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On the Economics of Hedge Fund Drawdown Status: Performance, Insurance Selling and Darwinian Selection*

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Abstract

In this paper we study the drawdown status of hedge funds as a hedge fund characteristic related to performance. A hedge fund's *drawdown status* is the decile to which the fund belongs in the industry's drawdown distribution (at a given point in time). Economic reasoning suggests that both the current level and the past evolution of a fund's drawdown status are informative of key fund aspects, including the manager's talent, as well as fund investors' assessment of the fund, and, hence, are predictive of future performance. The analysis delivers four completely new insights on hedge funds. First, the presence of insurance selling (shorting deep out-of-the-money puts) in the industry is large enough to make portfolios of low drawdown funds weak performers, in general, and bad performers in times of turmoil. Second, the market operates a *Darwinian selection process* according to which funds running large drawdowns for a prolonged period of time (survivers) are managed by truly talented traders who deliver outstanding future performance. Third, a completely new dimension of risk arises as a distinctive feature of hedge funds: risk conditional on survival is tantamount to outstanding performance. Fourth, drawdown status analysis raises serious concerns about the role played by other hedge fund characteristics –such as total delta– on fund performance and casts doubts on the validity of some performance evaluation measures –such as the Calmar and Sterling ratios– that are widely used in practice.

Journal of Economic Literature Classification Numbers: G11, G12, G19, G22, G23.

Keywords: Drawdowns, Hedge Funds, Fund Characteristics, Return Predictability, Darwinian Selection, Insurance Sellers, Survival.

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1 Introduction

The drawdown of an investment is a measure of the decline of the value of that investment from its historical peak. Drawdown analysis plays an important role in investment management, as the extent to which large drawdowns occur is an essential aspect of the evaluation of managers and their strategies. This is reflected in the widespread industry use of drawdown based performance evaluation measures, such as the Calmar and the Sterling ratios.[1] These measures are, ceteris paribus, negatively related to the maximum drawdowns that funds experience, which makes large drawdowns a negative signal about the quality of the manager. In essence, large drawdowns proxy for risk and, consequently, play a negative role on performance evaluation. In this paper we look deeper into the economics behind drawdowns in the context of the hedge fund industry. We theoretically argue and empirically corroborate that drawdowns are related to future performance and that, in sharp contrast to the previous view, large drawdowns (plus fund survival) are predictive of outstanding performance. But these are just two of the many new insights into hedge funds that drawdown analysis delivers.

Our first departure from the traditional view consists of looking at a fund's drawdowns *relative* to the drawdowns of other funds in the market instead of in isolation. The second main departure is to analyze the *dynamics* of hedge funds drawdowns instead of its maximum past level. We argue that relative drawdowns and their dynamics are both predictive of the hedge fund's future performance. To develop these ideas, we define the *drawdown status* of a fund at a given moment in time as the decile to which the fund belongs in the drawdown distribution of the industry. Economic reasoning suggests that both the current level and the past evolution of this drawdown status are related to key aspects of hedge funds –such as the manager's talent and interests– and hedge fund investors' decisions –to exit or remain in the fund, to research more or less thoroughly, etc.– and are therefore predictive of future performance. This means that, *ex ante*, drawdown status is indeed a hedge fund *characteristic* related to performance. Our empirical analysis corroborates this hypothesis and also indicates that drawdown status is, from a quantitative standpoint, one of the most important performance-related hedge fund characteristics –despite being (incomprehensibly) neglected in the literature.

[1] The Calmar ratio is defined as the absolute value of the ratio of compound annualized rate of return to maximum drawdown, typically computed over a period of 3 years. The Sterling ratio is defined similarly but its denominator uses the average annual maximum drawdown plus 10%. In some variations, the risk-free rate is subtracted from the numerator, which results in a return-to-risk metric akin to the Sharpe ratio.

To illustrate the power of drawdown status as a key hedge fund characteristic related to performance, in Figure 1 we plot the cumulative returns of several comparable portfolios based on fund characteristics and performance measures. Panel A plots the cumulative returns of portfolios sorted by characteristics identified in the literature as being predictive of hedge fund performance: return, size, volatility and total delta;[2] Panel B plots the cumulative returns of portfolios sorted by performance evaluation measures widely accepted by academics or practitioners: alpha, Sharpe ratio, Calmar ratio and Sterling ratio. Each return series corresponds to a value weighted portfolio that each year holds the funds in the relevant extreme decile of the corresponding characteristic or performance measure in the previous three years. More specifically, we consider portfolios that each year hold all funds that belong to the intersection of the previous three years top versus bottom deciles. Figure 1 plots the one that performs best out of these two for each characteristic and performance measures analyzed. In brackets and next to the label of each strategy we indicate if the strategy holds the funds in the "1st" or "10th" decile. For instance, the line labeled 'Size (1st)', plots the cumulative return of a portfolio that each year (from 1996 to 2009) holds all hedge funds that belong to the intersection of the first size decile (smallest funds measured by assets under management, AUM) of the previous three consecutive years in the Hedge Fund Research (HFR) universe of hedge funds.[3] Notice that by reporting the 1st decile portfolio we are implicitly revealing that the portfolio of funds in the 10th decile performs worse than this one.

As we can observe in Panel A, the strategy labeled 'Drawdown' exhibits the most outstanding performance among all the characteristics based portfolios. The reader must acknowledge some surprise upon realizing that this portfolio holds every year all hedge funds in the intersection of the largest drawdown decile of the previous three years.[4] This result is indeed remarkable for at least three reasons. First, it indicates that drawdown status is a hedge fund characteristic that predicts outstanding performance. Second, in quantitative terms, drawdown status is a better predictor of hedge fund returns than

[2]See, for instance, Agarwal and Naik (2000, 2005), Brorsen and Harri (2004), Agarwal, Daniel and Naik (2009).

[3]For comparison we also include the cumulative return of the portfolio labeled 'HFR', which includes all funds in the HFR database.

[4]Panel A reports raw returns –that is, returns that are not risk-adjusted. We have computed risk-adjusted returns in the context of the Fung and Hsieh (2004) seven-factor model. We find that the largest alpha corresponds to the Drawdown portfolio. Thus, the superior performance of the drawdown based portfolio holds in terms of both raw and risk-adjusted returns. Finally, results are even more striking when we compare the performance of the 'Drawdown' strategy with the one associated to portfolios sorted on the basis of previous year status (as opposed to the previous three years status).

other well-known characteristics. Third, outstanding performance is associated precisely with the funds that experienced large drawdowns in the past and are very far from their all time record when incorporated in the portfolio –in other words, funds that would tend to qualify as bad performers (and be viewed as managed by untalented traders) according to the standard drawdown based measures of performance. Another remarkable result inferred from Panel A is that total delta predicts future returns in the opposite direction as expected. In particular, we plot the portfolio of funds with the smallest total delta precisely because it outperforms the portfolio of funds with the largest total delta. This is in sharp contrast with the traditional view (Agarwal et al. (2009)) that performance is positively related to incentives (total delta). This result is further analyzed later on.

Panel B reveals a very similar phenomena. Again, the best performance is associated to the Drawdown portfolio. Interesting enough, while alpha and Sharpe ratio operate in the expected way (best performance associated to the portfolio of funds in the 10th decile, that is, funds with the largest alpha and Sharpe ratio), the opposite occurs in the case of the Calmar and Sterling ratios: outstanding performance is associated to funds with the smallest ratios. Although this is conflictive with the use of these ratios as performance evaluation measures, it is consistent with the outstanding performance of the drawdown portfolio: low Sterling and Calmar ratios very likely are associated to funds that experienced large drawdowns in the recent past, that is, funds that most likely also belong to the Drawdown portfolio.

To summarize, the analysis of Figure 1 points at drawdown status as a legitimate candidate in the literature of hedge funds characteristics and shows the naiveté in the treatment of hedge funds' large negative returns (or volatility), in general, and drawdowns, in particular, both in the academia and according to industry standards (Calmar and Sterling ratios).

[Insert Figure 1: Performance of Characteristics Based Portfolios]

Why is drawdown status related to performance? The past drawdown status of a hedge fund is related to its future performance because it is informative of the manager's talent. A key distinctive feature of the hedge fund industry is a remuneration system for managers whereby success is extremely well compensated but in a very specific manner. The typical arrangement includes a fixed fee plus an incentive fee that is subject to a "high-water mark" clause. The fixed fee is applied to the AUM of the fund and ranges (across funds) from 0 to 6% with an average of 1.5%. The incentive fee ranges from 0 to 50% with an average of 19.1%.[5] Given these figures, it is obvious that the main goal for any manager is to collect incentive fees. However, the high-water mark clause allows the manager to collect incentives fees only from a particular investor when the net asset value (NAV) of the fund at the end of the measurement period is above its record during the measurement periods since the investor entered the fund. This is where the fund's drawdown history enters the picture: incentive fees are collected from both old and new investors in the fund when the fund is above the high-water mark –in other words, when its current drawdown is zero. Furthermore, funds currently at the high-water mark level are also expected to generate larger incentive fees in the near future because doing so will require only a strictly positive future return.[6] The opposite dynamics applies to funds currently facing a large drawdown: they do not collect incentive fees from old investors (those who entered the fund before the large drawdown occurred); and most likely they forgo fees from potential new investors who declined to enter the fund after observing the large drawdown. Moreover, managers should not expect incentive fees in the near future because that would require large returns that lift the fund's net asset value to the high-water mark. This means that, on the supply side, all managers seek to keep drawdown to a minimum. One way to achieve this, but perhaps not the only one, is talent in asset management. On the demand side, funds that currently experience large drawdowns are relatively cheap, in terms of incentive fees, for old investors: these do not pay them if they stay in the fund, but most likely will pay them if they leave and enter a new fund. Hence, it may be worthwhile to research them thoroughly and retain only those that are managed by talented traders. This process could result in the death of funds facing large drawdowns and managed by untalented traders. The last two points directly link drawdown status to talent in asset management. We contend that analyzing the *evolution* of drawdown status, which is just a measure of the relative position over time of each fund's drawdown with respect to the other hedge funds, allows one to discern talented managers. In essence, *drawdown status analysis* uses economic reasoning to predict the future performance of hedge funds by sorting out talented and untalented traders on the basis of past evolution of their drawdown status. The strategy 'Drawdown' plotted in Figure 1 is just one example of this new methodology's success.

In principle, talented managers –and especially those implementing a sound risk management technology– will tend to exhibit small drawdowns. Outstanding performance should therefore be associated with hedge funds that persistently exhibit a low

[5]These figures refer to the universe of hedge funds in the HFR data set, which is the one used in this paper. They are in line with those reported in other studies where alternative data sets are used.

[6]Or a return higher than hurdle rate, if it exists.

drawdown status (in the 1st drawdown decile). However, in this paper we argue (and provide corroborating evidence) for this not being the case owing to the "contaminating" presence of funds that merely mimic low-drawdown funds.[7] These are funds managed by untalented traders (i.e., those unable to deliver pure alpha returns) who specialize in strategies akin to selling insurance.[8] These strategies resemble a dynamic strategy of rolling over short positions in deep out-of-the-money put options on some broad stock or commodity index. All of them share the property of delivering positive returns in normal times but have the (hidden) cost of large losses in times of turmoil. By their very nature these strategies usually place the fund in the lowest drawdown decile. They differ from the strategies of talented investors in that they are not associated with outstanding performance once proper account is taken of the true risks involved.

On the other hand, at any given time, the high drawdown decile is populated by both unlucky talented managers and untalented managers. In principle, we could expect this decile being associated to poor performance, as untalented managers will hit the decile more frequently. This reasoning is too simplistic as it ignores the death of funds. In this paper we argue and offer evidence consistent with a *Darwinian selection process* within the hedge fund industry: funds that "survive" in the largest drawdown decile for several periods are managed by talented managers and exhibit outstanding performance. Notice that these are funds that the traditional approach would consider very risky (after all, they suffered the largest drawdowns in the industry). They are, however, managed by talented managers, which means that high risk conditional on survival is tantamount to outstanding performance. This is one of our key insights and merits closer examination.

As mentioned previously, a distinctive feature of the hedge fund industry is an incentive structure that depends on the high-water mark clause. This means that old investors in a fund that suffers a large drawdown face a choice between staying in the fund (and saving a lot of fees, since incentive fees will not be paid until the fund returns to the high-water mark) and leaving to enter a new fund (where the investor starts at the high-water mark and must therefore expect to pay large fees). Clearly, the high-water mark clause plays in favor of staying in, but only when the fund's expected return remains positive –that is, when the manager is talented. Hence, it is at the time of such decisions that it is most worthwhile to gather extra relevant information about the manager's investment philosophy, strategy and reasons behind the large drawdown. If

[7] We also document other factors contributing to this finding, such as the existence of systematic risk in hedge funds strategies and the backfilling bias.

[8] For instance, see Lo (2001), and Jorion (2007), for further details on these strategies.

investors perform their analysis efficiently, then they will leave the funds managed by untalented traders and stick to the talented ones. This process may result in a *Darwinian selection mechanism* whereby funds managed by untalented managers die fast. Under this hypothesis, these funds populate the high drawdown decile temporarily but are excluded from the set of funds that experience large drawdowns for a large enough number of periods. It is important to notice that while this latter set excludes all funds that die due to the Darwinian selection mechanism, it does not include all the "surviving" funds, but just those that survive in the highest drawdown decile –that is, it does not include the funds that move to lower drawdown deciles. In any case, it does include funds that survive for several periods beside remaining in the largest drawdown decile. According to our previous reasoning, this is only possible if investors are fully convinced that these funds are managed by talented traders.

At this point we should acknowledge that managerial self-confidence could also play a role in the survival of talented managers after a prolonged period of large drawdowns. First, some degree of self-confidence is required as incentive fees would only be collected if (large) positive returns materialize in the future and management fees are probably not enough to cover the fund's running costs. Second, we do not believe, however, that managerial *rational self-confidence* constitutes an alternative hypothesis to the *Darwinian selection* for the same phenomena, the survival of talented managers. The main reason is that if investors leave the fund, a rational self confident (talented) trader would find marginally optimal closing the fund and start a new one, as long as there is at least one potential investor to fool in the future.

In this paper we find portfolios of funds experiencing the largest drawdowns to have outstanding performance. Furthermore, this performance improves (monotonically in the number of years) when we restrict the portfolios to funds that survive in the highest drawdown decile for several years –which is consistent with the Darwinian selection hypothesis. We also provide additional evidence on the average number of consecutive periods that liquidated funds remain in the largest drawdown decile, on the evolution of flows into the funds and on the evolution of managerial ownership that further corroborate the existence of a Darwinian mechanism. The evidence indicates that these are not funds run by self-confident managers abandoned by external investors.

In this paper we deviate from the standard methodology used in the hedge funds characteristics literature, which consists of regression analysis employing a predictive variable while controlling for previously identified characteristics related to performance.

Instead, we use the *portfolio sort* methodology to assess the predictability of hedge funds returns. This approach is not new; in fact, it is the most widely used approach in the literature on asset pricing anomalies and has also been recently used in a hedge fund context in Jagannathan, Malakhov and Navikov (2010). Our basic construction consists of sorting portfolios on the basis of different lags in the drawdown status of hedge funds and then testing the performance of these portfolios in the context of the most widely accepted model in the hedge funds literature –namely the Fung and Hsieh (2004) seven-factor model.[9] The portfolio sorts methodology presents both advantages and disadvantages. On the positive side, it is versatile and allows for a rich set of variables to be tested. Also, and crucially, it enables direct assessment of outstanding performance in a risk-adjusted manner. Furthermore, as pointed in Jagannathan et al. (2010), the portfolio approach allows us to reduce measurement errors and to take into account the performance of funds at the sorting and portfolio formation stage as they remain in the analysis up to the time of their disappearance from the database. Finally, the methodology has the clear practical advantage of investors in general, and managers of funds of hedge funds in particular, exhibiting a genuine interest in its output. On the negative side, we highlight that unlike the case of stocks where the market portfolio exhibits no alpha, it turns out that the portfolio that includes all hedge funds in the HFR data set (henceforth, “the HFR portfolio”) exhibits a strictly positive alpha.[10]

Both methodologies, however, suffer from an identification problem when analyzing the relationship between hedge fund characteristics and hedge fund performance. It is well known that the regression approach may yield faulty results when some relevant control variables are not properly accounted for. More specifically, outstanding performance may be attributed to a given characteristic just because what is actually a more dominating characteristic has not been identified and controlled for. Yet, the portfolio sort methodology may suffer form a similar problem. Simply put, a given sorting hedge fund characteristic may seem to explain outstanding performance, when in fact that performance is partially (or even completely) explained by some other characteristic. This problem can be addressed by imposing “conditional” sorts that control for the alternative characteristics, but data availability may impose a serious limitation on this

[9]In the Fung and Hsieh (2004) model, hedge fund excess returns are regressed on seven factors that have proven to have high explanatory power. These factors are the excess return on the S&P 500 index; the spread factors on size, term structure, and credit risk; and the excess returns on portfolios of lookback straddle options on currencies, commodities, and bonds.

[10]While this is consistent with the existence of talent in the overall industry, it has been recently challenged in papers such as Fung et al. (2008) on account of the backfilling bias (the fact that funds only enter the HFR database after several years of good performance) and structural breaks in the return series.

approach. For all these reasons –and in order to dispel any suspicion that our results are driven solely by the use of portfolio sorting– in Section 8 we test our hypothesis in the context of the more traditional regression methodology.

At this point we must argue in favor of drawdown status analysis even when identifying some hedge fund characteristic that partially explain the performance of some of our drawdown based portfolios (which, indeed, is not the case as we will see later on). This is better illustrated by means of an example. It is well known that hedge fund performance tends to deteriorate as funds receive large inflows and grow in size (Agarwal, Daniel and Naik (2006), Fung et al. (2008), Jagannathan et al. (2010)). This suggests that there is a "threshold" size for each hedge fund above which the manager is unable to keep up with outstanding performance. Now assume that we find that most of the outstanding performance of the large drawdown portfolios is related to size (small funds). In this case, the economic channel could be operating as follows. Some hedge funds managed by talented managers grow too much, above the threshold size. Then, some factors that affect performance, such as operational risk, starts negatively affecting the fund. At some point the fund suffers a large drawdown that places it in the largest drawdown decile, what generates large capital outflows. Now that the fund size is below the threshold size, it is expected to deliver outstanding performance in the future again (as it still is managed by a talented trader). Aware of this, many old investors in the fund do not let the fund go (Darwinian selection) and stick to it through several periods of large drawdown status. This story is perfectly consistent with our analysis and indeed highlights the importance of drawdown status analysis to predict performance. The story just points at a specific channel (fund size) for which drawdown status analysis works.

Our results are of interest on their own right but also when balanced against existing theories and empirical results in the literature and with industry standards. First, results reported here severely question the role played by managers' incentives in hedge funds performance. In a recent paper, Agarwal et al. (2009) test the hypothesis of a positive relationship between managers' incentives and hedge funds performance. Incentives are measured by total delta and, consequently, are high when the fund is at its high-water mark (maximum option delta). This contrasts sharply with our results, which indicate that outstanding performance is associated with funds that are far from the high-water mark (i.e., funds with very low option delta). Second, our results also challenge the validity of the drawdown-based performance measures (the Calmar and Sterling ratios) frequently used by practitioners. Our analysis makes it clear that hedge funds drawdowns contain more information about manager talent than the one summarized in the maximum historical drawdown. Furthermore, Figure 1 shows that it is the inverse of the Calmar and Sterling ratios that predict performance. This shows that, consistent with our analysis, large drawdown plays a better role as proxies of talent than risk. In general, the main message of our analysis on this issue is that in the case of hedge funds, large negative returns (and survival) is very informative about talent and constitutes a very noisy proxy for risk. Third, on a more philosophical front, our analysis points to a paradox concerning the behavior of hedge fund investors: the Darwinian selection process cannot operate without a fairly high level of investor sophistication, but the huge inflows attracted by funds in the low-drawdown decile suggest a fairly low level of sophistication because these funds, as a group, do not deliver outstanding performance. This dynamic may be explained, in part, by market segmentation whereby professional investors dominate participation in large-drawdown funds and individual investors dominate in low-drawdown funds. Alternatively, because we have looked at only aggregate figures, it may be that the large inflows to the low-drawdown funds are mainly allocated to the good managers in the pool. Finally, we believe the Darwinian selection process could be at place in many other corners of finance. One of the lessons that can be drawn from our analysis is that risk conditional on survival has dimensions beyond the standard notion of risk. To the extent that the Darwinian process may be operating in stocks, our theory may have some bearing on the debate on the value premium and the risk associated to financial distress.[11]

As a premier on the drawdown status of hedge funds, this paper leaves many issues unaddressed. First, our analysis focuses only on the analysis of the two extreme deciles; naturally, a more comprehensive analysis is a fruitful topic for future research. In particular, the analysis of the portfolio of funds that after hitting the highest drawdown decile survive, irrespectively of whether they stay in the highest drawdown decile (analyzed here) or move to lower deciles (not analyzed here) deserves special attention as it fits closer the Darwinian dichotomy between death and survival. Second, we believe that much could be learned by comparing the role played by drawdown status in hedge funds versus mutual funds. Some of our results here depend critically on the high-water mark clause, which is ubiquitous in the hedge fund industry but nearly absent in the world of mutual funds; hence, mutual funds are a good control group for testing our hypothesis.

[11] On this front, it is important to notice the different opportunities open for investors to punish unfitted managers: while in hedge funds investors can do it by withdrawing funds at NAV, the mechanisms available in the case of stocks are very different.

The balance of the paper is organized as follows. In Section 2 we analyze the economics behind drawdown status and state our hypotheses on the relationship between drawdown status and hedge fund performance. In Section 3 we describe the methodology employed and relate our analysis to the existing literature on hedge fund characteristics. Section 4 is dedicated to describing the data and defining the variables used in our empirical analysis. In Section 5 we present our leading empirical results that corroborate the hypothesized relationship between drawdown status and hedge fund performance. In Section 6 we further explore the economics underlying the results obtained in Section 5 by testing the presence of insurance sellers in the lowest drawdown status portfolios, and the existence of a Darwinian selection mechanism among the funds in the largest drawdown decile. Section 7 is dedicated to robustness checks of our results. In Section 8 we set the analysis in the context of the standard regression methodology, and in Section 9 we include some concluding remarks.

2 The Economics of Hedge Fund Drawdown Status

The relationship between drawdown status and future performance would be relatively straightforward in a simple world of investment with just two types of long-lived traders: talented and untalented. We are aware that the word "talent" has many dimensions in investment management (and elsewhere). For instance, from a finalist perspective, a trader who delivers outstanding performance is no more talented than one who cannot deliver such performance but does succeed at raising a lot of capital. Indeed, both succeed at their core business (i.e., maximizing profits) and so must be endowed with a comparable amount of talent. That being said, in this paper, and more specifically in the context of the simple economy we describe next, we will view as talented those managers who can deliver outstanding performance in the form of pure (and persistent) alpha investing, and view as untalented those managers who deliver identically and independently distributed returns with zero mean each period. In this benchmark world, talented managers lie more often and more persistently in the lowest drawdown decile than untalented managers. This means that, in general, we should expect that portfolios of hedge funds drawn from the lowest drawdown decile outperform portfolios of hedge funds drawn from the highest drawdown decile.[12] Be means of a purely heuris-

[12]For limitations of scope and other reasons that will become apparent later on, in this paper we focus on analyzing the two extreme deciles. Note also that, abusing in the use of language, we will often refer to funds in the lowest (highest) drawdown decile as small (large) drawdown funds or funds with low (high) drawdown status.

tic argument we can actually make even stronger and more precise predictions on the expected performance of portfolios sorted on the basis of the past history of drawdown status:

- In the case of portfolio sorts on *one-lag* drawdown status (that is, each year's portfolio is sorted from the distribution of drawdowns of the previous year), we should expect the following prediction to hold:
  - **Prediction 1**: The lowest drawdown status portfolio will outperform the highest drawdown status portfolio. This follows because, at any given point in time, talented managers are more likely than untalented managers to hit the lowest drawdown decile. Hence, the relative pool of talented managers must be larger in the lowest than in the highest drawdown decile.
- In the case of portfolio sorts on T-*lag* drawdown status,[13] we should expect the following predictions to hold:
  - **Prediction 2**: The performance of the lowest drawdown status portfolios will increase in the length T of the lag. This prediction is based solely on the stronger return persistence of talented managers. Lucky untalented managers will only lie in the lowest drawdown decile transitorily. Hence, a requirement of lying in the low drawdown decile for several consecutive years will sort out most of the lucky untalented managers picked in the one-lag draw, and increasing the the lag will increase the odds that a manager remaining in the pool is talented.
  - **Prediction 3**: The performance of the highest drawdown status portfolios will decrease in the length T of the lag. This result follows using a symmetric argument to the previous one. Unlucky talented managers will only lie in the highest drawdown decile transitorily. Hence, a requirement that managers lie in the highest drawdown decile for several consecutive years will sort out most of the unlucky talented managers picked in the one-lag draw, which will increase the odds that a manager remaining in the pool is untalented.

Of course, the world of hedge funds is considerably more complex than assumed in our benchmark economy, and in general we should not expect the data to support all of these

[13] We define T-lag drawdown status as the intersection of deciles. For instance, a fund enters the 2-lag lowest drawdown decile portfolio in year t if it belongs *both* to the lowest decile of the drawdown distribution of year $t-1$ *and* to the lowest decile of the drawdown distribution of year $t-2$.

predictions. Using our knowledge and experience in the world of investments, we can identify four main challenges to the assumptions behind our benchmark economy. Three are of an economic nature and either follow from well-known stylized facts about hedge funds or are a direct by-product of the incentives fees and high-water mark mechanism that characterizes the hedge fund industry; the fourth is related to the way in which hedge funds report to databases. We analyze each of these challenges in turn.

The first critical simplification in our benchmark economy is that it ignores the death of hedge funds. The death (or survival) of hedge funds is endogenous. In particular, many funds that experience large drawdowns die mainly because investors withdraw their money. If investors are able to sort talented from untalented managers during the period in which a fund experiences a large drawdown, then hedge funds managed by untalented traders will die faster. This means that the pool of talented managers in the largest drawdown sort may improve, rather than deteriorate, as we increase the sorting lag. Simply put: if, for instance, untalented traders are abandoned by investors one year after they hit the highest drawdown decile, then they will be selected in the one-lag sort, but not in any of the other lagged shorts. Hence these longer lagged sorts in the highest drawdown decile will tend to be more dominated by unlucky talented managers. All this means that Prediction 3 could be reversed when hedge funds survival is endogenous. This is one of the key insights to be derived from this paper. The market may operate a Darwinian selection mechanism whereby talented managers (the fittest) are more likely to survive several periods after large drawdowns. Remarkably, this selection mechanism is incentive compatible for old investors because of the industry's incentive structure. As we explained in the introduction, old investors in a fund experiencing large drawdowns have two choices: stay in or leave and move to a new fund. If they stay in, they will save a lot of money in incentive fees as these will not be charged until the fund goes back to the high-water mark; if they leave, they will start at the high-water mark in the new fund and will pay incentive fees as the fund realizes positive returns. Obviously the incentive fees game plays in favor of staying in, but only when the expected return of the fund is positive; that is, when the manager is talented. Hence, these are times when it is worthwhile gathering extra relevant information on the manager's investment philosophy and strategy. As stated before, if old investors perform diligently this *Darwinian selection process*, then performance could be increasing, rather than decreasing, in the length of the lag used to sort funds in the 10th decile (largest drawdowns).

The second key assumption that could be violated in the real world is that of lack of persistency in the returns of untalented managers. Under this assumption, untalented managers only hit the low drawdown decile transitorily. However, as we previously mentioned, due to the high-water mark clause, all managers are interested in hitting the low drawdown status as often as possible. Being endowed with talent is one way of achieving this. There are, at least, two well-known alternatives. First, fund managers can specialize on "insurance selling" like strategies.[14] These strategies resemble a dynamic strategy of rolling over short positions in deep out-of-the-money put options on some broad stock or commodity index. All of them share the property of delivering positive returns in normal times with the (hidden) cost of large loses in turmoil times. By its own nature, these strategies set the fund in the lowest drawdown decile most of the time. But they are very different to the strategies of talented investors, as they are not associated to outstanding performance when properly accounting for the true risk of the strategy. Hence, *insurance sellers* are missing in our benchmark economy as they would correspond to the case of untalented traders with persistent returns in the lowest drawdown decile. Their presence in the real world will tend to deteriorate the performance of the low drawdown status portfolios when measured in samples that include crisis periods. On the other hand, another way of reaching the lowest drawdown status frequently without talent consists on implementing a sound risk control technology.[15] Although these traders seldom deliver large returns, they tend to lie in the low drawdown decile as large drawdowns are explicitly avoided. In sum: at any time the lowest drawdown decile may be contaminated (relative to our benchmark economy) by the presence of funds, that mimic low-drawdown funds, managed by untalented traders who use various techniques to maximize fees.[16] Since these funds are not associated with outstanding performance, a strong presence of these funds in the lowest drawdown decile will damage the performance of the lowest drawdown portfolio sorts up to the point of possibly reversing predictions 1 and 2. It is worthwhile mentioning that the presence of these mimicking funds can be partially tested. For instance, insurance sellers tend to experience very large losses during periods of crisis; therefore, if such losses are larger for the lowest drawdown decile portfolio than for the HFR portfolio then we could infer that the former was more heavily populated by insurance sellers.

[14] For instance, see Lo (2001), and Jorion (2007), for further details on these strategies.

[15] The risk control technology can be specified in terms of value at risk or, even, maximum drawdown constraints. The optimization problem in the presence of such constraints has been widely analyzed in the literature: see, for example Grossman and Zhou (1993), Cvitanic and Karatzas (1995), Lopez de Prado and Peijan (2004), and Gaivoronski and Pflug (2005).

[16] This last statement must be understood in the context of our definition of talented versus untalented managers. We are not associating the use of risk control techniques with a the lack of talent in asset management. Some talented managers may also use a sound risk control technology, and doing so would place them in the lowest drawdown decile even more often than otherwise. The presence of these does not alter the predictions of our benchmark economy.

The third key assumption in our benchmark economy is the absence of systematic risk in the strategies of both talented and untalented traders. The title "Talent Required"[17] of an article on hedge funds by Sanford Grossman in the Wall Street Journal probably reflects the essence of this industry: talent is assumed but is probably not always there. Indeed, it is well known that the industry offers some alpha, but mainly a lot of beta investing, what has given rise to a growing literature on hedge fund replication.[18] Introducing systematic risk alters our benchmark economy in several ways. First, it makes the lowest decile extremely crowded during "normal" periods –that is, most of the time.[19] Second, we expect that systematic risk will intensify the Darwinian selection process described previously. Recall that the drawdown status ranks funds with respect to other funds in the market. In the presence of systematic risk, large drawdown funds are specially singled out in normal times, which facilitates both the researching and identification of the talented ones among these funds.

The fourth possible deviation from our benchmark economy is related to the way in which hedge funds report to databases. First, it is well known that funds tend to enter data sets after several periods of good performance, and that this performance is backfilled. In terms of our economy, this backfilling bias will result again in the overcrowdness of the low-drawdown decile with funds that are not necessarily managed by talented traders. Second, some very successful funds cease reporting to databases when they are no longer interested in attracting investors. This may occur because the fund has reached the maximum allowed number of investors or because the manager believes that additional capital would deteriorate performance given his investment niche. In terms of empirical studies that rely on information from databases, such funds "die" (as they stop reporting) of success rather than failure. Since these successful funds most likely lie in the lowest drawdown decile they could be missed in the sequentially increasing lagged sorts. For example, if a very successful fund stops reporting one year after it hits the lowest drawdown decile, it will be picked in the one-lag sort, but not in any of the other lagged sorts. Thus, the *stop reporting process* operates in exactly the opposite direction to the Darwinian selection process, although it affects the lowest rather than the highest drawdown sorts. In terms of our predictions, if the stop reporting process is very intense, then Prediction 2 could be reversed.

[17]The Wall Street Journal, September 29, 2005, Page A18.

[18]For instance, see Leibowitz (2005) and Hasanhodzic and Lo (2007).

[19]Observe that the lowest decile will tend to be very crowded at every point in time because it picks all the funds with a good track record and a non-negative current return, without regard to how large the current return is.

We are now in a position to advance and interpret the most important results of our analysis. Using the universe of hedge funds in the HFR data set, we find that:

- On average, 72% of the funds have a drawdown equal to zero and so belong to the lowest drawdown decile. This confirms the lowest drawdown decile as an "absorbing" decile. It is explained by its own definition and is consistent with the existence of substantial systematic risk in hedge funds strategies, the backfilling bias and, more importantly, with the existence of many mimicking funds that implement either insurance-selling strategies or pure tight risk control techniques.
- The lowest drawdown status portfolio *underperforms* the highest drawdown status portfolio. This is just the opposite of what is expected in our benchmark economy. We interpret this as confirming that the lowest drawdown decile is highly contaminated by mimicking funds. Furthermore, the lowest drawdown portfolio underperforms the HFR portfolio, especially during periods of crisis. We interpret this result as corroborating a significant presence of insurance sellers in the lowest drawdown decile.
- Performance is monotonically increasing in the length of the sorting lag for the high drawdown status portfolios. This too is the opposite of what is expected in our benchmark economy. The evidence supports the existence of a strong and efficient Darwinian selection process, which is corroborated by a closer examination of the hedge funds included in the sorted portfolios.
- No clear pattern is found in the relationship between the length of the sort lag and the performance of portfolios in the lowest drawdown decile. This finding is consistent with the over-crowdedness of that decile and with the interaction between the self de-reporting process and the presence of mimicking funds.

In the next section we introduce some formal definitions and discuss the methodology employed in this paper. We also relate our work to the existing literature on hedge funds characteristics and performance.

3 Methodology and Related Literature

Our paper contributes to the literature on hedge fund characteristics and performance on two fronts. First, it introduces the drawdown status of hedge funds as a new and important characteristic related to performance. Second, from a methodological point of view, it deviates from the standard regression analysis and uses the portfolio sort methodology to identify outstanding performance.[20] We now turn to analyze these two issues in more detail.

We first define $NAV_{i,t}$ as the net asset value of hedge fund i at the end of measurement period t. We assume that all hedge funds use annual measurement periods and, consequently, $NAV_{i,t}$ corresponds to the net asset value of fund i at the end of December of year t. Then, the *drawdown* of hedge fund i at the end of year t is defined as

$$D_{i,t} \equiv 1 - \frac{NAV_{i,t}}{Max_{\tau \leq t} NAV_{i,\tau}}, \tag{1}$$

where τ applies to all years from fund i's inception date. Under this definition, $D_{i,t}$ lies in the interval $[0, 1]$. When $D_{i,t} = 0$, the fund has set a new high-water mark at the end of year t. When $D_{i,t} \neq 0$, the fund is below the high-water mark. The high-water mark clause directly links $D_{i,t}$ to the fees managers raise (and investors in the fund pay).[21] When $D_{i,t} = 0$, the manager collects incentives fees in year t both from old investors as well as new investors (year t investors) in the fund.[22] When $D_{i,t}$ is close to one, the fund ends the year very far from the high-water mark. Old investors in the fund are not paying incentive fees currently and very likely will not pay them in the near future. Hence, roughly speaking, from the investors point of view, $D_{i,t} = 0$ is associated to funds which are relatively expensive in the present and also very likely in the near future, while $D_{i,t}$ close to one is associated to funds which are cheap in the present and very likely in the near future too for old investors. Finally, notice that there is not a one to one relationship between $D_{i,t}$ and the fund return in year t. We only know that $D_{i,t} = 0$ is associated to funds whose return for the year is non-negative. But it may apply to funds whose returns are arbitrarily large or low. On the other hand $D_{i,t} \neq 0$ is consistent with positive and negative returns during year t, even when $D_{i,t}$ is very close to one.

The *drawdown status* of fund i at date t is just the decile $D_{i,t}$ belongs to in the distribution of the drawdowns of all hedge funds in the economy at date t. In this

[20]In any case, as previously stated, we also verify our results using the more conventional regression setting.

[21]In our sample, 91,6% of the funds have a high water mark clause. In the discussion that follows we implicitly assume that the fund does not have a hurdle rate. The relationship between $D_{i,t}$ and fees in the presence of a hurdle rate is very similar, with the only noticeable difference of the stronger requirement of the fund return being larger than the hurdle rate, instead of being larger than zero, in order for the manager to be able to collect the incentive fee.

[22]Strictly speaking, there is the critical case of $NAV_{i,t-1} = NAV_{i,t} = Max_{\tau \leq t}\ NAV_{i,\tau}$, for which $D_{i,t} = 0$ but the manager does not collect incentives fees, as the fund return for year t is zero.

paper we analyze the relationship between the current and past drawdown status of hedge funds and their future performance. The general treatment of this problem is complex and, definitively, beyond the scope of this paper that mainly aims to introduce the subject and present very appealing results to the academic debate. For this reason we restrict our attention to the analysis of hedge funds for which our analysis in the previous section provides sharp predictions. In particular, we focus on the analysis of hedge funds in: 1) the two extreme deciles, $d = 1$ and $d = 10$; and, 2) in the intersection of consecutive deciles. Formally, with $DS_{d,t}(T)$ we denote the set of all funds that belong to the drawdown decile d in the T consecutive years preceding and including year t. For example, $DS_{10,t}(1)$ is the set of all hedge funds in the 10^{th} drawdown decile of year t; $DS_{1,t}(3)$ is the set of all hedge funds that belong to the intersection of the 1^{st} drawdown decile of years t, $t-1$ and $t-2$; and so on. Due to data limitations, we will further restrict our analysis to the case of three lags, $T \leq 3$.

In order to test the relationship between drawdown status and performance, we adopt a portfolio sort approach. The portfolio sort approach is not new, but rather the contrary. It is the most standard and widely used approach in the literature on asset pricing anomalies.[23] In this context, the analysis starts with an assumed asset pricing model, which currently mainly consists of a four-factor specification which includes the three Fama and French (1993) factors plus a fourth momentum factor. Then portfolios of securities sorted on a variety of economic variables are tested in the context of the asset pricing model.[24] In this paper we adopt this approach to assess the outstanding performance of portfolios sorted according to hedge funds past drawdown status. To do this we assume the most widely accepted model of performance evaluation in the hedge fund literature, the Fung and Hsieh (2004) seven-factor model. This model builds on the original Sharpe's style regression model (Sharpe (1992)) and assesses performance in a risk-adjusted manner while accounting for hedge funds' investment styles and heavy use of non-linear strategies. The model exhibits a very high explanatory power.[25]

In the Fung and Hsieh (2004) seven-factor model, hedge fund excess returns are

[23] It has also been used recently for hedge fund performance analysis in Jagannathan et al. (2010).

[24] The set of sorting variables used in the literature is very large, including many accounting variables, such as accruals (Sloan (1996), profitability (Haugen and Baker (1996) and Cohen, Gompers, and Vuolteenaho (2002)), asset growth (Titman, Wei, and Xie (2004)), pension plan funding status (Franzoni and Marin (2006), and net stock issues (Daniel and Titman (2006)), and many other variables, such as the stock's past returns (Jegadeesh and Titman (1993)), etc. For a summary of the current debate on pricing anomalies and the use of the portfolio sort methodology see Fama and French (2008).

[25] See Fung and Hsieh (2001, 2004), Kosowski, Naik and Teo (2007), Fung et al. (2008), Bollen and Pool (2009) and Jagannathan et al. (2010).

regressed on the following factors: the excess return on the S&P 500 index (SNP); a small minus large factor (SizeSpr) constructed as the difference between the returns of the Wilshire Small Cap 1750 Index and the Wilshire Large Cap 750 Index; the excess returns on portfolios of lookback straddle options on currencies (FXOpt), commodities (ComOpt), and bonds (BdOpt), which are constructed to replicate the maximum possible return to trend-following strategies on their respective underlying assets; the excess return on Fama treasury bond portfolio with maturities greater than 10 years (Bd10Yr) and the excess return on the CitiGroup Corporate BBB 10+yr index less Bd10Yr (CredSpr).[26] Hence, the performance of a portfolio of hedge funds i is assessed by inspecting the "alpha" in the following model:

$$\begin{aligned} R_{i,t} = \alpha_i + \beta_{i,1} SNP_t + \beta_{i,2} SizeSpr_t + \beta_{i,3} FXOpt_t + \beta_{i,4} ComOpt_t \\ + \beta_{i,5} BdOpt_t + \beta_{i,6} Bd10Yr_t + \beta_{i,7} CredSpr_t + \epsilon_{i,t}, \end{aligned} \tag{2}$$

where $R_{i,t}$ is the excess return of portfolio i during period t.

In our empirical exercise we create both equally and value weighted portfolios that at each year t hold all the hedge funds in the corresponding $DS_{d,t-1}(T)$. More specifically, using the information available in December of year t we sort funds into deciles and then form portfolios in January of year $t+1$. This portfolios can be viewed as anticipating because the information arrives to the data providers several months after January.[27] In any case, in order to avoid suspicions on the results being driven by the use of anticipating information, in not tabulated results available from the authors upon request, we verify that none of our results change significantly when portfolios are formed at the beginning of May of each year. The reason for this is obvious. Unlike stocks, where the portfolio formation date is critical because information is impounded into prices very fast, in hedge funds shares are market at the fund's NAV. Hence, information related to the talent of the manager will only be revealed slowly over time as the NAV reflects the manager's trading skills. For this reason, the differences in performance between the January and May portfolios should be small and mainly obey to considerations such as the different

[26] Some of the factors in the original Fung and Hsieh (2004) model were not tradable. Following Sadka (2010) critique to the use of these factors, in this paper we substitute the not tradable factors with the tradable ones used in Jagannathan (2010). We have verified, however, that our results hold when using the original Fung and Hsieh (2004) factors (results are available from the authors upon request).

[27] This is the case for several reasons. First, although HFR database provides a flash update at the beginning of each month, most of the data is missing as the funds report the data later during the month. Second, managers often send corrections to data previously reported. Indeed, HFR states that data is subject to revision during the trailing four months.

lifespan of the portfolios or the asymmetric death of funds in the portfolios.[28] Once portfolios are formed, we compute the monthly returns and estimate model (2). Fung et al. (2008) extend model (2) allowing for time variation in risk exposures arising from structural breaks. We have also analyzed this modified version and have verified that all our results hold. These results are also available from the authors upon request.

Setting up performance evaluation in the context of the portfolio analysis methodology presents several advantages. First, the methodology is very versatile and allows for a rich set of variables to be tested. Furthermore, it allows to assess if hedge funds performance is outstanding in a risk-adjusted manner. It also presents some inconveniences. In particular, unlike the case of securities where the market portfolio exhibits no alpha, it turns out that the portfolio that includes all hedge funds in the HFR data set (the HFR portfolio) exhibits a strictly positive alpha. For this reason we refer to outstanding performance as an alpha above the one of the HFR portfolio. As noticed in the introduction, both methodologies suffer from an identification problem when applied to the hedge fund characteristics-performance debate. To alleviate this problem, we rely on the use of conditional sorts, in the portfolio sorts methodology, and include all controls that the literature has suggested so far, in the regression analysis. For all these reasons we strongly believe that these two approaches complement each other and must be taken into account in the analysis of hedge fund characteristics. As we will see, all our results survive both methodologies, what place drawdown status as a genuine hedge fund characteristic related to performance.

The literature on hedge funds characteristics is too large to cover in detail here. The consensus so far is that the following hedge fund characteristics are related to performance: size (Brorsen and Harri (2004), Getmansky (2005), Ammann and Moerth (2005)), age (Liang (1999), Howell (2001), Amenc and Martellini (2003)), managerial incentives measured using fee structure (Ackermann, McEnally, and Ravenscraft (1999), Liang (1999), Edwards and Caglayan (2001)) or using delta (Agarwal et al. (2009)), fund provisions (Liang (1999), Agarwal et al. (2009)), past performance (Agarwal and Naik (2000), Bares, Gibson and Gyger (2003), Baquero, Horst and Verbeek (2005), Jagannathan et al. (2010)), flows (Getmansky (2005), Agarwal et al. (2006), Fung et al. (2008)), strategy (Amenc and Martellini (2003), Brown and Goetzmann (2003)) and volatility (Schneeweis (1998), Le Moigne and Savaria (2006)).[29] In Section 8 we

[28]This would not be the case if portfolios were formed using shares of funds that trade in secondary markets. In this case, like in the case of stocks, the use of non-anticipating information at the portfolio formation date is key.

[29]See Agarwal and Naik (2005) and Gehin (2006) for a review of main findings on hedge fund char-

use all these variables as controls when assessing the relevance of drawdown status as a performance related characteristic.

4 Data and Variable Construction

4.1 Data

Data on hedge fund performance and characteristics is provided by Hedge Fund Research Inc. (HFR). HFR builds its dataset based on surveys of hedge fund managers. Funds report to HFR mainly for marketing purposes, because they are prohibited from public advertisement. HFR tracks data on hedge funds from 1992, and from 1994 onwards keeps records of hedge funds that either stop reporting or are liquidated. As of May 2010, HFR covers 10,931 hedge funds in its database.[30] All funds are classified into the "active" and "dead" funds categories. In our study, active funds are those that are reporting as of May 17, 2010. Once a fund is no longer reporting or liquidated, it is transferred to the dead funds category. Out of these 10,931 funds, 4,427 are classified as active funds, and 6,504 as dead funds.

HFR reports the monthly time series of returns, assets under management (AUM) and net asset value (NAV) of the hedge funds in its database. Monthly returns are defined as the change in net asset value during the month divided by the net asset value at the beginning of the month. Most of our analysis is performed at a monthly frequency. For this reason we drop 146 funds that report returns quarterly, 24 funds that have missing return values during reporting period and 47 funds that do not report returns at all.[31] This leaves us with 10,714 funds. We do a similar revision for assets under management. Unfortunately, 2,046 funds do not report AUM at all and 943 funds report AUM with missing or zero year-end values.[32] Dropping these funds reduces the sample to 7,725 funds. Most of the funds do not report NAVs. However, following the

acteristics. Le Moigne and Savaria (2006) compare the relative importance of thirteen hedge fund characteristics in explaining the cross-sectional variations and find that style, performance, volatility and fee structure are the most important characteristics.

[30]This figure does not include a total of 4102 funds of funds which are also covered by HFR but not included in our analysis.

[31]None of these funds reported NAV when return was not reported, so we were unable to recuperate missing returns from NAV.

[32]A total of 50 funds that have year-end AUM value set at zero (during their reporting period) are eliminated as these would create problems in the formation of portfolios, as well as in the computation of the *Flow* variable.

method employed by TASS database, we can backfill NAV values from reported return values.[33]

Along with the time series variables, HFR database reports funds characteristics. These include management fees, incentive fees, lockup period, redemption period, advance days notice, hurdle rate and high-water mark provisions. Fund characteristics are reported one-time and, consistent with prior research, in our analysis we assume that hedge funds have kept these structures unchanged through time.[34] A total of 135 hedge funds have missing information related to these fund characteristics. Dropping them reduces the sample to 7,590 funds.

Returns can be reported net of all fees, net of only management fees or gross of all fees. In our sample, 98% of the returns are reported net of all fees. Following standard practice in academic studies, we consider only funds that report returns net of all fees, which leaves us with a sample of 7,408 funds. The vast majority of the funds report returns and assets under management in US Dollars. Dropping the remaining funds that report variables in different currencies leaves us with a sample of 6,540 funds.

The fee structure of hedge funds requires further data filtering. Incentive fees are based on performance over a predefined period, which in most cases is one year. Within a few months after the period is over, the monthly return data is corrected by fund management to be reported as net of all fees. This updated data is then sent to data vendors; hence it is important to leave a lag between data download and data analysis periods.[35] Consistent with this fact, HFR states that "the trailing four months of performance are subject to revision as HFR receives updates from lagged funds".[36] On account of these two facts, we decide not to include 2010 data in our analysis.

We further restrict the sample period in order to mitigate the well known survivorship

[33]Liang (2000) provides an in-depth explanation on this issue. For the funds that do not report NAV, TASS assigns some hypothetical initial NAV and then backfills the missing NAVs from the initial NAV and return numbers. HFR does not backfill the missing NAVs.

[34]Liang (2001) argues that hedge funds seldom modify their fee structure. He shows that less than 1% of the funds in his sample changed their fee levels from 1997 to 1998, and that the change was related to poor performance during 1998 financial crisis. We perform a similar study using characteristics reported to HFR as of March 2007 and May 2010. We find that less than 1.4% (2.8%) of the funds in the sample have changed their incentive fee (management fee) structure during this period. These numbers are very low considering that the period under study embeds the recent financial crisis which had significant negative effects in hedge fund performance. Hence, we believe that assuming fund characteristics to be fixed will not have any significant effect on our analysis. Similar results hold for other fund characteristics.

[35]See Ackermann et al. (1999) for a detailed explanation.

[36]See HFR Indices Basic Methodology and FAQ available at http://www.hedgefundresearch.com/index.php?fuse=indices-faq&1285989513.

bias. The survivorship bias is the tendency to exclude failed funds in performance studies, eventually leading to incorrect results. As HFR tracks failing funds since 1994, our final sample period covers the period January 1994 to December 2009. Note that this period not only incorporates the recent financial crisis, but also represents the longest period over which hedge funds have been studied. Given this period, we require funds to have 3 lags of annual variables defined in order to be included in the study. This implicitly restricts the sample to funds with at least three consecutive years of history. Our main goal in this restriction is to keep the universe of funds across portfolios fixed. Furthermore, the requirement of a two or three year length of return history is applied in all the previous studies in the hedge funds literature.[37] This is mainly done to ensure that each fund has a long enough corrected time series for meaningful regression results. Agarwal and Naik (2005) note that multi-period sampling bias occurs because academic research requires a minimum of 24 month or 36 month returns for a fund to be included in the sample. However, Fung and Hsieh (2000) find that this bias is small with its magnitude being close to 0.6% when a 36 month minimum return history is imposed.

The final sample includes 3,540 hedge funds during the period 1994-2009 with basic fund characteristics and 3 lags of annual variables defined. Of these funds, 1,644 are active, 877 are not reporting and 1,019 are liquidated.

4.2 Variable Construction

In addition to the drawdown related variables defined and discussed before, in this paper we also use other variables either for portfolio sorting or as controls in the regression analysis. In particular, the following variables are also used in the present paper: flow, total delta, fees, gross return, age, volatility, alpha, Sharpe ratio, Calmar ratio, and Sterling ratio.

In the construction of variables, we closely follow Agarwal et al. (2009), introducing natural modifications for the new variables used in this paper. We define the *monthly dollar flow* of fund i in month t as:

$$Monthly\ dollar\ flow_{i,t} = AUM_{i,t} - AUM_{i,t-1}(1 + Return_{i,t}).$$

Annual dollar flow of fund i in year t is the sum of the monthly dollar flows during year

[37]Note that requirement of two years return history is also implicitly applied in all studies where annual variables are regressed on lagged annual variables.

t. The *flow* for a portfolio (P) in year t is the sum of the annual dollar flows of the funds in the portfolio scaled by the total AUM of the funds in the portfolio at the end of the previous year:[38]

$$Flow_{p,t} = \frac{\sum_{i \epsilon P} Annual\ dollar\ flow_{i,t}}{\sum_{i \epsilon P} AUM_{i,t-1}}.$$

Total delta is the total expected dollar change in the manager's compensation for a 1% change in NAV of the fund at the end of year. It is the summation of the delta from investors' assets (option delta) and the delta from the manager's coinvestment assuming that manager reinvests in the fund all incentive fees collected over time. The computation of deltas requires the computation of fees and gross returns simultaneously and then use of Black-Scholes option pricing formula. See Appendix A in Agarwal et al. (2009) for the details of the computation. Note that option delta of the fund is the sum of the deltas from different sets of investors, each of whom have their own exercise price depending on when they entered the fund (which determines the high-water marks that apply to each investor). Hence, the computations are derived by tracking the entry/exit of investors in the funds according to the funds net flows. Once annual fees are computed, we add back one-twelfth of this each month for the past year to deduce monthly *gross returns*, as in Agarwal and Naik (2000). *Volatility* is the standard deviation of the monthly returns of the fund for a given year. *Age* is the age of the fund at the end of the year. In our portfolio analysis, as in other studies, we focus on the intercept directly obtained from the Fung and Hsieh (2004) seven-factor regressions. We denote this intercept as *alpha* and perform comparative analysis on its value and t-statistics.[39]

We follow Kestner (1996) for the computation of the Sharpe, Calmar and Sterling ratios. *Sharpe ratio* is defined as the average monthly excess returns divided by the standard deviation of the excess returns (excess of risk free rate). To facilitate comparison with Calmar and Sterling ratios, in the construction behind Figure 1 we calculate it for

[38] An exception to this definition is used in the regression analysis. Since we are following the regressions performed in Agarwal et al. (2009) where the analysis is done on an annual basis, we use their definition of *Flow* in the regression analysis. Here, the *Flow* of fund i is defined as the net dollar flow into the fund in year t, scaled by AUM of the fund at the end of the year $t-1$:

$$Flow_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1}(1 + Return_{i,t})}{AUM_{i,t-1}}.$$

[39] An exception is done in the analysis of characteristics based portfolios reported in Figure 1. Here, to obtain results comparable with those in Agarwal et al. (2009), *Monthly alpha* is estimated from the fund-level time-series regression of excess returns on Fung and Hsieh (2004) seven factors, allowing for structural breaks, and includes both the regression intercept and the regression residuals. *Annual alpha* is the sum of the monthly alphas in a given year.

a three-year period. *Calmar ratio* is defined as the average annual return over the past three years divided by the maximum drawdown (*MaxD*) suffered over these three years:

$$Calmar_{i,t} = \frac{(Return_{i,t} + Return_{i,t-1} + Return_{i,t-2})/3}{MaxD_{i,t-2\to t}}.$$

Finally, *Sterling ratio* is defined as the average annual return over past three years divided by average annual maximum drawdown over three years and 10% is added to the denominator:

$$Sterling_{i,t} = \frac{(Return_{i,t} + Return_{i,t-1} + Return_{i,t-2})/3}{(MaxD_{i,t} + MaxD_{i,t-1} + MaxD_{i,t-2})/3 + 10\%}.$$

4.3 Summary statistics

In Table 1 we report the descriptive statistics of all variables used in the analysis. The results show that our sample shares the main properties of other samples used elsewhere, including papers that use a larger set of funds. For instance, the comparison of our summary statics and those in Agarwal et al. (2009)[40] reveals that our funds are very similar in terms of average returns, lockup period, restriction period, age, fees and volatility. We notice that the presence of the high-water mark clause is more frequent in our sample (91.6% of the funds) than in theirs (80.1% of the funds) and that hurdle rates are much less frequent in our sample (12% versus 60.8%). The three most relevant differences relate to size, flows and the incentive related variables. In particular, our funds are relatively larger ($167 millions vs. $120.6 millions of AUM on average), receive more inflows as a percentage of AUM (173% vs. 120% on average) and have a larger average managerial ownership (11.6% versus 7.1% of AUM), option delta ($174.9 millions versus $100.1 millions) and total delta ($331.4 millions versus $188.8 millions). We believe these differences do not arise from a significant different composition of funds in the samples but rather from the fact that in our sample we include the period 2003-2009. During this, mostly bullish, period many funds grow in terms of AUM, receive large inflows and experience returns that get them closer to their high-water marks, what explains the larger option and total deltas.

[Insert Table 1: Summary Statistics of HFR Filtered Data Set]

[40]This paper uses a very comprehensive data set obtained as the union of funds in the CISDM, HFR, MSCI and TASS databases.

5 Drawdown Status and Performance: Portfolio Sorts Analysis

In this section we analyze the relationship between hedge fund drawdown status and performance using the portfolio sort methodology. We study a total of 6 portfolios corresponding to the two extreme deciles, $d = 1$ and $d = 10$, for lags 1, 2 and 3. These are the portfolios that at each period $t + 1$ hold all hedge funds that belong to the corresponding sets $DS_{d,t}(T)$, for $d = 1, 10$ and $T = 1, 2, 3$. In Table 2 we collect the basic properties of the funds included in these 6 portfolios.[41]

[Insert Table 2: Main Characteristics of the 6 Drawdown Status Based Portfolios]

Table 2 already reveals some very interesting properties of drawdown based portfolios. First notice that, as conjectured in Section 2, the lowest drawdown status portfolios are over crowded. On average, during the period January 1996 to December 2009, 72% of the funds have a one-lag drawdown equal to 0. This means that on a typical year, 72% of the funds in the sample end the year setting a new historical high-water mark. In principle, this stylized fact is consistent with both the existence of a lot of talent in the hedge fund industry and the existence of a lot of mimicking funds, which as we argued in Section 2, basically consist of untalented insurance sellers and (pure) risk managers. The large figure is also explained by a lot of systematic risk in hedge funds strategies. Also as expected, funds in the lowest drawdown decile are much larger than funds in the highest drawdown decile. Furthermore, while the former attract large inflows, the latter suffer capital outflows. Even more interestingly, low drawdown status funds have a much larger total delta and charge much more money in incentives fees than funds in the highest drawdown decile, which from an incentive perspective should result in superior performance, according to the *managers incentives hypothesis* (Agarwal et al. (2009)). Finally, regarding investment styles, the largest drawdown status portfolios are relatively more populated with equity-hedge funds and relatively less populated with event driven, macro and relative value funds.

In Figures 2 and 3 we plot the cumulative net returns of value weighted and equally weighted portfolios for lags 1, 2 and 3 for the lowest drawdown decile (Figure 2) and

[41] Notice that the sample period for the portfolios is January 1996-December 2009. This is due to the requirement of having at least 200 funds in any given year in order to have meaningful portfolio sorts. By January 1996 the sample included a total of 222 funds.

the highest drawdown decile (Figure 3). For comparison purposes, we also include the cumulative net return of the HFR portfolio in both figures. As we can observe in Figure 2, the cumulative returns of the lag 1, 2 and 3 portfolios are almost indistinguishable across lags, for both the equally and value weighted portfolios. Furthermore, the HFR portfolio tends to perform slightly better than the low drawdown portfolios, specially during the last year of the sample. In conclusion, in the case of the low drawdown status portfolios and performance measured in terms of cumulative returns: 1) there is no clear pattern of improvement or deterioration in performance as we increase the sorting lag, 2) all drawdown based portfolios perform worse than the HFR portfolio. The picture that arises from Figure 3 is completely different. In the case of the highest drawdown status portfolios and when performance is measured in terms of cumulative returns: 1) performance improves as we increase the sorting lag, and 2) all drawdown based portfolios do much better than the HFR portfolio. Two more points are in order. First, the outperformance of the highest drawdown status relative to the lowest drawdown status portfolios is huge. For instance, \$1 invested in January 1996 in a low drawdown status portfolio results in a maximum portfolio value of 3.01\$ in December 2009 (investing in the one-lag equally weighted portfolio). On the other hand, \$1 invested during the same period in the high drawdown status portfolio results in maximal portfolio value of 13.71\$ (investing in the 3-lag value weighted portfolio). The final observation is that while equally weighted portfolios perform better than value weighted portfolios in the case of the lowest drawdown status portfolios, the opposite occurs in the case of the highest drawdown status portfolios. This means that while in the former case the relatively small funds in the portfolios are the best performers, in the later case the relatively larger funds are the best performers.

[Insert Figure 2: Cumulative Net Returns of the Lowest Drawdown Status Portfolios ($d = 1$)]

[Insert Figure 3: Cumulative Net Returns of the Highest Drawdown Status Portfolios ($d = 10$)]

We now assess the performance of the portfolios in terms of risk adjusted net returns. Tables 3 and 4 report the estimation results of Fung and Hsieh (2004) seven-factor model for our 6 portfolios.[42] Table 3 reports the results for the lowest three and Table 4 for the

[42] We thank David Hsieh for providing the risk factors on his web site: http://faculty.fuqua.duke.edu/ dah7/DataLibrary/TF-FAC.xls.

highest three drawdown status portfolios. The tables corroborate that all the previous conclusions reached in terms of cumulative returns hold true in the case of risk adjusted returns. In particular, Table 3 shows that in the case of the lowest drawdown status portfolios: 1) alphas are almost constant across lags and only the one associated to the 3-lag portfolio is statistically significant at the standard significance levels, and 2) all drawdown based portfolios underperform the HFR portfolio. In the case of the highest drawdown status portfolios, Table 4 shows that: 1) all the alphas of the drawdown based portfolios are significant at the 1% level; 2) alphas are increasing in the lag; and, 3) all drawdown based portfolios outperform the HFR portfolio. It is important to notice that the outstanding performance of the largest drawdown portfolios is not only statistical but also economically significant. The alphas of the drawdown based portfolios are always more than double the alphas of the HFR portfolio. In the case of the value weighted 3-lag portfolio, it is more than 6 times larger! Finally, the improvement in performance as we increase the lag is also quantitatively important. For instance, in the case of value weighted portfolios alpha more than doubles, increasing from 0.64% in the one-lag portfolio to 1.23% in the 3-lag portfolio.

[Insert Table 3: Risk-adjusted Performance of the Lowest Drawdown Status Portfolios ($d = 1$)]

[Insert Table 4: Risk-adjusted Performance of the Highest Drawdown Status Portfolios ($d = 10$)]

The previous results are remarkable for several reasons. First, the poor performance of the lowest drawdown portfolios relative to both the highest drawdown and the HFR portfolio is against the predictions of our benchmark economy and quite paradoxical when accounting for the main characteristics of the funds included in the sorts: their expensiveness and their success at raising capital (large inflows). More important, our results question the relationship between managers incentives (measured in terms of total delta) and performance proposed elsewhere. The funds in the lowest drawdown decile have the largest total delta, but they deliver the worst, rather than the best as the incentives theory suggests, relative performance! Of course, we must take this evidence with caution as the inferior performance could be explained by another hedge fund characteristic that affects negatively the performance of the funds in the lowest drawdown decile. This issue is further explored in Section 8. In any case, following the insights stated in Section 2, in the next section we explore some of the factors behind the low performance of the lowest drawdown portfolios and conclude that the evidence points at the decile being heavily populated by insurance sellers who do not have skills to deliver outstanding performance. Hence, one view is that the presence of insurance sellers is (one of) the reason(s) behind the failure of the incentives hypothesis in our exercise. Strictly speaking, the incentives hypothesis does not apply to insurance sellers. However, these are funds that tend to have a large total delta. So, its heavy presence in the lowest drawdown decile distorts the relationship between incentives and performance, as for these funds we cannot expect superior performance (despite of having high incentives when measured in terms of total delta). The second striking result is that, again contrary to what is expected in our benchmark economy, the increase in the lag when sorting from the largest drawdown decile results in an increase in performance. The evidence is, hence, in favor of the Darwinian selection process being in place. In the next section we also explore this result in more detail.

6 Dissecting the Performance of Drawdown Status Based Portfolios

In this section we explore in further detail the performance of our six portfolios to get a better understanding of the striking results obtained in Section 5. Our analysis provides evidence in favor of a heavy presence of insurance sellers in the lowest drawdown portfolios and corroborates the existence of a Darwinian selection mechanism operating among the large drawdown funds.

6.1 Assessing the Presence of Insurance Sellers: Performance in Times of Crises

In Section 2 we argued that one of the reason that can revert the predictions of the benchmark economy is the presence of low drawdown mimicking hedge funds. Among these we included the case of hedge funds pursuing insurance selling strategies. These funds are characterized by the implementation of strategies that perform well in normal market conditions, but suffer large loses in times of crisis. Hence, one way to spot their presence in the lowest drawdown portfolios consists on comparing the performance of the low drawdown portfolios in normal versus crisis times. To facilitate comparisons, we explore next the performance in normal versus times of crisis for both the lowest and highest drawdown status portfolios.

We assess performance in periods of crisis in two alternative ways. The first approach consists on directly computing the average returns of the portfolios in times of crisis. This approach provides a direct assessment of performance in terms of raw returns (returns not adjusted to risk). The second approach consists on computing the alphas in the context of the Fung and Hsieh (2004) seven-factor model including only the normal times in the analysis. The comparison of these alphas in normal times to the alphas associated to all times, which include the crisis periods, is also revealing of the performance of the portfolios during crisis, but this time in terms of risk-adjusted returns. Given that insurance sellers implement strategies that resemble the rolling over of short position on deep out of the money put options, we define crisis periods as those months in which we should expect the largest losses for these type of strategies. In the case of equity funds, these loses must be associated to very negative returns of the S&P index. They do not need to coincide with the month in which the the S&P falls, but perhaps the next few months. This is so because of two main reasons that reinforce each other. First, the fund manager may choose to hold on to the short position to avoid realizing loses in the crash month. Second, it may be the case that liquidity dries up in the options market during the crash month and managers may find difficult closing the position. Given these considerations, we define crises periods as the quarter that includes the month in which the S&P falls by more than 10% and the two months afterward. This criteria results in the following crisis quarters: August-October 1998, September-November 2002, October-December 2008 and February-April 2009. These periods coincide with well-known events: the first is related to the LTCM crisis; the second, to the "market confidence" crisis related to the Argentine default, accounting restatements after ENRON, terrorist threat to the US, etc.; the third, to the collapse of Lehman Brothers; and, the last to the further deterioration of the current financial crisis. Finally, we define as "normal" times the rest of months in our sample, January 1996-December 2009.

In Table 5 we report the results of this exercise. Panel A of Table 5 reports the average raw net returns of the portfolios during periods of crisis for the equally and value weighted portfolios associated to the highest and lowest 3-lag drawdown status portfolios. As we can observe, during periods of crisis all the lowest drawdown status portfolios do worse than the HFR portfolio. While this is also true when looking at the whole sample (including both normal and crisis periods), the underperformance is much more pronounced in crisis periods. This result is specially strong in the case of equally weighted portfolios: while these portfolios only do marginally worse than the HFR portfolio in the whole sample, they have negative alphas in crisis periods that almost double in size the one of the HFR portfolio. For instance, the average monthly loss of 0.72% of the HFR portfolio is almost half the size of the average monthly loss of 1.29% associated to the 2-lag equally weighted lowest drawdown status portfolio. These results clearly point at a heavier presence of insurers in the lowest drawdown portfolios than in the whole HFR universe. They also suggest that insurers tend to be relatively small funds. On the other hand, the opposite picture arises when looking at the performance of the highest drawdown status portfolios. These portfolios not only do better than the HFR portfolio during crisis periods, but remarkably exhibit positive returns during these periods (in all but the one-lag value weighted portfolio). For instance, while the value weighted HFR portfolio suffers an average monthly *loss* of 1.37% during crisis periods, the 3-lag highest drawdown status portfolio yields and average *gain* of 2.87%. Furthermore, the overperformance relative to the HFR portfolio is much stronger in periods of crisis than during the whole period. These results suggest a very small presence, if not the complete absence, of insurers among the funds in the largest drawdown status portfolios.

Panel B of Table 5 reports the alphas and their levels of significance of the different portfolios in normal times, that is excluding the crisis periods. To facilitate the comparisons, we also include the alphas for the whole period (including crisis periods) reported in Tables 3 and 4. The results are truly remarkable and clearly reinforce all the conclusions inferred from the examination of Panel A. As we can observe, while the lowest drawdown status portfolios always do better, in terms of risk adjusted returns, in normal times than during the whole period, the opposite happens to the highest drawdown status portfolios, whose performance is much better in the whole period than in normal times (with the only exception of the one-lag value weighted portfolio). The first observation is, again, consistent with the heavy presence of insurers among the funds in the lowest drawdown status portfolios; the second is consistent with the absence of insurers in the highest drawdown status portfolios. Notice also that the comparison of alphas in normal times versus the whole period allows us to conjecture about risk adjusted returns in times of crisis. In particular, the results reported in table B suggest that while risk adjusted returns are negative for the lowest drawdown status portfolios in times of crisis, they are positive for the highest drawdown status portfolios in such periods. Hence, our conclusion on raw returns in times of crisis (Panel A) also apply to risk adjusted returns during these periods (Panel B).

In summary, the evidence reported in Table 5 is supportive of the following three important conclusions: 1) there is a heavy presence of insurance sellers among the funds in the lowest drawdown status portfolios, 2) insurance sellers are probably absent among the funds in the highest drawdown status portfolios; and 3) very remarkable, while the highest drawdown status portfolios perform extraordinarily well in times of crisis, both in terms of raw as well as risk adjusted returns, the opposite occurs to the lowest drawdown status portfolios.

[Insert Table 5: Performance in Normal Times and in Times of Crisis]

6.2 Assessing the Stop Reporting and Darwinian Survival Processes

In Section 2 we argued that the predictions of the benchmark economy in terms of the sequential T-lags analysis could be reversed if the "stop reporting" and the "Darwinian selection" processes were very intense. In the previous section we did not find any patterns on the performance of the lowest drawdown portfolios as we increase the sorting lag. But we did find strong evidence consistent with the Darwinian selection process in the performance of the largest drawdown portfolios. In this subsection we explore these processes in more detail. A first approximation to this issue consist of computing the average number of consecutive years that a fund that stops reporting during the portfolio formation period stays in the $d = 1$ decile, and the average number of consecutive years that a fund that is liquidated during the portfolio formation period stays in the $d = 10$ decile. In Figure 4 we report the time series of these average times. Panel A of Figure 4 reveals that on average funds in the lowest drawdown decile that stop reporting during the portfolio formation period stay in the low drawdown decile for 3.09 consecutive years (that is, more than 3 years). This means that the *stop reporting process* cannot impose a clear bias in the relative performance of the lagged portfolios. In plain words, it cannot be the case that the lag 2 and 3 portfolios do better or worse than the lag 1 portfolio because the good funds that stop reporting are mechanically excluded from those portfolios. On the other hand, Panel B of Figure 4 reports that on average funds in the highest drawdown decile that liquidate in the portfolio formation period stay in the highest drawdown decile for 1.78 consecutive years (that is, less than 2 years). This number constitutes corroborating evidence for the *Darwinian selection hypothesis*. If we associate liquidating funds to funds managed by untalented traders, the fact that on average these funds survive in the highest drawdown decile for just 1.78 consecutive years imply that these funds will tend to be excluded from the portfolios as we increase the sorting lag from 1 to 3 years.

[Insert Figure 4: Stop Reporting and Liquidation of Funds in the Portfolios]

In summary, the statistics reported in Figure 4 corroborate that: 1) the stop reporting problem does not generate any explicit bias in the relative performance of the lowest drawdown portfolios as we increase the lag, and 2) the *Darwinian selection process* is, at least, one of the mechanisms that generates an improvement in the relative performance of the lowest drawdown portfolios as we increase the sorting lag.

From now until the rest of the section we concentrate on the Darwinian selection process. If the Darwinian selection mechanism is in place, then we should expect that funds that survive for several periods in the largest drawdown decile experience less outflows than funds that belong to the same decile but stop reporting. After all, according to the hypothesis, lag-3 high drawdown funds survive because (some) investors decide that it is best for them to stay than to exit and move to a new fund. We now test this prediction of the Darwinian selection hypothesis. In order not to contaminate the measurement of the flows of the liquidated funds with the flows of the liquidation month, we use 12-month lagged flows excluding the liquidation month. In Figure 5 we plot the time series of the 12-month lagged total flows to AUM of the portfolio of funds that survive in the lag-3 highest drawdown decile (surviving funds) versus the portfolio of funds in lag-3 highest decile that liquidate (liquidating funds). The figure clearly shows that surviving funds suffer much less outflows than liquidating funds. In particular, in all but three years the outflows associated to the portfolio of liquidating funds are much larger than the ones associated to surviving funds. In years such as 1998, 2000, 2002, 2004, 2006, 2008 and 2009 the differences in outflows are truly remarkable. This is clear evidence in favor of the Darwinian selection mechanism that adds to the one already reported in terms of outstanding performance of the high drawdown status portfolios.

[Insert Figure 5: Flows of Surviving vs. Liquidating funds]

Finally, we analyze managerial ownership as a final test of the Darwinian selection mechanism. In the Introduction we argued that funds in the highest drawdown status portfolio may survive because of management self-confidence rather than investors extended trust. If managerial self-confidence were the main driving force, then we should expect surviving funds to be (almost) fully owned by managers. In there we also argued that if this were the case we should expect talented managers to opt for closing the fund and start a new one. To clarify matters, we compute the time series of the the average managerial ownership of the funds in the 3-lag highest drawdown status portfolios. Managerial ownership is computed following Agarwal et al. (2009). The construction assumes that the manager starts the fund with zero ownership but from that point on reinvests in the fund all incentive fees collected over time. On the one hand, assuming a zero initial ownership may end up underestimating the true managerial stake in the fund; but, on the other hand, the assumption of full reinvestment of fees may result in an upward bias. In any case, the exercise is worthwhile undertaking. In Figure 6 we plot the time series of managerial ownership of the portfolio of funds in the 3-lag large drawdown status portfolio. As we can observe, the average managerial ownership is always below 25%; furthermore, at every point in time more than 80% of funds have a managerial ownership below 50%. These figures are clearly in favor of the Darwinian selection hypothesis as they corroborate that external investors in the fund opt to stay through hard times of large drawdowns.

[Insert Figure 6: Managerial Ownership in Surviving Funds]

7 Robustness Checks

In this subsection we explore in further detail the performance of our six drawdown based portfolios. First, we verify that our previous results also hold when analyzing the performance of the portfolios in terms of the funds' gross rather than net returns. Second, we establish robustness when controlling for economically relevant hedge fund characteristics. In particular we show that our results hold when controlling for the number of funds, size, style, and age of the funds in the portfolios. Third, we show the robustness of the results when making extreme assumptions on the returns of liquidated funds. Finally, we verify that the results are not driven by the well documented backfilling bias.

7.1 Performance in Terms of Gross Returns

In the previous section we found that the lowest drawdown status portfolios underperform the highest drawdown status portfolios. This result was derived using the funds' net return as reported by hedge fund managers. Since net returns are returns net of fees, the result can be driven by the largest fees charged by the lowest drawdown status funds. In other words, it may be the case that the under performance of the lowest drawdown portfolios may vanish when we measure performance in terms of gross, rather than net, returns. In this subsection we redo the whole analysis of the previous section but using the funds' gross returns.

Gross returns are derived from net returns using the methodology in Agarwal et al. (2009). As explained in Section 4, each fund's gross returns are derived by tracking the entry/exit of investors in the funds according to the funds inflows/outflows and taking into account the individual high-water marks that apply to each investor in the fund to derive the fees charged by the fund manager. We believe the fees estimated with this methodology constitute the best possible proxy to the actual fees charged by the fund. Consequently, in our view, gross returns are computed using a sound methodology.

Tables 6 and 7 are the equivalent to Tables 3 and 4 when using hedge funds' gross returns, instead of the funds' net returns. According to Table 6, the performance of the low-drawdown portfolios improves when measured in terms of gross returns, but still all alphas are smaller than the alpha of the HFR portfolio. Consequently, our previous result regarding the small drawdown portfolios remains valid. The outperformance of the large drawdown portfolios, both in isolation and when compared with the HFR portfolio, is confirmed in Table 7. All this means that: 1) the under-performance of the lowest drawdown status portfolios is not explained by the larger fees they charge to investors, and that 2) the over-performance, and the increasing performance in the lag, of the highest drawdown status portfolios are not driven by small fees. Hence, we conclude asserting that all the conclusions on performance obtained in Section 5 are robust to the type of returns used for performance evaluation.

[Insert Table 6: Risk-adjusted Performance of the Lowest Drawdown Status Portfolios: Gross Returns]

[Insert Table 7: Risk-adjusted Performance of the Highest Drawdown Status Portfolios: Gross Returns]

7.2 Controlling for the number of funds in the portfolios and other hedge fund characteristics (size, age and strategy)

Table 2 reveals that the lowest and largest drawdown portfolios are very different in terms of the number of funds in the portfolios and in terms of some well-known characteristics that the literature has identified as related to performance. In this subsection we investigate whether our results in the previous section are explained by these factors.

A few remarks are in order before analyzing the role played by these factors in our analysis. First, notice that the different number of hedge funds included in the portfolios can not be the explanation of our results *per se*. This is obvious when observing that the lowest drawdown portfolios not only underperform the largest drawdown ones, but also the HFR portfolio, which is the largest portfolio in terms of number of funds. In any case, in the exercises that follow we do control for the number of funds in the portfolios. Second, regarding the role played by alternative characteristics on our results, as noticed in the introduction, the finding of a hedge fund characteristic that is very important in explaining our results would definitively tone down the value of drawdown status as a hedge fund characteristic, but would not challenge the value of drawdown status analysis.

Using the portfolio sorts methodology, in the previous subsection we obtained two main results. First, we found that largest drawdown status portfolios exhibit outstanding performance and that the performance is increasing in the sorting lag. Second, we showed that the highest drawdown status portfolios outperform the lowest drawdown status portfolios. One way to test if these results are explained by an alternative characteristic consists of checking for the robustness of the results to conditional sorting. For instance, in order to check if the results are driven by size, we would verify if the results still hold true for the sub-portfolios sorted by size within each of the drawdown status categories. One of the necessary conditions for this approach is the existence of enough funds and heterogeneity in terms of the new alternative characteristic in each of the drawdown status categories. Unfortunately this is not our case. First notice that the number of funds in the largest drawdown status portfolios ranges between 29 and 109. Any sub-portfolio of these according to some characteristic would necessarily result on a meaningless portfolio due to lack of diversification. On the other hand, regarding heterogeneity, consider for instance a characteristic such as total delta. Even if we had more funds in the largest drawdown status portfolios, so that a double sort on total delta could result in meaningful portfolios, we still would have a pool of hedge funds whose total delta is not comparable to the one of the lowest drawdown status portfolios. Hence a conditional sorts exercise is just not feasible in our case. Instead we rely on a weaker test that only addresses our second finding in the previous subsection, namely, that the largest drawdown status portfolios outperform the lowest drawdown status portfolios. For this reason, the results in this section should be taken together with those in Section 8 where we can better control for alternative hedge fund characteristics.

To analyze the role played by the number of funds in the portfolios and alternative characteristics on the superior performance of the largest drawdown portfolios we compare the performance of the largest drawdown portfolios to matching portfolios in number of funds, size, strategy and age drawn from the lowest drawdown decile.[43] More specifically, we proceed as follows. First, at the end of each period t, for each lag T we sort all funds in the lowest drawdown set, $DS_{1,t}(T)$, in size quintiles and age terciles. Second, for each fund in the largest drawdown portfolio, $DS_{10,t}(T)$, we randomly draw a matching hedge fund from the corresponding $DS_{1,t}(T)$ with the same strategy and in the intersection of the quantiles to which the hedge fund characteristics belong to. For instance, suppose a fund has the following characteristics: it has \$500 million of AUM, it is an event driven fund and it is 6 years old. Then the matching fund is an event driven fund randomly chosen from those funds in the intersection of the size quintile that includes \$500 million and the age tercile that includes 6 years. We then compute the returns of this matching control portfolio, and compare its performance to the corresponding largest drawdown portfolio. Table 8 reports the performance of the matching portfolios. Comparing Table 8 and Table 3 we verify an overall improvement in the performance of the small drawdown portfolios when funds are sorted according to the characteristics of the large drawdown portfolios (matching portfolios). In the case of value weighted portfolios, the 3-lag portfolio now exhibits a significant alpha, which is larger than the alpha of the HFR portfolio; in the case of the equally weighted portfolios, all alphas remain significant but now are in line with the alpha of HFR, while before they were much lower. But, although performance improves, it still is short to explain the out-performance of the large drawdown portfolios. In particular, comparing Table 8 and Table 4, we see that the alphas of the large drawdown portfolios are close to three times bigger than the alpha of the matching portfolios. This means that the characteristics included in the present exercise only explain a small fraction of the outstanding performance of the high drawdown status portfolios. Hence, we conclude that drawdown status is a hedge fund characteristic that predicts future performance both

[43]Table 2 also shows that the lowest and largest drawdown portfolios are very different in terms of total delta. Unfortunately, we have not been able to control for this characteristic in our exercise as reasonable matching funds in terms of this characteristic do not exist in the lowest drawdown portfolios.

unconditionally and when controlling for the relevant characteristics.

[Insert Table 8: Performance Controlling for Size, Age, Strategy and the Number of Funds]

7.3 De-reporting Returns

Hedge funds stop reporting to databases for two very different reasons: success and death. *Ex ante* we should expect that the first reason is more relevant for the lowest and the second for the highest drawdown status portfolios. If this is the case, then it could be possible that the difference in performance of these two portfolios arises because we are not properly accounting for the actual returns of hedge funds when they stop reporting. Fortunately, HFR classify dead funds into the "not reporting" and "liquidated" categories.[44] Hence we can make suitable assumptions on the de-reporting returns that apply to each of these cases in order to verify if our results are driven by this phenomena. This is the approach we adopt in this subsection.

Regarding liquidated funds, following Posthuma and van der Sluis (2003) we add an extra -50% return in their last month of reporting. This is extremely conservative as inferred from the analysis of Ackermann et al (1999), Fung and Hsieh (2006) and Hodder et al. (2008). Regarding the de-reporting return for funds that stop reporting (but are not liquidated), there is not much we can do. It is true that investors in these funds probably will continue enjoying large returns, but any assumption regarding this in our analysis would be arbitrary. So, for these funds we just keep the last return provided by the manager as we did before. Tables 9 and 10 report the equivalent results to Tables 3 and 4, but when using the previous criteria for the returns of liquidated funds.

[Insert Table 9: Risk-adjusted Performance of the Lowest Drawdown Status Portfolios: Liquidated Funds Returns]

[Insert Table 10: Risk-adjusted Performance of the Highest Drawdown Status Portfolios: Liquidated Funds Returns]

[44] In the previous versions of HFR database, the information on whether a fund is "not reporting" or "liquidated" was missing for some funds and the fund was classified as "liquidated/no longer reporting". Hence some papers had developed diagnosis to classify funds into "not reporting" and "liquidated" categories. See for instance, Fung et al. (2008). But in our recent version of HFR database, this information is available for all funds, hence we do not need further diagnosis.

The comparison of Table 9 (correcting liquidated fund returns) and Table 3 (without correction) reveals that the correction severely reduces the performance of the portfolios, which implies either a heavy presence of liquidated funds in the low drawdown status portfolios or that the correction is too strong to take it seriously. Under the correction, none of the portfolios exhibit statistically significant alphas. If we ignore the lack of statistical significance, we can observe that the main qualitative properties of Table 3 remain true in Table 9, namely: all the drawdown based portfolios underperform the HFR portfolio and there is no improvement nor deterioration in performance as we increase the sorting lag. The comparison of Tables 10 and 4 also reveals a heavy presence of liquidated funds in the high drawdown status portfolios or that the correction imposed in returns is too strong. Unlike in the previous case, all alphas remain larger than the alpha of the HFR portfolio (which is not statistically significant) and all, but the one-lag portfolio, exhibit statistically significant alphas. In particular, the 3-lag value weighted portfolio has an alpha of 0.99% which is statistically significant at the 99% confidence level and almost 10 times bigger than the alpha of the HFR portfolio (not significant). Hence, we observe that Table 10 delivers the same qualitative results as Table 4, namely: all the drawdown based portfolios outperform the HFR portfolio (with the single exception of the one-lag portfolios) and performance increases as we increase the sorting lag. In summary, our results in Section 5 are not challenged at all when correcting returns to account for funds liquidation using, perhaps, a too strong criteria. Hence, the different returns of the low versus high drawdown status portfolios cannot be explained by the returns of liquidated funds.

7.4 Controlling for the Backfilling Bias

It is well known that hedge funds typically undergo an incubation period to build a good track record. Then the manager enters the fund into databases to attract new investors. The incubation period performance is backfilled at the entry date, what generates a clear bias in hedge fund performance as it is reported in databases. In order to correct the bias some of the early history of hedge funds performance must be disregarded. In general, researchers eliminate from one to two of the first years of data of hedge funds. We take a conservative approach in the present robustness check and eliminate the first two years. Tables 11 and 12 report the performance of our drawdown portfolios. Again all of our previous results remain true. Indeed, the results improve qualitatively as in this case, while the HFR portfolio stops exhibiting outstanding performance, our large drawdown based portfolios continue exhibiting positive and significant alphas.

[Insert Table 11: Risk-adjusted Performance of the Lowest Drawdown Status Portfolios: Controlling for the "Backfilling bias"]

[Insert Table 12: Risk-adjusted Performance of the Highest Drawdown Status Portfolios: Controlling for the "Backfilling bias"]

8 Drawdown Status and Performance: Regression Analysis

In this section we put our theory in the context of the more traditional regression analysis methodology. Our main reference in this section is Agarwal et al. (2009) for two reasons. First, because it provides the most comprehensive setting we are aware of for the testing of hedge funds characteristics. Second, because it analyzes throughfully managerial incentives (total delta), the only hedge fund characteristic that we could not control for in the portfolio sorts methodology.

Following Agarwal et al. (2009), we regress fund returns on a set of controls that include all the hedge characteristics identified as predictive of performance in the existing literature. To be more precise, we estimate the following regressions:

$$\begin{aligned} Return_{i,t} = {} & \alpha_0 + \alpha_1 Total\ Delta_{i,t-1} + \alpha_2 Hurdle\ Rate_i + \alpha_3 High\text{-}water\ Mark_i + \alpha_4 Lockup_i \\ & + \alpha_5 Restriction_i + \alpha_6 Size_{i,t-1} + \alpha_7 Flow_{i,t-1} + \alpha_8 Volatility_{i,t-1} + \alpha_9 Age_{i,t-1} \\ & + \alpha_{10} Management\ Fee_i + \alpha_{11} Return_{i,t-1} + \sum_{s=1}^{3} \alpha_{11+s} I\ Strategy_{i,s} + \xi_{i,t} \end{aligned} \quad (3)$$

$$\begin{aligned} Return_{i,t} = {} & \alpha_0 + \alpha_1 Option\ Delta_{i,t-1} + \alpha_2 Managerial\ Ownership_{i,t-1} + \alpha_3 Hurdle\ Rate_i \\ & + \alpha_4 high\text{-}water\ Mark_i + \alpha_5 Lockup_i + \alpha_6 Restriction_i + \alpha_7 Size_{i,t-1} + \alpha_8 Flow_{i,t-1} \\ & + \alpha_9 Volatility_{i,t-1} + \alpha_{10} Age_{i,t-1} + \alpha_{11} Management\ Fee_i + \alpha_{12} Return_{i,t-1} \\ & + \sum_{s=1}^{3} \alpha_{12+s} I\ Strategy_{i,s} + \xi_{i,t} \end{aligned} \quad (4)$$

where, $Return_{i,t}$ is the net annual return of fund i in year t; $Total\ Delta_{i,t-1}$ is the total expected dollar change in the manager's compensation for a 1% change in the fund i's NAV at the end of year t-1; $Option\ Delta_{i,t-1}$ is the manager's delta from investors' assets in fund i at the end of year t-1; $Managerial\ Ownership_{i,t-1}$ is the ratio of the manager's investment in the fund to the AUM of the fund i at the end of year t-1; $Hurdle\ Rate_i$ is an indicator variable that takes value one if fund i has a hurdle rate, and zero otherwise; $High\text{-}water\ Mark_i$ is an indicator variable that takes value one if fund i has high-water mark, and zero otherwise; $Lockup_i$ and $Restriction_i$ are, respectively, the length of the lockup and restriction periods applied by fund i; $Size_{i,t-1}$ is the natural logarithm of the AUM of fund i at the end of year t-1; $Flow_{i,t-1}$ is the total dollar flows into (or out of, if negative) fund i during year t-1, scaled by AUM of fund i at the end of year t-1; $Volatility_{i,t-1}$ is the annualized standard deviation of the monthly returns of fund i during year t-1; $Age_{i,t-1}$ is the age of fund i at the end of year t-1; $Management\ Fee_i$ is the management fee charged by fund i; $Return_{i,t-1}$ is the net annual return of fund i in year t-1; each $I\ Strategy_{i,s}$ is a dummy variable that takes value one if fund i belongs to strategy s, and zero otherwise; and $\xi_{i,t}$ is the error term.[45]

As in Agarwal et al. (2009), the analysis in the present section is performed on an annual basis. In order to avoid suspicions on our analysis being biased because of the use of a different data set and sample period to the ones in Agarwal et al. (2009), we first corroborate that their main results hold in our sample. In Table 13 we first restate Agarwal et al. (2009) estimation results (for the period 1994-2002). Columns (A) and (B) report their results using the Fama and Macbeth (1973) regression methodology (FMB) for equations (3) and (4), respectively. Column (C) collects their results after excluding the first two years of data of each fund from the analysis to control for the well-known *backfilling bias*.[46] In columns (D) to (F) we replicate the previous exercises using the HFR data set for the period 1996-2009.[47] Note that in Column (F) the significance level of managerial ownership decreases substantially and option delta even looses significance at conventional levels. Our replication supports the findings of Agarwal et al. (2009) in that: 1) both option delta and managerial ownership have a significant positive effect

[45]We have constructed all the variables using the method of Agarwal et al. (2009). For a detailed explanation on the construction of option delta and managerial ownership, see Appendix A in their paper. All variables are winsorized at the 1% level in order to limit the effect of outliers.

[46]See Table VII, row 12, in Agarwal et al. (2009). *Backfilling bias* occurs because when a fund enters the database, the database providers typically request the full performance history for that fund. Since the choice of entering database typically follows a period of good track-record, this back-filled return history tends to be upward biased. See Ackermann et al. (1999) for a detailed explanation.

[47]In order for the results to be comparable to portfolio analysis and among each other, for all regressions we fix the period at 1996-2009.

on performance; and, 2) the importance of these variables on performance deteriorates, both in terms of the size of the coefficient and its significance level, when we eliminate the first two years of data of each fund. This last observation is critical for the purposes of the present paper. The result corroborates that as hedge funds get older, variables that proxy managerial incentives loose their importance. Columns (G) and (H) in table 13 further corroborate this conjecture. Here, equations (3) and (4) are replicated using HFR filtered data set (the first three years of data of each fund are excluded from the analysis in order to define 3-lag drawdown variables). Notice that total delta looses its significance at conventional levels. Hence, it cannot be that incentives are behind our results, as these do not play a very significant role in the context of our filtered data set.

[Insert Table 13: Regressions Analysis: First Results]

Now we analyze if drawdown status is a hedge fund characteristic related to performance. We focus on equation (4) as this is the base model in Agarwal et al. (2009).[48] First of all, we re-estimate the equation after introducing $Drawdown_{i,t-1}$, which is one minus the ratio of the fund's NAV at the end of year t-1 to the maximum NAV reached over the fund's entire history, into the analysis:

$$\begin{aligned} Return_{i,t} = \alpha_0 + \alpha_1 Drawdown_{i,t-1} + \alpha_2 Option\ Delta_{i,t-1} + \alpha_3 Managerial\ Ownership_{i,t-1} \\ + \alpha_4 Hurdle\ Rate_i + \alpha_5 High\text{-}water\ Mark_i + \alpha_6 Lockup_i + \alpha_7 Restriction_i \\ + \alpha_8 Size_{i,t-1} + \alpha_9 Flow_{i,t-1} + \alpha_{10} Volatility_{i,t-1} + \alpha_{11} Age_{i,t-1} \\ + \alpha_{12} Management\ Fee_i + \alpha_{13} Return_{i,t-1} + \sum_{s=1}^{3} \alpha_{13+s} I\ Strategy_{i,s} + \xi_{i,t}. \end{aligned} \quad (5)$$

We report the results of the FMB regression in Table 14 Column (A). Note that drawdown variable is not only highly significant and positively related to performance, but also decreases the effect and significance of option delta and managerial ownership.

Next, we want to analyze how funds in our portfolios perform in regression analysis. For this, we define two indicator variables: $Low\ Drawdown_{i,t-1}$ that takes value one if fund i has been in the lowest decile in the last three years (from t-1 to t-3), and zero otherwise; and $High\ Drawdown_{i,t-1}$ that takes value one if fund i has been in the highest decile in the last three years, and zero otherwise. Then we estimate equation (4), but

[48]Our equation (4) is referred as the base model (Model 2) in Agarwal et al. (2009) as it includes all available proxies for managerial incentives: manager's option delta, managerial ownership, hurdle rate, and high-water mark.

this time including the *Low Drawdown* and *High Drawdown* variables. More specifically, we estimate the following regression:

$$\begin{aligned}
Return_{i,t} = \alpha_0 + \alpha_1 Low\ Drawdown_{i,t-1} + \alpha_2 High\ Drawdown_{i,t-1} + \alpha_3 Option\ Delta_{i,t-1} \\
+\alpha_4 Managerial\ Ownership_{i,t-1} + \alpha_5 Hurdle\ Rate_i + \alpha_6 high\text{-}water\ Mark_i \\
+\alpha_7 Lockup_i + \alpha_8 Restriction_i + \alpha_9 Size_{i,t-1} + \alpha_{10} Flow_{i,t-1} \\
+\alpha_{11} Volatility_{i,t-1} + \alpha_{12} Age_{i,t-1} + \alpha_{13} Management\ Fee_i \\
+\alpha_{14} Return_{i,t-1} + \sum_{s=1}^{3} \alpha_{14+s} I\ Strategy_{i,s} + \sum_{s=1}^{13} \alpha_{17+s} I\ Year_{i,s} + \xi_{i,t} \quad (6)
\end{aligned}$$

In Table 14 Column (B), we report the results of this FMB estimation.[49] The variable *High Drawdown* has a significant positive effect on performance whereas *Low Drawdown* does not have a significant effect. In the remaining columns, we report the results of the ordinary least squares (OLS) estimation of these equations under different alternative specifications.[50] In Column (C) we report results from OLS estimation of equation (5). Notice that here drawdown has a much stronger effect. Further, the effect of proxies of managerial incentives decrease significantly. In particular, option delta has a significant negative coefficient. This result seriously questions the relationship between incentives and performance. Indeed, according to the incentives theory it should be positive and significant. The negative sign is indeed consistent with our drawdown based theory of performance. Funds with large (small) option delta are funds that tend to be close to (far from) their high-water mark. That is, they tend to be funds in the low (high) drawdown decile. Many of them are just insurance sellers (surviving talented managers). Our analysis suggests that these should exhibit poor (outstanding) performance. Hence, the negative sign of option delta is consistent with our theory and inconsistent with the incentives theory.

In Column (D) we include the two new variables simultaneously in OLS regression, while in Columns (E) and (F) we include them separately. As we can observe, the *High Drawdown* variable always has a highly significant positive coefficient.

In summary, the results derived in this section clearly establish that drawdown status

[49] Since the number of funds in high drawdown decile portfolios are very few for first three years, we exclude these years from FMB regression and use a sample period of 1999-2009 to get meaningful results.

[50] We focus on pooled OLS regressions because the Fama and MacBeth (1973) regressions deliver very low R^2. In return, year dummies are included in OLS regressions. As in Agarwal et al. (2009), the OLS methodology delivers the strongest results.

is a genuine hedge fund characteristic related to performance. These results together with those derived in the portfolio sorts methodology further corroborate that drawdown status is also a very relevant characteristic in quantitative terms. Finally, we reiterate that our analysis severely questions the role played by incentives in hedge funds' performance.

[Insert Table 14: Regression Analysis: Drawdown Variables]

9 Concluding Remarks

This paper introduces drawdown status analysis as a new way of thinking about hedge fund performance. The analysis combines hedge fund management meritocracy with investors revealed preferences and results in drawdown status as a key hedge fund characteristic related to performance.

The analysis delivers four, we believe, completely new insights on hedge funds. First, the presence of insurance selling in the industry is large enough to make portfolios of low drawdown funds weak performers in general and bad performers in times of turmoil. Second, the market operates a Darwinian selection process according to which funds running large drawdowns for a prolonged period of time are managed by truly talented traders who deliver outstanding future performance. Third, a completely new dimension of risk arises as a distinctive feature of hedge funds: risk conditional on survival is tantamount to outstanding performance. Fourth, drawdown status analysis raises serious concerns about the role played by other hedge fund characteristics –such as total delta– on fund performance and cast doubt on the validity of some performance evaluation measures –such as the Calmar and Sterling ratios– that are widely used in practice.

As a premier on drawdown status analysis, this paper leaves many issues unaddressed. First, our analysis focuses only on the analysis of the two extreme drawdown deciles; naturally, a more comprehensive analysis is a fruitful topic for future research. In particular, the analysis of the portfolio of funds that after hitting the largest drawdown decile survive, irrespectively of whether they stay in the largest drawdown decile (analyzed here) or move to lower deciles (not analyzed here) deserves special attention as it fits closer the Darwinian dichotomy between death and survival. Second, we believe that much could be learned by comparing the role played by drawdown status in hedge funds versus mutual funds. Some of our results here depend critically on the high-water mark clause, which is ubiquitous in the hedge fund industry but nearly absent in the world of mutual funds; hence, mutual funds are a good control group for testing our hypothesis. This also seems to be a good venue for future research. Third, the present analysis is short to fully account for the seemingly paradoxical situation of an investment community sophisticated enough to sort talented managers among those suffering large drawdowns, but naive when investing in low drawdown funds. Finally, we open but do not address the debate on the Darwinian mechanism operating in other markets. In particular, we suggest that it can have some bearing on the anomalous pricing of distress stocks. The analysis of these two last issues is also a top priority in our research agenda.

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Table 1: Summary Statistics of HFR Filtered Data Set

This table reports the summary statistics of HFR filtered data set. The sample period is 1994-2009. *Returns* are the annual returns of the fund net of all fees. *Gross returns* are the annual gross returns of the fund derived from net returns after taking into consideration fees, inflows and fund provisions. *Drawdown* is one minus the ratio of the fund's net asset value (NAV) to its maximum reached over the fund's entire history. *Total delta* is the total expected dollar change in the manager's compensation for a 1% change in the fund's NAV. *Option delta* is the manager's delta from investors' assets in the fund. *Managerial ownership* is the ratio of the manager's investment in the fund to the AUM of the fund. *Hurdle rate* is a provision that allows the manager to collect incentive fees only above a pre-specified rate of return. *High-water mark* is a provision that allows the manager to collect incentive fees only after recovering all past losses if they exist. In the table, we report the percentage of funds that have *hurdle rate* and *high-water mark* provisions. *Lockup period* is the pre-specified period of time that an investor cannot redeem her shares after investing in the fund. We report its statistics for the subsample of funds that impose lockup period. *Restriction period* is given by the sum of the *advanced days notice* and *redemption period*, where *advanced days notice* is the pre-specified period of time that the investor must notify the fund's managers of her intent to withdraw money and *redemption period* is the time she has to wait to get her money after advanced days notice is over. *Flow* is the net dollar flows into (or out of, if negative) the fund during the year, scaled by AUM of the fund at the end of the year. *Volatility* is the annualized standard deviation of the monthly returns of the fund during the year. *Age* is the age of the fund in years. *Management fee* is the percentage of fund's net AUM that is paid annually to the fund management for administering the fund. *Incentive fee* is the percentage of annual profits captured by the fund management in reward for positive performance and is defined over some benchmark or high-water mark.

Fund Characteristics	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
Returns (% per year)	12.9	34.5	1.4	9.7	20.4
Gross returns (% per year)	15.9	41.7	1.7	11.5	24.4
Drawdown (% per year)	5.3	13.0	0.0	0.0	2.1
Total delta ($'000)	331.4	1064.7	15.3	65.9	245.1
Option delta ($'000)	174.9	563.2	5.8	31.9	125.6
Managerial ownership (% of AUM)	11.6	19.6	1.6	4.8	11.8
Hurdle rate (% of funds)	12.0				
High watermark (% of funds)	91.6				
Lockup period (years)	1.0	0.5	1.0	1.0	1.0
Restriction period (years)	0.3	0.3	0.2	0.3	0.4
Flow (%)	173.2	8935.8	-17.0	4.6	53.5
AUM ($M)	167.0	481.6	11.1	39.3	130.0
Volatility (%)	3.8	3.5	1.6	2.9	4.9
Age (years)	5.5	3.9	2.7	4.5	7.3
Management fee (%)	1.5	0.7	1.0	1.5	2.0
Incentive fee (%)	19.1	5.0	20.0	20.0	20.0

Table 2: Main Characteristics of the 6 Drawdown Status Based Portfolios

This table reports the main characteristics of the six drawdown status based portfolios. The sample period is January 1996-December 2009. At the end of each year t, we sort the drawdown of funds into ten deciles. Lowest drawdown status (DS) Lag 1 portfolio is the the set of all hedge funds in the 1^{st} drawdown decile of year $t-1$. Highest drawdown status Lag 1 portfolio is the the set of all hedge funds in the 10^{th} drawdown decile of year $t-1$. Lag 2 portfolios are the set of all hedge funds that belong to the intersection of the corresponding drawdown decile of years $t-1$ and $t-2$. Lag 3 portfolios are the set of all hedge funds that belong to the intersection of the corresponding drawdown decile of years $t-1$, $t-2$ and $t-3$. *Number of funds* is the total number of funds in the portfolio at the beginning of formation period. *Annual dollar flow* is the annualized net dollar flows into (or out of, if negative) the funds in the portfolio during the year. See Table 1 for the definition of variables. Regarding number of funds and AUM, we report their percentages over corresponding HFR portfolio values in parenthesis. The percentages reported in parenthesis for dollar flow, total delta, option delta, manager delta and incentive fees are defined over their portfolio values. To facilitate comparison, we report the averages of the all variables over 14 years. All numbers are rounded to the nearest integer (for precision, numbers that are less than one percent are are rounded to the first decimal in percentage).

	Lowest DS Portfolios			**Highest DS Portfolios**			**HFR**
	Lag 1	Lag 2	Lag 3	Lag 1	Lag 2	Lag 3	
Number of funds	752	648	567	109	51	29	1089
	(72%)	(61%)	(53%)	(10%)	(5%)	(3%)	(100%)
AUM ($M)	164,081	151,871	140,907	8,269	2,008	775	211,212
	(80%)	(71%)	(64%)	(5%)	(2%)	(0.4%)	(100%)
Annual dollar flow ($M)	17,011	18,849	17,362	-1,182	-754	-194	11,164
	(12%)	(17%)	(18%)	(-10%)	(-24%)	(-16%)	(7%)
Total delta ($M)	359	331	305	14	4	2	431
	(0.3%)	(0.3%)	(0.3%)	(0.1%)	(0.1%)	(0.2%)	(0.2%)
Option delta ($M)	196	184	173	4	1	0.4	222
	(0.1%)	(0.2%)	(0.2%)	(0.0%)	(0.0%)	(0.0%)	(0.1%)
Manager delta ($M)	163	147	133	10	3	1	209
	(0.1%)	(0.1%)	(0.1%)	(0.1%)	(0.1%)	(0.1%)	(0.1%)
Incentive fees ($M)	3,521	3,210	2,953	12	11	6	3,546
	(3%)	(3%)	(3%)	(0.2%)	(0.6%)	(1%)	(2%)
Mean age (years)	6.3	6.3	6.1	6.6	6.9	7.3	6.4
Mean lockup period (years)	0.3	0.3	0.3	0.3	0.4	0.4	0.3
Mean restriction period (years)	0.3	0.3	0.3	0.3	0.3	0.3	0.3

Table 3: Risk-adjusted Performance of the Lowest Drawdown Status Portfolios ($d = 1$)

This table reports OLS coefficient estimates when excess returns of the lowest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors. The sample period is January 1996-December 2009. See Table 2 for the description of portfolio formation. Factors are described in the text. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.13	0.13	0.12	0.18*	0.23**	0.22**	0.22**	0.34***
	(1.18)	(1.19)	(1.22)	(1.82)	(2.16)	(2.14)	(2.31)	(3.77)
SNP	0.18***	0.16***	0.15***	0.21***	0.22***	0.21***	0.20***	0.29***
	(5.22)	(5.12)	(5.09)	(7.05)	(7.12)	(7.22)	(7.34)	(11.75)
SizeSpr	0.13***	0.13***	0.14***	0.14***	0.19***	0.19***	0.18***	0.22***
	(2.86)	(2.77)	(3.11)	(4.03)	(4.06)	(4.23)	(4.22)	(6.54)
FXOpt	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01*
	(1.30)	(1.37)	(1.03)	(1.35)	(1.25)	(1.20)	(0.78)	(1.69)
ComOpt	0.01*	0.01*	0.01	0.01	0.02**	0.02*	0.01*	0.01*
	(1.83)	(1.67)	(1.41)	(1.59)	(2.19)	(1.93)	(1.84)	(1.75)
BdOpt	-0.02*	-0.02*	-0.02*	-0.02*	-0.01	-0.01	-0.01	-0.00
	(-1.78)	(-1.72)	(-1.67)	(-1.68)	(-1.19)	(-1.12)	(-0.93)	(-0.08)
Bd10Yr	0.09*	0.09*	0.08*	0.08*	0.10**	0.10**	0.09*	0.06
	(1.93)	(1.83)	(1.71)	(1.88)	(2.09)	(2.00)	(1.82)	(1.64)
CredSpr	0.13	0.15	0.14	0.17**	0.11	0.13	0.12	0.16**
	(1.41)	(1.62)	(1.64)	(2.47)	(1.14)	(1.39)	(1.32)	(2.38)
Adjusted R^2	41.8%	42.4%	44.3%	56.2%	49.9%	51.6%	51.6%	69.3%
Number of obs.	168	168	168	168	168	168	168	168

Table 4: Risk-adjusted Performance of the Highest Drawdown Status Portfolios ($d = 10$)

This table reports OLS coefficient estimates when excess returns of the highest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors. The sample period is January 1996-December 2009. See Table 2 for the description of portfolio formation. Factors are described in the text. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.64**	1.01***	1.23***	0.18*	0.80***	1.05***	1.10***	0.34***
	(2.48)	(3.89)	(3.35)	(1.82)	(3.40)	(4.13)	(3.32)	(3.77)
SNP	0.54***	0.59***	0.47***	0.21***	0.61***	0.60***	0.49***	0.29***
	(7.87)	(9.03)	(4.88)	(7.05)	(10.37)	(9.02)	(6.47)	(11.75)
SizeSpr	0.25***	0.38***	0.48***	0.14***	0.35***	0.46***	0.81***	0.22***
	(3.01)	(4.21)	(4.29)	(4.03)	(4.64)	(4.87)	(6.54)	(6.54)
FXOpt	0.01	0.02	0.03	0.01	0.02	0.02	0.03	0.01*
	(0.50)	(1.11)	(1.65)	(1.35)	(1.28)	(1.29)	(1.26)	(1.69)
ComOpt	-0.02	0.01	0.01	0.01	-0.01	0.01	0.00	0.01*
	(-1.04)	(0.42)	(0.55)	(1.59)	(-0.65)	(0.54)	(0.06)	(1.75)
BdOpt	0.01	0.02	0.02	-0.02*	0.04**	0.03	0.03	-0.00
	(0.68)	(1.01)	(0.60)	(-1.68)	(2.33)	(1.62)	(1.16)	(-0.08)
Bd10Yr	-0.08	-0.11	-0.12	0.08*	-0.15	-0.16	-0.06	0.06
	(-0.78)	(-0.91)	(-0.69)	(1.88)	(-1.57)	(-1.46)	(-0.47)	(1.64)
CredSpr	0.20	-0.11	0.01	0.17**	0.21	0.05	0.10	0.16**
	(1.20)	(-0.70)	(0.06)	(2.47)	(1.21)	(0.32)	(0.46)	(2.38)
Adjusted R^2	47.5%	44.6%	25.2%	56.2%	57.6%	53.1%	44.2%	69.3%
Number of obs.	168	168	168	168	168	168	168	168

Table 5: Performance in Normal Times and in Times of Crisis

Panel A of this table reports the mean monthly raw returns of the portfolios during periods of crisis for the drawdown based portfolios. The periods of crisis are: August-October 1998, September-November 2002, October-December 2008, February-April 2009. Panel B reports OLS intercepts when excess returns of drawdown based portfolios are regressed on Fung and Hsieh (2004) seven factors, excluding the periods of crisis. In explanation, the sample period is January 1996-December 2009; but excluding periods of crisis from the regression. See Table 2 for the description of portfolio formation. Factors are described in the text. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

Panel A: Performance in Times of Crisis (Mean Returns in %)

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Lowest DS Portfolios								
in times of crisis	-1.58	-1.58	-1.54	-1.37	-1.21	-1.29	-1.17	-0.72
in the whole period	0.57	0.55	0.54	0.63	0.68	0.66	0.65	0.79
Highest DS Portfolios								
in times of crisis	-0.54	1.59	2.87	-1.37	0.70	1.17	1.88	-0.72
in the whole period	1.11	1.49	1.71	0.63	1.24	1.53	1.65	0.79

Panel B: Performance in Normal Times (Regression Coefficients)

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Lowest DS Portfolios								
in normal times	0.27***	0.26***	0.26***	0.30***	0.33***	0.32***	0.32***	0.40***
in the whole period	0.13	0.13	0.12	0.18*	0.23**	0.22**	0.22**	0.34***
Highest DS Portfolios								
in normal times	0.68***	0.88***	1.03***	0.30***	0.72***	0.95***	0.92***	0.40***
in the whole period	0.64**	1.01***	1.23***	0.18*	0.80***	1.05***	1.10***	0.34***

Table 6: Risk-adjusted Performance of the Lowest Drawdown Status Portfolios: Gross Returns

This table reports OLS coefficient estimates when excess gross returns of the lowest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors. The sample period is January 1996-December 2009. See Table 2 for the description of portfolio formation. Factors are described in the text. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.31***	0.30***	0.29***	0.35***	0.43***	0.41***	0.41***	0.53***
	(2.75)	(2.80)	(2.88)	(3.43)	(3.99)	(3.99)	(4.20)	(5.71)
SNP	0.18***	0.17***	0.15***	0.21***	0.23***	0.21***	0.21***	0.29***
	(5.28)	(5.17)	(5.14)	(7.08)	(7.21)	(7.31)	(7.44)	(11.79)
SizeSpr	0.13***	0.13***	0.14***	0.14***	0.19***	0.19***	0.18***	0.22***
	(2.82)	(2.74)	(3.08)	(3.98)	(4.00)	(4.17)	(4.15)	(6.42)
FXOpt	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01
	(1.25)	(1.34)	(0.99)	(1.31)	(1.19)	(1.14)	(0.72)	(1.63)
ComOpt	0.01*	0.01*	0.01	0.01	0.02**	0.02**	0.01*	0.01*
	(1.88)	(1.72)	(1.45)	(1.64)	(2.28)	(2.01)	(1.91)	(1.82)
BdOpt	-0.02*	-0.02*	-0.02*	-0.02*	-0.01	-0.01	-0.01	-0.00
	(-1.76)	(-1.72)	(-1.67)	(-1.67)	(-1.09)	(-1.04)	(-0.85)	(-0.01)
Bd10Yr	0.09*	0.08*	0.07	0.07*	0.09*	0.09*	0.08*	0.06
	(1.80)	(1.73)	(1.60)	(1.75)	(1.90)	(1.82)	(1.65)	(1.45)
CredSpr	0.13	0.15	0.14	0.17**	0.10	0.13	0.12	0.16**
	(1.40)	(1.62)	(1.64)	(2.45)	(1.09)	(1.35)	(1.27)	(2.32)
Adjusted R^2	41.6%	42.3%	44.2%	55.9%	49.3%	51.0%	51.0%	68.7%
Number of obs.	168	168	168	168	168	168	168	168

Table 7: Risk-adjusted Performance of the Highest Drawdown Status Portfolios: Gross Returns

This table reports OLS coefficient estimates when excess gross returns of the highest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors. The sample period is January 1996-December 2009. See Table 2 for the description of portfolio formation. Factors are described in the text. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.76***	1.15***	1.43***	0.35***	0.94***	1.24***	1.32***	0.53***
	(2.93)	(4.42)	(3.73)	(3.43)	(3.96)	(4.80)	(3.92)	(5.71)
SNP	0.54***	0.59***	0.47***	0.21***	0.61***	0.60***	0.49***	0.29***
	(7.80)	(9.06)	(4.77)	(7.08)	(10.20)	(8.93)	(6.36)	(11.79)
SizeSpr	0.25***	0.38***	0.48***	0.14***	0.35***	0.46***	0.81***	0.22***
	(3.00)	(4.23)	(4.28)	(3.98)	(4.60)	(4.86)	(6.51)	(6.42)
FXOpt	0.01	0.02	0.03	0.01	0.02	0.02	0.03	0.01
	(0.49)	(1.11)	(1.61)	(1.31)	(1.26)	(1.24)	(1.21)	(1.63)
ComOpt	-0.02	0.01	0.01	0.01	-0.01	0.01	0.00	0.01*
	(-1.00)	(0.44)	(0.55)	(1.64)	(-0.61)	(0.60)	(0.13)	(1.82)
BdOpt	0.01	0.02	0.02	-0.02*	0.04**	0.03*	0.03	-0.00
	(0.69)	(1.05)	(0.67)	(-1.67)	(2.34)	(1.71)	(1.26)	(-0.01)
Bd10Yr	-0.08	-0.11	-0.12	0.07*	-0.15	-0.17	-0.08	0.06
	(-0.80)	(-0.91)	(-0.72)	(1.75)	(-1.60)	(-1.52)	(-0.58)	(1.45)
CredSpr	0.21	-0.11	0.03	0.17**	0.21	0.06	0.10	0.16**
	(1.23)	(-0.68)	(0.13)	(2.45)	(1.24)	(0.34)	(0.47)	(2.32)
Adjusted R^2	47.4%	44.6%	24.9%	55.9%	57.2%	52.6%	43.6%	68.7%
Number of obs.	168	168	168	168	168	168	168	168

Table 8: Performance Controlling for Size, Age, Strategy and the Number of Funds

This table reports OLS coefficient estimates when excess returns of the matching portfolios are regressed on Fung and Hsieh (2004) seven factors. The sample period is January 1996-December 2009. Matching portfolios are created as follows. First, at the end of each period t, we sort all funds in the lowest drawdown set, into quintiles according to size and into terciles according to age. Second, for each fund in the largest decile portfolio, we randomly draw a matching hedge fund from the lowest decile portfolio with the same strategy and in the intersection of the corresponding quantiles in which hedge fund characteristics belong to. Factors are described in the text. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.26	0.24	0.48**	0.18*	0.34***	0.31**	0.34*	0.34***
	(1.45)	(1.36)	(2.10)	(1.82)	(2.67)	(2.34)	(1.75)	(3.77)
SNP	0.26***	0.30***	0.37***	0.21***	0.32***	0.34***	0.45***	0.29***
	(4.95)	(5.85)	(5.73)	(7.05)	(8.29)	(7.69)	(7.48)	(11.75)
SizeSpr	0.26***	0.27***	0.14**	0.14***	0.23***	0.30***	0.19***	0.22***
	(5.24)	(3.52)	(2.02)	(4.03)	(5.11)	(5.39)	(3.20)	(6.54)
FXOpt	0.02**	0.01	0.02	0.01	0.01*	0.01*	0.00	0.01*
	(2.47)	(0.84)	(1.32)	(1.35)	(1.75)	(1.87)	(0.37)	(1.69)
ComOpt	-0.00	0.03**	0.02	0.01	0.00	0.01	0.02	0.01*
	(-0.36)	(2.53)	(1.33)	(1.59)	(0.24)	(1.17)	(1.29)	(1.75)
BdOpt	-0.03	-0.01	-0.02	-0.02*	-0.01	-0.01	-0.02	-0.00
	(-1.29)	(-0.94)	(-0.81)	(-1.68)	(-0.74)	(-0.82)	(-0.89)	(-0.08)
Bd10Yr	0.08	0.17**	0.08	0.08*	0.07	0.06	0.02	0.06
	(1.49)	(2.45)	(1.01)	(1.88)	(1.31)	(1.38)	(0.31)	(1.64)
CredSpr	0.05	0.13	0.03	0.17**	0.08	-0.03	-0.03	0.16**
	(0.51)	(1.02)	(0.22)	(2.47)	(0.90)	(-0.31)	(-0.27)	(2.38)
Adjusted R^2	41.3%	39.4%	31.8%	56.2%	55.4%	54.9%	46.3%	69.3%
Number of obs.	168	168	168	168	168	168	168	168

Table 9: Risk-adjusted Performance of the Lowest Drawdown Status Portfolios: Liquidated Funds Returns

This table reports OLS coefficient estimates when excess returns of the lowest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors after correcting for liquidated funds returns. Returns are corrected in the sense that for the funds that are liquidated, we respectively add an extra negative return of 50% in their last month of reporting. The sample period is January 1996-December 2009. See Table 2 for the description of portfolio formation. Factors are described in the text. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.07	0.07	0.06	0.10	0.05	0.04	0.04	0.11
	(0.65)	(0.62)	(0.63)	(1.03)	(0.44)	(0.35)	(0.43)	(1.17)
SNP	0.18***	0.17***	0.16***	0.21***	0.23***	0.22***	0.21***	0.29***
	(5.51)	(5.46)	(5.51)	(7.23)	(7.06)	(7.19)	(7.34)	(11.83)
SizeSpr	0.13***	0.13***	0.14***	0.14***	0.18***	0.19***	0.18***	0.21***
	(2.82)	(2.74)	(3.08)	(3.80)	(3.73)	(3.96)	(3.95)	(5.96)
FXOpt	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01
	(1.18)	(1.26)	(0.91)	(1.25)	(0.92)	(0.87)	(0.48)	(1.27)
ComOpt	0.01*	0.01*	0.01	0.01	0.02**	0.02*	0.02*	0.01*
	(1.83)	(1.67)	(1.42)	(1.57)	(2.17)	(1.92)	(1.86)	(1.74)
BdOpt	-0.02*	-0.02*	-0.02*	-0.02*	-0.01	-0.01	-0.01	-0.00
	(-1.94)	(-1.91)	(-1.89)	(-1.80)	(-1.41)	(-1.46)	(-1.32)	(-0.23)
Bd10Yr	0.09*	0.08	0.08	0.07	0.10*	0.10*	0.09	0.06
	(1.73)	(1.63)	(1.51)	(1.63)	(1.76)	(1.73)	(1.54)	(1.24)
CredSpr	0.12	0.13	0.13	0.16**	0.10	0.12	0.11	0.15**
	(1.29)	(1.49)	(1.49)	(2.28)	(0.96)	(1.19)	(1.08)	(2.00)
Adjusted R^2	41.5%	42.2%	44.0%	55.2%	47.3%	49.4%	49.1%	67.3%
Number of obs.	168	168	168	168	168	168	168	168

Table 10: Risk-adjusted Performance of the Highest Drawdown Status Portfolios: Liquidated Funds Returns

This table reports OLS coefficient estimates when excess returns of the highest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors after correcting for liquidated funds returns. Returns are corrected in the sense that for the funds that are liquidated, we respectively add an extra negative return of 50% in their last month of reporting. The sample period is January 1996-December 2009. See Table 2 for the description of portfolio formation. Factors are described in the text. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.27	0.56*	0.99***	0.10	0.33	0.66**	0.73**	0.11
	(1.02)	(1.87)	(2.69)	(1.03)	(1.42)	(2.55)	(2.16)	(1.17)
SNP	0.57***	0.64***	0.48***	0.21***	0.63***	0.60***	0.52***	0.29***
	(8.24)	(6.99)	(4.94)	(7.23)	(11.06)	(8.59)	(6.79)	(11.83)
SizeSpr	0.24***	0.39***	0.49***	0.14***	0.35***	0.46***	0.81***	0.21***
	(2.81)	(4.30)	(4.39)	(3.80)	(4.62)	(4.69)	(6.28)	(5.96)
FXOpt	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.01
	(0.50)	(0.96)	(1.07)	(1.25)	(1.01)	(1.28)	(0.86)	(1.27)
ComOpt	-0.01	0.01	0.01	0.01	-0.01	0.01	-0.00	0.01*
	(-0.89)	(0.48)	(0.66)	(1.57)	(-0.53)	(0.41)	(-0.02)	(1.74)
BdOpt	0.01	0.03	0.02	-0.02*	0.04**	0.03*	0.03	-0.00
	(0.51)	(1.42)	(0.80)	(-1.80)	(2.08)	(1.83)	(1.22)	(-0.23)
Bd10Yr	-0.07	-0.09	-0.05	0.07	-0.16	-0.15	-0.06	0.06
	(-0.66)	(-0.73)	(-0.29)	(1.63)	(-1.59)	(-1.29)	(-0.40)	(1.24)
CredSpr	0.23	-0.05	0.13	0.16**	0.21	0.13	0.13	0.15**
	(1.34)	(-0.32)	(0.62)	(2.28)	(1.25)	(0.85)	(0.62)	(2.00)
Adjusted R^2	48.0%	41.3%	28.4%	55.2%	59.3%	53.8%	44.8%	67.3%
Number of obs.	168	168	168	168	168	168	168	168

Table 11: Risk-adjusted Performance of the Lowest Drawdown Status Portfolios: Controlling for the "Backfilling Bias"

This table reports OLS coefficient estimates when excess returns of the lowest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors after controlling for the backfilling bias. The sample period is January 1996-December 2009. The first 24 months data of each fund is eliminated in order to control for backfilling bias. See Table 2 for the description of portfolio formation. Factors are described in the text. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.11	0.13	0.12	0.16	0.23**	0.24**	0.23**	0.35**
	(1.03)	(1.26)	(1.21)	(1.57)	(2.07)	(2.29)	(2.25)	(3.62)
SNP	0.19***	0.18***	0.17***	0.22***	0.22***	0.21***	0.20***	0.28***
	(5.87)	(5.85)	(5.99)	(7.48)	(6.89)	(7.22)	(7.38)	(11.46)
SizeSpr	0.14***	0.13***	0.15***	0.16***	0.18***	0.18***	0.18***	0.22***
	(3.16)	(3.05)	(3.72)	(4.28)	(3.89)	(4.12)	(4.14)	(6.61)
FXOpt	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01*
	(1.37)	(1.48)	(1.08)	(1.43)	(1.48)	(1.50)	(1.17)	(1.95)
ComOpt	0.01	0.01	0.01	0.01	0.02**	0.02**	0.02*	0.02**
	(1.61)	(1.41)	(1.15)	(1.50)	(2.29)	(1.97)	(1.89)	(1.98)
BdOpt	-0.01	-0.01	-0.01	-0.01	-0.00	-0.00	-0.00	0.00
	(-1.40)	(-1.33)	(-1.28)	(-1.55)	(-0.48)	(-0.21)	(-0.29)	(0.40)
Bd10Yr	0.09*	0.08*	0.07	0.08*	0.13**	0.12**	0.11**	0.09**
	(1.83)	(1.68)	(1.51)	(1.83)	(2.31)	(2.19)	(2.01)	(2.06)
CredSpr	0.12	0.14	0.12	0.18**	0.13	0.16	0.15	0.18**
	(1.36)	(1.50)	(1.40)	(2.53)	(1.31)	(1.61)	(1.57)	(2.52)
Adjusted R^2	43.8%	43.4%	45.9%	58.2%	47.1%	48.7%	49.0%	67.5%
Number of obs.	168	168	168	168	168	168	168	168

Table 12: Risk-adjusted Performance of the Highest Drawdown Status Portfolios: Controlling for the "Backfilling Bias"

This table reports OLS coefficient estimates when excess returns of the highest drawdown status portfolios are regressed on Fung and Hsieh (2004) seven factors after controlling for the backfilling bias. The sample period is January 1996-December 2009. The first 24 months data of each fund is eliminated in order to control for backfilling bias. See Table 2 for the description of portfolio formation. Factors are described in the text. Standard errors are white heteroscedasticity-consistent. The t-statistics are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Value Weighted Portfolios				**Equally Weighted Portfolios**			
	Lag 1	Lag 2	Lag 3	HFR	Lag 1	Lag 2	Lag 3	HFR
Intercept	0.55**	0.82***	1.05**	0.16	0.80***	1.20***	1.48***	0.35***
	(2.04)	(2.72)	(2.53)	(1.57)	(3.27)	(4.00)	(3.23)	(3.62)
SNP	0.58***	0.61***	0.50***	0.22***	0.63***	0.61***	0.51***	0.28***
	(7.70)	(8.47)	(4.36)	(7.48)	(10.41)	(8.15)	(4.39)	(11.46)
SizeSpr	0.27***	0.41***	0.40***	0.16***	0.37***	0.54***	0.92***	0.22***
	(3.25)	(4.58)	(2.94)	(4.28)	(4.84)	(5.94)	(4.84)	(6.61)
FXOpt	0.01	0.02	0.03	0.01	0.03	0.02	0.02	0.01*
	(0.67)	(1.28)	(1.40)	(1.43)	(1.59)	(1.35)	(0.72)	(1.95)
ComOpt	-0.00	0.02	0.01	0.01	0.00	-0.01	-0.00	0.02*
	(-0.17)	(0.97)	(0.41)	(1.50)	(0.28)	(-0.33)	(-0.03)	(1.98)
BdOpt	0.01	0.02	0.01	-0.01	0.02	0.03	0.01	0.00
	(0.51)	(0.96)	(0.16)	(-1.55)	(1.49)	(1.47)	(0.27)	(0.40)
Bd10Yr	-0.09	-0.15	-0.17	0.08*	-0.12	-0.20	-0.11	0.09**
	(-0.87)	(-0.96)	(-1.02)	(1.83)	(-1.21)	(-1.61)	(-0.65)	(2.06)
CredSpr	0.13	-0.06	-0.14	0.18**	0.18	0.01	-0.17	0.18**
	(0.72)	(-0.29)	(-0.61)	(2.53)	(0.96)	(0.05)	(-0.77)	(2.52)
Adjusted R^2	45.7%	41.7%	18.0%	58.2%	55.4%	47.8%	27.9%	67.5%
Number of obs.	168	168	168	168	168	168	168	168

Table 13: Regression Analysis: First Results

This table reports Fama and MacBeth (1973) coefficient estimates when *Returns* are regressed on a set of controls using various data sets. Column (A) restates results of Fama and MacBeth (1973) regressions obtained by Agarwal et al. (2009) using the model:

$$
\begin{aligned}
Return_{i,t} = {} & \alpha_0 + \alpha_1 Total\ Delta_{i,t-1} + \alpha_2 Hurdle\ Rate_i + \alpha_3 High\text{-}water\ Mark_i + \alpha_4 Lockup_i \\
& + \alpha_5 Restriction_i + \alpha_6 Size_{i,t-1} + \alpha_7 Flow_{i,t-1} + \alpha_8 Volatility_{i,t-1} + \alpha_9 Age_{i,t-1} \\
& + \alpha_{10} Management\ Fee_i + \alpha_{11} Return_{i,t-1} + \sum_{s=1}^{3} \alpha_{11+s} I\ Strategy_{i,s} + \xi_{i,t}
\end{aligned}
$$

In Column (B), Agarwal et al. (2009) results are restated when *Total Delta* is replaced by *Option Delta* and *Managerial Ownership*:

$$
\begin{aligned}
Return_{i,t} = {} & \alpha_0 + \alpha_1 Option\ Delta_{i,t-1} + \alpha_2 Managerial\ Ownership_{i,t-1} + \alpha_3 Hurdle\ Rate_i \\
& + \alpha_4 High\text{-}water\ Mark_i + \alpha_5 Lockup_i + \alpha_6 Restriction_i + \alpha_7 Size_{i,t-1} + \alpha_8 Flow_{i,t-1} \\
& + \alpha_9 Volatility_{i,t-1} + \alpha_{10} Age_{i,t-1} + \alpha_{11} Management\ Fee_i + \alpha_{12} Return_{i,t-1} \\
& + \sum_{s=1}^{3} \alpha_{12+s} I\ Strategy_{i,s} + \xi_{i,t}
\end{aligned}
$$

To control for backfilling bias, Agarwal et al. (2009) excludes first two years' data of each fund from the regression and their results are restated in Column (C).

Columns (D) and (E) report the results of these regressions obtained using HFR data set, where sample period is 1996-2009. In Column (F), as in Agarwal et al. (2009), first two years' data of each fund is excluded from the regression. Finally, Columns (G) and (H) report the results of the regressions using HFR filtered data set (which consists of funds with 3-lag drawdown defined). To save from space, coefficients on lag *Size*, *Flow*, *Volatility*, *Age*, *Return* and *Management Fee* are not reported. *Size* is the natural logarithm of the AUM of the fund at the end of the year. *Hurdle rate* is an indicator variable that takes value one if the fund has a hurdle rate, and zero otherwise. *High-water mark* is an indicator variable that takes value one if the fund has high-water mark, and zero otherwise. See Table 1 for the definition of variables. All variables are winsorized at the 1% level. Standard errors are Newey-West heteroscedasticity and autocorrelation consistent. The p-values are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

	Agarwal et al. (2009)			HFR Data Sets				
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
Intercept	0.117***	0.113***	Yes	0.071***	0.071***	0.065***	0.052**	0.053**
	(0.000)	(0.000)		(0.001)	(0.001)	(0.001)	(0.026)	(0.019)
Total $\text{Delta}_{i,t-1}$	0.011***			0.006***			0.003	
	(0.003)			(0.000)			(0.420)	
Option $\text{Delta}_{i,t-1}$		0.015**	0.009*		0.007*	0.004		0.005
		(0.017)	(0.083)		(0.094)	(0.420)		(0.412)
Man. $\text{Own.}_{i,t-1}$		0.126***	0.117**		0.040***	0.043**		0.036**
		(0.009)	(0.013)		(0.009)	(0.019)		(0.032)
Hurdle Rate	0.004	0.008	0.006	-0.008	-0.007	-0.006	-0.008	-0.007
	(0.362)	(0.156)	(0.257)	(0.541)	(0.576)	(0.576)	(0.534)	(0.580)
High-water Mark	0.026***	0.026***	0.023***	0.009	0.007	0.008	0.014***	0.012**
	(0.002)	(0.002)	(0.006)	(0.174)	(0.230)	(0.167)	(0.007)	[illegible]
Lockup	0.029*	0.029*	0.028	0.006	0.006	0.011	0.005	0.005
	(0.096)	(0.095)	(0.112)	(0.286)	(0.256)	(0.204)	(0.406)	[illegible]
Restriction	0.018	0.019	0.018	0.012	0.012	-0.006	0.010	0.010
	(0.157)	(0.147)	(0.140)	(0.408)	(0.403)	(0.591)	(0.499)	[illegible]
Adjusted R^2	13.6%	13.8%	13.0%	2.5%	2.6%	1.8%	1.2%	[illegible]
Number of obs.	16,901	16,901	14.221	21,739	21,739	16,923	13,556	[illegible]

Table 14: Regression Analysis: Drawdown Variables

This table reports OLS coefficient estimates when *Returns* are regressed on various sets of controls using HFR filtered data set. Columns (A) and (C) use the model:

$$\begin{aligned} Return_{i,t} = \alpha_0 + \alpha_1 Drawdown_{i,t-1} + \alpha_2 Option\ Delta_{i,t-1} + \alpha_3 Managerial\ Ownership_{i,t-1} \\ + \alpha_4 Hurdle\ Rate_i + \alpha_5 High\text{-}water\ Mark_i + \alpha_6 Lockup_i + \alpha_7 Restriction_i \\ + \alpha_8 Size_{i,t-1} + \alpha_9 Flow_{i,t-1} + \alpha_{10} Volatility_{i,t-1} + \alpha_{11} Age_{i,t-1} \\ + \alpha_{12} Management\ Fee_i + \alpha_{13} Return_{i,t-1} + \sum_{s=1}^{3} \alpha_{13+s} I\ Strategy_{i,s} + \xi_{i,t} \end{aligned}$$

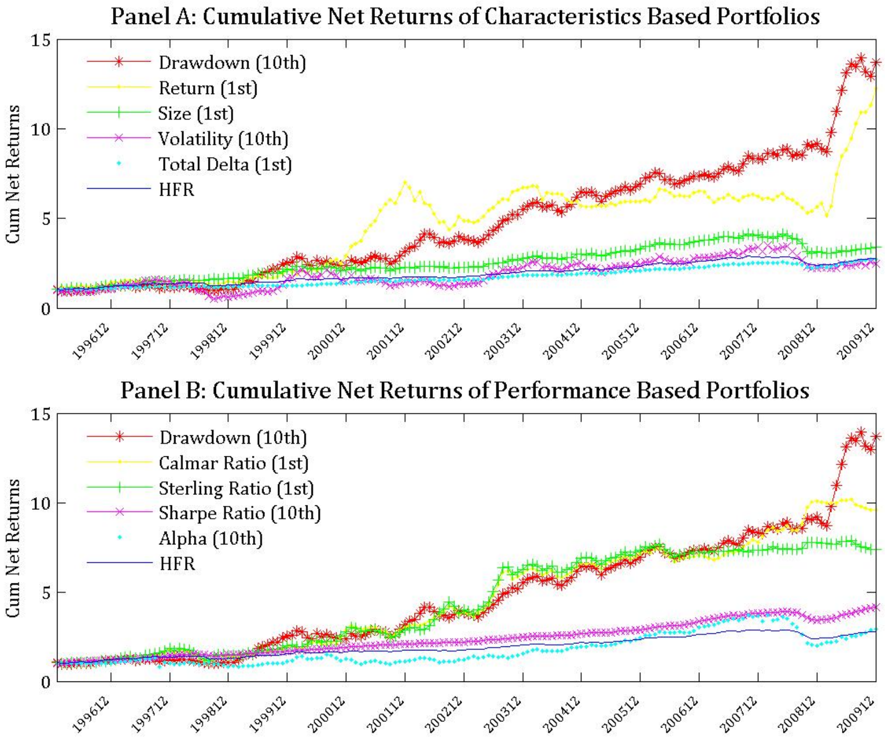
Columns (B) and (D) use the model:

$$\begin{aligned} Return_{i,t} = \alpha_0 + \alpha_1 Low\ Drawdown_{i,t-1} + \alpha_2 High\ Drawdown_{i,t-1} + \alpha_3 Option\ Delta_{i,t-1} \\ + \alpha_4 Managerial\ Ownership_{i,t-1} + \alpha_5 Hurdle\ Rate_i + \alpha_6 high\text{-}water\ Mark_i \\ + \alpha_7 Lockup_i + \alpha_8 Restriction_i + \alpha_9 Size_{i,t-1} + \alpha_{10} Flow_{i,t-1} \\ + \alpha_{11} Volatility_{i,t-1} + \alpha_{12} Age_{i,t-1} + \alpha_{13} Management\ Fee_i \\ + \alpha_{14} Return_{i,t-1} + \sum_{s=1}^{3} \alpha_{14+s} I\ Strategy_{i,s} + \sum_{s=1}^{13} \alpha_{17+s} I\ Year_{i,s} + \xi_{i,t} \end{aligned}$$

The type of regressions are also different. Columns (A) and (B) report Fama and and MacBeth (1973) coefficient estimates with Newey-West heteroscedasticity and autocorrelation consistent standard errors. Columns (C), (D), (E) and (F) report OLS regression results after correcting standard errors for within-cluster correlation, heteroskedasticity and autocorrelation. The sample period is 1996-2009, except in Column (B) where it is set as 1999-2009 for meaningful regression results. *Low Drawdown* is an indicator variable that takes value one if the fund has been in the lowest decile in the last three years, and zero otherwise. Similarly, *High Drawdown* is an indicator variable that takes value one if the fund has been in the highest decile in the last three years, and zero otherwise. To save from space, coefficients on lag *Size*, *Flow*, *Volatility*, *Age*, *Return* and *Management Fee* are not reported. See Tables 1 and 13 for the definition of variables. All variables are winsorized at the 1% level. The p-values are reported in parentheses. ***, **, and * denote statistical significance of coefficients at the 1%, 5%, and 10% levels, respectively.

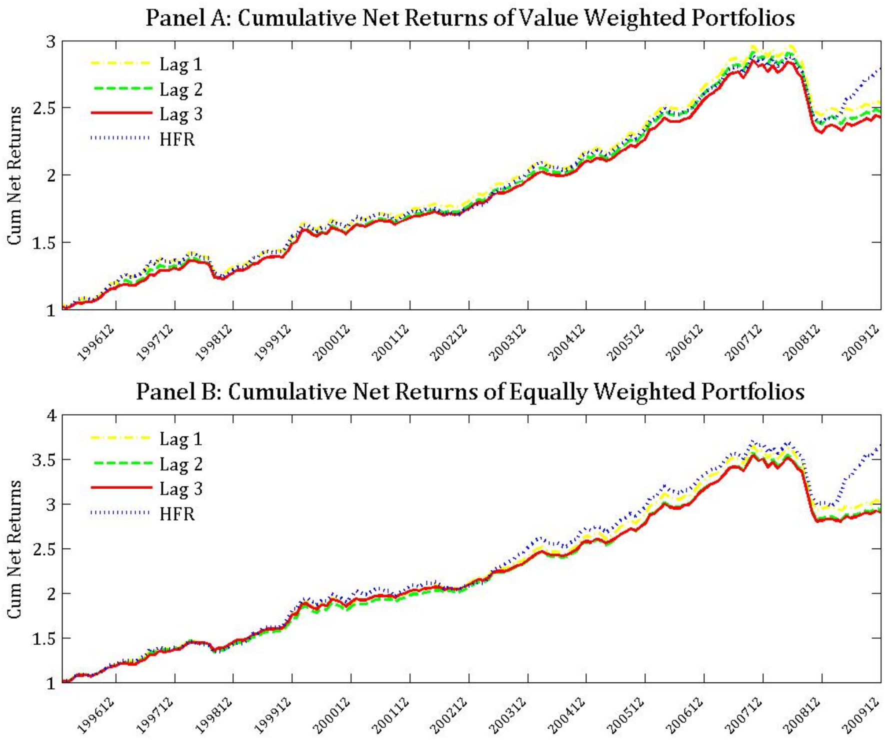
	FMB		OLS			
	(A)	(B)	(C)	(D)	(E)	(F)
Intercept	0.047**	0.045*	0.134***	0.146***	0.150***	0.146***
	(0.030)	(0.073)	(0.000)	(0.000)	(0.000)	(0.000)
Drawdown$_{i,t-1}$	0.181**		0.369***			
	(0.014)		(0.000)			
Low Drawdown$_{i,t-1}$		-0.006		-0.004	-0.006	
		(0.360)		(0.410)	(0.181)	
High Drawdown$_{i,t-1}$		0.070*		0.049***		0.050***
		(0.079)		(0.008)		(0.007)
Option Delta$_{i,t-1}$	0.004	0.006	-0.013**	-0.011**	-0.010*	-0.012**
	(0.456)	(0.513)	(0.019)	(0.039)	(0.063)	(0.033)
Man. Ownership$_{i,t-1}$	0.035**	0.041**	0.045***	0.045***	0.043***	0.045***
	(0.036)	(0.048)	(0.000)	(0.000)	(0.001)	(0.000)
Hurdle Rate	-0.011	0.002	0.006	0.010	0.010	0.010
	(0.391)	(0.862)	(0.253)	(0.110)	(0.111)	(0.115)
High-water Mark	0.013***	0.011**	0.008	0.010	0.007	0.007
	(0.008)	(0.033)	(0.202)	(0.120)	(0.280)	(0.257)
Lockup	0.005	0.002	0.005	0.005	0.006	0.006
	(0.407)	(0.715)	(0.181)	(0.203)	(0.163)	(0.163)
Restriction	0.011	0.002	0.010	0.007	0.014*	0.014*
	(0.441)	(0.879)	(0.194)	(0.265)	(0.082)	(0.088)
Adjusted R^2	2.9%	2.5%	25.0%	23.6%	23.5%	23.6%
Number of obs.	13,556	12,673	13,556	13,556	13,556	13,556

Figure 1: Performance of Characteristics Based Portfolios



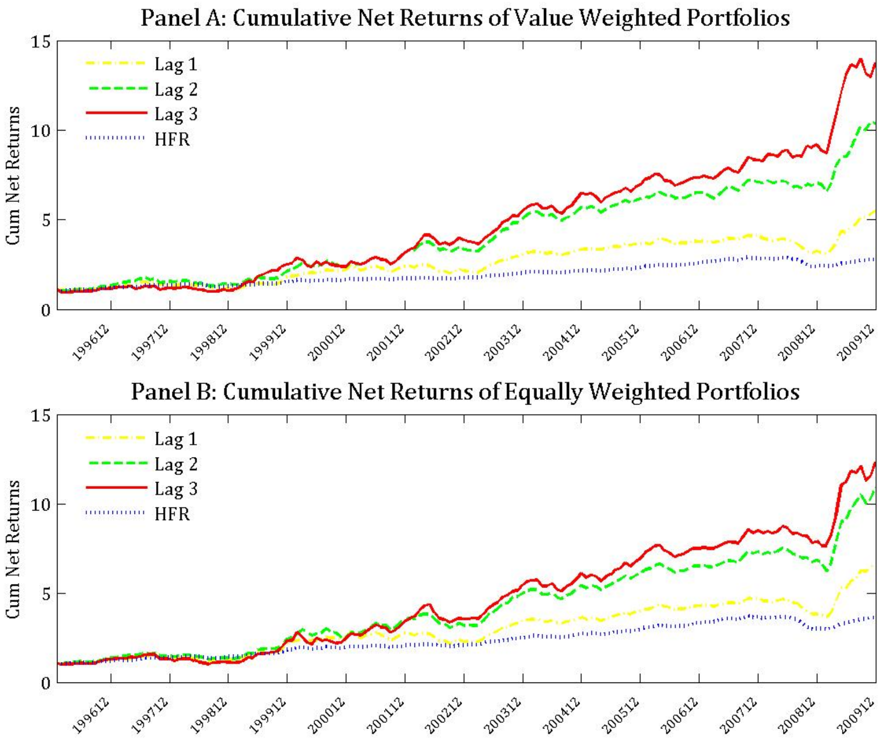
This figure presents the cumulative net returns of the characteristics based portfolios. The sample period is January 1996-December 2009. The characteristics under analysis are drawdown, return, size, volatility, total delta, alpha, Sharpe, Calmar, and Sterling ratios. See Table 1 for the definition of characteristics. For each year, alpha is calculated as the sum of the 12 monthly alphas that is estimated from the fund-level time-series regression of excess returns on Fung and Hsieh (2004) seven factors, allowing for structural breaks, and includes both the regression intercept and the regression residuals. Sharpe ratio is average monthly excess returns divided by the standard deviation of the excess returns (excess of risk free rate) over the past three years. Calmar ratio is average annual return over past three years divided by maximum drawdown suffered over three years. Sterling ratio is average annual return over past three years divided by average annual maximum drawdown over three years and 10% is added to the denominator. At the end of each year t, we sort the characteristics of funds into ten deciles. We create two value weighted portfolios for each characteristic: the set of all hedge funds that are in the 1^{st} decile of years $t-1$, $t-2$, $t-3$ and the the set of all hedge funds that are in the 10^{th} decile of years $t-1$, $t-2$, $t-3$. We plot the one that performs best out of these two for each characteristic and label it. In brackets and next to the label of each strategy we indicate if the strategy holds the funds in the "1st" or "10th" decile.

Figure 2: Cumulative Net Returns of the Lowest Drawdown Status Portfolios ($d = 1$)



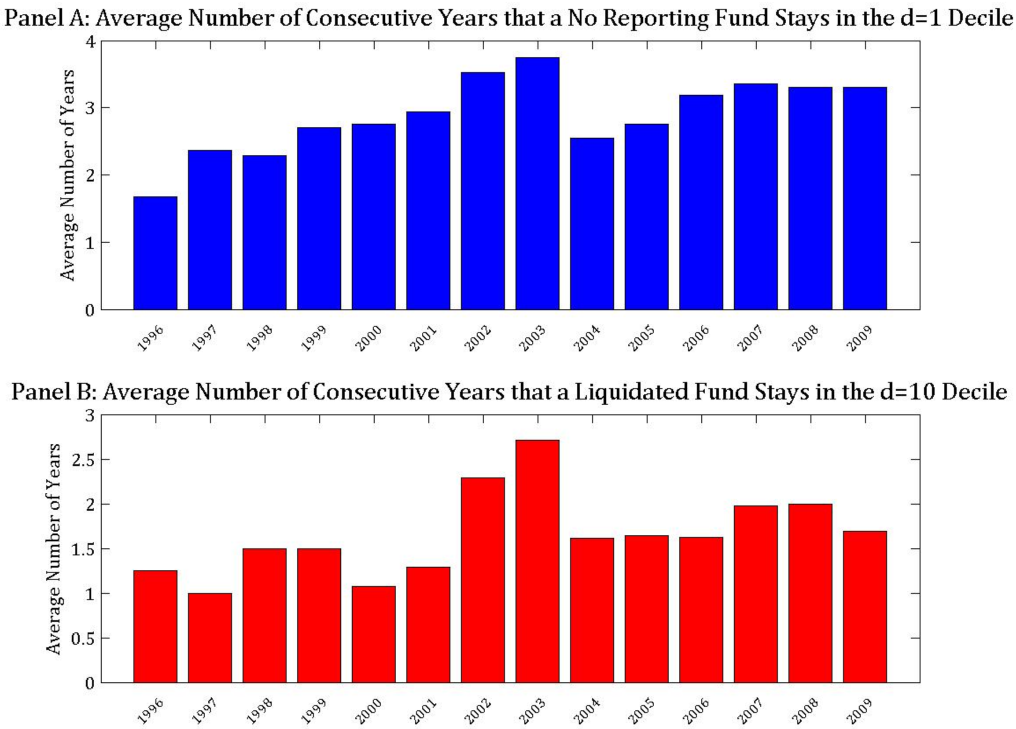
This figure presents the cumulative net returns of the lowest drawdown status portfolios. The sample period is January 1996-December 2009. See Table 2 for the description of portfolio formation.

Figure 3: Cumulative Net Returns of the Highest Drawdown Status Portfolios ($d = 10$)



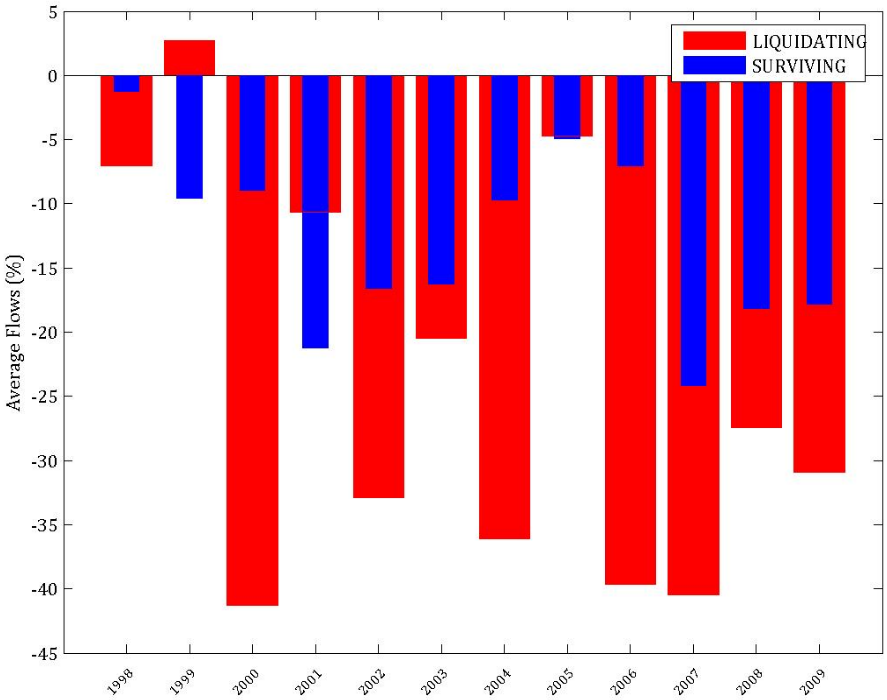
This figure presents the cumulative net returns of the highest drawdown status portfolios. The sample period is January 1996-December 2009. See Table 2 for the description of portfolio formation.

Figure 4: Stop Reporting and Liquidation of Funds in the Portfolios



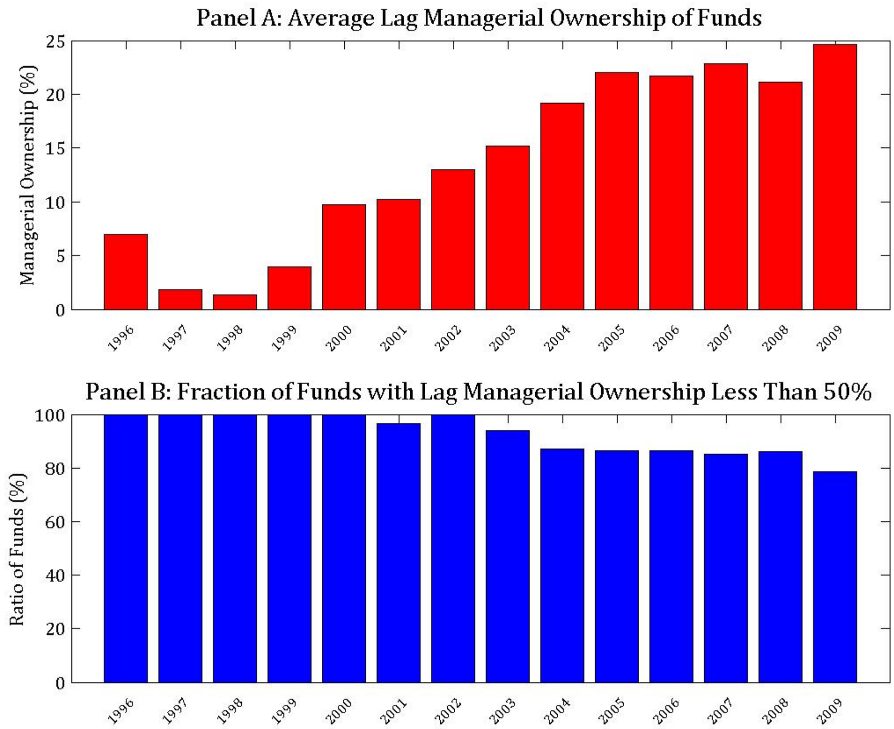
Panel A of this figure presents the average number of consecutive years that a fund that stops reporting during the portfolio formation period stays in the $d = 1$ decile. Panel B of this figure presents the average number of consecutive years that a fund that is liquidated during the portfolio formation period stays in the $d = 10$ decile. The sample period is 1996-2009.

Figure 5: Flows of Surviving vs. Liquidating Funds



This figure plots the time series of the average 12-month lagged flows –excluding the flows of the liquidation month– of the portfolio of funds in the 3-lag highest drawdown decile (surviving funds) vs. the portfolio of funds in the 3-lag highest drawdown status portfolio that are liquidated (liquidating funds). There are no liquidated funds in the latter portfolio during 1996-1997. Hence, the sample period of comparison is 1998-2009.

Figure 6: Managerial Ownership in Surviving Funds



Panel A of this figure plots the time series of managerial ownership of the portfolio of funds in the 3-lag high drawdown status portfolio. Panel B plots the fraction of funds in the lag 3 large-drawdown status portfolio that have a managerial ownership below 50%. The sample period is 1996-2009.