prior vintage.

Panel A. Probit regression without lag indicator

Revisions	**dF/dx**	**Mean**	**Robust SE**	**z**	
vintage v-1 AUM rank	0.0496	0.500	0.00656	19.640	***
vintage v-1 return rank	0.0157	0.500	0.00457	4.160	***
vintage v-1 ret std rank	0.0053	0.500	0.00305	1.660	*
vintage v-1 ret rho1 rank	0.0169	0.500	0.00379	4.700	***
vintage v-1 return count	0.0001	63.746	0.00001	7.460	***
offshore	-0.0046	0.503	0.00122	-3.760	***
lockup	0.0000	171.416	0.00000	11.490	***
audit	0.0305	0.691	0.00256	11.900	***
DB HFR	0.0051	0.258	0.00223	2.450	**
DB BarclayHedge	-0.0249	0.098	0.00858	-1.830	*
Macro	0.0251	0.284	0.00593	3.530	***
Relative Value	0.0238	0.065	0.00213	11.270	***
Directional Traders	0.0232	0.013	0.00449	7.970	***
Fund-of-Funds	-0.0048	0.128	0.00168	-3.100	***
Multi-Process	0.0597	0.262	0.00662	28.050	***
Emerging	0.0102	0.093	0.00232	4.690	***
Fixed Income	0.0134	0.043	0.00286	7.190	***
Other	0.0060	0.051	0.00151	4.100	***
Managed Futures	0.0245	0.009	0.00459	9.360	***
Number observations			571,477		
Log pseudolikelihood			-105,300.11		
Pseudo R2			9.74%		

Panel B. Probit regression with prior vintage revision indicator

Revisions	dF/dx	Mean	Robust SE	z	
vintage v-1 AUM rank	0.0313	0.50	0.00565	15.260	***
vintage v-1 return rank	0.0138	0.50	0.00477	4.060	***
vintage v-1 ret std rank	0.0017	0.50	0.00264	0.610	
vintage v-1 ret rho1 rank	0.0086	0.50	0.00252	3.550	***
vintage v-1 return count	0.0000	63.77	0.00001	3.920	***
prior vintage revision dummy	0.2345	0.068	0.02101	16.990	***
offshore	-0.0031	0.502	0.00111	-2.650	***
lockup	0.0000	171.214	0.00000	6.450	***
audit	0.0220	0.691	0.00257	10.520	***
DB HFR	0.0023	0.256	0.00184	1.290	
DB BarclayHedge	-0.0249	0.098	0.00620	-1.920	*
Macro	0.0160	0.285	0.00527	2.560	**
Relative Value	0.0147	0.065	0.00200	8.390	***
Directional Traders	0.0147	0.013	0.00406	5.600	***
Fund-of-Funds	-0.0020	0.128	0.00134	-1.610	
Multi-Process	0.0355	0.262	0.00597	18.800	***
Emerging	0.0078	0.093	0.00221	3.660	***
Fixed Income	0.0097	0.043	0.00271	5.550	***
Other	0.0043	0.051	0.00133	3.260	***
Managed Futures	0.0145	0.009	0.00384	6.200	***
Number observations			560,428		
Log pseudolikelihood			-90,475.48		
Pseudo R2			21.58%		

Table X
Regressions on Return Differences between Portfolios

This table shows the significance of the differences in returns between the Non-Reviser and Reviser portfolios. The monthly return differences are analysed against different risk models. Panel A uses factors from the Fung-Hsieh model, such as a market model using S&P 500, four of the market related Fung-Hsieh factors, and then the Fung-Hsieh 7 and 8 Factor model. Panel B uses an alternate specification with the Fama-French 3 factor model, and then adds a momentum factor, and finally the Pastor-Stambaugh Liquidity factor. The PS-Liquidity factors are only available to December 2010. Newey-West heteroskedasticity and autocorrelation robust standard errors (with three lags) are used. Regression betas are shown with *t*-statistics shown in brackets beneath.

Panel A: Return differences (Fung-Hsieh Model)

Factors	**Constant**	**Market**	**FH 4**	**FH 7**	**FH 8**
Constant	0.256	0.252	0.235	0.229	0.228
	(3.388)	**(4.202)**	**(2.993)**	**(2.877)**	**(2.922)**
SP500	-	0.019	0.017	0.018	0.015
	-	(1.631)	(1.166)	(1.422)	(0.952)
SMB	-	-	0.028	0.025	0.026
	-	-	**(2.025)**	(1.532)	(1.464)
BOND10YR	-	-	-0.163	-0.288	-0.280
	-	-	(-0.930)	(-1.049)	(-0.993)
CREDSPR	-	-	0.043	-0.026	-0.007
	-	-	(0.244)	(-0.107)	(-0.026)
PTFSBD	-	-	-	-0.288	-0.288
	-	-	-	(-0.439)	(-0.439)
PTFSFX	-	-	-	0.950	0.944
	-	-	-	(1.763)	(1.785)
PTFSCOM	-	-	-	-1.471	-1.457
	-	-	-	**(-2.147)**	**(-2.133)**
EMERGING	-	-	-	-	0.003
	-	-	-	-	(0.200)
Num. Observations	40	40	40	40	40
Adjusted R-Squared		6.11%	2.69%	7.38%	4.49%

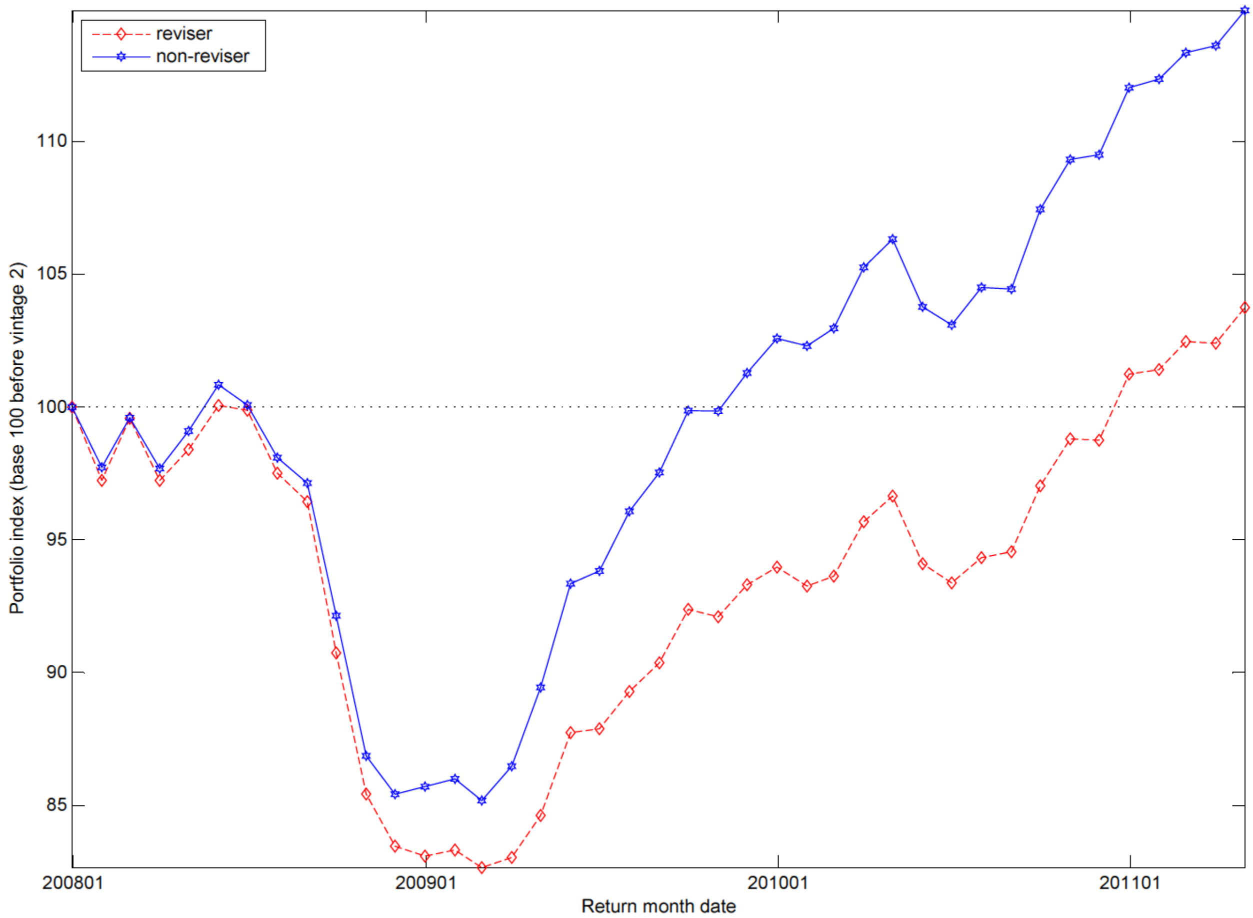
Panel B: Return differences (Fama-French 3 factors + Momentum + Pastor-Stambaugh Liquidity Model)

Factors	**FF3**	**FF3 + Mom**	**FF3 + Mom + Liquidity**
Constant	0.246	0.213	0.244
	(3.152)	**(3.963)**	**(4.982)**
MKTRF	0.755	-0.604	0.241
	(0.582)	(-0.648)	(0.304)
SMB	1.186	1.848	2.209
	(0.722)	(1.093)	(1.354)
HML	3.112	0.467	-2.649
	(2.083)	(0.385)	(-1.509)
UMD	-	-3.660	-3.420
	-	**(-9.312)**	**(-9.288)**
PSLIQ	-	-	-2.339
	-	-	**(-2.663)**
Number observations	40	40	36
Adjusted R-Squared	15.21%	9.47%	8.95%

Figure I
Portfolio Performance – Revisers and Non-Revisers

The figure shows the cumulative performance of the reviser and non-reviser portfolios. The non-reviser portfolio holds performance of funds that never revise between vintages plus the early records of funds before they become revisers. For example, if a fund first revises at vintage v; its earlier performance will be included in the non-reviser portfolio as it had not yet been classified as a reviser. But once it joins the reviser portfolio it stays out of the non-reviser portfolio. The index is based to 100 at 31 December 2007, just before the second vintage starts. Returns are equally weighted in portfolios. Flows calculations use average assets across vintages.

Panel A. Revision Portfolio Indices: Returns



Panel B. Revision Portfolio Indices: Flows

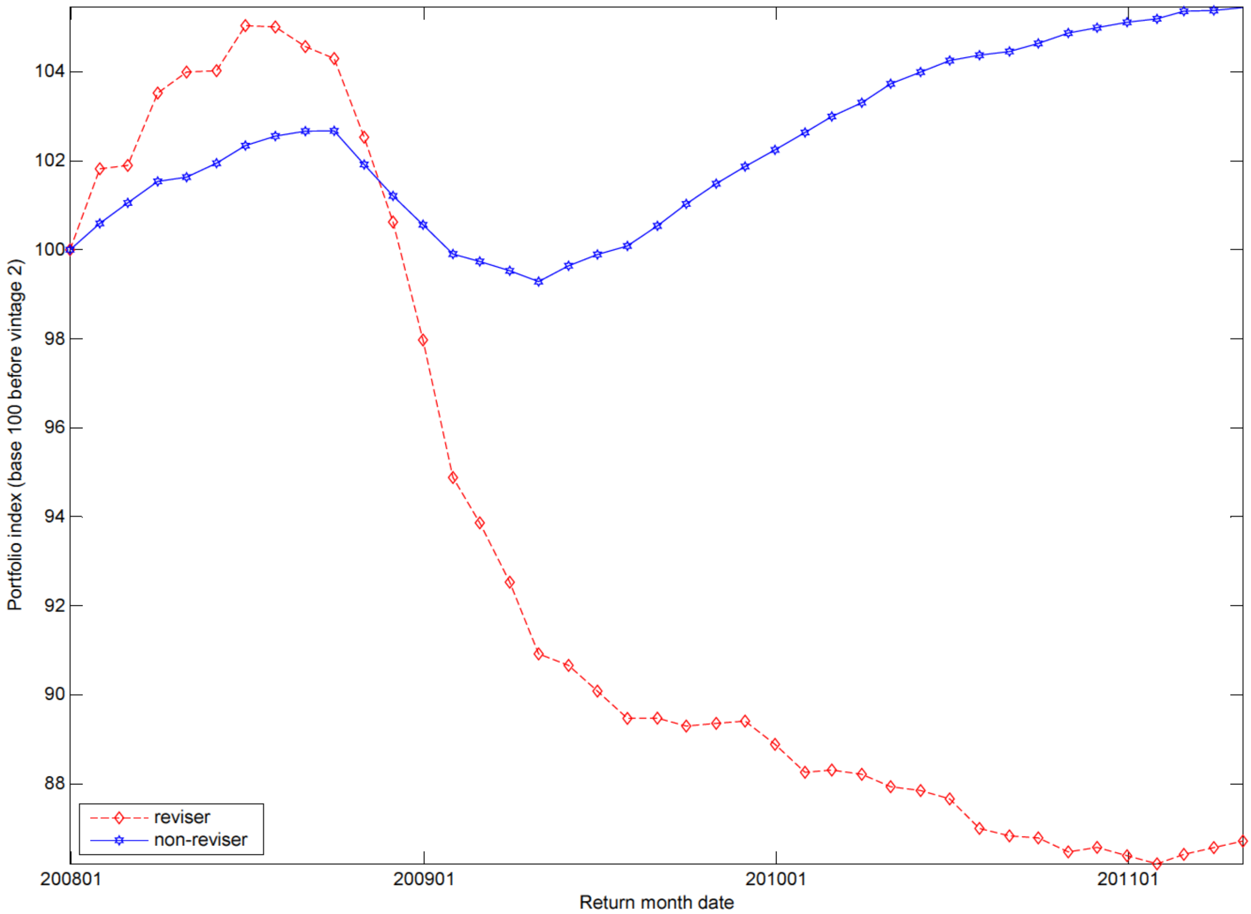


Figure II
Cumulative Alpha

The figure plots cumulative alphas using the Fung-Hsieh 7 Factor model for the respective Reviser portfolio and Non-Reviser portfolio. The index is based to 100 at 31 December 2007, just before the second vintage starts.

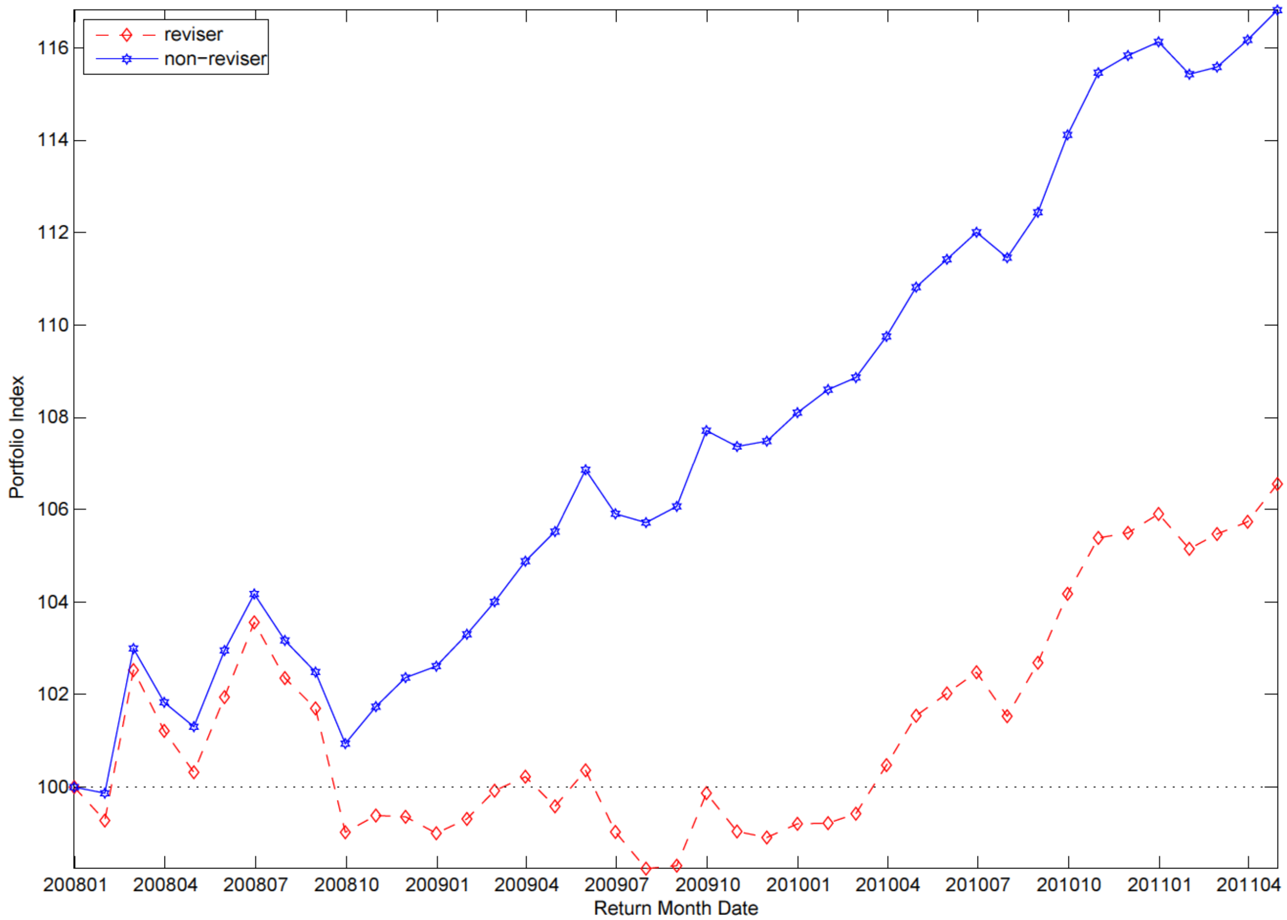
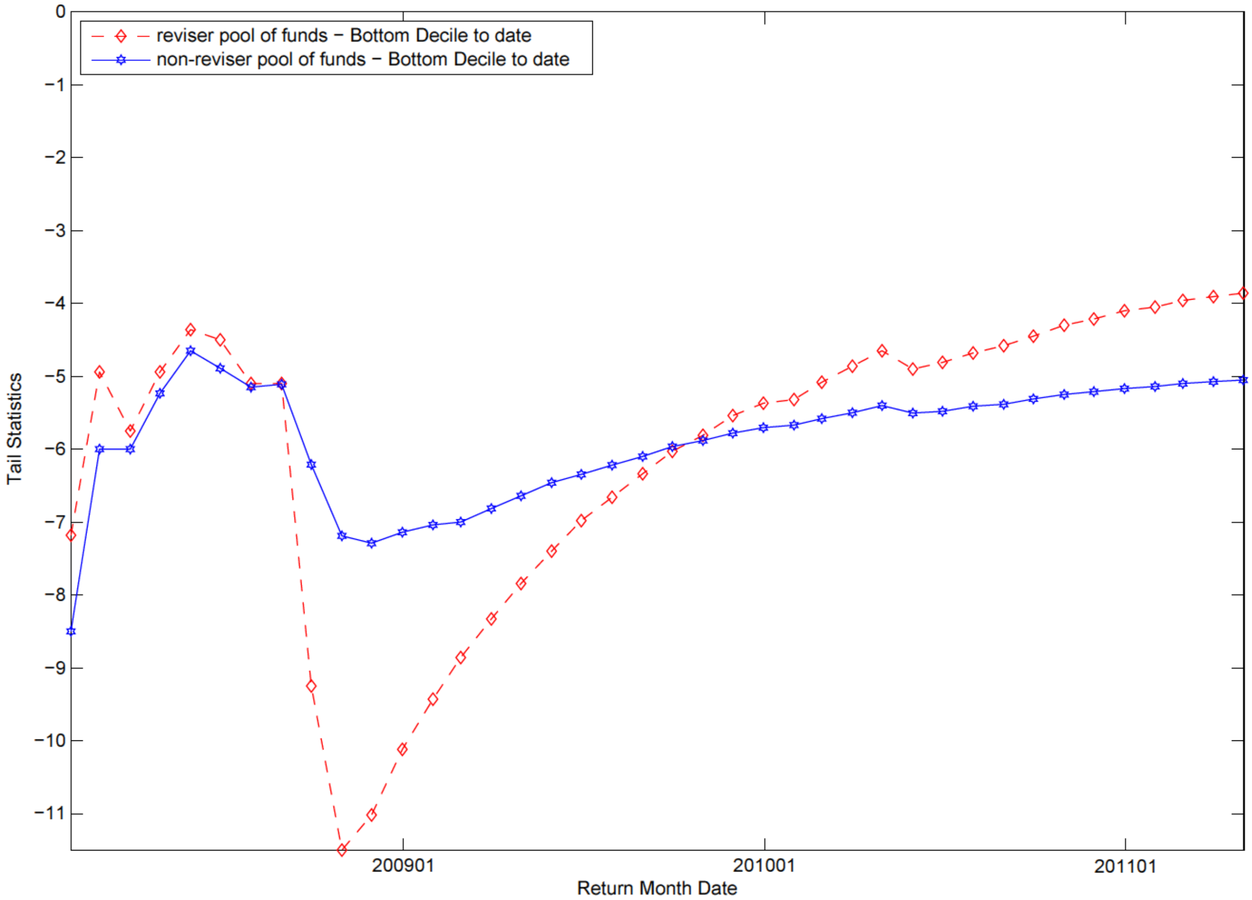


Figure III
Tail Risk Percentiles for Reviser and Non-Reviser Portfolios

The figure shows the bottom decile tail statistics for the Reviser portfolio and Non-Reviser portfolio. Panel A shows the empirical bottom decile for the portfolio fund returns using historical simulation. Panel B shows the average return of those portfolio fund returns in this bottom decile as a measure of expected shortfall.

Panel A. Tail Risk Bottom Decile – Portfolio's Fund Returns



Panel B. Tail Risk Average over Bottom Decile – Portfolio's Fund Returns

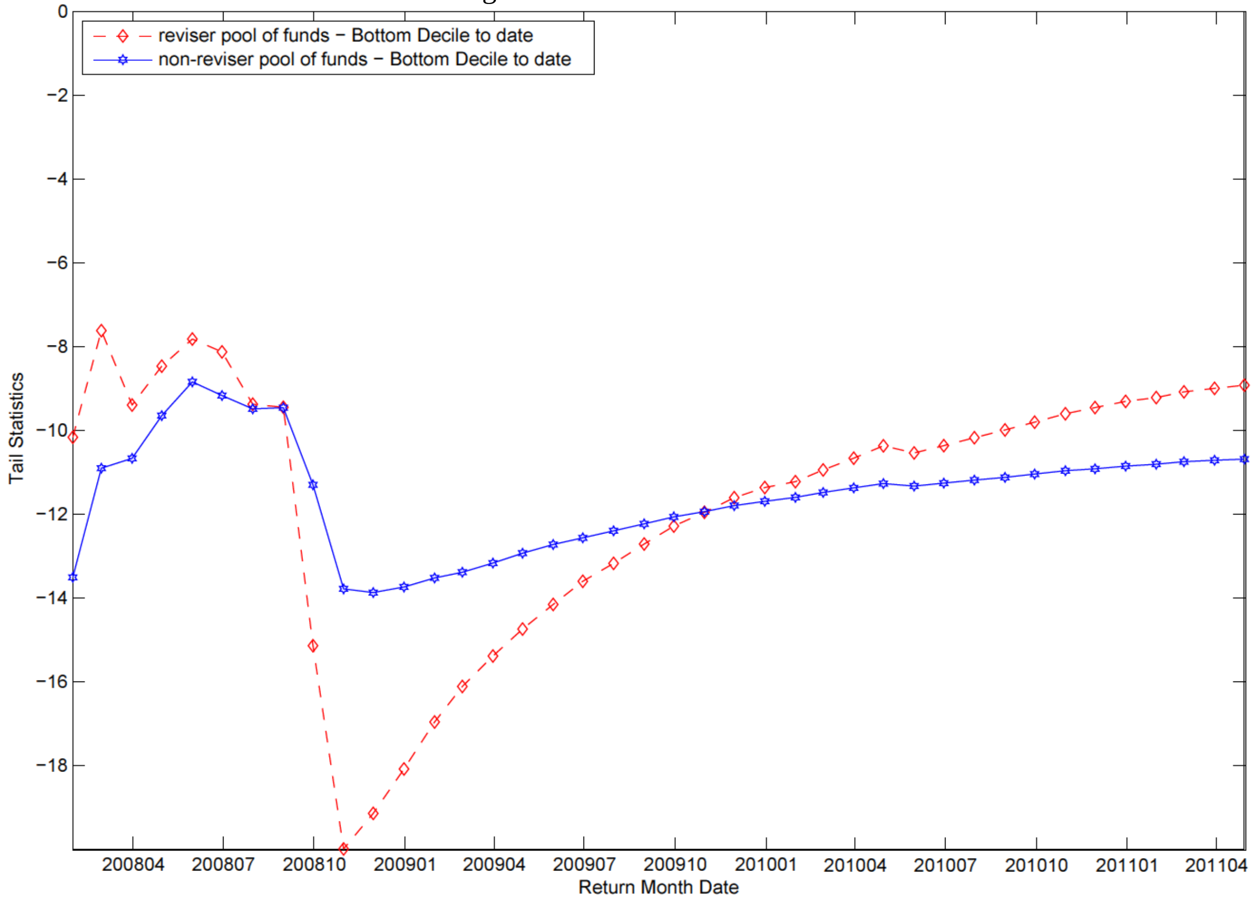


Figure IV
Differences between "True" and Initial Returns

The figure shows the mean positive and negative return differences between the last expression of the return at the most recent available vintage (denoted "True") and the first time the return is expressed in a database (denoted Initial). Significant differences only are shown (so zero differences and minor differences due to changes in expression of significant digits for the same return value are excluded). The vertical pink dashed lines are the points at which mean hedge fund returns in the universe are negative, and two standard deviations below the time-series mean. The horizontal lines are two standard deviations of the positive and negative revisions.

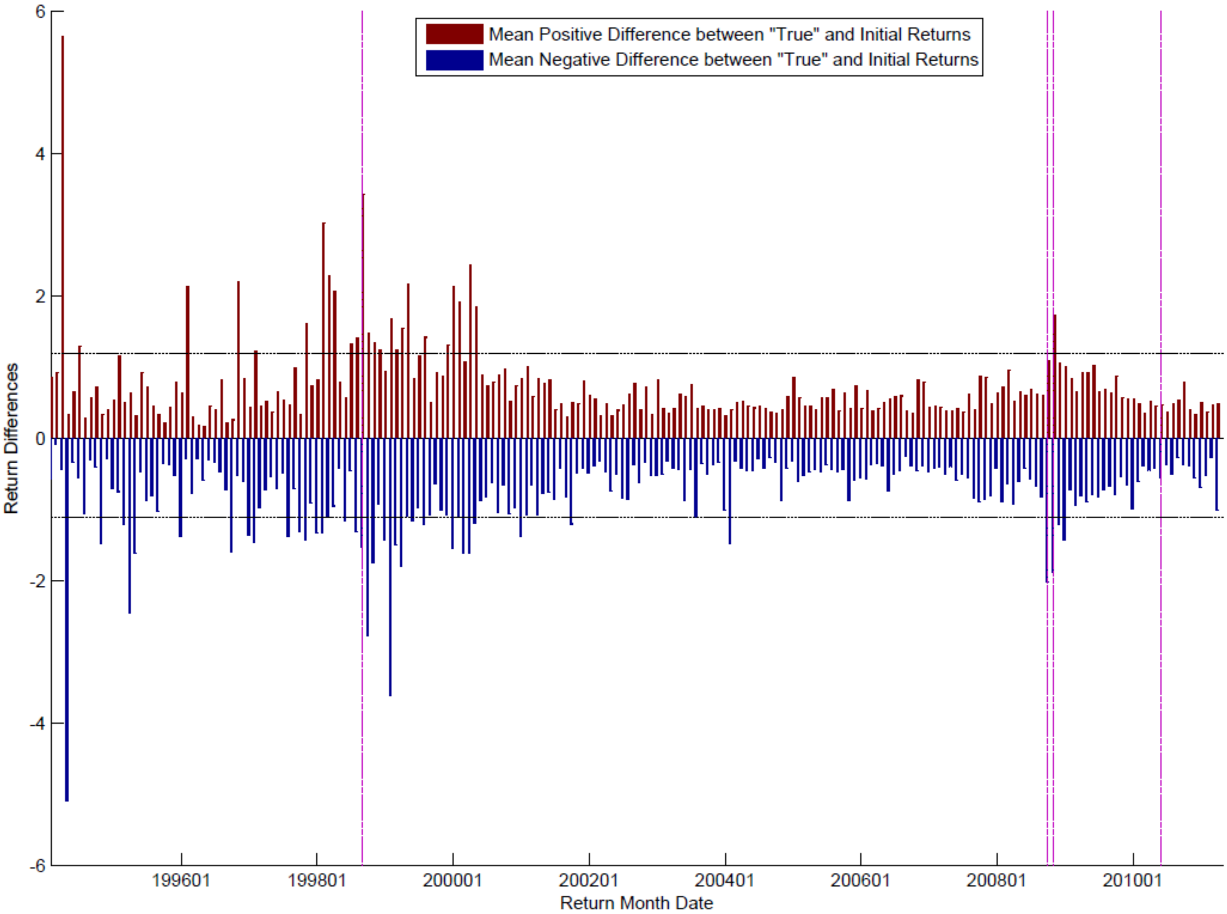


Figure V
Cumulative Differences between "True" and Initial Returns

The figure shows the cumulative average return differences between the last expression of the return at the most recent available vintage (denoted "True") and the first time the return is expressed in a database (denoted Initial). Significant differences only are shown. The index is based to 100 at the time of the start of the return data, January 1994.