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Determinants of Hedge Fund Performance

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Abstract

This dissertation consists of three essays which focus on the determinants of hedge fund performance. The first essay defines two distinct styles of active portfolio management: alpha active and beta active. I develop measures of beta activity and find ample evidence that top beta active managers deliver superior out-of-sample performance. In addition, I find that beta activity measure successfully captures the time varying nature of beta exposures that can be interpreted as the common factor driving the long term out-of-sample predictive power of both Systematic Risk and R^2.

The second essay attempt to span the space of potential risk factors with exchange traded funds and replicate hedge fund return through selected ETF portfolio. I find the portfolio of clones created with my procedure provides better out-of-sample performance than the portfolio of “cloneable” hedge funds. In contrast, “non-cloneable” hedge fund portfolio reflects the hedge fund active management style supported by the superior risk-adjusted performance.

The third essay investigates a new dimension of market timing activity. I decompose hedge fund excess return to alpha and beta return and find a strong monotonic mean reversal pattern in out of sample performances of portfolios sorted by beta return. I identify two types of managers: Multi-active Managers and Risk-writing Managers, and find the superior performance of bottom quartile beta return portfolio is mainly driven by Multi-active Managers. I find evidence that Risk-writing Managers exhibit the greatest total risk and beta risk, and generate returns through excessive risk taking. Multi-active Managers actively manage their market position that are reflective of their beliefs, continuously search for market opportunities and effectively adjust their beta positions to reflect their evolving market expectations.

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Dedication

For my wife, Yinglai Xie, my dad, Yongchi Duanmu and my mum, Wei Guo.

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I. Introduction

Hedge funds are considered the apex of professionally actively managed investment funds, and have experienced tremendous growth in recent years. Hedge fund researchers commonly focus on alpha, which is a proxy for superior performance relative to the factor returns. However, extant literature documents that relatively few funds produce significant alpha, in addition, funds exhibit exposure to systematic risk factors. In my studies, I focus on market exposure component of hedge fund performance and provide evidence of the efficacy of beta activity in explaining hedge fund returns.

In the first essay, I consider two distinct styles of active portfolio management: alpha active, wherein managers' positions are uncorrelated with particular benchmarks, and beta active, wherein managers take positions that are correlated with identifiable benchmark factors. Alpha activity is easily identified by a low R^2 from an asset-pricing model regression. For example, a traditional long-short stock picker should have a low R^2 as the variance in factor returns should not explain fund returns. If a manager is skilled, the alpha should be positive and significant, reflecting superior performance. However, beta active managers' time varying bets are revealed by changing factor loadings – beta coefficients – over time. Even in the absence of short term alpha production it is possible for a beta active manager to deliver superior returns if he executes strategies that are correlated with the most profitable factors. I construct a measure of overall beta activity of fund managers, and find ample evidence that top beta active managers deliver superior out-of-sample performance compared to top alpha active managers. I evaluate betas for non-overlapping two year periods to construct variables capturing the contemporaneous success of beta activity, dynamic changes in beta exposures, and a combination of these into overall measure of beta activity, *BA*. I find beta activity to be strongly predictive of future performance in both in-sample and out-of-sample tests. Further, I document that managerial talent is identifiable ex ante. I create portfolios of hedge funds based upon *BA* as well as traditional measures of alpha activity, alpha and alpha *t*-statistics. In out-of-sample tests we find beta active portfolios outperform portfolios formulated upon traditional measures of alpha active performance. We report ample evidence that beta active managers deliver superior long term risk adjusted performance in terms of excess returns, Sharpe ratios, Fung and Hsieh (2004) alphas, and information ratios. We therefore find beta activity to be a stronger predictor of superior future fund performance than alpha activity. Beta activity metrics expand our understanding of active portfolio management and managerial skill and are powerful complements to current alpha-centric methodology.

In the second essay, I attempt to span the space of potential risk factors with exchange traded funds (ETFs) from 1997 to 2012. During this time period of our study, the ETF coverage of alternative risk factors went from almost non-existent in 1997 to being comprehensive, with ETFs currently providing access to a great variety of alternative strategies that were previously available only to hedge funds or institutional investors. I split the sample into two sub-periods to highlight the effect of the broadened investment opportunity set for the matching procedure, I consider subperiods of 1997-2003 and 2003-2011 separately. I develop a new methodology for linear hedge fund return replication that overcomes multicollinearity among ETFs, and also minimizes data mining bias, while utilizing all ETFs available. I conduct cluster analysis among ETFs to specify the ETF with lowest SDI as the proxy for this particular cluster to be included in the later replication regression. Such approach allows for efficient spanning of the space of potential risk factors while minimizing the multicollinearity concerns. Equipped with a large space of risk factors, I then employ LAR LASSO (least absolute shrinkage and selection operator, least angle regression algorithm) over a set of two year window to quantify the dynamic nature of hedge funds' investment activities. Finally, I test the performance of our hedge fund clones in- and out-of-sample. I find that in the subperiod starting in 2005, the overall out-of-sample performance of the portfolio of all hedge funds is not statistically different from the portfolio of clones. In a departure from previous hedge fund replication studies, I go beyond considering replicating hedge fund indexes or average hedge fund performance. I consider portfolios of "cloneable" and "non-cloneable" hedge funds, defined as top and bottom in-sample R^2 matches. I find that the portfolio of clones created with our procedure provides better out-of-sample performance than the portfolio of "cloneable" hedge funds, which is likely due to the lower fee structure among the clones. Furthermore, the portfolio of "cloneable" hedge funds does not produce significantly positive risk-adjusted performance, measured by the Fung and Hsieh (2004) alpha. Hence I conclude that there is no statistical evidence of managerial skill in the set of "cloneable" hedge funds, and these funds can be successfully replicated with ETFs. Finally, the out-of-sample portfolio of "non-cloneable" hedge funds produces significantly positive mean excess returns along with a Fung and Hsieh (2004) alpha, outperforming the portfolio of clones. This can be interpreted as evidence of managerial skill among the managers of "non-cloneable" hedge funds.

In my third essay, I carefully decompose hedge fund excess returns into alpha and beta return by using a comprehensive selection model which accounts for all possible alternative risk factors undertaken by hedge fund managers. I conduct out-of-sample portfolio tests and find that alpha is a persistent indicator of future performance that lasts as long as three years. In addition, I find a strong and monotonic mean reversal pattern in portfolios sorted by beta return. I define another strand of market timing activity: active market testing, which requires managers to continuously form market expectations and actively manage their corresponding risk exposures. With the simple interaction between top alpha and bottom beta return, I find that multi-active managers possess superior active market timing ability and are the driving factors behind superior performance of low beta return portfolio. In contrast, for risk-writing managers, those with inferior preceding performance, have large incentive to take risk and exhibit the greatest beta risk pre and post portfolio formation window.

II. Essay 1: Beta Active Hedge Fund Management[1]

Jun Duanmu, Alexey Malakhov, and William R. McCumber

A. Abstract

We consider two distinct styles of active portfolio management: alpha active, wherein managers' positions are uncorrelated with particular benchmarks, and beta active, wherein managers take positions that are correlated with identifiable benchmark factors. We construct a measure of overall beta activity of fund managers, and find ample evidence that top beta active managers deliver superior out-of-sample performance compared to top alpha active managers. Furthermore, our measure of beta activity successfully captures the time varying nature of beta exposures that could be interpreted as a common factor driving the long term predictive power of both SR (systematic risk) and R2 measures.

JEL Classification: G11, G23

Keywords: hedge funds, alpha, beta, active management, factor timing, performance measurement, performance prediction

B. Introduction

Hedge funds are considered the apex of professionally actively managed investment funds. Hedge fund researchers commonly consider alpha, the constant in a regression specified by an asset pricing model, as a proxy for fund performance due to active portfolio management. In essence, alpha is the performance of a fund that cannot be explained by the model, and therefore positive alpha is a proxy for superior performance relative to the factor returns. Alpha

[1] We would like to thank Chris Clifford, Zhipeng (Alan) Yan, participants in the 2013 Financial Management Association Annual Meeting, 2013 FMA Applied Finance Conference; and seminar participants at Louisiana Tech University, St. Bonaventure University, and University of Arkansas for their helpful comments and suggestions. We are grateful to Eddy Yongjia Li for his outstanding research assistance. All errors remain our own.

is firmly entrenched in the common investment lexicon as a sophisticated measure of performance; fund managers, investment advisors, and investors all are "seeking alpha".[2]

It is questionable, however, whether alpha reliably encompasses all relevant information about hedge fund performance. Extant literature documents that relatively few funds produce significant alpha. Rather, funds exhibit exposure to systematic risk factors such that returns are driven by beta activity.[3] However, there is no consensus in the literature as to the efficacy of beta activity on a risk adjusted basis. For example, Titman and Tiu (2011) argue that successful managers hedge away systematic risk exposure and thus exhibit low R^2 in multifactor regressions. In contrast, Bali, Brown, and Caglayan (2012) find that hedge funds with greater exposure to systematic risk demonstrate higher risk adjusted performance. It is therefore important for investors to better understand the nature of beta management in addition to alpha production.

In this paper we attempt to provide a comprehensive view of hedge fund managerial activity by defining two styles of active management, "alpha active" and "beta active". We define alpha activity as that which is not ultimately reflected in factor loadings. Alpha activity is easily identified by a low R^2 from an asset-pricing model regression. For example, a traditional long-short stock picker should have a low R^2 as the variance in factor returns should not explain fund returns. If a manager is skilled, the alpha should be positive and significant, reflecting superior performance. We define beta activity as taking directional positions correlated with

[2] See, for example, Fung, Hsieh, Naik, and Ramadorai (2008) documenting that alpha producing funds attract greater and steadier investor inflows.

[3] For example, Fung, Hsieh, Naik, and Ramadorai (2008) document that 78% of the funds in their sample did not deliver alpha, instead exhibiting "beta only" return patterns. Still, demand for hedge fund shares remains strong, with $2.25 trillion invested in hedge funds globally, according to Hedge Fund Research (January 18, 2013 press release). If relatively few funds deliver persistent and significant alpha, then arguably investors reap some benefit from funds whose returns are driven by betas.

macroeconomic risk factors. Beta active managers' time varying bets are revealed by changing factor loadings – beta coefficients – over time. Even in the absence of short term alpha production it is possible for a beta active manager to deliver superior returns if he executes strategies that are correlated with the most profitable factors. We construct a measure of overall beta activity that captures both contemporaneous managerial success as well as dynamic changes in factor loadings.[4] Like Bali, Brown, and Caglayan (2012) we do not attempt to capture timing with respect to any specific factor, instead focusing on overall activity. That is, instead of attempting to improve model specification along any particular factor we construct an aggregate measure of activity across all factors[5] in an unconditional asset pricing model.

We employ a modified Fung and Hsieh (2004) eight factor model[6] to compare consecutive short term beta estimates. We evaluate betas for non-overlapping two year periods to construct variables capturing the contemporaneous success of beta activity, dynamic changes in beta exposures, and a combination of these into overall measure of beta activity, *BA*. We find beta activity to be strongly predictive of future performance in both in-sample and out-of-sample tests. Further, we document that managerial talent is identifiable ex ante. We create portfolios of hedge funds based upon *BA* as well as traditional measures of alpha activity, alpha and alpha *t*-statistics. In out-of-sample tests we find beta portfolios significantly outperform alpha portfolios

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[4] I.e. how successful managers were in rebalancing their investments in anticipation of changing economic conditions.

[5] This is most relevant in the context of hedge fund investing due to the multitude of investment opportunities available to hedge fund managers. In contrast to comparatively constrained mutual fund managers, hedge fund managers implement global time varying strategies across myriad asset classes potentially correlated with a multitude of risk factors.

[6] While Fung and Hsieh (2004) specify the seven factor model, the updated specification on David Hsieh's web site at http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm includes eight factors. Other papers utilizing the Fung and Hsieh (2004) model include Kosowski, Naik, and Teo (2007), Fung, Hsieh, Naik, and Ramadorai (2008), Jagannathan, Malakhov, and Novikov (2010), and Avramov, Kosowski, Naik, and Teo (2011), among others.

while also delivering a Fung and Hsieh (2004) alpha of over 5% per annum.

We further demonstrate that alpha and beta activity metrics capture different aspects of active portfolio management by comparing the return patterns generated by alpha and beta activity. It is conceptually important to emphasize that beta activity in no way implies a "passive" investment style. Overall, *BA* broadens the discussion of active management beyond alpha and is a complement to alpha-centric methodologies in the identification of superior managerial skill.

Finally, we investigate the relationship between *BA* and other measures of fund exposure to systematic risk, namely those of *SR* (Bali, Brown, and Caglayan, 2012) and R^2 as considered by Titman and Tiu (2011). Unsurprisingly there is considerable overlap in portfolios selected upon the basis of fund *BA*, *SR*, and R^2. Excluding funds from the *BA* portfolio that would also be present in *SR* or R^2 portfolios we find that remaining *BA* funds deliver superior and statistically significant out-of-sample performance. The converse is not true, however; when we exclude funds from *SR* and R^2 portfolios that would also be in the *BA* portfolio, *SR* and R^2 portfolios lose their predictive power. This suggests that *BA* successfully captures the time varying nature of beta exposures that can be interpreted as the common factor driving the long term out-of-sample predictive power of both *SR* and R^2.

C. Related Literature

Alpha activity, traditionally referred to as "active management", is identified by the low R^2 from an asset pricing model regression.[7] If a manager is skilled, the alpha should be positive and significant, reflecting superior returns as compared to passively holding factor-mimicking portfolios. However, alpha is only a relative measure of the fund performance as it is sensitive to

[7] See, for example, Jensen (1968), Sharpe (1992), and Amihud and Goyenko (2013).

benchmark factor specifications.[8] Furthermore, alpha provides a biased evaluation of the success of market timing strategies.[9] These shortcomings have led to the development of alternative approaches used to identify managerial activity and evaluate performance.

Our methodology extends three strands of literature. In identifying the differences between alpha and beta activity we conceptually borrow from the performance attribution literature that attempts to separate security selection from market timing activity.[10] Our focus on beta activity echoes the market timing literature as recognizing the importance of fund activity reflected in factor exposures. Finally, we test the power of beta activity metrics to predict future hedge fund performance, thereby contributing to the recent literature seeking to develop alternative methodologies that are predictive of future performance.[11]

Our attempt to identify and quantify overall alpha and beta activity is conceptually similar to identifying "security selection" and "market timing" as in the performance attribution and market timing literatures, though we point to three significant differences. First, hedge funds do not report positions and thus it is impossible to compare fund portfolio holdings against a benchmark to measure managers' security selections. Second, rather than exploring timing with regard to a *single* factor, we quantify aggregate timing across *all* factors.[12] Finally, time varying beta exposures may be driven by levered positions and those with option-like payoffs as

[8] See, for example, Roll (1978).
[9] See, for example, Jensen (1972).
[10] See, for example, Fama (1972), Brinson, Hood, and Beebower (1986), Daniel, Grinblatt, Titman, and Wermers (1997).
[11] See, for example, Grinblatt and Titman (1993), Kacperczyk, Sialm, and Zheng (2008), Cremers and Petajisto (2009), Jagannathan, Malakhov, and Novikov (2010), Titman and Tiu (2011), Avramov, Kosowski, Naik, and Teo (2011), Sun, Wang, and Zheng (2012), Amihud and Goyenko (2013).
[12] This is conceptually similar to the approach in Bali, Brown, and Caglayan (2012) considering the overall systematic risk, *SR*, as a proxy for overall time varying directional activity, i.e. beta activity in our terminology.

demonstrated by Jagannathan and Korajczyk (1986).[13] In sum, within the context of hedge funds it is impossible to definitively conclude that security selection is reflected in alphas while market timing is reflected in betas. We thus concentrate on studying overall "alpha activity" and "beta activity" as we can better identify and quantify these processes.

From the perspective of performance attribution our paper is closest to Daniel, Grinblatt, Titman, and Wermers (1997) who use return attribution analysis with respect to stock characteristic based benchmark portfolios. The authors separate and capture the effects of managers' security selection and market timing relative to benchmark portfolios by employing Average Style (AS), Characteristic Timing (CT), and Characteristic Selectivity (CS) measures. While the CT measure quantifies market timing activity in a way that is conceptually similar to the *FDBR* measure in this paper,[14] it relies on portfolio asset weights and style benchmarks matched to specific mutual fund asset holdings. In contrast, *FDBR* is constructed of time varying beta coefficients on benchmark portfolios that reflect hedge fund investment opportunity sets.

There are numerous studies dedicated to market timing with regard to mutual funds[15] and more recently, as data became available, among hedge funds.[16] Most mutual fund studies conclude that there is little evidence of successful market timing by mutual fund managers. Hedge fund managers, on the other hand, are shown to enjoy considerable market timing success

[13] Notice that even the conceptual difference between security selection and market timing becomes less clear in the context of the hedge fund activity. For example, a prescient hedge fund manager decides to synthetically short mortgage backed securities and purchase credit default swaps in 2007. Is that security selection or market timing?
[14] *FDBR* is one of the intermediate variables used in construction of the overall measure of beta activity, *BA*, and it is defined later in section 4.
[15] See, for example, Treynor and Mazuy (1966), Henriksson and Merton (1981), Jagannathan and Korajczyk (1986), Grinblatt and Titman (1989), Ferson and Schadt (1996), Bollen and Busse (2001), Jiang, Yao, and Yu (2007), Mamaysky, Spiegel, and Zhang (2008).
[16] See, for example, Fung, Xu, and Yau (2002), Chen (2007), Chen and Liang (2007), Bollen and Whaley (2009), Cai and Liang (2012a, 2012b), Cao, Chen, Liang, and Lo (2013).

made possible by the broad and dynamic strategies available to them. However, these strategies involve significant factor risk, as documented in Fung and Hsieh (1997, 2001, 2004), Asness, Krail, and Liew (2002), Agarwal and Naik (2000, 2004), Patton (2009), and Bali, Brown, and Caglayan (2011, 2012). For example, Bali, Brown, and Caglayan (2012) conclude that systematic risk is a powerful predictor of hedge fund returns, a finding consistent with managerial skill in beta activity. Our finding that overall beta activity is strongly predictive of hedge fund performance is consistent with the conclusions of Bali, Brown, and Caglayan (2012).

Finally, there is a realization that the success of active portfolio management may derive from a wide variety of strategies that defy simple categorization. A growing literature develops alternative methodologies to capture various aspects of managerial activity and skill. Grinblatt and Titman (1993) measure informed managerial activity apart from Jensen's alpha without reliance upon an exogenous benchmark. The authors construct a Portfolio Change Measure that compares past fund holdings to current fund holdings. Using quarterly holdings of a sample of mutual funds the authors document evidence of managerial skill, especially in aggressive growth mutual funds. While Grinblatt and Titman's (1993) Portfolio Change Measure is computationally similar to the *FDBR* measure employed in this paper[17] there are conceptual differences in the two measures and their interpretations. The Portfolio Change Measure uses past portfolio asset weights as benchmarks, thus combining the effects of alpha and beta active management, while *FDBR* accounts solely for beta active management by using past factor loadings as benchmarks. Also, *FDBR* measures the success of beta activity with respect to exogenously stipulated factor portfolios, unlike the Portfolio Change Measure, which does not rely on any external benchmark.

[17] *FDBR* uses past factor loadings, and the Portfolio Change Measure uses past portfolio weights, as benchmarks in a computationally similar way. Both aim to measure managerial attempts to capture time varying payoffs, though against different benchmarks.

Amihud and Goyenko (2013) consider $1 - R^2$ as a measure of the active management in a mutual fund, demonstrating that lower R^2 indicates greater security selectivity and predicts better performance. Kacperczyk, Sialm, and Zheng (2008) create a measure that quantifies "hidden" activity by mutual fund managers, that is, trades and other actions taken between disclosure periods. Specifically, the authors find that the "return gap", the difference between actual period fund returns and a synthetic return that would have been realized had managers held previously disclosed positions through the current period, is persistently predictive of future returns. Using a similar sample of mutual funds as that of Kacperczyk, Sialm, and Zheng (2008), Cremers and Petajisto (2009) create a measurement of active management that they dub "Active Share", which is most easily defined as the degree to which a fund's portfolio differs from its closest benchmark in composition and securities weighting. Cremers and Petajisto (2009) find that the highest Active Share mutual funds exhibit some skill in stock picking, outperforming their benchmarks.

Conceptually similar to the Amihud and Goyenko (2013), Kacperczyk, Sialm, and Zheng (2008), and Cremers and Petajisto (2009) studies of mutual funds, several recent hedge fund studies rely on return patterns and factor models[18] to create alternative measures to predict future performance.[19] Sun, Wang, and Zheng (2012) create a "Strategy Distinctiveness Index" (SDI) measuring the difference[20] between the variance in returns of any particular hedge fund and its statistically-determined closest peer group. The authors' clustering methodology overcomes the weaknesses inherent in relying upon self-declared style information. The authors find that funds

[18] As hedge fund studies do not have the benefit of portfolio holdings data.
[19] There are also studies investigating other hedge fund characteristics that affect future performance, such as investor liquidity provisions (Aragon, 2007, Agarwal, Daniel, and Naik, 2009), liquidity risk (Sadka, 2010, 2012), managerial incentives (Agarwal, Daniel, and Naik, 2009), and fund age (Aggarwal and Jorion, 2010).
[20] As quantified by correlation.

with higher SDI, those with more distinct strategies, outperform funds with more common strategies in terms of out-of-sample Sharpe ratios, appraisal ratios, alphas, and manipulation-proof performance measures.[21] Jagannathan, Malakhov, and Novikov (2010) also utilize peer benchmarks, as they identify superior funds by considering alphas that are calculated relative to best fitting fund peer benchmark factors from Hedge Fund Research (HFR) indices. Their approach allows them to identify superior funds that are able to persistently deliver alpha as measured by the Fung and Hsieh (2004) model.

Titman and Tiu (2011) test whether hedge funds with less exposure to identifiable factor portfolios are better performers. Utilizing both stepwise regression analysis with a broad set of risk factors and the Fung and Hsieh (2004) seven factor model the authors find that funds with lower R^2s are better performers on both a relative and risk-adjusted basis.[22] On the other hand, Bali, Brown, and Caglayan (2012) find that hedge funds taking higher systematic risk, *SR*,[23] demonstrate superior risk adjusted future performance. They conjecture that the predictive power of systematic risk emanates from hedge funds' competence in detecting shifts in financial markets and their ability to timely adjust positions to those changes in financial and economic conditions. This is consistent with our finding that overall beta activity is strongly predictive of performance.

Avramov, Kosowski, Naik, and Teo (2011) and Avramov, Barras, and Kosowski (2013) explicitly include macroeconomic variables[24] in hedge fund performance evaluation, finding

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[21] See Goetzmann, Ingersoll, Spiegel, and Welch (2007) for the description of the manipulation-proof performance measure.
[22] Though, Bollen (2013) finds higher probability of failure for zero-R^2s funds.
[23] *SR* is defined as the difference of the total fund risk minus the idiosyncratic risk from a factor regression.
[24] Avramov, Kosowski, Naik, and Teo (2011) use the credit spread and the VIX volatility index, while Avramov, Barras, and Kosowski (2013) use the default spread, the dividend yield, VIX,

strong evidence of return predictability conditional on economic conditions. Overall, the authors[25] address a broad and important question: How does one utilize macroeconomic variables in a way that identifies managers whose skills are valuable conditional on economic conditions? We ask a similar question, seeking to identify managers who are able to recognize and profit from changing economic conditions – those who alter their strategies in anticipation of changing opportunity sets – thus incorporating macroeconomic information into their decisions. Our beta activity (*BA*) variable measures these qualities independent of macroeconomic variables, providing additional insight into active portfolio management and performance.

D. Description of Data

In this study we utilize hedge fund data from Bloomberg[26] for the period 1994-2012, which includes 18,135 unique hedge funds.[27] The data are comprehensive, including fund returns net of management and performance fees, assets under management, manager information, and fund characteristics. To minimize survivorship bias, the sample includes all funds reporting during our sample period, including those that are acquired, liquidated, or chose to stop reporting. We partially offset the effects of backfill bias by eliminating the first 24 months of reported returns.[28] Since we require four years of data[29] to calculate the measure of beta activity,

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and aggregate capital flows into the hedge fund industry as proxies for general macroeconomic conditions.

[25] In Avramov, Kosowski, Naik, and Teo (2011) and Avramov, Barras, and Kosowski (2013).

[26] Bloomberg is the most common platform used by both hedge funds, who utilize news, analysis, research, and trading tools, and accredited investors, who use Bloomberg data to research hedge funds, private equity firms, and other alternative investment vehicles. Bloomberg aggregates data on live and dead funds inclusive of fund and parent company descriptions, manager and contact information, total assets under management, fees, past performance, and management style.

[27] We do not include funds of hedge funds in our sample.

[28] The 24 month backfill correction is in line with results in Jagannathan, Malakhov, and Novikov (2010) and Titman and Tiu (2011) suggesting dropping the first 25 and 27 months of returns.

[29] After deleting the first 24 months of observations.

BA, we only consider funds with inception dates prior to 2007, which leaves us with 8,530 unique funds. Finally, of the 8,530 funds with inception dates prior to 2007, 963 active and 1,051 inactive unique funds have sufficient longevity to enable our methodology.

Panel A of table I reports summary statistics of fund returns, fees, investor liquidity measures, and fund longevity. As medians are better measures of typical funds in our database we find that the typical fund has a 1.5% management fee, a 20% incentive fee on all profits over an investor's high water mark,[30] a $250,000 minimum initial investment, and a 30 day redemption period. Unsurprisingly, active funds display higher monthly excess returns and assets under management and greater longevity than inactive funds. Interestingly, however, inactive funds have longer redemption periods and lockup periods. Panels B and C of table I report percentages of funds with certain characteristics and declared styles, respectively. 88% of all funds have a high water mark provision, though only 6% allow hurdle rates in addition to high water marks. 69% of funds are non-U.S. domiciled. The most common declared style is long-short equity, at 28% of all funds, while capital structure arbitrage is the least common style, accounting for 1% of hedge funds.

E. Research Methodology

1. Baseline Model

The baseline model employed in our regression analysis is a modified Fung and Hsieh (2004) model with tradable portfolio factors such that

$$\begin{aligned} r_i - r_f &= \alpha_i + \beta_{i1}\,SP500 + \beta_{i2}\,EM + \beta_{i3}\,10Year + \beta_{i4}\,SizeSpread\, + \\ &\quad + \beta_{i5}\,CreditSpread + \beta_{i6}\,BondTrend + \beta_{i7}\,ComTrend + \beta_{i8}\,FxTrend + \varepsilon_i. \end{aligned} \qquad \text{[M]}$$

[30] High water marks are investor relevant, that is, an investor will not be charged incentive fees until profits accrue over a previous high, net of flows. Thus, not all investors are charged incentive fees in any given year; it is partially determined by when the investor capital was employed by the fund manager. An investor whose fund shares are worth more this year than last will be charged incentive fees. An investor who suffered a loss previously will not pay incentive fees until previous losses are regained.

r_i is the monthly return of fund *i*, r_f is a risk free rate proxied by the monthly return of the 30-day U.S. Treasury bill. *SP500* is the market risk premium proxied by the S&P 500 index return minus the risk free rate. *EM* is the MSCI Emerging Market index return minus the risk free rate. *10Year* is the monthly excess return of a 10-year U.S. treasury bond, proxied by the 10-year U.S. Treasury bond portfolio return from the Center for Research in Security Prices (CRSP), minus the risk free rate. *SizeSpread* is an equity-based risk factor, the Russell 2000 Index return minus the S&P 500 Index return. *CreditSpread* is a fixed income-based risk factor, calculated as the total return on the Citi BBB corporate bond index minus the total return on the Fama U.S. Treasury bond portfolio as per CRSP. Both portfolios are comprised of bonds with maturities of 10 years or more. *BondTrend*, *ComTrend*, and *FxTrend* are excess returns on trend following factors constructed of look-back straddles on futures contracts of bonds, commodities, and currencies, respectively. All factors are therefore arbitrage (zero cost) portfolios.

All returns and yields data are from Bloomberg, while trend-following risk factors are courtesy of David Hsieh's website.[31] Finally, Getmansky, Lo, and Makarov (2004) show that hedge funds exhibit serial correlation in returns due to fund positions in illiquid assets and/or due to deliberate smoothing by managers. We therefore apply an MA(2) smoothing correction for all in-sample regressions [M], and also as a robustness check for out-of-sample portfolio results.

2. Short Term Rolling Window Estimates

In order to quantify the dynamic nature of beta active management and identify beta active managers we construct short term rolling window regression metrics using model [M] above. We consider rolling two year windows, rolling them annually over the entire sample

[31] Data may be found at http://faculty.fuqua.duke.edu/~dah7/HFData.htm.

period between 1996 and 2012. We then run individual fund regressions [M] for every two year window. Short term window estimates of alpha and beta coefficients, standard errors, adjusted-R^2, and systematic risk, SR_i = □$^2{}_i$ – □$^{□}{}_{□□i}$ are then employed to construct measures of beta activity in the following section.

3. Measures of Beta Active Management

As previously discussed, beta active management is the attempt to take active positions that are correlated with factors yielding the highest absolute returns in the future. The efficacy of such activity depends both upon the choice of factor betas and the returns to those factors. First, we introduce two variables that capture different aspects of beta activity across all factors utilized in the model [M]. "Scaled Beta Success," *SBS*, measures contemporaneous success, and "Difference in Beta Returns," *DBR*, captures time varying effects of beta activity. We then introduce a combined measure of beta activity, *BA*, as an equally weighed average of normalized individual variables, *SBS* and *DBR*.

In order to measure the relative degree to which beta active managers are successful, i.e. make wise strategic choices in betas in anticipation of future economic conditions, we create a measure of beta active management, *SBS*, or "*Scaled Beta Success*", by benchmarking a fund *i* beta return[32] against the maximum and the minimum average factor returns over two preceding 24-month windows *w* and *w – 1*:

$$SBS_i = \frac{1}{2}\frac{\beta'_{w,i}\,\overline{f}_w - \min_j\{\overline{f}_{w,j}\}}{\max_j\{\overline{f}_{w,j}\} - \min_j\{\overline{f}_{w,j}\}} + \frac{1}{2}\frac{\beta'_{w-1,i}\,\overline{f}_{w-1} - \min_j\{\overline{f}_{w-1,j}\}}{\max_j\{\overline{f}_{w-1,j}\} - \min_j\{\overline{f}_{w-1,j}\}}, \qquad [1]$$

[32] Beta return is the portion of the total return attributed to betas, which is the weighted average of factor returns with observed factor loadings from the base model [M]. This is equivalent to the observed average excess return, less of observed alpha from the base model [M].

where $\beta_{w,i}$ is the vector of factor loadings for fund *i* in window *w*, $\bar{f}_w$ is the vector of average factor returns in window *w*, and $\min_j\{\bar{f}_{w,j}\}$ and $\max_j\{\bar{f}_{w,j}\}$ are the lowest and the highest average monthly returns amongst the eight factor portfolios for window *w*.

In other words, *SBS* allows us to measure how well the manager chose his beta positions relative to the range between the best and worst performing factors. Intuitively, high *SBS* is good – managers are delivering strong contemporaneous performance. The reality is more complicated, however, as it is impossible for even the most prescient managers to precisely time a broad set of macroeconomic factors. In fact, once a manager takes a macro factor driven position, it may not be profitable for some time until macroeconomic conditions play out.[33] Hence, low contemporaneous *SBS* could be an indication of skillful risk taking, consistent with anticipatory bets on mean reversing factors in the future. On the other hand, high contemporaneous *SBS* could be due to simple luck.

As *SBS* is a measure of contemporaneous performance and does not address the dynamic nature of beta activity we introduce another variable, *DBR*, to capture the dynamic aspect of beta active management.

In order to measure the relative degree of active managers' success in making timely strategic changes in overall factor allocations, we compare two-year window realized beta returns to forward and backward looking "what-if" synthetic beta returns. This allows us to quantify how well managers anticipate and react to changing economic conditions.

In the forward looking scenario, we consider the difference between the realized beta return and the forward synthetic beta return, which is the beta return the manager *would* have

[33] For example, Michael Burry's bets against subprime mortgage backed securities taken in 2005 were not profitable for two years until 2007 (see "The Big Short" (2010) by Michael Lewis).

realized *if* he had not changed strategies from the previous two-year window.[34] The "gap" between realized and forward synthetic returns for fund *i* is *FDBR*, or "*Forward Difference in Beta Returns*", such that

$$FDBR_{w,i} = \beta'_{w,i}\,\overline{f}_{w} - \beta'_{w-1,i}\,\overline{f}_{w}, \qquad [2]$$

where $\beta_{w,i}$ is the vector of factor loadings for fund *i* in window *w*, and $\bar{f}_w$ is the vector of average factor returns in window *w*. Notice that the second term inside the summation in [2] utilizes the vector of beta coefficients from the previous window (*w* – 1) regression multiplied by the vector of current window factor return averages in window *w*.

A positive *FDBR* may be indicative of manager skill if ex-ante the manager correctly anticipated changing macroeconomic opportunities; his beta return is higher than it would have been had he not made changes to factor loadings. *FDBR* captures how well a manager performed in relation to a "change nothing"[35] strategy. However, a manager may also have a higher *FDBR* if he simply jumps on the right bandwagon, adopting strategies correlated with the most successful factors from the previous period. If a trend continues into the next period, such strategy would result in a positive *FDBR*, while not truly reflecting anticipatory managerial skill. Consider that economic conditions may persist for years, e.g. low interest rate environments and/or rising real estate prices. If we solely rely upon *FDBR* to identify skilled strategy changers

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[34] Specifically, we carry forward beta coefficients from the previous two-year window and multiply them by the factor returns from the current window, finally averaging these to create a synthetic return.

[35] "Change nothing" refers to only the beta active portion of the manager's portfolio, that is, the allocation of portfolio funds to strategies whose variance in returns is attributable to the variance in factor returns. Strategies not attributable to factors are captured by alpha, and these strategies may vary considerably. Finally, the manager's day to day real activity level may be quite high, especially with regard to options and futures based trend following strategies. Managers may be quite busy "changing nothing".

we would overestimate the skill of managers who are merely trend chasers.[36] We wish to find managers who anticipate changing economic conditions and make strategic changes to portfolio allocations regardless of past trends. We therefore also look backward to establish the relationship between current and past beta strategies with respect to past factor performance. We calculate *RDBR*, or "*Reverse Difference in Beta Returns*", such that

$$RDBR_{w,i} = \beta'_{w-1,i}\overline{f}_{w-1} - \beta'_{w,i}\overline{f}_{w-1}, \qquad [3]$$

where, as before in [2], $\beta_{w,i}$ is the vector of factor loadings for fund *i* in window *w*, and $\bar{f}_w$ is the vector of average factor returns in window *w*. *RDBR* measures the "gap" between the realized beta performance in the previous window and the "what-if" scenario of taking current factor loading into the previous window, and calculating synthetic beta return in the past.[37] While *FDBR* shows improvement as compared to the "change nothing" strategy, *RDBR* simultaneously captures how well a manager chose betas in the past, and also whether he had the foresight to change betas in a way to deviate from previous trends, i.e. not "copy today what worked yesterday". Indeed, if a manager adopts betas that would have worked best in the past it would result in the highest possible $\beta'_{w,i}\overline{f}_{w-1}$, lowering the value of *RDBR*. However, if a manager chose betas in a prescient way, his contemporaneous beta return, $\beta'_{w-1,i}\overline{f}_{w-1}$, would've been high, while the backward looking "what if" return, $\beta'_{w,i}\overline{f}_{w-1}$, would be low, resulting in high values of *RDBR*.

Finally, as *FDBR* and *RDBR* capture complimentary time varying aspects of beta active

[36] Simple U.S. examples could be buying "dot com" companies in 1998 or taking long positions in real estate in 2004. Both strategies were profitable prior to the years referenced, were profitable in the subsequent two years, and then were markedly unprofitable after that.

[37] Specifically, we carry backward beta coefficients from the current two-year window and multiply them by the factor returns from the previous window, finally averaging these to create a synthetic return.

management, we take an average of normalized *FDBR* and *RDBR* to create a combined variable, *DBR*, or "*Difference in Beta Returns*", such that

$$DBR_{w,i} = \frac{1}{2}\frac{FDBR_{w,i} - \min_i\{FDBR_{w,i}\}}{\max_i\{FDBR_{w,i}\} - \min_i\{FDBR_{w,i}\}} + \frac{1}{2}\frac{RDBR_{w,i} - \min_i\{RDBR_{w,i}\}}{\max_i\{RDBR_{w,i}\} - \min_i\{RDBR_{w,i}\}}. \qquad [4]$$

DBR captures overall beta activity across all factors and *SBS* provides a benchmark for performance. We thus consider these variables in combination in the following sections.

F. Empirical Results

1. Correlations

Table II reports correlations between traditional measures of alpha performance, i.e. alpha and alpha *t*-statistic,[38] newly introduced *SBS* and *DBR*, and also adjusted-R^2 and *SR*. Both *SBS* and *DBR* exhibit negative correlations with measures of alpha activity, while correlations of *SBS* and *DBR* with *SR* and R^2 are close to zero. As expected, the highest correlations are observed between alpha and alpha *t*-statistic and between *SR* and R^2.

2. Out-of-Sample Portfolio Comparisons of Single Variables

Here we consider out-of-sample portfolio performance based on alpha, alpha *t*-statistic, *SBS*, *DBR*, *SR*, and R^2. We concentrate our analysis on out-of-sample portfolio tests for several reasons. First, our *SBS* and *DBR* measures rely on imprecise estimates of alpha and beta coefficients from the baseline regression [M], and hence it is measured with error.[39] We mitigate this problem by considering out-of-sample performance of portfolios of funds selected according

[38] We include alpha *t*-statistic as Kosowski, Naik, and Teo (2007) and Jagannathan, Malakhov, and Novikov (2010) find alpha *t*-statistic to be predictive of future performance.

[39] Notice that is addition to measurement errors, there is also a model misspecification error, as the baseline model [M] assumes constant beta coefficients over two year windows.

to our variables of alpha and beta activity.[40] Second, by considering all funds up until the moment of their disappearance from the database, we minimize any effects of survivorship bias. Third, out-of-sample portfolio comparisons allow us to evaluate alpha and beta performance over long periods of time and interpret results in terms of economic significance.

We form portfolios based upon top and bottom quartiles (25%) of past values of each variable. Each "top" and "bottom" portfolio is initially formed on December 31, 1999. We invest the same dollar amount into each fund within a portfolio in the beginning, and follow its performance until December 31, 2012, rebalancing it once a year based on updated rankings with respect to individual variables.[41] When a portfolio fund disappears from the database we redistribute the remaining capital in the fund equally amongst surviving portfolio funds.[42] This procedure produces a time series of 156 monthly returns for each portfolio, allowing us to evaluate long term portfolio performance across various economic conditions, including the most recent financial crisis of 2008 - 2009. We then calculate end dollar values based upon a $1 initial investment, mean excess monthly returns, Sharpe ratios, Fung and Hsieh (2004) alphas, information ratios, and average annual attrition rates for each time series of monthly portfolio returns from January 2000 until December 2012.[43]

Table III reports out-of-sample performance results. We find that the bottom *SBS*

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[40] We don't directly address the statistical significance of our measures, concentrating instead on out-of-sample performance of portfolios constructed by utilizing point estimates. In an effort to get more accurate estimates we also control for serial correlation in reported returns by way of an MA(2) correction procedure as outlined above.

[41] *SBS* and *DBR* calculations are based on immediately preceding two two-year windows, while alpha, alpha *t*-statistic, *SR*, and R^2 only require a single two-year window.

[42] This is somewhat conservative as it is possible that a fund simply choses to stop reporting to the database, which is likely for well performing funds that are no longer accepting new investor flows. However, without returns data we obviously cannot keep the fund in the portfolio.

[43] A drawback of relying on a single long term time series for each portfolio is that we can calculate *t*-statistic and evaluate statistical significance only for mean monthly returns and long term Fung and Hsieh (2004) alphas.

portfolio statistically dominates the top *SBS* portfolio in alpha, while also producing higher mean monthly excess return, Sharpe ratio, and information ratio. This is consistent with the argument that managers with lower *SBS* are making factor related bets that are less profitable contemporaneously but that become profitable in the future as economic conditions change.[44]

While the difference between top and bottom portfolios is not statistically significant for most variables,[45] we do observe a broad pattern of top portfolios doing better than bottom portfolios in alpha, alpha *t*-statistic, *DBR*, and *SR*. Bottom portfolios do better in *SBS* and R^2, the latter consistent with Titman and Tiu (2011). Hence we concentrate on comparing of top performing portfolios across all variables, i.e. top quartile portfolios with respect to alpha, alpha *t*-statistic, 1 – *SBS*, *DBR*, *SR*, and $1 - R^2$. We also calculate the performance of the benchmark portfolio "Bloomberg Peers" that consists of all funds in the database with the history of at least of four years, i.e. of funds for which we can calculate all the variables mentioned above. The results are presented in table IV. With respect to measures of alpha activity, while alpha portfolios produce higher returns, alpha *t*-statistic portfolios produce better and statistically significant long term alpha, consistent with Kosowski, Naik, and Teo (2007) and Jagannathan, Malakhov, and Novikov (2010). Consistent with Bali, Brown, and Caglayan (2012) and Titman and Tiu (2011), top *SR* and $1 - R^2$ portfolios produces statistically significant alphas, although $1 - R^2$ portfolios yielded lower returns that the benchmark Bloomberg Peers portfolio. Both 1 – *SBS* and *DBR* portfolios outperform Bloomberg Peers portfolios in returns and Sharpe ratios,

[44] Given that *SBS* is equivalent to the observed average excess return, less of alpha, the superior performance of the bottom *SBS* portfolio could potentially be attributed to mean reversal of past hedge fund performance, measured by the average past excess return. We compare performance of portfolios selected on the basis of *SBS* and the average excess return in Appendix A, and conclude that *SBS* captures a unique aspect of hedge fund beta activity consistent with long term factor bets, which is not reflected in average past returns.

[45] Except for *SBS* in Fung and Hsieh (2004) alpha and for *SR* in mean monthly returns.

also yielding higher and statistically significant long term alphas. Finally, we introduce a combined measure of the overall beta activity, *BA*, by combining 1 – *SBS* and *DBR* variables as described in the next subsection. The top *BA* portfolio demonstrates outstanding out-of-sample performance, outperforming all other portfolios on all risk-adjusted metrics.

3. Combined Measure of Beta Activity

It is important to note that though both of the introduced metrics of beta activity, *SBS* and *DBR*, point to the possibility of successful beta management, each variable alone cannot be definitively interpreted as direct evidence of skill. Success predicted on the basis by either 1 – *SBS*[46] or *DBR* can be alternatively interpreted as evidence of skill or mere luck. Considering these variables in concert allows us to simultaneously capture different aspects of beta activity reflected in *SBS* and *DBR*, while reducing the likelihood of reflecting random luck, as it is unlikely for managers to be lucky in both variables. Hence we define the overall measure of beta activity, *BA*, as the equally weighted average of normalized *DBR* and 1 – *SBS*, i.e.

$$BA_{w,i} = \frac{1}{2}\frac{DBR_{w,i} - \min_i\{DBR_{w,i}\}}{\max_i\{DBR_{w,i}\} - \min_i\{DBR_{w,i}\}} + \frac{1}{2}\frac{\max_i\{SBS_{w,i}\} - SBS_{w,i}}{\max_i\{SBS_{w,i}\} - \min_i\{SBS_{w,i}\}} \qquad [5]$$

To summarize, *BA* is a more comprehensive measure of beta activity, as *SBS* and *DBR* capture different aspects of overall beta activity. *SBS* is a contemporaneous measure with external factors as benchmarks, while *DBR* captures the time varying aspect of overall beta activity across all factors, benchmarking against its own past and present betas.

We also consider an alternative approach of quantifying the combined effect of *SBS* and *DBR*, through double sorting of hedge funds based on both variables. The analysis is presented in

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[46] We know from the previous subsection that low values of *SBS* are predictive of superior performance, hence higher values of 1 – *SBS* are indicative of future “success”.

Appendix B, and mirrors our methodology with *BA* that follows.

Table V presents the results of out-of-sample performance for portfolios selected with respect to the combined measure of beta activity, *BA*. We compare performance of the top and bottom beta active portfolios[47] and find that top beta active portfolios significantly outperform bottom portfolios while delivering superior long term returns, alphas, Sharpe, and information ratios. Furthermore, as an additional robustness check accounting for the difference in attrition rates between top and bottom portfolios, panels C and D in table V report portfolio performance under the assumption of 50% and 100% losses for all funds that dropped out of the database. While Ackerman, McEnally, and Ravenscraft (1999), Liang (2000), and Fung and Hsieh (2000) document inferior collective performance[48] of the "dropout" funds, Jagannathan, Malakhov, and Novikov (2010) document significant variations in performance prior to leaving the database across dropout funds. Funds that are closed to new investors tend to have better performance than liquidated funds prior to disappearing from the database; however the magnitude of this pattern changes across time as well. While a 100% loss assumption is, perhaps, not completely realistic for all funds that dropped out of the database, it is the most adverse scenario possible. We consider it as the lowest possible benchmark, as we don't have information about the missing funds. We observe that top beta active portfolios outperform bottom beta active portfolios under all scenarios illustrating that *BA* predictive power is robust.

4. Out-of-Sample Portfolio comparisons of Alpha and Beta Activity

We further examine the nature of beta activity by comparing the out-of-sample performance of portfolios formed on the basis of our measure of beta activity, *BA*, to the

[47] We consider both quartile and quintile cutoffs for forming top and bottom portfolios. For robustness, we also calculate all the performance measures correcting for smoothed portfolio returns by applying the MA(2) correction suggested in Getmansky, Lo, and Makarov (2004).
[48] Which is still much better than a 100% assumption.

performance of portfolios formed upon traditional measures of alpha active management, alpha and alpha *t*-statistic.[49] The results for the top quartile and quintile portfolios are presented in table VI. Figure 1 illustrates cumulative returns of a dollar investment in each portfolio and the portfolio of Bloomberg Peer funds. Top beta active portfolios dominate both top alpha and alpha *t*-statistic portfolios in overall returns, Sharpe ratios, and Fung and Hsieh (2004) alphas, indicating the superior predictive power of measures of beta activity over alpha activity. We interpret this as evidence that successful beta activity among top beta active funds delivers superior performance compared to successful alpha activity among top alpha active funds.

Tables VII and VIII provide robustness checks for the quartile and quintile portfolio results reported in table VI. The results of correcting for smoothed portfolio returns by applying the MA(2) correction suggested in Getmansky, Lo, and Makarov (2004) are provided in panels A. Furthermore, beta active portfolios display higher attrition rates than those selected on alpha active metrics, alpha and alpha *t*-statistic, which is consistent with the finding of Fung, Hsieh, Naik, and Ramadorai (2008) that alpha producing funds are less likely to liquidate than funds that do not deliver alpha.[50] Panels B in tables VII and VIII provide robustness checks under the assumption of 50% and 100% losses for all funds that dropped out of the database. We find that beta active portfolios outperform alpha and alpha *t*-statistic portfolios on a risk-adjusted basis in all but one scenario.[51]

In order to further examine the nature of the relative predictive power of measures of

[49] We consider both alpha and alpha *t*-statistic as Kosowski, Naik, and Teo (2007) and Jagannathan, Malakhov, and Novikov (2010) find alpha *t*-statistic to be predictive of future performance.
[50] However, attrition rates of top beta active portfolios of 10.68% and 10.30% are lower than the overall attrition rate of the Bloomberg Peers portfolio of 11.36%.
[51] Only under a 100% loss assumption do top alpha portfolios yield slightly higher returns, while still producing lower alphas as compared to beta active portfolios.

alpha and beta activity, we compare time series of returns generated by alpha and beta portfolios, which are presented in table VI and figures 2 and 3. Figure 2 illustrates the difference in cumulative returns between the top quartile *BA* and *alpha* portfolios over the time period of this study.[52] Figure 3 provides the difference in cumulative returns between the top quartile *BA* and alpha *t*-statistic portfolios. Notice that the *BA* portfolio underperformed the alpha portfolio from mid-2005 through mid-2007, which is the period prior to the most dramatic macroeconomic shift during the period of this study.[53] Given the timing, a plausible conjecture is that top beta active managers were anticipating changing economic conditions prior to the financial crisis of 2008-2009, reallocating portfolios in anticipation of changes to come. Beta active portfolio performance therefore declined relative to the alpha portfolio prior to the actual change in conditions. Even the most skilled managers do not have perfectly accurate timing foresight and thus relative beta performance may be low in anticipatory periods prior to changes in economic conditions. However, as conditions changed, the difference between beta and alpha cumulative portfolio performance increased significantly as top beta active manager bets became profitable.

Finally, to highlight that the out-of-sample predictive power of our measure of beta activity, *BA*, is not driven by alpha, we calculate the average pre-out-of-sample alpha for top performing *BA*, *SR*, R^2, alpha *t*-statistic, and alpha portfolios. Specifically, for each portfolio we calculate the average of the two year alphas of individual funds for the period preceding every portfolio formation and rebalancing. This indicates what preceding in-sample portfolio alphas

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[52] The difference in cumulative return is simply the cumulative return of the top *BA* portfolio minus the cumulative return of the top alpha portfolio as of month *t*. This could be interpreted as the total wealth at month *t* of a portfolio with $1 long investment in the top *BA* and $1 short investment in the top alpha portfolios.

[53] This pattern is less pronounced in the comparison of the top *BA* and top alpha *t*-statistic portfolios, which is consistent with the fact that alpha *t*-statistic provides better out-of-sample risk-adjusted predictions, as measured by the Fung and Hsieh (2004) alpha, along with Sharpe and information ratios.

were for each portfolio prior to tracking its out-of-sample performance. As we see from table IX, the top *BA* portfolio has the second lowest mean pre-out-of-sample short term alpha, while delivering the highest long term out-of-sample alpha. This highlights that beta activity, *BA*, captures a different aspect of active portfolio management that yields the highest long term out-of-sample alpha while selecting portfolios with the lowest preceding short term in-sample alphas.

5. Out-of-Sample Portfolio comparisons of Beta Activity with SR and R^2

We now examine the relationship between *BA*, systematic risk (*SR*) studied in Bali, Brown, and Caglayan (2012), and R^2 as considered in Titman and Tiu (2011). All three variables relate to the concept of beta management and have been shown to have out-of-sample predictive power.

Table X provides out-of-sample comparisons between top quartile *BA* and *SR* portfolios. While the *SR* and the *BA* portfolios produce almost identical mean monthly excess returns, the *BA* portfolio outperforms in all risk-adjusted measures, i.e. in Fung and Hsieh (2004) alpha and Sharpe and information ratios. This is not surprising, given that the top *SR* portfolio by construction provides the highest possible level of systematic risk of all portfolios of the same size.

Next we consider the performance of both *SR* and *BA* portfolios after excluding the funds which are common to both portfolios. We observe that the top *BA* portfolio without the funds also present in the top *SR* portfolio delivers a statistically significant alpha of 0.26, while the top *SR* portfolio excluding funds common to the top *BA* portfolio fails to deliver a statistically significant alpha of 0.13. We also observe that the portfolio of funds common to both *SR* and *BA* portfolios delivers the best out-of-sample returns, as well as statistically significant alpha of 0.83.

Table XI provides out-of-sample comparison between top quartile *BA* and $1 - R^2$

portfolios. While the top 1 – R^2 portfolio delivers a statistically significant alpha of 0.20, the *BA* portfolio outperforms the R^2 portfolio in all performance measures. We then consider the performance of both R^2 and *BA* portfolios after excluding the funds which are common to both portfolios. We observe that the top *BA* portfolio without the funds also present in the top 1 – R^2 portfolio delivers a statistically significant alpha of 0.46, while the top 1 – R^2 portfolio excluding funds common to the top *BA* portfolio fails to deliver a statistically significant alpha. We also observe that the portfolio of funds common to both R^2 and *BA* portfolios delivers a statistically significant alpha of 0.34.

This suggests that *BA* could be interpreted as a common factor driving the long term out-of-sample predictive power of both *SR* and R^2. We conjecture that *BA* successfully captures the time varying nature of beta exposures that is not directly reflected in either *SR* or R^2.

6. In Sample Portfolio comparisons of Beta Activity with SR and R^2

Here we investigate the short term relationship between *BA*, *SR*, and R^2 in the context of an in sample regression. This allows for the multitude of control variables, representing various hedge fund characteristics that may affect future performance. We regress each of the previously calculated performance measures on *BA*, *SR*, and R^2, while controlling for fund characteristics as follows:

$$Performance_{i,w} = a_w + b_{BA,w} BA_{i,w-} + b_{C,w} Controls_{i,w-} + \varepsilon_{i,w} \quad [6]$$

$$Performance_{i,w} = a_w + b_{SR,w} SR_{i,w-} + b_{C,w} Controls_{i,w-} + \varepsilon_{i,w} \quad [7]$$

$$Performance_{i,w} = a_w + b_{BA,w} BA_{i,w-} + b_{SR,w} SR_{i,w-} + b_{C,w} Controls_{i,w-} + \varepsilon_{i,w} \quad [8]$$

$$Performance_{i,w} = a_w + b_{R2,w} R^2{}_{i,w-} + b_{C,w} Controls_{i,w-} + \varepsilon_{i,w} \quad [9]$$

$$Performance_{i,w} = a_w + b_{BA,w} BA_{i,w-} + b_{R2,w} R^2{}_{i,w-} + b_{C,w} Controls_{i,w-} + \varepsilon_{i,w} \quad [10]$$

where $Performance_{i,w}$ variables include excess returns, alphas, and the Sharpe and information ratios. Dependent variables are calculated for each available two year window *w*, while all the independent variables, with the exception of *BA*,[54] are calculated during the preceding two year window *w-*. As we calculate all performance measures annually, we include annual fixed effects. Fund specific control variables include the volatility of fund excess returns in the past two years, *Vol2Yr*;[55] the hurdle rate, *HurdleRate*, the natural logarithm of fund age in months, *Log(age)*, the natural log of asset under management, *Log(AUM)*, the logarithm of one plus redemption notice and lockup periods in months; *Lockup*, the logarithm of one plus minimum investment requirement, *Log(MinInvestment)*, the management fee, *Mgmt_Fee*, the performance fee, *Perf_Fee*, and indicator variables for the high water mark provision, *HighWaterMark*, and whether the fund is offshore, *Offshore*. We also control for potential fund clustering effect by allowing for standard error clustering by fund, as suggested by Petersen (2009).

The results from regressions [6] – [10] are provided in tables XII and XIII. *BA* shows strongly significant predictive power over future short term excess returns and Sharpe ratios, while registering only weak significant predictive power over the short term alpha. This is as expected, given that beta activity is not likely to manifest itself in short term alphas – we only expect to see significant alphas from beta activity over the long term, as only then dynamic changes in beta loadings would play out.[56]

Most important, the magnitude and the strength of statistical significance of *BA* with respect to future two year excess returns and Sharpe ratios holds after the inclusion of *SR* and R^2 as independent variables. This confirms that *BA* captures a unique dimension of active

[54] *BA* is calculated based on the two preceding two year windows.
[55] We don't include *Vol2Yr* as a control variable in regressions [7] and [8], since *Corr*(*SR*,*Vol2yr*) = 0.71. *Vol2Yr* is utilized in regression [9] and [10], as *Corr*(R^2,*Vol2yr*) = 0.16.
[56] This is also indirectly suggested by out-of-sample comparisons in table IX.

management not captured in the short term by either *SR* or R^2. Finally, notice that while both *SR* and R^2 mostly retain their significance after inclusion of *BA* as an independent variable in short term in-sample regressions, the long term out-of-sample predictive power of *BA* takes away statistical significance from both *SR* and R^2. This is consistent with the increasing predicting power of *BA* over longer horizons, as mentioned above.

G. Conclusion

We develop a methodology by which we comprehensively identify and quantify active hedge fund management, as provided by alpha active and beta active performance measures. Alpha active management results in fund alpha, the fund performance unexplained by the returns of arbitrage portfolios. Beta active management, which involves taking directional positions correlated with macroeconomic risk factors, results in time varying values of beta coefficients, and is captured by the introduced measure of beta activity, *BA*.

We report ample evidence that beta active managers deliver superior long term risk adjusted performance in terms of excess returns, Sharpe ratios, Fung and Hsieh (2006) alphas, and information ratios. Beta active portfolios outperform portfolios formulated upon traditional measures of alpha active performance, i.e. alpha and alpha *t*-statistic. We therefore find beta activity to be a stronger predictor of superior future fund performance than alpha activity. Beta activity metrics expand our understanding of active portfolio management and managerial skill and are powerful complements to current alpha-centric methodology.

Finally, we conclude that our measure of beta activity, *BA*, captures a unique aspect of active portfolio management, not captured in the short term by either SR or R^2. Furthermore, there is an indication that over the long term *BA* successfully captures the time varying nature of beta exposures that can be interpreted as a common factor driving the long term predictive power of both *SR* and R^2. This paper examines the spillover effects of long-term issuer credit-downgrades on similar firms in the same industry. We show the opacity of firms hinders information efficiency. Investors infer adverse changes in the creditworthiness and intrinsic values of peer firms at credit downgrade announcements. Increased uncertainty among investors about economic fundamentals, however, limits arbitrage and enables noise trading. The inflated share price declines at credit downgrade announcements are reversed post announcement as information uncertainties about peer firms are resolved. Transparent firms benefit the most from the reduction in information asymmetry and increased informed trading post announcement.

H. References

Ackerman, C., R. McEnally, and D. Ravenscraft. 1999. The Performance of Hedge Funds: Risk, Return, and Incentives. Journal of Finance 54: 833–74.

Agarwal, V., N.D. Daniel, and N.Y. Naik. 2009. Role of Managerial Incentives and Discretion in Hedge Fund Performance. Journal of Finance 64: 2221–56.

Agarwal, V., and N.Y. Naik. 2000. On Taking the Alternative Route: Risks, Rewards, and Performance Persistence of Hedge Funds. Journal of Alternative Investments 2: 6–23.

Agarwal, V., and N.Y. Naik. 2004. Risk and Portfolio Decisions Involving Hedge Funds. Review of Financial Studies 17: 63–98.

Amihud, Y., and R. Goyenko. 2013. Mutual Fund's R2 as Predictor of Performance. Review of Financial Studies 26: 667–94.

Aragon, G. 2007. Share Restriction and Asset Pricing: Evidence from the Hedge Fund Industry. Journal of Financial Economics 83: 33–58.

Asness, C., R. Krail, and J. Liew. 2001. Do Hedge Funds Hedge? Journal of Portfolio Management 28: 6–19.

Avramov, D., L. Barras, and R. Kosowski. 2013. Hedge Fund Return Predictability under the Magnifying Glass. Journal of Financial and Quantitative Analysis 48: 1057–83.

Avramov, D., R. Kosowski, N.Y. Naik, and M. Teo. 2011. Hedge Funds, Managerial Skill, and Macroeconomic Variables. Journal of Financial Economics 99: 672–92.

Bali, T.G., S.J. Brown, and M.O. Caglayan. 2011. Do Hedge Funds' Exposures to Risk Factors Predict Their Future Returns? Journal of Financial Economics 101: 36–68.

Bali, T.G., S.J. Brown, and M.O. Caglayan. 2012. Systematic Risk and the Cross Section of Hedge Fund Returns. Journal of Financial Economics 106: 114–31.

Bollen, N.P.B. 2013. Zero-R2 Hedge Funds and Market Neutrality. Journal of Financial and Quantitative Analysis 48: 519–47.

Bollen, N.P.B., and J.A. Busse. 2001. On the Timing Ability of Mutual Fund Managers. Journal of Finance 56: 1075–94.

Bollen, N.P.B., and R.E. Whaley. 2009. Hedge Fund Risk Dynamics: Implications for Performance Appraisal. Journal of Finance 64: 985–1035.

Brinson, G.P., L.P. Hood, and G.L. Beebower. 1986. Determinants of Portfolio Performance. Financial Analysts Journal 42: 39–44.

Cai, L., and B. Liang. 2012a. On the Dynamics of Hedge Fund Strategies. Journal of Alternative Investments 14: 51–68.

Cai, L., and B. Liang. 2012b. Asset Allocation Dynamics in the Hedge Fund Industry. Journal of Investment Management 10: 35–59.

Cao, C., Y. Chen, B. Liang, and A.W. Lo. 2013. Can Hedge Funds Time Market Liquidity? Journal of Financial Economics 109: 493–516.

Chen, Y. 2007. Timing Ability in the Focus Market of Hedge Funds. Journal of Investment Management 5: 66–98.

Chen, Y., and B. Liang. 2007. Do Market Timing Hedge Funds Time the Market? Journal of Financial and Quantitative Analysis 42: 827–56.

Cremers, K.J.M., and A. Petajisto. 2009. How Active Is Your Fund Manager? A New Measure That Predicts Performance. Review of Financial Studies 22: 3329–65.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers. 1997. Measuring Mutual Fund Performance with Characteristic-Based Benchmarks. Journal of Finance 52: 1035–58.

Fama, E.F. 1972. Components of Investment Performance. Journal of Finance 27: 551–67.

Ferson, W., and R. Schadt. 1996. Measuring Fund Strategy and Performance in Changing Economic Conditions. Journal of Finance 51: 425–60.

Fung, H.G., X.E. Xu, and J. Yau. 2002. Global Hedge Funds: Risk, Return, and Market Timing. Financial Analysts Journal 58: 19–30.

Fung, W., and D.A. Hsieh. 1997. Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds. Review of Financial Studies 10: 275–302.

Fung, W., and D.A. Hsieh. 2000. Performance Characteristics of Hedge Funds and Commodity Funds: Natural vs. Spurious Biases. Journal of Financial and Quantitative Analysis 35: 291–307.

Fung, W., and D.A. Hsieh. 2001. The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers. Review of Financial Studies 14: 313–41.

Fung, W., and D.A. Hsieh. 2002. Hedge Fund Benchmarks: Information Content and Biases. Financial Analysts Journal 58: 22–34.

Fung, W., and D.A. Hsieh. 2004. Hedge Fund Benchmarks: A Risk-Based Approach. Financial Analysts Journal 60: 65–80.

Fung, W., D.A. Hsieh, N.Y. Naik, and T. Ramadorai. 2008. Hedge Funds: Performance, Risk, and Capital Formation. Journal of Finance 63: 1777–803.

Getmansky, M., A.W. Lo, and I. Makarov. 2004. An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns. Journal of Financial Economics 74: 529-609.

Goetzmann, W., J. Ingersoll, M. Spiegel, and I. Welch. 2007. Portfolio Performance Manipulation and Manipulation-proof Performance Measures. Review of Financial Studies 20: 1503–46.

Grinblatt, M., and S. Titman. 1989. Portfolio Performance Evaluation: Old Issues and New Insights. Review of Financial Studies 2: 393–421.

Grinblatt, M., and S. Titman. 1993. Performance Measurement without Benchmarks: An Examination of Mutual Fund Returns. Journal of Business 66: 47–68.

Henriksson, R., and R. Merton. 1981. On Market Timing and Investment Performance II: Statistical Procedures for Evaluating Forecasting Skills. Journal of Business 54: 513–34.

Jagannathan, R., and R.A. Korajczyk. 1986. Assessing the Market Timing Performance of Managed Portfolios. Journal of Business 59: 217–35.

Jagannathan, R., A. Malakhov, and D. Novikov. 2010. Do Hot Hands Exist among Hedge Fund Managers? An Empirical Evaluation. Journal of Finance 65: 217–55.

Jensen, M. 1968. The Performance of Mutual Funds in the Period 1954-1964. Journal of Finance 23: 389–416.

Jensen, M. 1972. Optimal Utilization of Market Forecasts and the Evaluation of Investment Portfolio Performance. In: Szego, G., and K. Shell (eds.), Mathematical Methods in Investment and Finance, Amsterdam: North-Holland.

Jiang, G., T. Yao, and T. Yu. 2007. Do Mutual Funds Time the Market? Evidence from Portfolio Holdings. Journal of Financial Economics 86: 724–58.

Kacperczyk, M., C. Sialm, and L. Zheng. 2008. Unobserved Actions of Mutual Funds. Review of Financial Studies 21: 2379–416.

Kosowski, R., N.Y. Naik, and M. Teo. 2007. Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis. Journal of Financial Economics 84: 229–64.

Lewis, M. 2010. The Big Short: Inside the Doomsday Machine. W. W. Norton & Company, New York.

Liang, B. 2000. Hedge Funds: The Living and the Dead. Journal of Financial and Quantitative Analysis 35: 309–26.

Mamaysky, H., M. Spiegel, and H. Zhang. 2008. Estimating the Dynamics of Mutual Fund Alphas and Betas. Review of Financial Studies 21: 233–64.

Patton, A.J. 2009. Are “Market Neutral” Hedge Funds Really Market Neutral? Review of Financial Studies 22: 2495–530.

Petersen, M. 2009. Estimating Standard Errors in Finance Panel Datasets: Comparing Approaches. Review of Financial Studies 22: 435–80.

Roll, R. 1978. Ambiguity when Performance Is Measured by the Securities Market Line. Journal of Finance 33: 1051–69.

Sadka, R. 2010. Liquidity Risk and the Cross-Section of Hedge-Pund Returns. Journal of Financial Economics 98: 54–71.

Sadka, R. 2012. Hedge-Fund Performance and Liquidity Risk. Journal of Investment Management 10: 60–72.

Sharpe, W.F. 1992. Asset Allocation: Management Style and Performance Management. Journal of Portfolio Management 18: 7–19.

Sun, Z., A. Wang, and L. Zheng. 2012. The Road Less Traveled: Strategy Distinctiveness and Hedge Fund Performance. Review of Financial Studies 25: 96–143.

Titman, S., and C. Tiu. 2011. Do the Best Hedge Funds Hedge? Review of Financial Studies 24: 123–68.

Treynor, J., and K. Mazuy. 1966. Can Mutual Funds Outguess the Market? *Harvard Business Review* 44: 131–6.Alissa, W., Bonsall, S., Koharki, K., Penn, M., 2013, Firms’ Use of Discretion to Influence their Credit Ratings, *Journal of Accounting and Economics* 55: 129-147.

Figure 1: Cumulative Wealth, 2000-2012

Cumulative wealth (in logarithmic scale) from a $1 investment in beta active and alpha active portfolios of funds in the top quartile of respective metrics and compared to an equally weighted index of all Bloomberg Peer hedge funds. Initial portfolios are constructed as of 12/31/1999 and rebalanced annually.

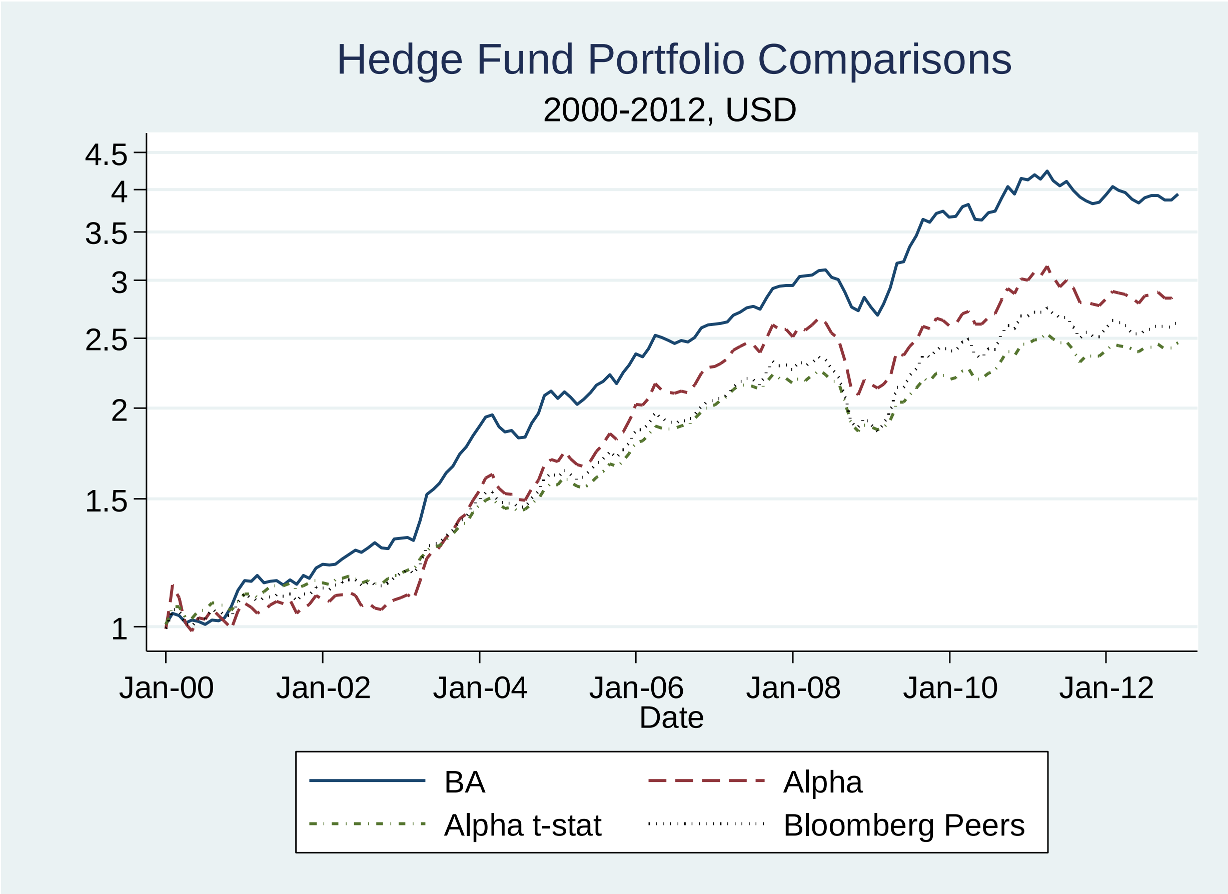

Figure 2: Cumulative difference between *BA* and alpha portfolio returns, 2000-2012

The line represents the difference between the cumulative returns of the BA and alpha portfolios, previously defined. It is equivalent to the return generated by investing \$1 in the BA portfolio and taking a \$1 short position in the alpha portfolio.

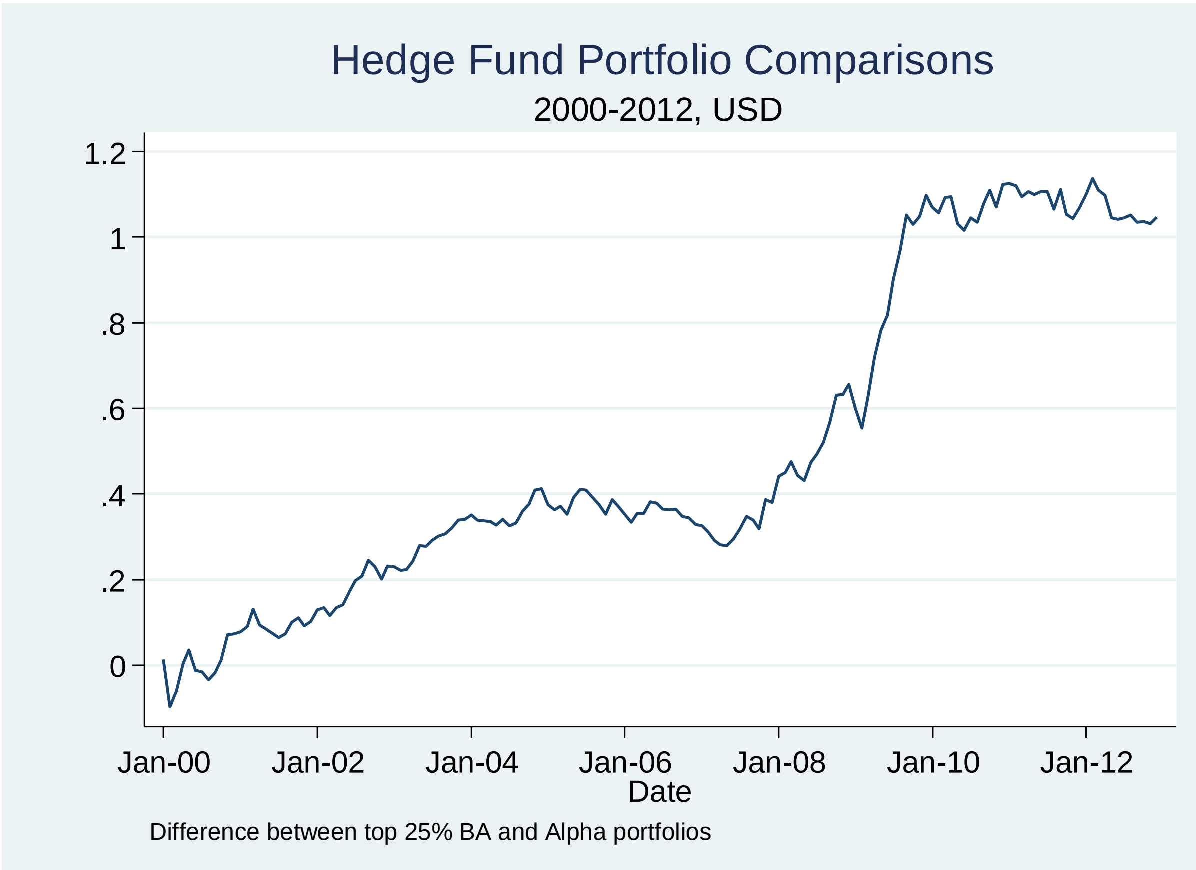

Figure 3: Cumulative difference between *BA* and alpha t-stat portfolio returns, 2000-2012

The line represents the difference between the cumulative returns of the BA and alpha t-stat portfolios, previously defined. It is equivalent to the return generated by investing $1 in the BA portfolio and taking a $1 short position in the alpha t-stat portfolio.

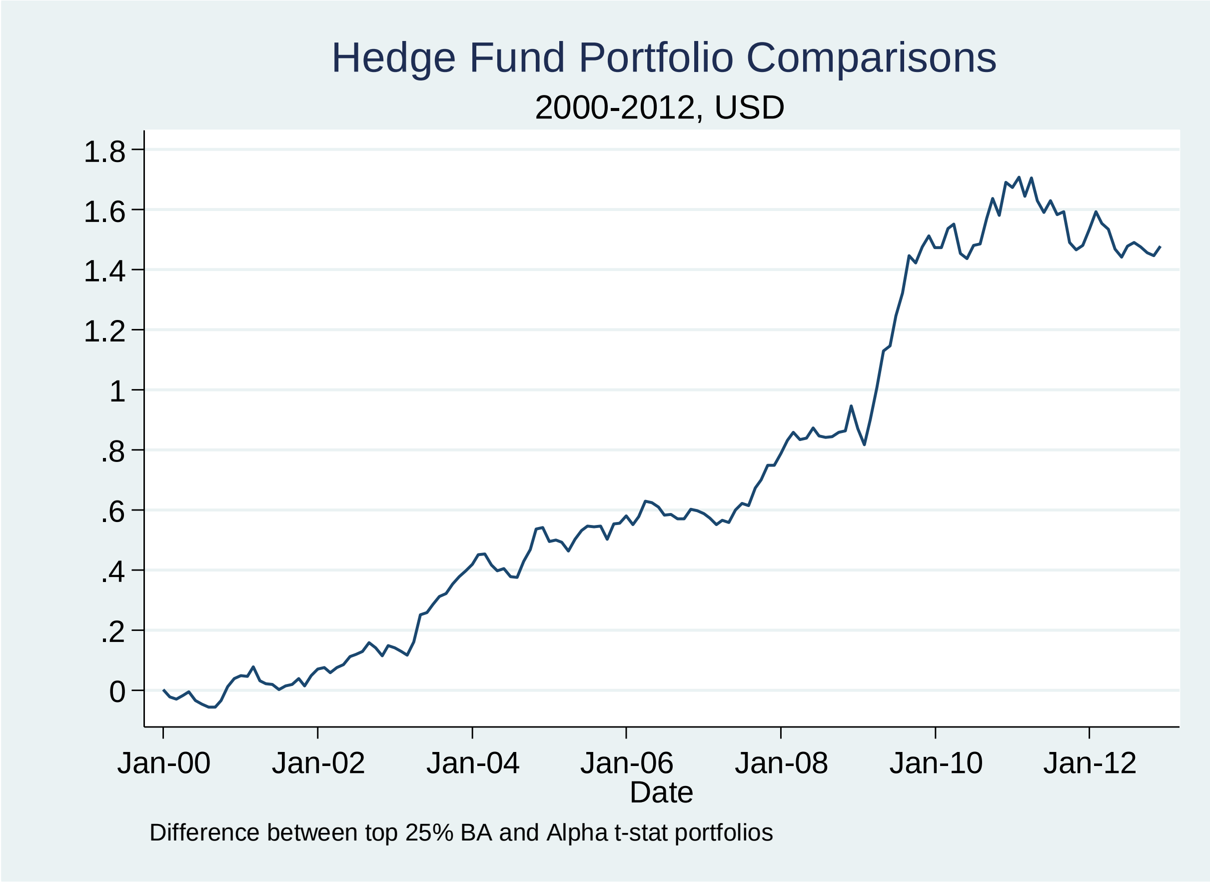

Table I: Summary Statistics

Summary statistics of all hedge funds 1994-2012, reporting as of March, 2013. Panel A reports returns, fees, investor liquidity measures, and fund longevity. Panel B reports means of indicator variables for fund characteristics while panel C reports self-declared fund styles.

Table I: Summary Statistics (Cont.)

Panel A	Full Sample (2,014 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly excess return	0.70	0.58	-4.38	5.95	5.46
Assets ($M)	279.39	34.63	2.50	394.50	2,365.85
Min Invest ($M)	1.08	0.25	0.02	1	12.50
Mgmt Fee (%)	1.47	1.5	0.75	2	0.76
Perf Fee (%)	17.48	20	5	20	6.75
Hurdle Rate (%)	0.37	0	0	0	1.73
Lockup Period (days)	79.80	0	0	360	189.20
Redemption Notice (days)	6.84	0	0	30	17.92
Redemption Period (days)	62.66	30	30	90	65.09
Total Redemption (days)	69.76	40	30	120	68.74
Longevity (months)	146.27	139	102	206	38.42

	Active Funds (963 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly excess return	0.85	0.68	-4.72	6.58	5.81
Assets ($M)	359.24	51.80	3.92	634.00	2,454.73
Min Invest ($M)	0.60	0.25	0.02	1	1.91
Mgmt Fee (%)	1.44	1.5	0.8	2	0.71
Perf Fee (%)	17.55	20	7.5	20	6.55
Hurdle Rate (%)	0.41	0	0	0	1.74
Lockup Period (days)	66.53	0	0	360	176.17
Redemption Notice (days)	9.74	0	0	30	20.74
Redemption Period (days)	56.57	30	15	90	55.58
Total Redemption (days)	66.37	40	15	120	61.21
Longevity (months)	153.11	144	103	227	42.02

	Inactive Funds (1,051 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly excess return	0.58	0.51	-4.11	5.44	5.15
Assets ($M)	187.82	24.55	1.29	247.94	2,256.17
Min Invest ($M)	1.63	0.25	0.015	1	18.23
Mgmt Fee (%)	1.50	1.5	0.75	2	0.82
Perf Fee (%)	17.39	20	4	20	6.98
Hurdle Rate (%)	0.33	0	0	0	1.71
Lockup Period (days)	96.23	0	0	360	203.00
Redemption Notice (days)	3.48	0	0	0	13.17
Redemption Period (days)	70.23	30	30	90	74.56
Total Redemption (days)	73.98	40	30	120	76.88
Longevity (months)	139.48	132	102	191	33.11

Table I: Summary Statistics (Cont.)

Panel B - Indicator	% of Funds		
	Full Sample	Active Funds	Inactive Funds
High Water Mark	0.88	0.87	0.89
Hurdle Rate	0.06	0.07	0.04
Offshore (non-US)	0.69	0.65	0.73
Closed to New Inv	0.07	0.07	0.07
Liquidated	0.19	0.00	0.37
Acquired	0.02	0.00	0.03

Panel C - Fund Styles	% of Funds		
	Full Sample	Active Funds	Inactive Funds
Long Short Equity	0.28	0.34	0.22
Managed Futures	0.14	0.18	0.10
Multi-Style	0.11	0.09	0.13
Macro	0.09	0.08	0.11
Undisclosed	0.08	0.01	0.16
Equity Fundamental Neutral	0.06	0.05	0.07
Long Bias Equity	0.06	0.06	0.05
Emerging Markets	0.05	0.07	0.04
Distressed Securities	0.04	0.02	0.05
Merger Arbitrage	0.02	0.03	0.02
Fixed Income Arbitrage	0.02	0.03	0.02
Convertible Arbitrage	0.02	0.01	0.03
Fixed Income	0.02	0.02	0.02
Equity Statistical Arbitrage	0.01	0.01	0.02
Capital Structure Arbitrage	0.01	0.01	0.01

Table II: Pairwise Correlations of Activity Metrics

Correlations of alpha, beta, systematic risk, and R2 metrics upon which portfolios are formed for out of sample performance tests.

	Alpha	Alpha t-stat	SBS	DBR	SR	R^2
Alpha						
Alpha t-stat	0.4029					
SBS	-0.2742	-0.0860				
DBR	-0.1258	-0.1400	-0.1722			
SR	0.0040	-0.1320	0.0081	0.1381		
R^2	-0.1356	-0.1903	-0.0253	0.1552	0.2987	

Table III: Comparisons of Portfolios Formulated upon a Single Variable, 2000-2012

Portfolios are based upon funds exhibiting top and bottom quartiles of single metrics on December 31, 1999 and rebalanced annually. Attrition rate is the average annual rate at which funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio funds.

Table III: Comparisons of Portfolios Formulated upon a Single Variable, 2000-2012 (Cont.)

Panel A Variables of Alpha Activity

	Alpha					Alpha t-stat				
	Attrition Rate	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio	Attrition Rate	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio
Top 25% Portfolio	8.17%	0.55** (2.35)	0.19	0.18 (1.40)	0.11	10.06%	0.42*** (2.90)	0.23	0.21** (2.54)	0.22
Bottom 25% Portfolio	14.68%	0.52** (2.54)	0.20	0.19 (1.46)	0.13	14.30%	0.48** (2.42)	0.19	0.15 (1.29)	0.11
Top-Bottom Portfolio	-	0.03 (0.21)	0.02	-0.01 (-0.07)	-0.01	-	-0.06 (1.43)	-0.04	0.06 (0.52)	0.04

Panel B Variables of Beta Activity

	SBS					DBR				
	Attrition Rate	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio	Attrition Rate	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio
Top 25% Portfolio	9.66%	0.46* (1.80)	0.14	0.05 (0.37)	0.03	9.76%	0.58*** (2.83)	0.23	0.24* (1.67)	0.16
Bottom 25% Portfolio	11.92%	0.66*** (3.29)	0.26	0.38*** (3.05)	0.27	11.38%	0.51** (2.10)	0.17	0.16 (1.35)	0.11
Top-Bottom Portfolio	-	-0.20 (-1.22)	-0.10	-0.33* (-1.93)	-0.18	-	0.08 (0.56)	0.04	0.09 (0.68)	0.06

Panel C SR and R^2 Variables

	SR					R^2				
	Attrition Rate	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio	Attrition Rate	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio
Top 25% Portfolio	9.69%	0.79** (2.39)	0.19	0.29* (1.77)	0.16	10.45%	0.55* (2.07)	0.17	0.17 (1.51)	0.14
Bottom 25% Portfolio	13.64%	0.30*** (3.94)	0.31	0.17** (2.53)	0.26	13.78%	0.42*** (3.10)	0.25	0.20** (2.05)	0.17
Top-Bottom Portfolio	-	0.49* (1.74)	0.14	0.12 (0.70)	0.07	-	0.12 (0.61)	0.05	-0.02 (-0.22)	-0.02

Table IV: Top Quartile Out-of-Sample Performing Portfolios, 2000-2012

Portfolios are based upon funds exhibiting top quartiles of single metrics on December 31, 1999 and rebalanced annually. Portfolio ending value is as of December 31, 2012. Attrition rate is the average annual rate at which funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio funds.

	End Value	Attrition Rate	Mean Return (t-stat)	Sharpe Ratio	α (t-stat)	Information Ratio
Bloomberg Peers	2.64	11.36%	0.47*** (2.63)	0.21	0.17* (1.78)	0.16
Alpha	2.89	8.17%	0.55** (2.35)	0.19	0.18 (1.40)	0.11
Alpha t-stat	2.46	10.06%	0.42*** (2.90)	0.23	0.21** (2.54)	0.22
SR	3.93	9.69%	0.79** (2.39)	0.19	0.29* (1.77)	0.16
$1 - R^2$	2.48	13.78%	0.42*** (3.10)	0.25	0.20** (2.05)	0.17
1 - SBS	3.49	11.92%	0.66*** (3.29)	0.26	0.38*** (3.05)	0.27
DBR	3.08	9.76%	0.58*** (2.83)	0.23	0.24* (1.67)	0.16
BA	3.94	10.68%	0.74*** (3.86)	0.31	0.43*** (3.12)	0.28

Table V: Top and Bottom Beta Active Portfolio Comparisons

Panels A and B report performance attributes of portfolios in the top and bottom 25% and 20%, respectively, of beta activity. As reported results are as provided by fund managers, while Corrected results are after applying the MA(2) unsmoothing correction. Panels A and B assume that returned capital from disappearing funds is equally reinvested in remaining portfolio funds while panels C and D assume investors suffer 50% of 100% losses of invested capital regardless of reported fund returns prior to fund attrition. Results in panels C and D are as reported. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Panel A BA Quartiles

	Top BA		Bottom BA		Top - Bottom	
	As reported	Corrected	As reported	Corrected	As reported	Corrected
Mean Return	0.74***	0.74***	0.41	0.41	0.32*	0.32*
(t-stat)	(3.86)	(3.96)	(1.55)	(1.56)	(1.71)	(1.71)
Sharpe Ratio	0.31	0.32	0.12	0.12	0.14	0.14
α	0.43***	0.44***	0.05	0.06	0.38**	0.38*
(t-stat)	(3.12)	(3.11)	(0.38)	(0.43)	(2.17)	(2.18)
Info Ratio	0.28	0.28	0.03	0.04	0.19	0.19

Panel B BA Quintiles

	Top BA		Bottom BA		Top - Bottom	
	As reported	Corrected	As reported	Corrected	As reported	Corrected
Mean Return	0.79***	0.79***	0.41	0.41	0.38*	0.38*
(t-stat)	(3.93)	(4.03)	(1.44)	(1.45)	(1.81)	(1.82)
Sharpe ratio	0.32	0.32	0.12	0.13	0.14	0.15
α	0.48***	0.49***	0.06	0.07	0.42**	0.42**
(t-stat)	(3.29)	(3.28)	(0.41)	(0.44)	(2.19)	(2.23)
Info Ratio	0.30	0.29	0.05	0.04	0.19	0.20

Panel C BA Quartiles with Loss Assumptions

	Assuming 50% loss			Assuming 100% loss		
	Top	Bottom	Top-Bottom	Top	Bottom	Top-Bottom
Mean Return	0.36*	0.03	0.33*	-0.02	-0.36	0.33
(t-stat)	(1.81)	(0.10)	(1.69)	(-0.11)	(-1.27)	(1.58)
Sharpe Ratio	0.15	0.01	0.14	-0.01	-0.10	0.13
α	0.05	-0.37**	0.42**	-0.33*	-0.79***	0.46**
(t-stat)	(0.35)	(-2.49)	(2.30)	(-1.88)	(-4.37)	(2.20)
Info Ratio	0.03	-0.21	0.20	-0.16	-0.39	0.20

Panel D BA Quintiles with Loss Assumptions

	Assuming 50% loss			Assuming 100% loss		
	Top	Bottom	Top-Bottom	Top	Bottom	Top-Bottom
Mean Return	0.42**	0.05	0.37*	0.06	-0.31	0.37
(t-stat)	(2.03)	(0.17)	(1.72)	(0.24)	(-1.05)	(1.54)
Sharpe ratio	0.16	0.01	0.14	0.02	-0.09	0.12
α	0.11	-0.33**	0.44**	-0.27	-0.73***	0.46**
(t-stat)	(0.69)	(-2.09)	(2.09)	(-1.44)	(-3.75)	(1.98)
Info Ratio	0.06	-0.18	0.19	-0.12	-0.34	0.18

Table VI: Annual and Cumulative Beta Active and Alpha Active Portfolio Comparisons, 2000-2012

Annual returns and cumulative performance of portfolios formed on the basis of beta and alpha activity metrics, previously defined. Panels A and B report performance of portfolios formulated as of December 31, 1999 and rebalanced annually for funds in the top quartile and quintile, respectively, of their respective metrics. *BA – Alpha* portfolios are equivalent to taking a long position in the *BA* portfolio and a short position in the alpha portfolio. End value is as of December 31, 2012. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table VI: Annual and Cumulative Beta Active and Alpha Active Portfolio Comparisons, 2000-2012 (Cont.)

Panel A Quartiles

	BA	Alpha t-stat	Alpha	BA - AlphaT	BA-Alpha
Year	Annual Return				
2000	12.43	8.64	5.10	3.19	4.02
2001	7.35	6.75	5.06	0.49	1.96
2002	9.56	1.38	-1.27	7.97	10.71
2003	38.83	22.32	37.15	13.87	1.31
2004	15.18	9.48	13.84	5.45	1.16
2005	8.39	10.20	12.85	-1.62	-4.07
2006	13.72	15.72	18.51	-1.68	-4.23
2007	13.16	9.57	12.87	3.26	0.04
2008	-3.61	-13.75	-14.91	11.40	12.45
2009	31.51	17.29	20.76	12.57	9.18
2010	10.78	10.14	14.32	0.76	-3.07
2011	-7.28	-3.79	-8.18	-3.73	0.77
2012	2.65	4.48	4.45	-1.72	-1.74
End Value	3.94	2.46	2.89	1.61	1.30
Mean Return	0.74***	0.42***	0.55**	0.32***	0.19
(t-stat)	(3.86)	(2.90)	(2.35)	(2.67)	(1.33)
Sharpe Ratio	0.31	0.23	0.19	0.21	0.11
α	0.43***	0.21**	0.18	0.22*	0.25*
(t-stat)	(3.12)	(2.54)	(1.40)	(1.78)	(1.95)
Info Ratio	0.31	0.22	0.11	0.16	0.16
Attrition rate	10.68%	10.06%	8.17%	-	-

Panel B Quintiles

	BA	Alpha t-stat	Alpha	BA - AlphaT	BA-Alpha
Year	Annual Return				
2000	12.64	11.13	3.51	0.95	5.47
2001	5.97	7.37	4.20	-1.30	1.51
2002	11.72	2.30	-3.25	9.12	15.10
2003	41.65	16.98	40.39	21.46	0.97
2004	17.06	8.83	14.96	7.88	1.92
2005	8.71	10.53	15.96	-1.58	-6.46
2006	14.12	15.93	18.84	-1.50	-4.15
2007	14.41	8.33	12.43	5.61	1.59
2008	-0.93	-10.94	-13.92	11.01	14.20
2009	32.44	16.22	19.49	14.43	11.09
2010	11.09	10.69	14.41	0.58	-2.89
2011	-8.51	-3.66	-8.71	-5.18	-0.01
2012	1.64	5.14	3.58	-3.29	-1.90
End Value	4.25	2.50	2.90	1.71	1.40
Mean Return	0.79***	0.43***	0.56**	0.36**	0.23
(t-stat)	(3.93)	(3.16)	(2.28)	(2.59)	(1.54)
Sharpe Ratio	0.32	0.25	0.18	0.21	0.12
α	0.48***	0.23***	0.19	0.25*	0.29**
(t-stat)	(3.29)	(2.77)	(1.39)	(1.83)	(2.11)
Info Ratio	0.29	0.24	0.11	0.16	0.17
Attrition rate	10.30%	10.21%	7.64%	-	-

Table VII: Beta and Alpha Portfolio Comparisons, Quartiles, Robustness

Cumulative performance of portfolios formed on the basis of beta and alpha activity metrics, previously defined. As reported results are as provided by fund managers, while Corrected results are after applying the MA(2) unsmoothing correction. Panel A assumes that returned capital from disappearing funds is equally reinvested in remaining portfolio funds while panel B assumes investors suffer 50% of 100% losses of invested capital regardless of reported fund returns prior to fund attrition. Results in panel B are as reported. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Panel A	BA		Alpha t-stat		Alpha		BA - Alpha t-stat		BA - Alpha	
	As reported	Corrected	As reported	Corrected	As reported	Corrected	As reported	Corrected	As reported	Corrected
Mean Return	0.74***	0.74***	0.42***	0.42***	0.55**	0.55**	0.32***	0.32***	0.19	0.19
(t-stat)	(3.86)	(3.96)	(2.90)	(3.00)	(2.35)	(2.37)	(2.67)	(2.70)	(1.33)	(1.32)
Sharpe Ratio	0.31	0.32	0.23	0.24	0.19	0.19	0.21	0.22	0.11	0.11
α	0.43***	0.44***	0.21**	0.22**	0.18	0.19	0.22*	0.22*	0.25*	0.25*
(t-stat)	(3.12)	(3.11)	(2.54)	(2.56)	(1.40)	(1.43)	(1.78)	(1.76)	(1.95)	(1.93)
Info Ratio	0.28	0.28	0.22	0.22	0.11	0.11	0.16	0.16	0.16	0.16

Panel B	Assuming 50% loss					Assuming 100% loss				
	BA	Alpha T	Alpha	BA-AlphaT	BA-Alpha	BA	Alpha T	Alpha	BA-AlphaT	BA-Alpha
Mean Return	0.36*	0.08	0.29	0.28**	0.07	-0.02	-0.27	0.02	0.25*	-0.04
(t-stat)	(1.81)	(0.57)	(1.21)	(2.28)	(0.49)	(-0.11)	(-1.61)	(0.09)	(1.80)	(-0.29)
Sharpe Ratio	0.15	0.04	0.10	0.18	0.04	-0.01	-0.13	0.01	0.14	-0.02
α	0.05	-0.16	-0.10	0.21	0.15	-0.33*	-0.53***	-0.38**	0.20	0.05
(t-stat)	(0.35)	(-1.59)	(-0.75)	(1.58)	(1.14)	(-1.88)	(-3.89)	(-2.53)	(1.32)	(0.35)
Info Ratio	0.03	-0.14	-0.06	0.14	0.09	-0.16	-0.35	-0.20	0.12	0.03

Table VIII: Beta and Alpha Portfolio Comparisons, Quintiles, Robustness

Cumulative performance of portfolios formed on the basis of beta and alpha activity metrics, previously defined. As reported results are as provided by fund managers, while Corrected results are after applying the MA(2) unsmoothing correction. Panel A assumes that returned capital from disappearing funds is equally reinvested in remaining portfolio funds while panel B assumes investors suffer 50% of 100% losses of invested capital regardless of reported fund returns prior to fund attrition. Results in panel B are as reported. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Panel A	BA		Alpha t-stat		Alpha		BA - Alpha t-stat		BA - Alpha	
	As reported	Corrected	As reported	Corrected	As reported	Corrected	As reported	Corrected	As reported	Corrected
Mean Return	0.79***	0.79***	0.43***	0.43***	0.56**	0.56**	0.36**	0.36***	0.23	0.23
(t-stat)	(3.93)	(4.03)	(3.16)	(3.24)	(2.28)	(2.30)	(2.59)	(2.65)	(1.54)	(1.53)
Sharpe Ratio	0.32	0.32	0.25	0.26	0.18	0.18	0.21	0.21	0.12	0.12
α	0.48***	0.49***	0.23***	0.24***	0.19	0.20	0.25*	0.25*	0.29*	0.29*
(t-stat)	(3.29)	(3.28)	(2.77)	(2.76)	(1.39)	(1.42)	(1.83)	(1.88)	(2.11)	(2.12)
Info Ratio	0.30	0.29	0.24	0.24	0.11	0.11	0.16	0.16	0.17	0.17

Panel B	Assuming 50% loss					Assuming 100% loss				
	BA	Alpha T	Alpha	BA-AlphaT	BA-Alpha	BA	Alpha T	Alpha	BA-AlphaT	BA-Alpha
Mean Return	0.42**	0.08	0.31	0.34**	0.11	0.06	-0.27	0.07	0.32*	-0.01
(t-stat)	(2.03)	(0.57)	(1.26)	(2.31)	(0.70)	(0.24)	(-1.56)	(0.27)	(1.92)	(-0.07)
Sharpe Ratio	0.16	0.05	0.10	0.19	0.06	0.02	-0.12	0.02	0.15	-0.01
α	0.11	-0.14	-0.07	0.25*	0.18	-0.27	-0.52***	-0.33**	0.25	0.06
(t-stat)	(0.69)	(-1.37)	(-0.49)	(1.66)	(1.24)	(-1.44)	(-3.51)	(-2.13)	(1.41)	(0.39)
Info Ratio	0.06	-0.12	-0.04	0.15	0.10	-0.12	-0.32	-0.17	0.13	0.03

Table IX: Comparison of Preceding In-Sample with Resulting Out-of-Sample Alphas

Preceding in-sample alphas are calculated for each portfolio as alphas for the two year period preceding portfolio formation period of individual funds, averaging across all funds in a portfolio and across time. Out-of-sample alphas are based on the entire out-of-sample time period from 2000 until 2012. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

	BA	SR	R^2	Alpha t-stat	Alpha
Average preceding in-sample alpha	0.44	0.43	0.53	1.06	1.40
Out-of-sample alpha	0.43***	0.29*	0.20**	0.21**	0.18

Table X: Out-of-Sample *SR* and *BA* Portfolio Comparisons, 2000-2012

Annual returns and cumulative performance of portfolios formed on the basis of SR and BA metrics, previously defined. Portfolios are formed as of December 31, 1999 and rebalanced annually for funds in the top quartile of their respective metrics. End value is as of December 31, 2012. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table X: Out-of-Sample *SR* and *BA* Portfolio Comparisons, 2000-2012 (Cont.)

	SR			BA			Top BA excluding top SR			Top SR excluding top BA			Top SR and top BA		
Year	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds
2000	2.00	36	36	12.43	36	36	14.99	26	26	0.55	26	26	5.79	10	10
2001	0.15	51	51	7.35	51	51	9.75	27	27	-3.84	27	27	4.64	24	24
2002	-4.45	70	65	9.56	70	68	10.03	46	46	-11.02	46	43	8.66	24	22
2003	45.04	90	86	38.83	90	84	23.02	53	50	33.57	53	52	61.95	37	34
2004	16.66	112	109	15.18	112	108	11.89	66	62	14.47	66	63	19.72	46	46
2005	20.97	140	132	8.39	140	130	8.19	87	81	28.23	87	83	8.75	53	49
2006	18.35	189	172	13.72	189	174	14.13	164	152	19.48	164	150	10.64	25	22
2007	18.75	226	203	13.16	226	200	11.61	180	161	18.55	180	164	19.45	46	39
2008	-18.52	270	214	-3.61	270	208	-10.07	215	171	-28.31	215	177	24.46	55	37
2009	52.35	276	233	31.51	276	229	17.84	180	149	49.85	180	153	56.90	96	80
2010	19.32	295	258	10.78	295	228	8.93	233	173	19.89	233	203	17.07	62	55
2011	-13.65	325	246	-7.28	325	238	-5.90	265	190	-14.02	265	198	-12.16	60	48
2012	9.34	249	215	2.65	249	225	1.61	160	141	12.30	160	131	4.45	89	84
End Value		3.93			3.94			2.91			2.97			7.03	
Mean Return		0.79**			0.74***			0.53***			0.63*			1.15***	
(t-stat)		(2.39)			(3.86)			(3.45)			(1.69)			(3.83)	
Sharpe Ratio		0.19			0.31			0.27			0.14			0.31	
α		0.29*			0.43***			0.26**			0.13			0.83***	
(t-stat)		(1.77)			(3.12)			(2.03)			(0.70)			(3.39)	
Info Ratio		0.16			0.31			0.19			0.06			0.31	
Attrition rate		9.69%			10.68%			10.78%			9.53%			10.58%	

Table XI: Annual and Cumulative Out-of-Sample R^2 and *BA* Portfolio Comparisons, 2000-2012

Annual returns and cumulative performance of portfolios formed on the basis of R2 and BA metrics, previously defined. Portfolios are formed as of December 31, 1999 and rebalanced annually for funds in the top quartile of their respective metrics. End value is as of December 31, 2012. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table XI: Annual and Cumulative Out-of-Sample R^2 and *BA* Portfolio Comparisons, 2000-2012 (Cont.)

	$1-R^2$			BA			Top BA excluding top $1-R^2$			Top $1-R^2$ excluding top BA			Top $1-R^2$ and top BA		
Year	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds
2000	9.81	36	35	12.43	36	36	9.00	19	19	3.97	19	18	16.27	17	17
2001	10.43	51	51	7.35	51	51	5.31	36	36	9.68	36	36	12.23	15	15
2002	7.44	70	65	9.56	70	68	9.03	57	55	6.45	57	52	11.90	13	13
2003	19.04	90	84	38.83	90	84	41.40	75	70	17.74	75	70	26.16	15	14
2004	10.89	112	105	15.18	112	108	13.02	89	86	7.58	89	83	23.16	23	22
2005	8.43	140	128	8.39	140	130	9.12	105	97	9.15	105	95	6.18	35	33
2006	10.83	189	173	13.72	189	174	15.56	118	109	10.95	118	108	10.61	71	65
2007	12.23	226	188	13.16	226	200	14.60	143	129	13.18	143	117	10.59	83	71
2008	-3.86	270	212	-3.61	270	208	-6.69	167	123	-7.12	167	127	1.14	103	85
2009	8.46	276	228	31.51	276	229	41.81	199	166	9.49	199	165	5.66	77	63
2010	6.72	295	201	10.78	295	228	11.60	198	166	5.72	198	139	8.83	97	62
2011	-4.72	325	225	-7.28	325	238	-6.27	185	138	-1.59	185	125	-8.55	140	100
2012	0.82	249	197	2.65	249	225	5.12	170	160	2.70	170	132	-2.99	79	65
End Value		2.48			3.94			4.21			2.29			3.04	
Mean Return		0.42***			0.74***			0.78***			0.37***			0.57***	
(t-stat)		(3.10)			(3.86)			(3.78)			(2.92)			(2.86)	
Sharpe Ratio		0.25			0.31			0.30			0.23			0.23	
α		0.20**			0.43***			0.46***			0.13			0.34**	
(t-stat)		(2.05)			(3.12)			(2.98)			(1.53)			(2.12)	
Info Ratio		0.17			0.31			0.27			0.13			0.18	
Attrition rate		13.78%			10.68%			9.92%			14.56%			12.13%	

Table XII: In Sample Regressions of *BA* and *SR*

In sample regressions. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table XII: In Sample Regressions of *BA* and *SR* (Cont.)

	Excess return	Sharpe ratio	Alpha	Information ratio	Excess return	Sharpe ratio	Alpha	Information ratio	Excess return	Sharpe ratio	Alpha	Information ratio
BA	3.375***	0.391***	1.197*	0.127					3.248***	0.532***	0.170*	0.263*
	(4.09)	(3.48)	(1.80)	(0.91)					(4.07)	(4.43)	(1.77)	(1.86)
SR					1.439***	-0.215**	0.499	-0.298***	1.743***	-0.165**	0.608	-0.274***
					(3.89)	(-2.49)	(1.18)	(-3.32)	(4.80)	(-2.02)	(1.41)	(-3.14)
Vol2Yr	0.080***	-0.018***	0.027**	-0.022***								
	(9.01)	(-2.71)	(2.42)	(-3.36)								
HightWaterMark	-0.134*	-0.040	-0.227**	-0.079	-0.158**	-0.046	-0.236**	-0.083	-0.129	-0.041	-0.226**	-0.080
	(-1.65)	(-0.85)	(-2.36)	(-1.44)	(-1.98)	(-0.98)	(-2.42)	(-1.51)	(-1.54)	(-0.86)	(-2.31)	(-1.45)
HurdleRate	-0.016	0.015	-0.006	0.019	-0.014	0.012	-0.006	0.015	-0.010	0.012	-0.005	0.016
	(-1.13)	(0.99)	(-0.41)	(1.17)	(-1.04)	(0.80)	(-0.39)	(1.01)	(-0.72)	(0.84)	(-0.30)	(1.02)
Log(Age)	-0.061	-0.045*	-0.041	-0.030	-0.075	-0.041*	-0.045	-0.025	-0.080	-0.042*	-0.047	-0.026
	(-1.12)	(-1.95)	(-0.70)	(-1.18)	(-1.38)	(-1.78)	(-0.78)	(-1.00)	(-1.46)	(-1.81)	(-0.81)	(-1.02)
Log(AUM)	0.083***	0.024***	0.065***	0.030***	0.082***	0.025***	0.064***	0.031***	0.084***	0.025***	0.065***	0.031***
	(8.09)	(5.99)	(5.99)	(6.87)	(8.09)	(5.98)	(5.97)	(6.83)	(8.28)	(6.05)	(6.10)	(6.87)
Lockup	-0.006	-0.013	-0.034*	-0.010	-0.023	-0.010	-0.039*	-0.005	-0.019	-0.009	-0.038*	-0.005
	(-0.26)	(-0.77)	(-1.51)	(-0.62)	(-0.98)	(-0.53)	(-1.71)	(-0.30)	(-0.82)	(-0.50)	(-1.66)	(-0.29)
Log(MinInvestment)	0.062	0.016	0.076*	0.030	0.023	0.027	0.064	0.043**	0.026	0.028	0.065	0.043**
	(1.38)	(0.85)	(1.66)	(1.40)	(0.51)	(1.57)	(1.37)	(2.04)	(0.56)	(1.59)	(1.41)	(2.06)
Mgmt_Fee	0.032	-0.013	0.104***	0.019	0.039	-0.016	0.106***	0.015	0.035	-0.017	0.105***	0.015
	(1.00)	(-0.95)	(3.01)	(1.39)	(1.23)	(-1.19)	(3.13)	(1.08)	(1.09)	(-1.22)	(3.10)	(1.06)
Perf_Fee	0.008**	0.003	0.021***	0.007*	0.011***	0.004	0.022***	0.007*	0.009**	0.003	0.021***	0.006*
	(2.08)	(1.09)	(4.18)	(1.83)	(2.85)	(1.20)	(4.36)	(1.86)	(2.22)	(1.05)	(4.20)	(1.79)
Offshore	-0.195***	-0.063	-0.330***	-0.112***	-0.239***	-0.055	-0.336***	-0.102***	-0.223***	-0.052	-0.331***	-0.101***
	(-4.03)	(-1.52)	(-6.26)	(-3.10)	(-4.74)	(-1.37)	(-6.25)	(-2.86)	(-4.46)	(-1.31)	(-6.21)	(-2.82)
Adj R-squared	0.248	0.096	0.075	0.058	0.223	0.085	0.072	0.046	0.230	0.087	0.074	0.047
Number of obs	4154	4154	4154	4154	4154	4154	4154	4154	4154	4154	4154	4154

Table XIII: In Sample Regressions of *BA* and R^2

In sample regressions. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table XIII: In Sample Regressions of *BA* and R^2 (Cont.)

	Excess return	Sharpe ratio	Alpha	Information ratio	Excess return	Sharpe ratio	Alpha	Information ratio	Excess return	Sharpe ratio	Alpha	Information ratio
BA	3.375***	0.391***	1.197*	0.127					3.314***	0.274**	1.012	-0.048
	(4.09)	(3.48)	(1.80)	(0.91)					(3.97)	(2.42)	(1.52)	(-0.34)
R^2					-0.188**	-0.217**	-0.356***	-0.313***	-0.110	-0.211**	-0.332***	-0.314***
					(-2.10)	(-2.54)	(-3.80)	(-3.53)	(-1.20)	(-2.45)	(-3.55)	(-3.51)
Vol2Yr	0.080***	-0.018***	0.027**	-0.022***	0.073***	-0.016***	0.029***	-0.017***	0.082***	-0.015***	0.031***	-0.017***
	(9.01)	(-2.71)	(2.42)	(-3.36)	(8.06)	(-2.85)	(2.60)	(-3.22)	(8.79)	(-2.68)	(2.80)	(-3.20)
HightWaterMark	-0.134*	-0.040	-0.227**	-0.079	-0.156**	-0.035	-0.224**	-0.068	-0.130	-0.033	-0.216**	-0.068
	(-1.65)	(-0.85)	(-2.36)	(-1.44)	(-2.03)	(-0.74)	(-2.38)	(-1.24)	(-1.60)	(-0.69)	(-2.29)	(-1.25)
HurdleRate	-0.016	0.015	-0.006	0.019	-0.019	0.015	-0.007	0.019	-0.015	0.015	-0.006	0.019
	(-1.13)	(0.99)	(-0.41)	(1.17)	(-1.42)	(0.98)	(-0.47)	(1.20)	(-1.12)	(1.00)	(-0.39)	(1.19)
Log(Age)	-0.061	-0.045*	-0.041	-0.030	-0.051	-0.036	-0.026	-0.017	-0.057	-0.037*	-0.028	-0.017
	(-1.12)	(-1.95)	(-0.70)	(-1.18)	(-0.95)	(-1.63)	(-0.45)	(-0.70)	(-1.04)	(-1.65)	(-0.48)	(-0.69)
Log(AUM)	0.083***	0.024***	0.065***	0.030***	0.082***	0.025***	0.065***	0.032***	0.084***	0.025***	0.066***	0.032***
	(8.09)	(5.99)	(5.99)	(6.87)	(8.14)	(6.25)	(6.20)	(7.27)	(8.21)	(6.27)	(6.27)	(7.27)
Lockup	-0.006	-0.013	-0.034*	-0.010	-0.005	-0.008	-0.025	-0.001	-0.003	-0.007	-0.025	-0.001
	(-0.26)	(-0.77)	(-1.51)	(-0.62)	(-0.23)	(-0.44)	(-1.13)	(-0.06)	(-0.12)	(-0.42)	(-1.10)	(-0.06)
Log(MinInvestment)	0.062	0.016	0.076*	0.030	0.048	0.006	0.059	0.016	0.057	0.006	0.061	0.016
	(1.38)	(0.85)	(1.66)	(1.40)	(1.09)	(0.28)	(1.26)	(0.71)	(1.27)	(0.31)	(1.33)	(0.70)
Mgmt_Fee	0.032	-0.013	0.104***	0.019	0.032	-0.015	0.100***	0.015	0.030	-0.016	0.100***	0.015
	(1.00)	(-0.95)	(3.01)	(1.39)	(1.03)	(-1.15)	(2.88)	(1.10)	(0.96)	(-1.15)	(2.88)	(1.10)
Perf_Fee	0.008**	0.003	0.021***	0.007*	0.010**	0.002	0.019***	0.004	0.008*	0.002	0.019***	0.004
	(2.08)	(1.09)	(4.18)	(1.83)	(2.41)	(0.66)	(3.90)	(1.19)	(1.87)	(0.60)	(3.79)	(1.20)
Offshore	-0.195***	-0.063	-0.330***	-0.112***	-0.217***	-0.069*	-0.335***	-0.118***	-0.197***	-0.067	-0.329***	-0.119***
	(-4.03)	(-1.52)	(-6.26)	(-3.10)	(-4.46)	(-1.67)	(-6.43)	(-3.33)	(-4.08)	(-1.62)	(-6.40)	(-3.32)
Adj R-squared	0.248	0.096	0.075	0.058	0.236	0.102	0.077	0.074	0.249	0.103	0.079	0.074
Number of obs	4154	4154	4154	4154	4154	4154	4154	4154	4154	4154	4154	4154

Table XIV: Portfolios Formulated upon *SAR*, 2000-2012

Portfolios are based upon funds exhibiting top and bottom quartiles of single metrics on December 31, 1999 and rebalanced annually. Attrition rate is the average annual rate at which funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio funds.

	SAR				
	Attrition Rate	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio
Top 25% Portfolio	6.89%	0.44 (1.65)	0.13	-0.01 (-0.04)	-0.00
Bottom 25% Portfolio	16.92%	0.60*** (3.55)	0.29	0.37*** (2.85)	0.26
Top-Bottom Portfolio	-	-0.16 (-0.78)	-0.06	-0.37* (-1.84)	-0.16

Table XV: Out-of-Sample *SBS* and *SAR* Portfolio Comparisons, 2000-2012

Annual returns and cumulative performance of portfolios formed on the basis of SBS and SAR metrics, previously defined. Portfolios are formed as of December 31, 1999 and rebalanced annually for funds in the bottom quartile of their respective metrics. End value is as of December 31, 2012. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table XV: Out-of-Sample *SBS* and *SAR* Portfolio Comparisons, 2000-2012 (Cont.)

	Bottom SBS			Bottom SAR			Btm SBS excluding btm SAR			Btm SAR excluding btm SBS			Btm SBS and btm SAR		
Year	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds
2000	10.16	36	36	10.22	36	35	10.44	23	23	10.47	23	22	9.65	13	13
2001	6.97	51	50	6.44	51	50	4.41	25	25	3.42	25	25	9.47	26	25
2002	-1.66	70	65	6.23	70	66	-3.83	52	49	6.64	52	50	5.00	18	16
2003	33.27	90	82	24.89	90	81	36.81	50	45	21.64	50	44	28.93	40	37
2004	12.00	112	107	10.06	112	96	11.71	75	71	8.39	75	60	12.67	37	36
2005	8.33	140	131	9.20	140	125	8.03	106	103	9.20	106	97	9.22	34	28
2006	11.00	189	174	9.17	189	172	12.51	121	112	9.65	121	110	8.30	68	62
2007	11.59	226	198	11.53	226	183	11.66	132	118	11.50	132	103	11.51	94	80
2008	-0.95	270	212	-2.44	270	186	-3.77	157	128	-6.85	157	102	3.24	113	84
2009	44.83	276	221	41.31	276	202	42.58	134	117	34.91	134	98	47.40	142	104
2010	11.08	295	238	7.32	295	212	13.02	195	171	7.74	195	145	6.23	100	67
2011	-7.57	325	236	-6.30	325	224	-7.32	232	170	-5.52	232	158	-8.15	93	66
2012	2.08	249	205	2.52	249	176	2.32	181	160	2.78	181	131	2.07	68	45
End Value		3.49			3.24			3.38			2.82			3.66	
Mean Return		0.66***			0.60***			0.65***			0.51***			0.69***	
(t-stat)		(3.29)			(3.55)			(3.00)			(3.19)			(3.36)	
Sharpe Ratio		0.26			0.29			0.24			0.26			0.27	
α		0.38***			0.37***			0.36***			0.29**			0.42**	
(t-stat)		(3.29)			(2.85)			(2.91)			(2.34)			(2.54)	
Info Ratio		0.27			0.26			0.24			0.22			0.22	
Attrition rate		11.92%			16.92%			9.52%			17.45%			16.52%	

Table XVI: Top and Bottom "Beta" and "Alpha" Portfolio Comparisons

Panels A and B report performance of top and bottom portfolios based on double sorts of variables of beta and alpha activity. As reported results are as provided by fund managers, while Corrected results are after applying the MA(2) unsmoothing correction. Panels A and B present results for "Beta" portfolios, and panels C and D present results for "Alpha" portfolios. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table XVI: Top and Bottom “Beta” and “Alpha” Portfolio Comparisons (Cont.)

"Beta" Portfolios

Panel A. 1-SBS * DBR

	Top		Bottom		Top - Bottom	
	As reported	Corrected	As reported	Corrected	As reported	Corrected
Mean Return	0.87***	0.87***	0.32	0.32	0.55*	0.55*
(t-stat)	(4.01)	(4.08)	(0.95)	(0.96)	(1.86)	(1.88)
Sharpe Ratio	0.32	0.33	0.08	0.08	0.15	0.15
α	0.62***	0.63***	-0.12	-0.11	0.74***	0.74***
(t-stat)	(3.46)	(3.46)	(-0.62)	(-0.55)	(2.74)	(2.76)
Info Ratio	0.29	0.30	-0.05	-0.05	0.24	0.24
Attrition Rate	10.17%		8.62%		-	

Panel B. DBR * 1-SBS

	Top		Bottom		Top - Bottom	
	As reported	Corrected	As reported	Corrected	As reported	Corrected
Mean Return	0.75***	0.75***	0.23	0.23	0.53*	0.53*
(t-stat)	(3.77)	(3.81)	(0.72)	(0.73)	(1.90)	(1.92)
Sharpe ratio	0.30	0.30	0.06	0.06	0.15	0.15
α	0.54***	0.54***	-0.12	-0.10	0.66***	0.65***
(t-stat)	(2.96)	(3.00)	(-0.72)	(-0.59)	(2.72)	(2.65)
Info Ratio	0.26	0.27	-0.06	-0.05	0.25	0.24
Attrition Rate	7.72%		9.71%		-	

"Alpha" Portfolios

Panel C. Alpha * Alpha t-stat

	Top		Bottom		Top - Bottom	
	As reported	Corrected	As reported	Corrected	As reported	Corrected
Mean Return	0.50***	0.50***	0.42*	0.43*	0.08	0.08
(t-stat)	(3.05)	(3.12)	(1.74)	(1.76)	(0.41)	(0.40)
Sharpe Ratio	0.24	0.25	0.14	0.14	0.03	0.03
α	0.21**	0.22**	-0.00	0.01	0.22	0.21
(t-stat)	(2.20)	(2.25)	(-0.02)	(0.08)	(1.24)	(1.20)
Info Ratio	0.17	0.17	-0.00	0.01	0.10	0.10
Attrition Rate	9.55%		20.90%		-	

Panel D. Alpha t-stat * Alpha

	Top		Bottom		Top - Bottom	
	As reported	Corrected	As reported	Corrected	As reported	Corrected
Mean Return	0.78***	0.78***	0.49*	0.49*	0.29	0.29
(t-stat)	(3.25)	(3.28)	(1.69)	(1.71)	(1.21)	(1.22)
Sharpe ratio	0.26	0.26	0.14	0.14	0.10	0.10
α	0.49***	0.49***	0.09	0.11	0.40*	0.39
(t-stat)	(2.88)	(2.88)	(0.44)	(0.52)	(1.66)	(1.57)
Info Ratio	0.24	0.24	0.04	0.04	0.14	0.13
Attrition Rate	8.13%		19.59%		-	

Table XVII: Annual and Cumulative "Beta" and "Alpha" Portfolio Comparisons, 2000-2012

Annual returns, cumulative performance, and long/short performance of "Beta" and "Alpha" portfolios, based on double sorts of variables of beta and alpha activity. Portfolios are formed on December 31, 1999 and rebalanced annually. End value is as of December 31, 2012. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table XVII: Annual and Cumulative "Beta" and "Alpha" Portfolio Comparisons, 2000-2012 (Cont.)

Panel A

	1-SBS_DBR	Alpha_AlphaT	AlphaT_Alpha	1-SBS_DBR-Alpha_AlphaT	1-SBS_DBR-AlphaT_Alpha
Year	Annual Return				
2000	24.79	14.11	17.27	7.62	5.02
2001	9.58	5.40	4.34	3.93	4.47
2002	-2.83	-0.02	1.18	-2.84	-4.17
2003	40.94	26.23	45.22	12.02	-3.01
2004	15.92	8.87	14.10	6.74	1.42
2005	7.38	12.45	27.60	-4.57	-16.71
2006	12.01	16.85	19.81	-4.18	-6.66
2007	12.82	10.00	12.31	2.50	0.28
2008	11.18	-11.33	-2.82	24.61	14.09
2009	36.87	13.59	10.67	20.94	23.53
2010	14.43	12.38	16.38	2.10	-1.60
2011	-8.59	-2.84	-10.26	-6.10	1.33
2012	2.39	5.38	3.84	-2.86	-1.54
End Value	4.80	2.77	4.11	1.71	1.12
Mean Return	0.87***	0.50***	0.78**	0.37**	0.09
(t-stat)	(4.01)	(3.05)	(3.25)	(1.98)	(0.54)
Sharpe Ratio	0.32	0.24	0.26	0.16	0.04
α	0.62***	0.21**	0.49***	0.41**	0.14
(t-stat)	(3.46)	(2.20)	(2.88)	(2.11)	(0.75)
Info Ratio	0.29	0.17	0.24	0.18	0.06
Attrition rate	10.17%	9.55%	8.13%	-	-

Table XVII: Annual and Cumulative “Beta” and “Alpha” Portfolio Comparisons, 2000-2012 (Cont.)

Panel B

	DBR_1-SBS	Alpha_AlphaT	AlphaT_Alpha	DBR_1-SBS-Alpha_AlphaT	DBR_1-SBS-AlphaT_Alpha
Year	Annual Return				
2000	17.76	14.11	17.27	0.54	-1.89
2001	2.64	5.40	4.34	-2.83	-2.44
2002	5.36	-0.02	1.18	5.18	3.83
2003	35.31	26.23	45.22	7.38	-7.23
2004	15.95	8.87	14.10	6.60	1.12
2005	7.52	12.45	27.60	-4.41	-16.53
2006	11.25	16.85	19.81	-4.82	-7.28
2007	19.21	10.00	12.31	8.34	6.06
2008	8.06	-11.33	-2.82	21.25	10.94
2009	23.35	13.59	10.67	8.89	11.30
2010	13.70	12.38	16.38	1.44	-2.22
2011	-10.24	-2.84	-10.26	-7.89	-0.64
2012	3.93	5.38	3.84	-1.39	-0.26
End Value	4.03	2.77	4.11	1.41	0.92
Mean Return	0.75***	0.50***	0.78**	0.25	-0.03
(t-stat)	(3.77)	(3.05)	(3.25)	(1.26)	(-0.13)
Sharpe Ratio	0.30	0.24	0.26	0.10	-0.01
α	0.54***	0.21**	0.49***	0.32	0.05
(t-stat)	(2.96)	(2.20)	(2.88)	(1.60)	(0.23)
Info Ratio	0.26	0.17	0.24	0.14	0.02
Attrition rate	7.72%	9.55%	8.13%	-	-

Table XVIII: "Beta" and "Alpha" portfolio comparisons, robustness

Cumulative performance and long/short performance of "Beta" and "Alpha" portfolios, based on double sorts of variables of beta and alpha activity. As reported results are as provided by fund managers, while Corrected results are after applying the MA(2) unsmoothing correction. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table XVIII: "Beta" and "Alpha" portfolio comparisons, robustness (Cont.)

Panel A	1-SBS*DBR		Alpha*AlphaT		AlphaT*Alpha		1-SBS*DBR - Alpha*AlphaT		1-SBS*DBR - AlphaT*Alpha	
	As reported	Corrected	As reported	Corrected	As reported	Corrected	As reported	Corrected	As reported	Corrected
Mean Return	0.87***	0.87***	0.50***	0.50***	0.78***	0.78***	0.37**	0.37**	0.09	0.09
(t-stat)	(4.01)	(4.08)	(3.05)	(3.12)	(3.25)	(3.28)	(1.98)	(1.99)	(0.54)	(0.55)
Sharpe Ratio	0.32	0.33	0.24	0.25	0.26	0.26	0.16	0.16	0.04	0.04
α	0.62***	0.63***	0.21**	0.22**	0.49***	0.49***	0.41**	0.41**	0.14	0.14
(t-stat)	(3.46)	(3.46)	(2.20)	(2.25)	(2.88)	-2.88	(2.11)	(2.14)	(0.75)	(0.78)
Info Ratio	0.29	0.30	0.17	0.17	0.24	0.24	0.18	0.18	0.06	0.07

Panel B	DBR*1-SBS		Alpha*AlphaT		AlphaT*Alpha		DBR*1-SBS - Alpha*AlphaT		DBR*1-SBS - AlphaT*Alpha	
	As reported	Corrected	As reported	Corrected	As reported	Corrected	As reported	Corrected	As reported	Corrected
Mean Return	0.75***	0.75***	0.50***	0.50***	0.78***	0.78***	0.25	0.25	-0.03	-0.03
(t-stat)	(3.77)	(3.81)	(3.05)	(3.12)	(3.25)	(3.28)	(1.26)	(1.26)	(-0.13)	(-0.13)
Sharpe Ratio	0.30	0.30	0.24	0.25	0.26	0.26	0.10	0.10	-0.01	-0.01
α	0.54***	0.54***	0.21**	0.22**	0.49***	0.49***	0.32	0.32	0.05	0.05
(t-stat)	(2.96)	(3.00)	(2.20)	(2.25)	(2.88)	-2.88	(1.60)	(1.61)	(0.23)	(0.23)
Info Ratio	0.26	0.27	0.17	0.17	0.24	0.24	0.14	0.14	0.02	0.02

Appendix A: Scaled Beta Success vs. Scaled Average Return Comparison

Given that *SBS* is equivalent to the observed average excess return, less of alpha, the superior performance of the bottom *SBS* portfolio could potentially be attributed to mean reversal of past hedge fund performance, measured by the average past excess return. We define a new variable, *SAR*, or *"Scaled Average Return"*, in a similar way as we defined *SBS*, i.e. benchmarking a fund *i* average return $\bar{r}_{w,i}$ against the maximum and the minimum of average returns across all funds over two preceding 24-month windows *w* and *w – 1*:

$$SAR_i = \frac{1}{2}\frac{\bar{r}_{w,i} - \min_j\{\bar{r}_{w,j}\}}{\max_j\{\bar{r}_{w,j}\} - \min_j\{\bar{r}_{w,j}\}} + \frac{1}{2}\frac{\bar{r}_{w-1,i} - \min_j\{\bar{r}_{w-1,j}\}}{\max_j\{\bar{r}_{w-1,j}\} - \min_j\{\bar{r}_{w-1,j}\}}, \qquad [11]$$

where $\bar{r}_{w,i}$ is the average return for fund *i* in window *w*, and $\min_j\{\bar{r}_{w,j}\}$ and $\max_j\{\bar{r}_{w,j}\}$ are the lowest and the highest average monthly returns amongst all the hedge funds for window *w*.

We then compare the out-of-sample performance of the top and bottom quartile portfolios selected on the basis of *SAR* according to the methodology in section 5.b. The results are provided in table XIV. Similar to *SBS*, the bottom *SAR* portfolio statistically dominates the top *SAR* portfolio in alpha, while also producing higher mean monthly excess return, Sharpe ratio, and information ratio. This is not surprising, given that *SBS* and *SAR* only differ in alpha, and that the correlation between them is 0.4285. However, in a direct out-of-sample comparison between bottom quartile *SBS* and *SAR* portfolios, provided in table XV, we observe that there is relatively little overlap in funds.[57] Furthermore, we observe that the performance and its statistical significance of the bottom *SBS* portfolio remains almost the same after excluding the funds that are also present in the bottom *SAR* portfolio, while the attrition rate gets reduced by

[57] On average, there is a 36.56% overlap between bottom quartile *SBS* and *SAR* portfolios.

2.4%. On the other hand, the bottom *SAR* portfolio after excluding funds common to the bottom *SBS* portfolio displays slightly lower statistical significance in alpha, along with a 0.53% increase in the attrition rate. Finally, the portfolio of funds common to both *SBS* and *SAR* portfolios delivers performance similar to single variable portfolios.

Hence we conclude that *SBS* captures a unique aspect of hedge fund management related to beta activity that is not captured by the average past return. The superior out-of-sample performance of the bottom *SBS* portfolio is consistent with the argument that managers with lower *SBS* are making long term factor related bets that are less profitable contemporaneously but that become profitable in the future as economic conditions change.

Appendix B: Comparisons of Alpha and Beta Activity Based on Double Sorts

Here we consider an alternative approach of evaluating overall beta activity based on the combined effect of *SBS* and *DBR*, through double sorting of hedge funds based on both variables. This facilitates a nonparametric comparison of the overall alpha activity, quantified by both *alpha* and *alpha t-stat*, and beta activity, quantified by both *SBS* and *DBR*. Such an approach complements the parametric approach of combining *SBS* and *DBR* into a single variable, *BA*.

We construct "Alpha" and "Beta" portfolios by double sorting of hedge funds based on both variables of alpha and beta activity. Specifically, for "Alpha" portfolios we first select the funds in the top (bottom) quartile with respect to *alpha*, then rank selected funds with respect to *alpha t-stat*, and select the funds in the top (bottom) quartile, forming the ultimate portfolio. We then repeat the exercise by switching the order of the sorting, i.e. first ranking funds with respect to *alpha t-stat*, followed by ranking the selected funds with respect to *alpha*. Similarly, for the "Beta" portfolio we first select funds in the bottom (top) quartile with respect to *SBS*, then rank selected funds with respect to *DBR*, and select the funds in the top (bottom) quartile, forming the ultimate portfolio. We then repeat the exercise by switching the order of the sorting, i.e. first ranking funds with respect to *DBR*, followed by ranking the selected funds with respect to *SBS*. The analysis that follows mirrors our methodology with *BA* in tables V - VII.

Table XVI presents the results from comparing top and bottom "Alpha" and "Beta" portfolios. We find top "Beta" portfolios statistically dominate bottom "Beta" portfolios,[58] while

[58] In terms of mean returns and Fung and Hsieh (2004) alphas.

there is no statistical difference between top and bottom "Alpha" portfolios.[59] Table XVII documents that "Beta" portfolios outperform "Alpha" portfolios in overall returns, Sharpe ratios, and Fung and Hsieh (2004) alphas.[60] Table XVIII reports the results of a robustness test with the MA(2) correction for serial correlation in hedge fund returns of the results in table. While tables XVII and XVIII document that the difference in performance of "Beta" and "Alpha" portfolios is statistically significant only in one comparison, the overall results are consistent with the parametric approach of comparing beta active and alpha active fund management in tables V – VII.

[59] With the exception of the Fung and Hsieh (2004) alpha in the top – bottom *alpha t-stat*alpha* sort. However, the above statistical significance disappears upon the MA(2) correction for serial correlation in hedge fund returns.

[60] With the exception of the mean return and the Sharpe ratio in the *DBR*1-SBS - alpha t-stat*alpha* long/short portfolio. Nevertheless, the mentioned portfolio yields a positive Fung and Hsieh (2004) alpha.

III. Essay 2: In Search of Missing Risk Factors: Hedge Fund Return Replication with ETFs[61]

Jun Duanmu, Yongjia Li and Alexey Malakhov

A. Abstract

Fully spanning the space of potential risk factors with tradable liquid portfolios is paramount in the context of a risk-based factor model. We develop a factor selection methodology of spanning the space of hedge fund risk factors with all available exchange traded funds (ETFs). We demonstrate the efficacy of the methodology with out-of-sample hedge fund return replication, and find that the replication accuracy increases with the number of ETFs available. This is consistent with our interpretation of ETF returns as proxies to alternative risk factors driving hedge fund returns. We further consider portfolios of "cloneable" and "non-cloneable" hedge funds, defined as top and bottom in-sample R^2 matches. We find superior risk-adjusted performance for "non-cloneable" funds, while "cloneable" funds fail to deliver significantly positive risk-adjusted performance. Our methodology provides value in both identifying skilled managers of "non-cloneable" hedge funds, as well as successfully replicating out-of-sample returns that are due to alternative risk exposures of "cloneable" hedge funds, thus providing a transparent and liquid alternative to investors who may find these return patterns attractive.

JEL Classification: G11, G23

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Keywords: hedge funds, risk factor exposures, factor selection, return replication, performance measurement, performance prediction

B. Introduction

Hedge funds have experienced tremendous growth in recent years, with more than $2.82 trillion currently invested in hedge funds globally,[62] and are now considered an essential part of alternative investment strategies by institutional investors and financial institutions. Hedge funds have been able to produce returns with relatively low correlations with major asset classes, like stocks and bonds, due to the multitude of investment opportunities available to fund managers. Unlike managers of more traditional mutual funds, hedge fund managers have the flexibility to invest in non-traditional asset classes (including derivative securities), employ leverage, and engage in short sales. However, such strategies also expose investors to alternative risk factors that may not be easy to quantify, given the opacity of the hedge fund industry. It is then natural to question whether the returns earned by hedge fund managers are due to managerial skill, or merely compensation for exposure to alternative risk factors.[63] If a significant portion of hedge fund returns comes from alternative risk factor exposures, then it is reasonable to presume that it is possible for investors to replicate that part of hedge fund returns at a lower cost by taking on these risk exposures themselves. However, such an exercise hinges on the investor's ability to identify and quantify these alternative risk factors via proxies of portfolios of tradable and liquid

[62] According to Hedge Fund Research, Inc. October 20, 2014 press release.
[63] For example, John H. Cochrane observes: "As I look across the hedge fund universe, 90% of what I see is not "picking assets to exploit information not reflected in prices," it is "taking exposure to factors that managers understand and can trade better than clients." (John H. Cochrane's "Hedge Funds" lecture notes at http://faculty.chicagobooth.edu/john.cochrane/teaching/35150_advanced_investments/hedge_notes_and_questions.pdf)

securities.[64] That is why the issue of choosing appropriate risk factors is central to any study of hedge fund performance, and currently there is no set of factors that is universally accepted across the literature.[65]

Properly identifying and fully accounting for all potential risk factors through tradable liquid portfolios in the context of a risk based factor model is paramount to quantifying the benefits of investing in hedge funds. If we could successfully span the entire space of alternative risk factors, then we would be able to achieve two important objectives: first, separate skill driven from risk driven hedge fund returns, thus identifying hedge fund managers who possess genuine skill (or the lack of thereof), and, second, replicate the risk driven hedge fund return component at a lower cost by avoiding hedge fund fee structure.

In this paper we attempt to span the space of potential risk factors with exchange traded funds (ETFs) from 1997 to 2012. This time period saw an explosion in ETFs available, with the number of U.S. listed passively managed ETFs going from 19 in 1997 to 1313 in 2012. During the time period of our study the ETF coverage of alternative risk factors went from almost non-existent in 1997 to being comprehensive, with ETFs currently providing access to a great variety of alternative strategies that were previously available only to hedge funds or institutional investors.[66] This provides us with a unique opportunity to investigate how the expanding space

[64] Notice that if there is no tradable option available to investors for a particular alternative risk factor, then it could be argued that hedge funds are valuable by merely providing access to that risk exposure. Such exposure through hedge funds comes at a high premium in the form of management and incentive fees.
[65] For example, return attribution studies Fung and Hsieh (2001, 2004) and Agarwal and Naik (2004) introduce new trend following and option based risk factors in addition to Fama and French (1993) and Carhart (1997) factors. On the other hand, hedge fund replication studies Hasanhodzic and Lo (2007), Amenc, Martellini, Meyfredi, and Ziemann (2010), and Giamouridis and Paterlini (2010) employ liquid index portfolios available to investors.
[66] As an example of available ETF strategies, consider ALPS U.S. Equity High Volatility Put Write Index Fund (ticker HVPW) that tracks NYSE Arca U.S. Equity High Volatility Put Write Index with an annual expense ratio of 0.95 percent. The ETF benchmark tracks the performance

of alternative risk factors affects the quality of hedge fund replication with ETFs available at the time.

While the large number of ETFs available in the later years of our study allows for more complete spanning of the space of risk factors, it also increases potential for spurious results due to excessive data mining. We develop a new methodology for linear hedge fund return replication that overcomes multicollinearity among ETFs, and also minimizes data mining bias, while utilizing all ETFs available. Our focus on hedge fund return replication with subsequent out-of-sample testing of hedge fund clones highlights the efficacy of our methodology in mitigating the data mining bias. We test the performance of our hedge fund clones in- and out-of-sample, and find that the overall accuracy of hedge fund replication with ETFs increases with the number of ETFs available. We find that in the subperiod starting in 2005, the overall out-of-sample performance of the portfolio of all hedge funds is not statistically different from the portfolio of clones. We attribute this to the sufficiently large number of available ETFs in the later years, which allow us to successfully span the space of hedge fund risk factors.

In a departure from previous hedge fund replication studies, we go beyond considering replicating hedge fund indexes or average hedge fund performance. We consider portfolios of "cloneable" and "non-cloneable" hedge funds, defined as top and bottom in-sample R^2 matches. Intuitively, we shouldn't expect success in hedge fund return replication for a truly skilled hedge fund manager who pursues investment opportunities uncorrelated with risk factors, delivering true alpha to investors. On the other hand, we fully expect success in return replication for a manager who follows a rigid formulaic strategy, like writing out of the money put options on the S&P 500 index, earning returns by exposing investors to an easily quantifiable alternative risk

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of options sold on a basket of 20 stocks chosen from the largest-capitalized equities that have the highest volatility, as determined by NYSE Arca Inc.

factor. An illustration of our success in out-of-sample return replication of a particular "cloneable" hedge fund[67] is provided in figure 1.

Consistent with the above intuition, we find that the portfolio of clones created with our procedure provides better[68] out-of-sample performance than the portfolio of "cloneable" hedge funds, which is likely due to the lower fee structure among the clones. Furthermore, the portfolio of "cloneable" hedge funds does not produce significantly positive risk-adjusted performance, measured by the Fung and Hsieh (2004) alpha. Hence we conclude that there is no statistical evidence of managerial skill in the set of "cloneable" hedge funds, and these funds can be successfully replicated with ETFs.

Finally, the out-of-sample portfolio of "non-cloneable" hedge funds produces significantly positive mean excess returns along with a Fung and Hsieh (2004) alpha, outperforming the portfolio of clones. This can be interpreted as evidence of managerial skill among the managers of "non-cloneable" hedge funds.

We conclude that our methodology provides value in both identifying skilled managers of "non-cloneable" hedge funds, and also successfully replicating out-of-sample returns that are due to alternative risk exposures of "cloneable" hedge funds, thus providing a transparent and liquid alternative to investors who may find these return patterns attractive.[69]

C. Related Literature

[67] This particular (anonymous) hedge fund is in the "fixed income" self-reported style, it has an inception year of 2004, and it was active at the end of our study period. Notice that the out-of-sample comparison begins in 2008, after dropping the first two years of observations to control for the backfill bias, and after using another two years for the in-sample clone matching.
[68] Although not to the point of statistical significance.
[69] Notice that portfolios of "cloneable" hedge funds as well as their clones produced higher average returns and end values compared to the portfolio of "non-cloneable" hedge funds.

Our methodology directly extends the factor based hedge fund replication literature that goes back to Sharpe (1992) style analysis approach. In its original form, it constructs a replicating portfolio by relying on constrained beta coefficients from a linear regression on a set of relevant factors. Hasanhodzic and Lo (2007) apply this methodology relying on six fixed factors to replicating hedge fund returns from TASS database, and demonstrate that replication works reasonably well for Dedicated Short Bias, Equity Market Neutral, Global Macro, Managed Futures, Fund of Funds, Convertible Arbitrage, Long/Short Equity Hedge, and Multi-Strategy categories. However, their clones underperform in Event Driven and Emerging Market categories. Amenc, Martellini, Meyfredi, and Ziemann (2010) extend Hasanhodzic and Lo (2007) by considering non-linear and conditional hedge fund replication models. They don't find that going beyond linear models enhances the replication power. On the other hand, they find that selecting factors for each hedge fund category based on economic rationale yields a substantial improvement in out-of-sample replication quality.

This is an intuitive result from the perspective of the literature on hedge fund risk and performance evaluation, as we don't have an equilibrium model of hedge fund performance evaluation, and instead rely on risk based factor models that approximate the true set of hedge fund risk factors. However, it is virtually impossible to observe the true set of hedge fund risk factors due to the myriad of available strategies to hedge fund managers and the opacity of the industry, and many hedge fund risk and performance evaluation studies[70] rely on statistical techniques, like stepwise regression, to identify the dominant risk factors. More recently, Giamouridis and Paterlini (2010) and Weber and Peres (2013) employ statistical techniques in

[70] See, for example, Fung and Hsieh (2001), Agarwal and Naik (2004), S.D.Vrontos, I.D.Vrontos, and Giamouridis (2008), and Titman and Tiu (2011).

the factor based hedge fund replication context, applying stepwise, as well as RIDGE, LASSO, and LAR LASSO regressions[71] to sets of sixteen and thirty risk based factors.

Our contribution lies in expanding the universe of available risk factors by considering all available U.S. listed passively managed ETFs. We argue that these ETFs represent reasonable proxies to a multitude of alternative risk factors affecting hedge fund returns. We develop a methodology based on cluster analysis and LASSO selection methodology that overcomes multicollinearity among ETFs, and also minimizes data mining bias, resulting in parsimonious factor selection. We test the performance of our hedge fund clones in- and out-of-sample, and find that the overall accuracy of hedge fund replication with ETFs increases with the number of ETFs available. Our out-of-sample portfolio approach allows minimizing the hedge fund attrition bias that Ben Dor, Jagannathan, Meier, and Xu (2012) find to be a major driver of poor hedge fund index clone performance against hedge fund index benchmarks.

Another major contribution is in considering risk adjusted performance of "cloneable" and "non-cloneable" hedge funds separately, which contributes to the literature on hedge fund risk and performance evaluation.[72] Consistent with results in Titman and Tiu (2011), we find superior out-of-sample risk adjusted performance[73] for "non-cloneable" funds, while "cloneable" funds fail to deliver significantly positive risk-adjusted performance. Hence our methodology provides value in hedge fund performance evaluation by identifying skilled managers who deliver superior out-of-sample risk adjusted performance.The purpose of our study is to examine the impacts that credit rating initiations have on the environment in which the firm's equity

[71] See Hoerl and Kennard (1970), Tibshirani (1996), and Efron, Hastie, Johnstone, and Tibshirani (2004) for descriptions of RIDGE, LASSO, and LAR methodologies.
[72] See, for example, Jagannathan, Malakhov, and Novikov (2010), Titman and Tiu (2011), Avramov, Kosowski, Naik, and Teo (2011), Sun, Wang, and Zheng (2012), Bali, Brown, and Caglayan (2011, 2012), Avramov, Barras, and Kosowski (2013), and Jurek and Stafford (2013).
[73] As quantified by the Fung and Hsieh (2004) alpha.

trades. More precisely, we seek to test for the relation between new credit ratings and measures of equity market liquidity and to examine the extent to which this relation affects the financing behavior of the firm. As such, this paper relates two strands of literature. The first examines the informativeness of credit ratings and their relation to equity market liquidity. And the second, the external financing implications of equity market liquidity.

D. Description of Data

In this study we utilize hedge fund data from Bloomberg[74] for the period 1997-2012, which includes 18,135 unique hedge funds.[75] The data are comprehensive, including fund returns net of management and performance fees, assets under management, manager information, and fund characteristics. To minimize survivorship bias, the sample includes all funds reporting during our sample period, including those that are acquired, liquidated, or chose to stop reporting. We partially offset the effects of backfill bias by eliminating the first 24 months of reported returns.[76] Since we require two years of data[77] to create a hedge fund clone, and at least a year to test the clone error, we only consider funds with inception dates prior to 2009, which leaves us with 3,190 unique funds. Finally, of the 3,190 funds with inception dates prior to 2009, 1,002 funds are active in our sample and 2,188 funds are inactive (i.e. acquired, liquidated or chose to stop reporting).

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[74] Bloomberg is the most common platform used by both hedge funds, who utilize news, analysis, research, and trading tools, and accredited investors, who use Bloomberg data to research hedge funds, private equity firms, and other alternative investment vehicles. Bloomberg aggregates data on live and dead funds inclusive of fund and parent company descriptions, manager and contact information, total assets under management, fees, past performance, and management style.
[75] We do not include funds of hedge funds in our sample.
[76] The 24 month backfill correction is in line with results in Jagannathan, Malakhov, and Novikov (2010) and Titman and Tiu (2011) suggesting dropping the first 25 and 27 months of returns.
[77] After deleting the first 24 months of observations.

Panel A of table I reports summary statistics of fund returns, fees, investor liquidity measures, and fund longevity. As medians are better measures of typical funds in our database we find that the typical fund has a 1.5% management fee, a 20% incentive fee on all profits over an investor's high water mark,[78] a $250,000 minimum initial investment, and a 30 day redemption period. Unsurprisingly, active funds display higher monthly returns and assets under management and greater longevity than inactive funds. Interestingly, however, inactive funds have longer redemption periods and lockup periods. Panels B and C of table I report percentages of funds with certain characteristics and declared styles, respectively. 76% of all funds have a high water mark provision, though only 4% allow hurdle rates in addition to high water marks. 68% of funds are non-U.S. domiciled. The most common declared style is long-short equity, at 29% of all funds, while equity statistical arbitrage is the least common style, accounting for 1% of hedge funds.

We collect the ETF data from Morningstar for the period 1994-2012, which contains 1,484 unique U.S. listed ETF funds. We manually check the description of each ETF, and exclude all ETFs that are not passively managed index tracking funds[79], as well as ETFs that track hedge fund style indexes; this leaves us with 1,387 unique ETFs. Then further data cleaning procedures are performed. In our study, we require ETFs to have at least 24 monthly observations starting from January. In addition, we drop those ETFs with missing management

[78] High water marks are investor relevant, that is, an investor will not be charged incentive fees until profits accrue over a previous high, net of flows. Thus, not all investors are charged incentive fees in any given year; it is partially determined by when the investor capital was employed by the fund manager. An investor whose fund shares are worth more this year than last will be charged incentive fees. An investor who suffered a loss previously will not pay incentive fees until previous losses are regained.

[79] Benchmark indexes that retained ETFs track may not be publicly available. Some funds track in-house indexes.

fee information. In the end, 1,313 unique ETFs for the period 1997-2012[80] are included in this study. Figure 2 reports the number of ETFs available each year in our sample period. As shown, ETFs have experienced a significant growth in our sample, from 19 ETFs available in 1997 to 1,313 ETFs available in year 2012. This implies that with the increase of the number of ETFs available, the investment opportunity set has broadened dramatically, and our hedge fund replicating process gains more accuracy when approaching the later years in our sample. In this study, we employ cluster analysis and LASSO regression procedure to find the best fit risk factors to clone real hedge fund returns, and we utilize two years of previous monthly ETF returns for the matching process. Figure 3 reports the actual number of ETFs used for each two year window. In the early years, there are relatively few ETFs around, which makes the cloning procedure less accurate. So as to provide a better picture of the replication outcome, we split our whole sample period into two subperiods, period 1997-2004 and period 2005-2012, where in the first period, we have fewer than 100 ETFs available for matching procedures, while more than 100 ETFs can be included in the cluster analysis and later LASSO matching regression in the second period. Arguably, we expect to see better matching and replications for the second period 2005-2012.

E. Research Methodology

1. Style Analysis with ETFs

Our ETF database includes a total number of 1,313 unique ETFs across the whole sample period. In order to clone a hedge fund using the large set of risk factors, we must choose the appropriate replicating factors first. We employ a factor selection model termed "LASSO" (least

[80] There are fewer ETFs than 5 ETFs available prior to 1997, which makes our methodology meaningless in 1994-1996, and we exclude these years from further analysis.

absolute shrinkage and selection operator) proposed in Tibshirani (1996). For a given parameter t, LASSO regression identifies an optimal set of factors with non-zero coefficients such that

$$\hat{\beta}_{Lasso} = \arg\min_{\beta} \| \mathbf{r} - \mathbf{X}\beta \|^2, \\ \text{such that } \sum_{j=1}^{m} |\beta_j| \leq t. \tag{1}$$

where $\mathbf{r}$ is the vector of hedge fund monthly returns in our research and $\mathbf{X}$ is the vector of ETF monthly returns.

Conceptually, provided a set of factors, LASSO regression determines the appropriate factors to be selected through an optimization approach. In the constrained form of ordinary least squares regressions, the sum of absolute values of the beta coefficients are estimated and constrained to be smaller than a specific parameter. For a given selection parameter t, some of the beta coefficients could be zero if the corresponding factors reveals little or no information about the dependent variable. As a result, LASSO regression "shrinks" the set of regression factors until the beta coefficients are the solution of the optimization problem. The degree of "shrinking" depends on the chosen value of the parameter t, with lower values of t resulting in fewer factors being selected for the model. We calculate LASSO regression solutions across a range of t values by employing a computationally efficient least angle regression (LAR) modification of the LASSO procedure introduced in Efron, Hastie, Johnstone, and Tibshirani (2004). Finally, we employ Schwarz (1978) Bayesian information criterion (SBC) as the model selection criterion, selecting the model with the lowest SBC value.

However, before adding all ETFs as explanatory variables in LASSO regression, we need to tackle the multicollinearity in the comprehensive set of ETFs. Although our ETFs database has factored in a broad set of trading strategies, it is not surprising that some ETFs are exposed to similar risk factors therefore exhibiting similar or even the same return patterns. And even though LASSO regression could be a powerful selection method in dealing with collinearity, it is not feasible for LASSO regressions to handle collinearity for such a large number of closely correlated ETF factors in a meaningful way.

To address this problem, we conduct cluster analysis among ETFs in order to reduce the number of ETF factors prior to running LASSO regressions. For every ETF in each cluster we calculate the distance away from the center of its cluster, as defined by the *SDI* measure from Sun, Wang, and Zheng (2012). This distance measure for an ETF *i* is calculated as one minus the correlation of the ETF's return with the mean return of all ETFs from the same cluster *I*, i.e.

$$SDI_i = 1 - corr(r_i, \mu_I), \\ \text{where } \mu_I = \frac{\sum_{i \in I} r_i}{count(i \in I)}. \qquad (2)$$

The lower the *SDI*, the closer the ETF is from the center of its cluster. We specify the ETF with the lowest *SDI* as a proxy for all the ETFs in the same cluster, and then we include this ETF as a replicating factor in LASSO regression. This approach allows efficient spanning of the space of potential risk factors, while mitigating multicollinearity by maximizing the distance between ETFs used.

Because the number of ETFs changes over time and we don't know the true number of clusters, we assume that the number of clusters ranges from 1 to 100. We set the maximum number to 100 since we believe it is an efficient and sufficiently large set of investment opportunities (since there are less than 100 ETFs for years before 2003, we set the maximum number of cluster as the number of ETFs during those years). We then iteratively run cluster analysis for a hundred times and use the corresponding number of ETFs (each selected ETF is located at the center of its cluster) in LASSO regression. Consequently, after running cluster analysis and LASSO regressions, each fund would have one hundred corresponding models. We then choose the model which yields the lowest SBC score as our clone model. Such an approach minimizes data mining bias, resulting in parsimonious factor selection.

The basic model for LASSO regression is as follows:

$$r_{i,gross} - r_f = \beta_1(ETF_1 - r_f) + \beta_2(ETF_2 - r_f) + ... + \beta_{100}(ETF_{100} - r_f) + \varepsilon_i \qquad [M]$$

where $r_{i,gross}$ is the gross monthly return of fund i, and r_f is the risk free rate proxied by the monthly return of the 30-day U.S. Treasury bill. We use gross hedge fund returns[81] on the left hand side, since we try replicating hedge fund return patterns that are driven by exposure to alternative risk factors. Otherwise, the true factor risk driven hedge fund returns would be altered if we consider them net-of-fees, and hence the matched ETF risk profile would not reflect the true factor risk exposures. We also suppress the intercept in regressions because intercept captures the management fees incorporated in hedge fund returns and we have already added back the fees. In a slight departure from Sharpe (1992) style analysis methodology, we don't restrict beta coefficients to be positive or add up to one, as imposing such restrictions would likely result in model misspecification in the context of hedge funds that are free to take leverage and short positions.[82]

In order to quantify the dynamic nature of hedge funds' investment activities, we run the LAR LASSO methodology for model [M] for every hedge fund in our data over a set of two year windows, rolling them annually over the sample period. We consider adjusted-R^2 and SBC values from these matching regressions as in-sample proxies of the "overall quality" of our matching procedure. We interpret higher R^2 and lower SBC values as indicators of our

[81] See Appendix A for details on the gross returns calculations.
[82] ter Horst, Nijman, and de Roon (2004) demonstrate that imposing unwarranted style based constraints can lead to biased risk exposure estimates.

methodology's success in capturing hedge fund risk factors, and thus potential for cloning hedge fund returns with ETFs.

However, the ultimate goal is to test the predictive power of the methodology, as to validate the in-sample explanatory power manifested by high R^2 and low SBC values. For each hedge fund, we consider the corresponding ETF matches selected through the previous two year window LASSO regression and their coefficients, and then construct the hedge fund clone by loading selected ETFs with regression determined weights. The hedge fund clone performance after the matching period is then given by

$$CloneRet_{i,t} = r_{f,t} + \sum_{j=1}^{n} \beta_{j,t-1}(ETF_{j,t} - r_{f,t}), \tag{3}$$

where $\beta_{j,t-1}$ is the coefficient from the previous two year window LASSO selected ETF j. We rely on net-of-fees returns for both hedge funds and their ETF matches in our out-of-sample analysis,[83] as we compare future returns from an investor perspective. Finally, we address the survivorship bias among hedge funds by constructing out-of-sample portfolios and rebalancing them when hedge funds drop out of the database.

2. "Cloneable" and "Non-Cloneable" Hedge Funds

In a departure from previous hedge fund replication studies, we go beyond exploring aggregate characteristics of clones versus hedge funds they replicate. Instead we concentrate on comparing "cloneable" and "non-cloneable" hedge funds, defined as top and bottom in-sample R^2 matches. We argue that the success in hedge fund replication depends on a hedge fund manager's style, and that properly deconstructing that style is paramount for assessing the true

[83] Where we consider the performance of hedge funds and their clones past the two year matching period.

value of a hedge fund for investors. For example, if a hedge fund manager has genuine ability and pursues a unique strategy uncorrelated with identifiable risk factors in a "non-cloneable" fund, then we shouldn't expect success in replicating such fund performance. On the other hand, if a manager pursues algorithmic strategies highly correlated with risk factors in a "cloneable" fund, then we expect success in out-of-sample replication, as our hedge fund clone would deliver a similar risk and return profile, but at a lower cost compared to the "cloneable" fund. Furthermore, it would be unlikely to find evidence of superior risk adjusted managerial skill in "cloneable" funds in the context of a return attribution model, as their performance would be driven mostly by factor risk exposures.

F. Empirical Results

1. Matching Regressions

Our matching (or "cloning") procedure is based on in-sample LAR LASSO regressions for model [M], with the best model chosen according to the Schwarz Bayesian Criterion (SBC), as described in the previous section. Table II reports the results for annual rolling two-year matching regressions from 1997 to 2011.[84] To highlight the effect of the broadened investment opportunity set for our matching procedure, we also consider subperiods of 1997-2003 and 2003-2011 separately.[85] The results confirm our expectation of better matching in later years, reflecting a greater degree of success in spanning the space of available risk factors as more ETFs become available. On average, in 1997-2003 there are only 45 ETFs available, and the average matching R^2 is 0.42, while in 2003-2011 there are 365 ETFs available for the matching

[84] While our date extends until 2012, we don't use 2012 in matching regressions, as we need at least one year of data for out-of-sample tests of our matches.
[85] We chose 2003 as the break year, since it is the first year when there are more than 100 ETFs available, which allows full utilization of our methodology based on a variable number of ETF clusters up to 100.

regressions, and the average R^2 is 0.57. We also observe that the mean SBC has declined through time, from 59.47 in 1997-2003 to 45.81 in 2003-2011. This suggests that matching quality has improved along with the broadened investment opportunity set, as more ETFs become available. Lastly, the average number of factors selected by the LAR LASSO procedure is 2.22 for the whole sample period, which indicates that our methodology results in a parsimonious factor selection.

2. Out-of-Sample Clone Performance

As noted before, our methodology of running LASSO regressions on a variable number of ETFs, and using SBC or a statistical model selection does minimizes data mining bias and yields a parsimonious factor selection. However, the ultimate test of our methodology lies in considering out-of-sample performance of hedge fund clones versus hedge funds they replicate. As described in the methodology section, we construct a hedge fund clone as a linear combination of model selected ETFs with the matching regression determined weights. Then the out-of-sample performance of a hedge fund clone is given by the equation (3). It is important to reiterate that out-of-sample, we rely on net-of-fees returns for both hedge funds and their ETF clones, as we compare out-of-sample returns from an investor perspective.[86] Finally, we calculate tracking errors as the differences in returns between the clone and the corresponding hedge fund, i.e.

$$TrackingError_{i,t} = CloneRet_{i,t} - HedgeFundRet_{i,t}. \qquad (4)$$

Table III reports the results of comparing out-of-sample performance of hedge funds and their clones for one year following each two year in-sample matching period. Consistent with in-

[86] Recall that the in-sample matching regressions rely on gross returns, as we want to get closest possible matches to “true” hedge fund strategies, as carried out by hedge fund managers.

sample results, reported in table II, the average out-of-sample accuracy has increased over the years with the average mean tracking error going from -0.63 in 1999-2004 to -0.05 in 2005-2012, and average tracking error volatility going from 4.31 in 1999-2004 to 3.54 in 2005-2012.[87] This is consistent with improved matching quality in the later years, as more ETFs become available to span the set of potential hedge fund risk factors.

3. "Cloneable" and "Non-Cloneable" Hedge Funds

While the results in table III indicate that the performance of clones is comparable with performance of hedge funds in aggregate, they hide a wide discrepancy among individual funds. In this section we consider two groups of hedge funds, selected as top and bottom in-sample R^2 matches. We define the funds that are well matched with high R^2 as "cloneable", and the funds with relatively low matching R^2 as "non-cloneable".

As our methodology allows to effectively span the space of potential risk factors, the R^2 could be viewed as a proxy for how easily quantifiable or "decipherable" the investment strategy of a hedge fund manager is. Moreover, there is a fundamental difference in risk profiles between the top and bottom R^2 groups of hedge funds. For example, it is plausible that a manager of a cloneable (i.e. high R^2) fund generates returns by simply loading up on risk factors, identifiable with our methodology, while a manager of a non-cloneable (i.e. low R^2) fund likely has genuine ability and pursues a truly unique strategy uncorrelated with identifiable risk factors. Hence we don't expect success in replicating out-of-sample performance of non-cloneable funds, while we fully expect success in replication of cloneable funds, as our clones would deliver similar risk and return profiles, but at a lower cost compared to the cloneable funds.

[87] The choice of 2004 as the out-of-sample break year is consistent with 2003 being the in-sample break year, since it is the first year when out-of-sample predictions based on more than 100 ETFs available.

We consider cloneable and non-cloneable hedge funds and their clones based on their in-sample LASSO R^2 rank, on both quartile and quintile bases. Tables IV and V report in-sample characteristics of cloneable and non-cloneable funds for quartile and quintile cutoffs, while tables VI and VII report out-of-sample results for cloneable and non-cloneable hedge funds[88] and their clones. We pay particular attention to the results from the second time period of our study, when we can more successfully span the space of hedge fund risk factors with more than 100 ETFs available.

Consistent with full sample results from table II, the overall quality[89] of in-sample matches increases over time for both cloneable and non-cloneable funds, as more ETFs become available for spanning the space of potential risk factors. However, on average, cloneable funds register larger magnitudes of increases in the matching R^2 and decreases in SBC compared to non-cloneable funds. Another striking feature of tables IV and V is the difference in skewness of net returns between cloneable and non-cloneable funds, with the overall average skewness of -0.23 for cloneable funds, and 0.11 for non-cloneable funds.[90]

Next we study the out-of-sample performance of clones for cloneable and non-cloneable fund groups, which is arguably the most meaningful comparison, since our definitions of "cloneable" and "non-cloneable" funds are based on R^2 from in-sample matching regressions. Tables VI and VII report the results of comparing out-of-sample performance of both groups of hedge funds and their clones for one year following each two year in-sample matching period. Overall, cloneable funds yield higher quality out-of-sample matches with closer means and smaller volatilities of tracking errors compared to non-cloneable funds. This difference is

[88] Defined as top and bottom quartiles in tables IV and VI, and quintiles in tables V and VII.
[89] As reflected by higher in-sample R^2 and lower SBC values from matching regressions.
[90] Based on table IV for quartile cutoffs. The skewness results for quintile cutoffs are -0.24 for cloneable funds, and 0.07 for non-cloneable funds, reported in table V.

especially pronounced in the second part of our study period, which is consistent with the previous results showing increased effectiveness of our methodology when the number of available ETFs exceeds 100.[91]

It is important to point out that we rely on gross returns for the in-sample matching with the objective to fully account for all the risk factors inherent in the strategies pursued by hedge fund managers, or, in other words, to "decipher" any passive strategies being used by hedge fund managers. On the other hand, we use net-of-fees returns in our out-of-sample analysis, as we compare returns form an investor perspective. This means that we shouldn't expect a 100% out-of-sample match, even if we were 100% successful in uncovering the true passive strategy of a hedge fund manager, since our ETF based clone has a much lower fee structure compared to the hedge fund being cloned. In fact, if we were indeed successful in "deciphering" of the true strategy of a hedge fund, the ETF clone should have a positive mean tracking error due to the fee structure advantage. Hence it is not surprising to see positive average tracking errors for cloneable funds in 2005-2012, when our ETF matching methodology has the most power.

Notice that cloneable funds demonstrate negative average skewness both in- and out-of-sample during the time period when applying our ETF matching methodology yields the most meaningful results, i.e. in 2005-2012. While it is not possible to unequivocally claim an underlying reason for this phenomenon, it is certainly consistent with the interpretation that cloneable hedge funds mostly load up on exotic risk factors with asymmetric payoffs,[92] while providing very little in terms of truly active portfolio management. Furthermore, the fact that the

[91] In fact, there is almost no difference in the overall accuracy of out-of-sample clone performance between cloneable and non-cloneable funds in 1999-2004, as we don't have enough ETFs to span the space of potential hedge fund risk factors.
[92] Payoffs from such strategies, like writing out of the money put options on the S&P 500 index, may look pretty attractive from the point of not very sophisticated investors.

clones of “cloneable” hedge funds also demonstrate negative average out-of-sample skewness could be interpreted as our methodology’s success in “deciphering” strategies of cloneable funds, and producing clones with similar risk and return profiles.

Finally, tables VI and VII demonstrate that our methodology could not provide a good in-sample match for non-cloneable funds, and the clones were not successful in delivering comparable out-of-sample performance.[93] This is consistent with the interpretation of truly active hedge fund management of non-cloneable funds that could be of benefit to potential investors. However, the non-cloneable hedge funds have almost one and a half time higher average attrition rate than cloneable funds, which could be indicative of higher risks, not quantifiable with our methodology, among non-cloneable hedge funds.[94]

4. Out-of-Sample Portfolio Analysis

We now concentrate on out-of-sample portfolio tests for the following reasons. First, by considering all funds up until the moment of their disappearance from the database, we minimize the effects of the survivorship bias. Second, the portfolio approach allows for out-of-sample risk adjusted performance evaluation of hedge funds and their clones over long periods of time.

We form portfolios on December 31, 1998. We invest the same dollar amount into each fund within a portfolio in the beginning, and follow its net-of-fees performance until December 31, 2012, rebalancing it once a year based on updated LASSO regression matches. When a portfolio fund disappears from the database we redistribute the remaining capital in the fund

[93] As clones yielded negative average tracking errors, high tracking error volatility, and could not match the skewness of non-cloneable funds.
[94] This is consistent with Bollen (2013) findings of higher probability of failure for zero-R^2 hedge funds.

equally amongst surviving portfolio funds.[95] This procedure produces a time series of 168 monthly returns for each portfolio, allowing us to evaluate long term portfolio performance across various economic conditions, including the most recent financial crisis of 2008 - 2009. We then calculate end dollar values based upon a $1 initial investment, mean excess monthly returns, Sharpe ratios, Fung and Hsieh (2004) alphas,[96] information ratios, skewness, and attrition rates for each time series of monthly portfolio returns from January 1999 until December 2012. In addition, we also examine the out-of-sample performance in two different time spans so as to reflect the nature of the booming ETF industry. The first period is from 1999 to 2004, where we have fewer than 100 ETFs that could be used for the matching procedure, while the second period is from 2005 to 2012, where we have more than 100 ETFs, resulting in comprehensive coverage of the space of potential hedge fund risk factors. Hence we expect to observe increased replicating quality in the second period.

Table VIII reports out-of-sample performance results for the portfolio of all available hedge funds. For the whole sample period, our clones fail to compete with real hedge fund returns in every performance measure. However when digging into the details, we observe that these unfavorable results are driven by the inferior clone performance in the first period, 1999-2004. This confirms our suggestion that the quality of replication is highly influenced by the number of available ETFs. Looking at the first period performance alone, we find that real hedge funds deliver significantly better returns than the clones, which is consistent with our previous observations of the matching quality in the first period being worse than in the second. In the second period of 2005-2012, we find that the clones do reasonably well in terms of

[95] This is somewhat conservative as it is possible that a fund simply choses to stop reporting to the database, which is likely for well performing funds that are no longer accepting new investor flows. However, without returns data we obviously cannot keep the fund in the portfolio.
[96] See Appendix B for details on Fung and Hsieh (2004) alpha calculation.

producing similar return patterns and skewness, almost the same monthly excess returns, as well as pretty close risk adjusted measures, i.e. Fung and Hsieh (2004) alphas, Sharpe ratios, and information ratios. We then conclude that our matching methodology can produce hedge fund clones that on average deliver similar payoffs to real hedge funds, given a broad selection of ETFs representing potential hedge fund risk factors.

5. Out-of-Sample Portfolio Analysis for "Cloneable" and "Non-Cloneable" Funds

We now apply the out-of-sample portfolio approach to analyzing portfolios of cloneable and non-cloneable hedge funds, defined as top and bottom R^2 from in-sample LASSO regression matches. We form portfolios of cloneable and non-cloneable hedge funds and their clones based on their in-sample R^2 rank, on both quartile and quintile basis. Tables IX and X report top and bottom quartile portfolio comparisons for the whole period and two subperiods. Tables XI and XII repeat the analysis for top and bottom quintiles. While clone portfolios underperform both cloneable and non-cloneable hedge fund portfolios over the whole 1999-2012 period, this is mostly driven by the poor quality of the ETF investment opportunity set in the first subperiod of 1999-2004. This is further confirmed in panel A of tables X and XII, dedicated to the analysis of the first subperiod of 1999-2004.

The out-of-sample portfolio analysis for the second subperiod of 2005-2012 yields some interesting results, presented in panel B of tables X and XII. We find that the portfolio of clones delivers slightly better out-of-sample performance, with a very similar risk and skewness profile, compared to the portfolio of cloneable hedge funds. However, both hedge funds and clones fail to deliver statistically significant Fung and Hsieh (2004) alphas. This implies that hedge fund managers of cloneable hedge funds mostly produce returns driven by risk factors, and do not add value to their managed portfolio, at least not statistically. From this perspective it is not surprising that our ETF clones can replicate, or even slightly improve,[97] the overall performance of cloneable hedge funds.

On the other hand, the portfolio of non-cloneable hedge funds outperforms the portfolio of ETF clones, and produces a statistically significant Fung and Hsieh (2004) alpha, though delivering lower returns than portfolios of cloneable hedge funds and of their ETF clones.[98] This is consistent with non-cloneable hedge fund managers adding value through actively managing their funds. Furthermore, the active investment management skills of these managers seem to be truly unique, and cannot be replicated with ETFs, or by simply taking positions in well defined risk factors. However, as mentioned before, the non-cloneable hedge funds have almost one and a half time higher average attrition rate than cloneable funds, which could be indicative of high hidden risks associated with their active management style.[99] Unfortunately, these risks might be impossible to quantify, given that the investment styles of managers of non-cloneable hedge funds cannot be well explained with our methodology.

We conclude that our methodology provides value in both identifying skilled managers of non-cloneable hedge funds, and also successfully replicating out-of-sample returns that are due to alternative risk exposures of cloneable hedge funds, thus providing a transparent and liquid alternative to investors who may find these return patterns attractive.

G. Conclusion

We develop a methodology of hedge fund return replication with ETFs based on cluster analysis and LAR LASSO factor selection that overcomes multicollinearity among ETFs and

[97] Such an improvement is likely driven by the ETFs lower fee structure compared to their benchmark hedge funds.
[98] Positive alpha production for low R^2 hedge funds is also consistent with results in Titman and Tiu (2011).
[99] This is consistent with Bollen (2013) findings of higher probability of failure for zero-R^2 hedge funds.

also minimizes data mining bias, resulting in parsimonious factor selection. We test the performance of our hedge fund clones in- and out-of-sample, and find that the overall out-of-sample accuracy of hedge fund replication with ETFs increases with the number of ETFs available. This is consistent with our interpretation of ETF returns as proxies to a multitude of alternative risk factors that could be driving hedge fund returns.

We further consider portfolios of “cloneable” and “non-cloneable” hedge funds, defined as top and bottom in-sample R^2 matches. We find that the portfolio of clones created with our procedure provides better out-of-sample performance than the portfolio of “cloneable” hedge funds. We find superior risk-adjusted performance for “non-cloneable” funds, while “cloneable” funds fail to deliver significantly positive risk-adjusted performance, which is consistent with our success in cloning them. This approach contributes to the literature on hedge fund risk and performance evaluation, enabling investors to identify skilled managers who deliver superior out-of-sample performance.

We conclude that our methodology provides value in both identifying skilled managers of “non-cloneable” hedge funds, and also successfully replicating out-of-sample returns that are due to alternative risk exposures of “cloneable” hedge funds, thus providing a transparent and liquid alternative to investors who may find these return patterns attractive.

H. References

Agarwal, V., and N.Y. Naik. 2004. Risk and Portfolio Decisions Involving Hedge Funds. *Review of Financial Studies* 17: 63–98.

Amenc, N., L. Martellini, J.-C. Meyfredi, and V. Ziemann. 2010. Passive Hedge Fund Replication – Beyond the Linear Case. *European Financial Management* 16: 191–210.

Avramov, D., L. Barras, and R. Kosowski. 2013. Hedge Fund Return Predictability under the Magnifying Glass. *Journal of Financial and Quantitative Analysis* 48: 1057–83.

Avramov, D., R. Kosowski, N.Y. Naik, and M. Teo. 2011. Hedge Funds, Managerial Skill, and Macroeconomic Variables. *Journal of Financial Economics* 99: 672–92.

Bali, T.G., S.J. Brown, and M.O. Caglayan. 2011. Do Hedge Funds' Exposures to Risk Factors Predict Their Future Returns? *Journal of Financial Economics* 101: 36–68.

Bali, T.G., S.J. Brown, and M.O. Caglayan. 2012. Systematic Risk and the Cross Section of Hedge Fund Returns. *Journal of Financial Economics* 106: 114–31.

Ben Dor, A., R. Jagannathan, and I. Meier. 2012. What Drives the Tracking Error of Hedge Fund Clones? *Journal of Alternative Investments* 15: 54–74.

Bollen, N.P.B. 2013. Zero-R^2 Hedge Funds and Market Neutrality. *Journal of Financial and Quantitative Analysis* 48: 519–47.

Efron, B., T. Hastie, I. Johnstone, and R. Tibshirani. 2004. Least Angle Regression. *Annals of Statistics* 32: 407–499.

Fung, W., and D.A. Hsieh. 2001. The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers. *Review of Financial Studies* 14: 313–41.

Fung, W., and D.A. Hsieh. 2004. Hedge Fund Benchmarks: A Risk-Based Approach. *Financial Analysts Journal* 60: 65–80.

Giamouridis, D., and S. Paterlini. 2010. Regular(ized) Hedge Fund Clones. *Journal of Financial Research* 3: 223–47.

Hasanhodzic, J., and A. W. Lo. 2007. Can Hedge-Fund Returns Be Replicated? The Linear Case. *Journal of Investment Management* 5: 5–45.

Hoerl, A. E., and R. Kennard, 1970, Ridge Regression: Biased Estimation for Nonorthogonal Problems, *Technometrics* 8: 27–51

Jagannathan, R., A. Malakhov, and D. Novikov. 2010. Do Hot Hands Exist among Hedge Fund Managers? An Empirical Evaluation. *Journal of Finance* 65: 217–55.

Jurek J., and E. Stafford. 2013. The Cost of Capital for Alternative Investments. *Working Paper*, Princeton University and Harvard Business School.

Schwarz, G. 1978. Estimating the Dimension of a Model. *Annals of Statistics* 6: 461–464.

Sharpe, W.F. 1992. Asset Allocation: Management Style and Performance Management. *Journal of Portfolio Management* 18: 7–19.

Sun, Z., A. Wang, and L. Zheng. 2012. The Road Less Traveled: Strategy Distinctiveness and Hedge Fund Performance. *Review of Financial Studies* 25: 96–143.

ter Horst, J. R., T. E. Nijman, and F. A. De Roon. 2004. Evaluating Style Analysis. *Journal of Empirical Finance* 11: 29–53.

Tibshirani, R. 1996. Regression Shrinkage and Selection via the Lasso. *Journal of the Royal Statistical Society B* 58: 267–88.

Titman, S., and C. Tiu. 2011. Do the Best Hedge Funds Hedge? *Review of Financial Studies* 24: 123–68.

Vrontos, S.D., I.D. Vrontos, and D. Giamouridis. 2008. Hedge Fund Pricing and Model Uncertainty, *Journal of Banking and Finance* 32: 741–53.

Weber, V., and F. Peres. 2013. Hedge Fund Replication: Putting the Pieces Together, *Journal of Investment Strategies* 3: 61-119.

Figure 1: An Example of Hedge Fund and Clone Out-of-Sample Returns

The figure presents the out-of-sample comparison of an anonymous hedge fund and its clone, constructed according to our in-sample matching methodology. This hedge fund is in the "fixed income" self-reported style, it has an inception year of 2004, and it was active at the end of our study period. The out-of-sample comparison begins in 2008, after dropping the first two years of observations to control for the backfill bias, and after using another two years for the in-sample clone matching.

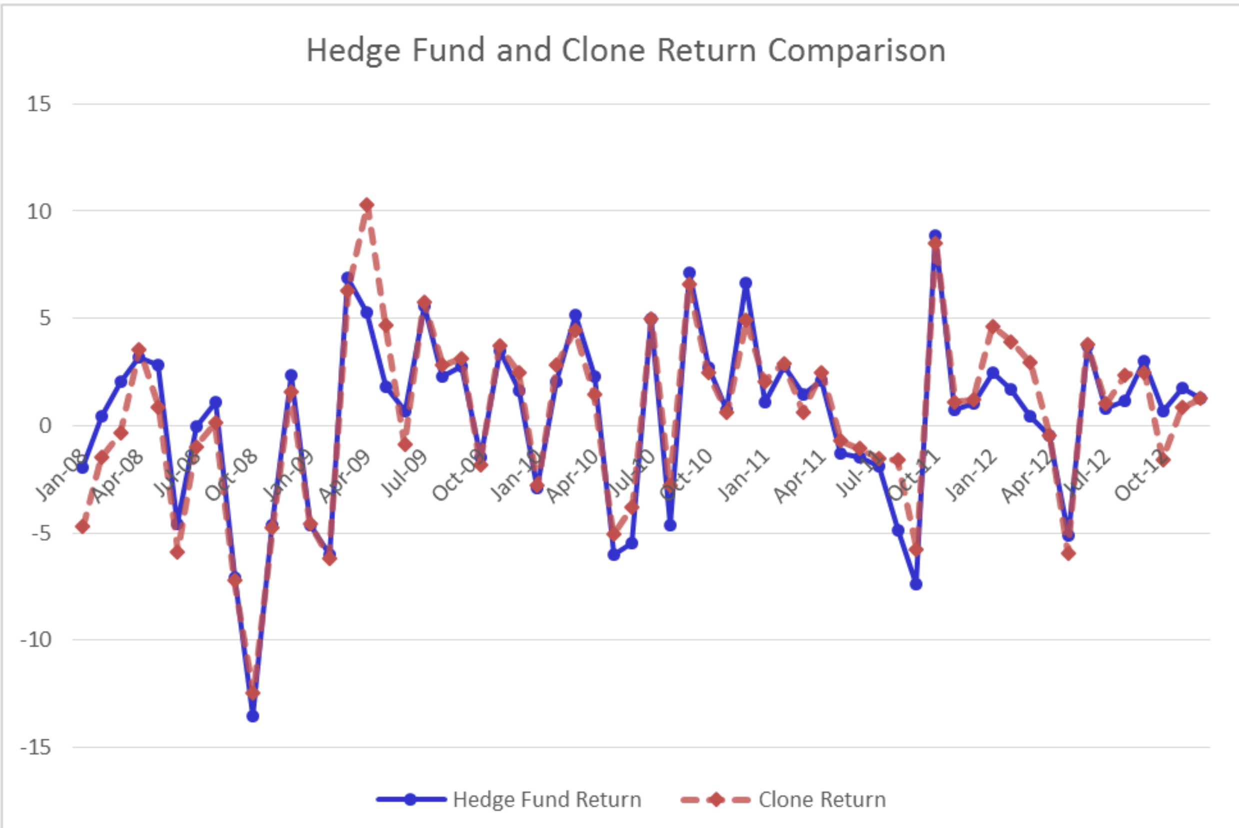

Figure 2: Number of ETFs Available, 1999-2012

Number of ETFs available each year from 1999 to 2012 is reported. ETF data is collected from Morningstar.

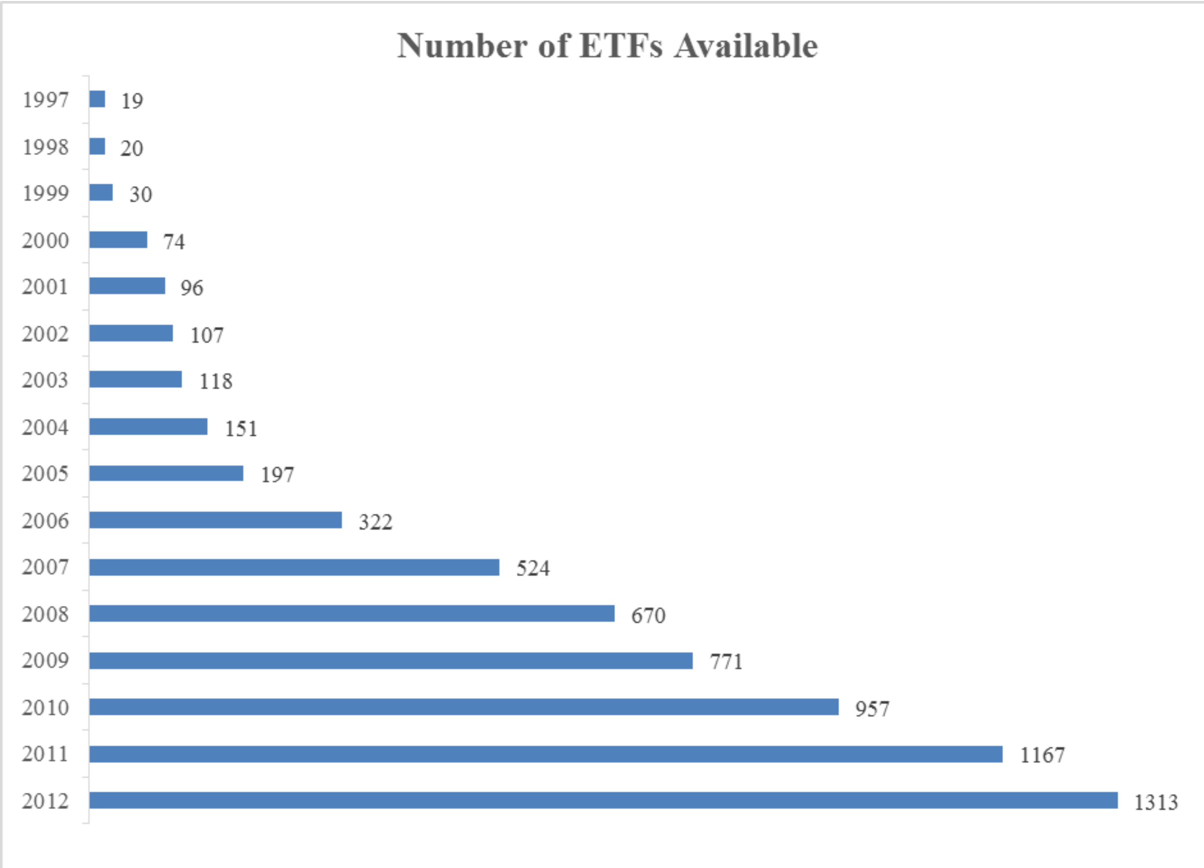

Figure 3: Number of ETFs Used

Number of ETFs used in LASSO matching regressions is reported. ETF data is collected from Morningstar.

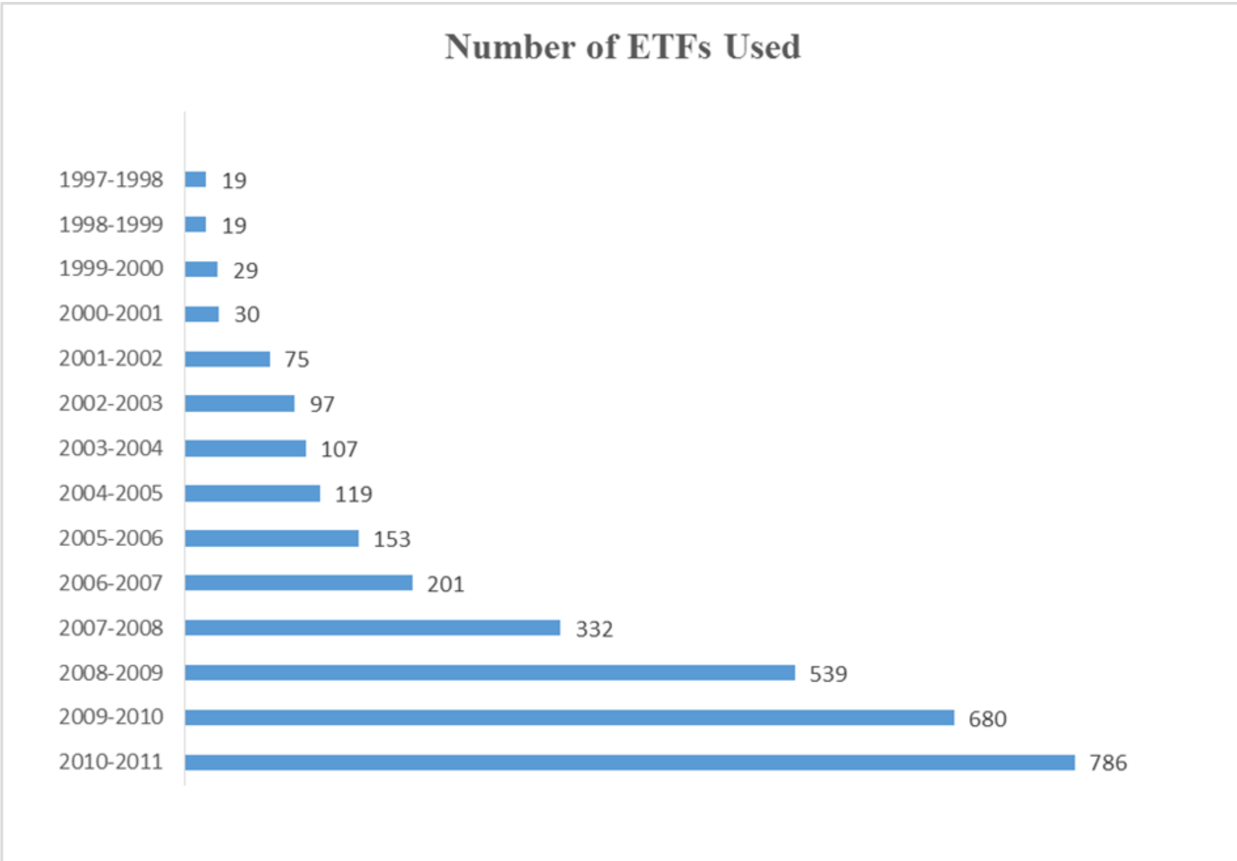

Table I: Summary Statistics

Summary statistics of all hedge funds 1994-2012, reporting as of March, 2013. Panel A reports returns, fees, investor liquidity measures, and fund longevity. Panel B reports means of indicator variables for fund characteristics while panel C reports self-declared fund styles.

Table I: Summary Statistics (Cont.)

Panel A	Full Sample (3,190 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly return	0.76	0.65	-4.25	5.60	56.48
Assets ($M)	243.86	28.47	2.02	337.83	2,153.37
Min Invest ($M)	1.19	0.25	0.03	1	14.63
Mgmt Fee (%)	1.46	1.5	0.8	2	0.71
Perf Fee (%)	17.41	20	4.4	20	6.69
Hurdle Rate (%)	0.32	0	0	0	1.64
Lockup Period (days)	78.29	0	0	360	179.20
Redemption Notice (days)	5.01	0	0	30	15.61
Redemption Period (days)	60.42	30	30	90	58.93
Longevity (months)	109.65	103	53	179	45.65

	Active Funds (1,002 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly return	1.04	0.68	-4.61	6.19	88.63
Assets ($M)	375.61	50.61	3.92	634.77	2,757.83
Min Invest ($M)	0.58	0.25	0.02	1	1.91
Mgmt Fee (%)	1.43	1.5	0.8	2	0.67
Perf Fee (%)	17.60	20	7.75	20	6.50
Hurdle Rate (%)	0.40	0	0	0	1.72
Lockup Period (days)	67.44	0	0	360	178.62
Redemption Notice (days)	9.84	0	0	30	20.69
Redemption Period (days)	54.39	30	15	90	52.37
Longevity (months)	130.08	122	79	204	43.00

	Inactive Funds (2,188 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly return	0.58	0.63	-4.01	5.20	5.48
Assets ($M)	177.25	20.99	1.53	243.00	1,768.02
Min Invest ($M)	1.50	0.25	0.03	1	17.95
Mgmt Fee (%)	1.48	1.5	0.75	2	0.72
Perf Fee (%)	17.31	20	0.1	20	6.78
Hurdle Rate (%)	0.28	0	0	0	1.60
Lockup Period (days)	84.53	0	0	360	179.28
Redemption Notice (days)	2.54	0	0	0	11.47
Redemption Period (days)	63.85	30	30	90	62.10
Longevity (months)	95.61	89	44	157	41.86

Table I: Summary Statistics (Cont.)

Panel B - Indicator	% of Funds		
	Full Sample	Active Funds	Inactive Funds
High Water Mark	0.76	0.87	0.71
Hurdle Rate	0.04	0.07	0.03
Offshore (non-US)	0.68	0.68	0.68
Liquidated	0.29	0.00	0.42
Acquired	0.02	0.00	0.03

Panel C - Fund Styles	% of Funds		
	Full Sample	Active Funds	Inactive Funds
Long/Short Equity	0.29	0.34	0.27
CTA/Managed Futures	0.11	0.16	0.09
Multi Style	0.11	0.07	0.12
Macro	0.08	0.08	0.08
Undisclosed	0.07	0.05	0.08
Equity Market Neutral	0.07	0.05	0.08
Long Bias Equity	0.05	0.06	0.05
Emerging Market Equity	0.03	0.04	0.02
Emerging Market Debt	0.02	0.02	0.02
Distressed Securities	0.04	0.02	0.05
Merger_Arb	0.02	0.02	0.02
Fixed Income_Arb	0.03	0.03	0.03
Convertible_Arb	0.03	0.02	0.03
Fixed_Income	0.03	0.02	0.03
Capital Structure_Arb	0.02	0.01	0.02
Equity Statistical_Arb	0.01	0.00	0.02

Table II: LASSO Matching Regression Results

LASSO matching regression results are reported. Regressions are run over 24 months window. ETFs used represent all ETFs available for LASSO regressions, while ETFs selected represent ETFs that were selected by LASSO as regressors for individual hedge funds. LASSO adjusted-R2, SBC and number of matched LASSO regressors are reported for each matching window. Standard deviations are reported in parentheses.

Table II: LASSO Matching Regression Results (Cont.)

Year	Number of Hedge Funds	Number of ETFs Used	Number of ETFs Selected	Adj. R^2	SBC	Number of Regressors	Adj. R^2	SBC	Number of Regressors	Adj. R^2	SBC	Number of Regressors
1997-1998	234	19	19	0.41	62.10	1.75	0.41	62.10	1.75			
				(0.26)	(36.03)	(1.05)	(0.26)	(36.03)	(1.05)			
1998-1999	306	19	19	0.41	66.50	1.85	0.41	66.50	1.85			
				(0.23)	(37.86)	(1.18)	(0.23)	(37.86)	(1.18)			
1999-2000	410	29	29	0.41	64.30	2.10	0.41	64.30	2.10			
				(0.22)	(39.04)	(1.26)	(0.22)	(39.04)	(1.26)			
2000-2001	539	30	30	0.38	61.35	1.93	0.38	61.35	1.93			
				(0.23)	(37.73)	(1.15)	(0.23)	(37.73)	(1.15)			
2001-2002	690	75	57	0.45	50.36	1.97	0.45	50.36	1.97			
				(0.23)	(36.24)	(1.16)	(0.23)	(36.24)	(1.16)			
2002-2003	932	97	68	0.47	52.22	2.14	0.47	52.22	2.14			
				(0.25)	(37.03)	(1.33)	(0.25)	(37.03)	(1.33)			
2003-2004	1125	107	87	0.53	46.07	2.26				0.53	46.07	2.26
				(0.23)	(35.00)	(1.37)				(0.23)	(35.00)	(1.37)
2004-2005	1390	119	88	0.52	34.85	2.13				0.52	34.85	2.13
				(0.24)	(32.85)	(1.30)				(0.24)	(32.85)	(1.30)
2005-2006	1667	153	100	0.51	32.48	2.13				0.51	32.48	2.13
				(0.24)	(31.14)	(1.37)				(0.24)	(31.14)	(1.37)
2006-2007	1889	201	115	0.56	34.87	2.43				0.56	34.87	2.43
				(0.23)	(31.98)	(1.51)				(0.23)	(31.98)	(1.51)
2007-2008	1918	332	117	0.63	50.82	2.79				0.63	50.82	2.79
				(0.27)	(30.90)	(1.72)				(0.27)	(30.90)	(1.72)
2008-2009	1675	539	132	0.59	62.87	2.59				0.59	62.87	2.59
				(0.25)	(29.03)	(1.54)				(0.25)	(29.03)	(1.54)
2009-2010	1230	680	113	0.63	54.52	2.72				0.63	54.52	2.72
				(0.25)	(29.98)	(1.57)				(0.25)	(29.98)	(1.57)
2010-2011	1072	786	122	0.57	49.98	2.29				0.57	49.98	2.29
				(0.24)	(28.98)	(1.36)				(0.24)	(28.98)	(1.36)
Average				**0.51**	**51.66**	**2.22**	**0.42**	**59.47**	**1.96**	**0.57**	**45.81**	**2.42**

Table III: Out-of-Sample Individual Matches

Summary statistics of out-of-sample individual matching of hedge funds and clones are reported. Attrition rate, mean tracking error and tracking error volatility are reported for each one year predicting window.

Year	Number of ETFs Used	Number of Hedge Funds		Attrition Rate	Tracking Error		Tracking Error		Tracking Error	
		Start	End		Mean	Volatility	Mean	Volatility	Mean	Volatility
1999	19	234	218	6.84%	-0.93	5.05	-0.93	5.05		
2000	19	306	297	2.94%	-0.52	5.24	-0.52	5.24		
2001	29	410	393	4.15%	-0.80	4.86	-0.80	4.86		
2002	30	539	499	7.42%	-0.27	4.14	-0.27	4.14		
2003	75	690	630	8.70%	-1.39	3.54	-1.39	3.54		
2004	97	932	840	9.87%	0.15	3.04	0.15	3.04		
2005	107	1125	1027	8.71%	0.04	2.74			0.04	2.74
2006	119	1390	1238	10.94%	0.02	2.53			0.02	2.53
2007	153	1667	1449	13.08%	-0.13	2.92			-0.13	2.92
2008	201	1889	1458	22.82%	-0.09	5.41			-0.09	5.41
2009	332	1918	1581	17.57%	-0.59	4.33			-0.59	4.33
2010	539	1675	1370	18.21%	-0.12	3.48			-0.12	3.48
2011	680	1230	1053	14.39%	0.28	3.92			0.28	3.92
2012	786	1072	904	15.67%	0.23	3.02			0.23	3.02
Average				**11.52%**	**-0.30**	**3.87**	**-0.63**	**4.31**	**-0.05**	**3.54**

Table IV: Cloneable and Non-Cloneable Funds - Matching Regression Results, Quartiles

Summary statistics of in-sample matching regressions are reported. LASSO Adj. R2, SBC and number of matched LASSO regressors are reported for each matching window. Skewness reports the mean skewness of individual hedge fund net returns for each matching window. Panel A reports the matches with LASSO Adj. R2 on the top quartile. Panel B reports the matches with LASSO Adj. R2 on the bottom quartile.

Table IV: Cloneable and Non-Cloneable Funds - Matching Regression Results, Quartiles (Cont.)

Panel A: In-Sample Matches, "Cloneable" Funds (Top R^2 Quartile)

Year	Number of ETFs Used	Number of Hedge Funds	Adj. R^2	SBC	Number of Regressors	Skewness	Adj. R^2	SBC	Number of Regressors	Skewness	Adj. R^2	SBC	Number of Regressors	Skewness
1997-1998	19	59	0.76	53.24	2.68	-0.95	0.76	53.24	2.68	-0.95				
1998-1999	19	77	0.71	70.41	3.03	-0.52	0.71	70.41	3.03	-0.52				
1999-2000	29	103	0.70	66.63	3.43	0.52	0.70	66.63	3.43	0.52				
2000-2001	30	135	0.69	62.26	2.98	0.24	0.69	62.26	2.98	0.24				
2001-2002	75	173	0.76	49.55	3.03	-0.19	0.76	49.55	3.03	-0.19				
2002-2003	97	233	0.80	41.65	3.33	-0.22	0.80	41.65	3.33	-0.22				
2003-2004	107	282	0.82	33.51	3.42	0.21					0.82	33.51	3.42	0.21
2004-2005	119	348	0.82	23.93	3.44	-0.15					0.82	23.93	3.44	-0.15
2005-2006	153	417	0.82	24.58	3.48	-0.14					0.82	24.58	3.48	-0.14
2006-2007	201	473	0.85	19.17	3.98	0.01					0.85	19.17	3.98	0.01
2007-2008	332	480	0.93	35.20	4.46	-1.28					0.93	35.20	4.46	-1.28
2008-2009	539	419	0.89	58.12	3.97	-0.61					0.89	58.12	3.97	-0.61
2009-2010	680	308	0.91	44.71	4.08	0.01					0.91	44.71	4.08	0.01
2010-2011	786	268	0.86	40.88	3.24	-0.14					0.86	40.88	3.24	-0.14
Average			**0.81**	**44.56**	**3.47**	**-0.23**	**0.74**	**57.29**	**3.08**	**-0.19**	**0.86**	**35.01**	**3.76**	**-0.26**

Table IV: Cloneable and Non-Cloneable Funds - Matching Regression Results, Quartiles (Cont.)

Panel B: In-Sample Matches, "Non-Cloneable" Funds (Bottom R^2 Quartile)

Year	Number of ETFs Used	Number of Hedge Funds	Adj. R^2	SBC	Number of Regressors	Skewness	Adj. R^2	SBC	Number of Regressors	Skewness	Adj. R^2	SBC	Number of Regressors	Skewness
1997-1998	19	59	0.09	73.61	1.00	0.20	0.09	73.61	1.00	0.20				
1998-1999	19	77	0.12	65.96	1.04	0.16	0.12	65.96	1.04	0.16				
1999-2000	29	103	0.13	48.33	1.07	0.11	0.13	48.33	1.07	0.11				
2000-2001	30	135	0.11	51.44	1.01	0.20	0.11	51.44	1.01	0.20				
2001-2002	75	173	0.16	52.68	1.12	0.14	0.16	52.68	1.12	0.14				
2002-2003	97	233	0.15	58.11	1.10	0.19	0.15	58.11	1.10	0.19				
2003-2004	107	282	0.22	52.59	1.19	0.18					0.22	52.59	1.19	0.18
2004-2005	119	348	0.20	37.73	1.12	0.11					0.20	37.73	1.12	0.11
2005-2006	153	417	0.20	33.60	1.16	0.04					0.20	33.60	1.16	0.04
2006-2007	201	473	0.24	45.72	1.29	-0.02					0.24	45.72	1.29	-0.02
2007-2008	332	480	0.24	58.73	1.28	-0.06					0.24	58.73	1.28	-0.06
2008-2009	539	419	0.23	63.00	1.30	0.09					0.23	63.00	1.30	0.09
2009-2010	680	308	0.26	57.76	1.34	0.05					0.26	57.76	1.34	0.05
2010-2011	786	268	0.24	59.36	1.37	0.10					0.24	59.36	1.37	0.10
Average			**0.18**	**54.19**	**1.17**	**0.11**	**0.13**	**58.36**	**1.06**	**0.17**	**0.23**	**51.06**	**1.26**	**0.06**

Table V: Cloneable and Non-Cloneable Funds - Matching Regression Results, Quintiles

Summary statistics of in-sample matching regressions are reported. LASSO Adj. R2, SBC and number of matched LASSO regressors are reported for each matching window. Skewness reports the mean skewness of individual hedge fund net returns for each matching window. Panel A reports the matches with LASSO Adj. R2 on the top quintile. Panel B reports the matches with LASSO Adj. R2 on the bottom quintile.

Table V: Cloneable and Non-Cloneable Funds - Matching Regression Results, Quintiles (Cont.)

Panel A: In-Sample Matches, "Cloneable" Funds (Top R^2 Quintile)

Year	Number of ETFs Used	Number of Hedge Funds	Adj. R^2	SBC	Number of Regressors	Skewness	Adj. R^2	SBC	Number of Regressors	Skewness	Adj. R^2	SBC	Number of Regressors	Skewness
1997-1998	19	47	0.78	51.40	2.77	-1.02	0.78	51.40	2.77	-1.02				
1998-1999	19	62	0.74	70.18	3.18	-0.45	0.74	70.18	3.18	-0.45				
1999-2000	29	82	0.72	64.17	3.57	0.49	0.72	64.17	3.57	0.49				
2000-2001	30	108	0.72	62.22	3.17	0.16	0.72	62.22	3.17	0.16				
2001-2002	75	138	0.79	49.24	3.12	-0.16	0.79	49.24	3.12	-0.16				
2002-2003	97	187	0.82	42.30	3.48	-0.26	0.82	42.30	3.48	-0.26				
2003-2004	107	225	0.83	32.00	3.64	0.19					0.83	32.00	3.64	0.19
2004-2005	119	278	0.84	21.44	3.58	-0.17					0.84	21.44	3.58	-0.17
2005-2006	153	334	0.85	22.92	3.69	-0.15					0.85	22.92	3.69	-0.15
2006-2007	201	378	0.87	16.79	4.13	0.03					0.87	16.79	4.13	0.03
2007-2008	332	384	0.94	32.67	4.63	-1.26					0.94	32.67	4.63	-1.26
2008-2009	539	335	0.90	56.24	4.07	-0.59					0.90	56.24	4.07	-0.59
2009-2010	680	246	0.93	41.90	4.21	-0.03					0.93	41.90	4.21	-0.03
2010-2011	786	216	0.88	39.16	3.31	-0.16					0.88	39.16	3.31	-0.16
Average			**0.83**	**43.05**	**3.61**	**-0.24**	**0.76**	**56.59**	**3.21**	**-0.21**	**0.88**	**32.89**	**3.91**	**-0.27**

Table V: Cloneable and Non-Cloneable Funds - Matching Regression Results, Quintiles (Cont.)

Panel B: In-Sample Matches, "Non-Cloneable" Funds (Bottom R^2 Quintile)

Year	Number of ETFs Used	Number of Hedge Funds	Adj. R^2	SBC	Number of Regressors	Skewness	Adj. R^2	SBC	Number of Regressors	Skewness	Adj. R^2	SBC	Number of Regressors	Skewness
1997-1998	19	47	0.07	68.73	1.00	0.05	0.07	68.73	1.00	0.05				
1998-1999	19	62	0.11	59.58	1.03	0.06	0.11	59.58	1.03	0.06				
1999-2000	29	82	0.11	47.16	1.01	0.00	0.11	47.16	1.01	0.00				
2000-2001	30	108	0.10	53.29	1.00	0.17	0.10	53.29	1.00	0.17				
2001-2002	75	138	0.14	54.18	1.08	0.09	0.14	54.18	1.08	0.09				
2002-2003	97	187	0.13	60.53	1.06	0.17	0.13	60.53	1.06	0.17				
2003-2004	107	225	0.19	52.81	1.15	0.17					0.19	52.81	1.15	0.17
2004-2005	119	278	0.17	38.24	1.06	0.08					0.17	38.24	1.06	0.08
2005-2006	153	334	0.17	34.03	1.11	0.06					0.17	34.03	1.11	0.06
2006-2007	201	378	0.21	45.78	1.23	-0.03					0.21	45.78	1.23	-0.03
2007-2008	332	384	0.20	57.89	1.20	-0.06					0.20	57.89	1.20	-0.06
2008-2009	539	336	0.20	62.62	1.22	0.06					0.20	62.62	1.22	0.06
2009-2010	680	246	0.22	59.95	1.24	0.01					0.22	59.95	1.24	0.01
2010-2011	786	215	0.20	62.41	1.26	0.07					0.20	62.41	1.26	0.07
Average			**0.16**	**54.09**	**1.12**	**0.07**	**0.11**	**57.24**	**1.03**	**0.09**	**0.20**	**51.72**	**1.18**	**0.05**

Table VI: Cloneable and Non-Cloneable Funds - Out-of-Sample Performance of Individual Matches, Quartiles

Summary statistics of out-of-sample individual matching of hedge funds and clones formed on the basis of LASSO Adj. R2 are reported. Attrition rate, mean tracking error and tracking error volatility are reported for each one year predicting window. Skewness reports the mean skewness of individual hedge fund and clone net returns for one year predicting window. Panel A reports the matches with LASSO Adj. R2 on the top quartile. Panel B reports the matches with LASSO Adj. R2 on the bottom quartile.

Table VI: Cloneable and Non-Cloneable Funds - Out-of-Sample Performance of Individual Matches, Quartiles (Cont.)

Panel A: Out-of-Sample Matches, "Cloneable" Funds (Top R^2 Quartile)

Year	Number of ETFs Used	Number of Hedge Funds		Attrition Rate	Tracking Error		Skewness		Tracking Error		Skewness		Tracking Error		Skewness	
		Start	End		Mean	Volatility	Hedge Funds	Clones	Mean	Volatility	Hedge Funds	Clones	Mean	Volatility	Hedge Funds	Clones
1999	19	59	55	6.78%	-1.15	4.85	0.33	0.14	-1.15	4.85	0.33	0.14				
2000	19	77	75	2.60%	-0.78	5.61	0.45	0.43	-0.78	5.61	0.45	0.43				
2001	29	103	97	5.83%	-0.57	5.33	-0.02	-0.28	-0.57	5.33	-0.02	-0.28				
2002	30	135	129	4.44%	-0.09	4.16	-0.06	0.13	-0.09	4.16	-0.06	0.13				
2003	75	173	157	9.25%	-0.97	3.16	0.30	0.01	-0.97	3.16	0.30	0.01				
2004	97	233	211	9.44%	0.48	2.52	-0.04	-0.55	0.48	2.52	-0.04	-0.55				
2005	107	282	261	7.45%	0.19	2.21	-0.19	-0.24					0.19	2.21	-0.19	-0.24
2006	119	348	316	9.20%	0.10	2.17	-0.08	-0.35					0.10	2.17	-0.08	-0.35
2007	153	417	373	10.55%	-0.08	2.72	-0.20	-0.19					-0.08	2.72	-0.20	-0.19
2008	201	473	391	17.34%	0.18	4.49	-0.47	-0.53					0.18	4.49	-0.47	-0.53
2009	332	480	404	15.83%	-0.41	4.00	-0.06	-0.18					-0.41	4.00	-0.06	-0.18
2010	539	419	367	12.41%	0.49	2.99	-0.18	-0.29					0.49	2.99	-0.18	-0.29
2011	680	308	258	16.23%	0.35	4.15	0.04	-0.17					0.35	4.15	0.04	-0.17
2012	786	268	238	11.19%	0.27	2.62	-0.57	-1.06					0.27	2.62	-0.57	-1.06
Average				**9.90%**	**-0.14**	**3.64**	**-0.05**	**-0.22**	**-0.51**	**4.27**	**0.16**	**-0.02**	**0.13**	**3.17**	**-0.21**	**-0.38**

Table VI: Cloneable and Non-Cloneable Funds - Out-of-Sample Performance of Individual Matches, Quartiles (Cont.)

Panel B: Out-of-Sample Matches, "Non-Cloneable" Funds (Bottom R^2 Quartile)

Year	Number of ETFs Used	Number of Hedge Funds		Attrition Rate	Tracking Error		Skewness		Tracking Error		Skewness		Tracking Error		Skewness	
		Start	End		Mean	Volatility	Hedge Funds	Clones	Mean	Volatility	Hedge Funds	Clones	Mean	Volatility	Hedge Funds	Clones
1999	19	59	52	11.86%	-0.36	5.52	-0.07	0.08	-0.36	5.52	-0.07	0.08				
2000	19	77	76	1.30%	-0.34	5.01	0.31	-0.04	-0.34	5.01	0.31	-0.04				
2001	29	103	95	7.77%	-0.69	3.56	0.00	0.09	-0.69	3.56	0.00	0.09				
2002	30	135	123	8.89%	-0.47	3.41	-0.05	0.05	-0.47	3.41	-0.05	0.05				
2003	75	173	157	9.25%	-1.45	3.24	0.30	-0.02	-1.45	3.24	0.30	-0.02				
2004	97	233	207	11.16%	-0.27	3.44	0.10	0.08	-0.27	3.44	0.10	0.08				
2005	107	282	251	10.99%	-0.11	2.94	-0.03	-0.11					-0.11	2.94	-0.03	-0.11
2006	119	348	297	14.66%	-0.20	2.87	0.18	-0.31					-0.20	2.87	0.18	-0.31
2007	153	417	349	16.31%	-0.42	2.87	0.00	-0.06					-0.42	2.87	0.00	-0.06
2008	201	473	338	28.54%	-0.50	5.77	-0.25	-0.47					-0.50	5.77	-0.25	-0.47
2009	332	480	385	19.79%	-0.60	4.13	0.21	0.18					-0.60	4.13	0.21	0.18
2010	539	419	315	24.82%	-0.80	3.92	-0.03	-0.11					-0.80	3.92	-0.03	-0.11
2011	680	308	256	16.88%	0.32	3.49	0.09	-0.05					0.32	3.49	0.09	-0.05
2012	786	268	224	16.42%	0.11	3.81	0.18	-0.26					0.11	3.81	0.18	-0.26
Average				**14.19%**	**-0.41**	**3.85**	**0.07**	**-0.07**	**-0.60**	**4.03**	**0.10**	**0.04**	**-0.28**	**3.72**	**0.05**	**-0.15**

Table VII: Cloneable and Non-Cloneable Funds - Out-of-Sample Performance of Individual Matches, Quintiles

Summary statistics of out-of-sample individual matching of hedge funds and clones formed on the basis of LASSO Adj. R2 are reported. Attrition rate, mean tracking error and tracking error volatility are reported for each one year predicting window. Skewness reports the mean skewness of individual hedge fund and clone net returns for one year predicting window. Panel A reports the matches with LASSO Adj. R2 on the top quintile. Panel B reports the matches with LASSO Adj. R2 on the bottom quintile.

Table VII: Cloneable and Non-Cloneable Funds - Out-of-Sample Performance of Individual Matches, Quintiles (Cont.)

Panel A: Out-of-Sample Matches, "Cloneable" Funds (Top R^2 Quintile)

Year	Number of ETFs Used	Number of Hedge Funds		Attrition Rate	Tracking Error		Skewness		Tracking Error		Skewness		Tracking Error		Skewness	
		Start	End		Mean	Volatility	Hedge Funds	Clones	Mean	Volatility	Hedge Funds	Clones	Mean	Volatility	Hedge Funds	Clones
1999	19	47	44	6.38%	-0.95	4.70	0.36	0.18	-0.95	4.70	0.36	0.18				
2000	19	62	60	3.23%	-0.82	5.57	0.51	0.47	-0.82	5.57	0.51	0.47				
2001	29	82	78	4.88%	-0.50	4.99	-0.04	-0.28	-0.50	4.99	-0.04	-0.28				
2002	30	108	102	5.56%	-0.16	4.31	-0.09	0.18	-0.16	4.31	-0.09	0.18				
2003	75	138	125	9.42%	-0.89	3.03	0.32	0.04	-0.89	3.03	0.32	0.04				
2004	97	187	168	10.16%	0.49	2.59	-0.06	-0.61	0.49	2.59	-0.06	-0.61				
2005	107	225	209	7.11%	0.15	2.11	-0.16	-0.24					0.15	2.11	-0.16	-0.24
2006	119	278	249	10.43%	0.14	2.03	-0.09	-0.34					0.14	2.03	-0.09	-0.34
2007	153	334	303	9.28%	-0.07	2.70	-0.20	-0.21					-0.07	2.70	-0.20	-0.21
2008	201	378	311	17.73%	0.23	4.42	-0.49	-0.52					0.23	4.42	-0.49	-0.52
2009	332	384	330	14.06%	-0.41	3.81	-0.06	-0.19					-0.41	3.81	-0.06	-0.19
2010	539	335	297	11.34%	0.53	2.90	-0.15	-0.28					0.53	2.90	-0.15	-0.28
2011	680	246	202	17.89%	0.33	4.09	0.01	-0.16					0.33	4.09	0.01	-0.16
2012	786	216	191	11.57%	0.29	2.64	-0.59	-1.05					0.29	2.64	-0.59	-1.05
Average				**9.93%**	**-0.12**	**3.56**	**-0.05**	**-0.22**	**-0.47**	**4.20**	**0.16**	**0.00**	**0.15**	**3.09**	**-0.21**	**-0.37**

Table VII: Cloneable and Non-Cloneable Funds - Out-of-Sample Performance of Individual Matches, Quintiles (Cont.)

Panel B: Out-of-Sample Matches, "Non-Cloneable" Funds (Bottom R^2 Quintile)

Year	Number of ETFs Used	Number of Hedge Funds		Attrition Rate	Tracking Error		Skewness		Tracking Error		Skewness		Tracking Error		Skewness	
		Start	End		Mean	Volatility	Hedge Funds	Clones	Mean	Volatility	Hedge Funds	Clones	Mean	Volatility	Hedge Funds	Clones
1999	19	47	42	10.64%	0.29	5.08	-0.09	0.03	0.29	5.08	-0.09	0.03				
2000	19	62	61	1.61%	-0.54	4.63	0.33	-0.14	-0.54	4.63	0.33	-0.14				
2001	29	82	75	8.54%	-0.59	3.37	-0.01	0.11	-0.59	3.37	-0.01	0.11				
2002	30	108	99	8.33%	-0.53	3.44	-0.09	0.05	-0.53	3.44	-0.09	0.05				
2003	75	138	125	9.42%	-1.45	3.20	0.33	0.00	-1.45	3.20	0.33	0.00				
2004	97	187	168	10.16%	-0.35	3.61	0.17	0.10	-0.35	3.61	0.17	0.10				
2005	107	225	199	11.56%	-0.15	2.95	0.02	-0.11					-0.15	2.95	0.02	-0.11
2006	119	278	234	15.83%	-0.23	2.89	0.21	-0.29					-0.23	2.89	0.21	-0.29
2007	153	334	277	17.07%	-0.43	2.93	0.01	-0.07					-0.43	2.93	0.01	-0.07
2008	201	378	265	29.89%	-0.43	5.70	-0.29	-0.45					-0.43	5.70	-0.29	-0.45
2009	332	384	305	20.57%	-0.55	4.00	0.22	0.17					-0.55	4.00	0.22	0.17
2010	539	336	246	26.79%	-0.82	3.88	-0.03	-0.09					-0.82	3.88	-0.03	-0.09
2011	680	246	202	17.89%	0.34	3.48	0.11	-0.08					0.34	3.48	0.11	-0.08
2012	786	215	179	16.74%	0.09	4.03	0.21	-0.23					0.09	4.03	0.21	-0.23
Average				**14.65%**	**-0.38**	**3.80**	**0.08**	**-0.07**	**-0.53**	**3.89**	**0.11**	**0.03**	**-0.27**	**3.73**	**0.06**	**-0.14**

Table VIII: Comparisons of Hedge Fund Portfolios and Clones Portfolios

Comparisons of hedge funds portfolios and clones portfolios 1999-2012 are reported. Portfolios are formulated as of December 31, 1998, and rebalanced annually. Annual returns and cumulative risk-adjusted performances are reported. End value is as of December 31, 2012. Skewness reports the mean skewness of out-of-sample portfolio net returns for one year predicting window. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table VIII: Comparisons of Hedge Fund Portfolios and Clones Portfolios (Cont.)

Year	Number of ETFs Used	Adj. R^2	Annual Return		Annual Return		Annual Return	
			Hedge Funds	Clones	Hedge Funds	Clones	Hedge Funds	Clones
1999	19	0.408	26.24	11.26	26.24	11.26		
2000	19	0.411	8.16	0.91	8.16	0.91		
2001	29	0.405	7.94	-3.14	7.94	-3.14		
2002	30	0.385	3.63	-0.07	3.63	-0.07		
2003	75	0.451	25.23	7.36	25.23	7.36		
2004	97	0.474	10.72	13.40	10.72	13.40		
2005	107	0.528	8.46	8.66			8.46	8.66
2006	119	0.520	14.18	14.85			14.18	14.85
2007	153	0.513	12.44	10.33			12.44	10.33
2008	201	0.559	-17.40	-19.02			-17.40	-19.02
2009	332	0.633	24.14	15.21			24.14	15.21
2010	539	0.593	10.20	9.07			10.20	9.07
2011	680	0.629	-6.63	-3.59			-6.63	-3.59
2012	786	0.570	5.07	8.24			5.07	8.24
End Value			3.27	1.93	2.12	1.32	1.54	1.46
Monthly Return			0.73***	0.42**	1.07***	0.40**	0.48*	0.43*
(t-stat)			(4.18)	(2.53)	(4.46)	(2.37)	(1.95)	(1.65)
alpha			0.22**	-0.04	0.50***	0.01	0.10	0.00
(t-stat)			(2.47)	(-0.55)	(5.06)	(0.16)	(0.93)	(0.02)
Sharpe Ratio			0.24	0.11	0.41	0.11	0.14	0.11
Info Ratio			0.20	-0.05	0.51	0.02	0.10	0.00
Skewness			-0.18	-1.03	0.89	-0.44	-0.56	-1.03
Attrition Rate			11.52%		6.65%		15.17%	
Mean Adj. R2			0.506		0.422		0.568	

Table IX: Cloneable and Non-Cloneable Funds - Portfolio Comparisons, Quartiles, 1999-2012

Annual returns and cumulative risk-adjusted performances of portfolios 1999-2012 formed on the basis of LASSO Adj. R2. Portfolios of hedge funds and clones are formed as December 31, 1998, and rebalanced annually for funds in the top and bottom quartile of LASSO Adj. R2. End value is as of December 31, 2012. Skewness reports the mean skewness of out-of-sample portfolio net returns for one year predicting window. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Year	"Cloneable" Funds, Top R^2 Quartile			"Non-Cloneable" Funds, Btm R^2 Quartile		
	Adj. R^2	Annual Return		Adj. R^2	Annual Return	
		Hedge Funds	Clones		Hedge Funds	Clones
1999	0.757	36.88	19.97	0.087	13.56	2.83
2000	0.713	5.49	-3.88	0.123	9.15	4.25
2001	0.697	0.26	-8.18	0.126	14.41	3.04
2002	0.692	-3.98	-5.82	0.109	8.42	3.08
2003	0.762	33.69	20.93	0.156	18.24	0.61
2004	0.799	12.99	19.67	0.153	6.66	3.97
2005	0.815	9.25	11.32	0.215	7.00	6.26
2006	0.816	18.63	19.59	0.203	10.68	8.76
2007	0.824	16.89	15.16	0.196	11.76	6.64
2008	0.850	-26.66	-25.68	0.243	-4.10	-8.20
2009	0.925	38.31	29.74	0.237	7.69	0.55
2010	0.887	11.42	17.31	0.233	9.78	1.69
2011	0.913	-10.16	-7.79	0.263	-4.43	-0.06
2012	0.859	9.50	13.23	0.236	0.61	3.20
End Value		3.54	2.61		2.80	1.42
Monthly Return		0.82***	0.65**		0.63***	0.21***
(t-stat)		(3.02)	(2.18)		(5.06)	(3.76)
α		0.15	-0.01		0.25**	-0.06
(t-stat)		(1.43)	(-0.12)		(2.54)	(-1.27)
Sharpe Ratio		0.18	0.12		0.27	0.03
Info Ratio		0.12	-0.01		0.21	-0.11
Skewness		-0.41	-0.60		0.20	-1.84
Attrition Rate		9.90%			14.19%	
Mean Adj. R^2		0.808			0.184	

Table X: Cloneable and Non-Cloneable Funds - Portfolio Comparisons, Quartiles, 1999-2004 and 2005-2012

Annual returns and cumulative risk-adjusted performances of portfolios 1999-2012 formed on the basis of LASSO Adj. R2. Portfolios of hedge funds and clones are formed as December 31, 1998, and rebalanced annually for funds in the top and bottom quartile of LASSO Adj. R2. End value is as of December 31, 2012. Skewness reports the mean skewness of out-of-sample portfolio net returns for one year predicting window. Panel A reports the comparisons of performances 1999-2004. Panel B reports the comparisons of performances 2005-2012. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table X: Cloneable and Non-Cloneable Funds - Portfolio Comparisons, Quartiles, 1999-2004 and 2005-2012 (Cont.)

Panel A: Year 1999 to 2004

Year	"Cloneable" Funds, Top R^2 Quartile			"Non-Cloneable" Funds, Btm R^2 Quartile		
	Adj. R^2	Annual Return		Adj. R^2	Annual Return	
		Hedge Funds	Clones		Hedge Funds	Clones
1999	0.757	36.88	19.97	0.087	13.56	2.83
2000	0.713	5.49	-3.88	0.123	9.15	4.25
2001	0.697	0.26	-8.18	0.126	14.41	3.04
2002	0.692	-3.98	-5.82	0.109	8.42	3.08
2003	0.762	33.69	20.93	0.156	18.24	0.61
2004	0.799	12.99	19.67	0.153	6.66	3.97
End Value		2.10	1.44		1.94	1.19
Monthly Return		1.08***	0.56		0.94***	0.24***
(t-stat)		(3.05)	(1.56)		(4.42)	(7.08)
α		0.47***	0.03		0.43***	-0.03
(t-stat)		(3.92)	(0.24)		(3.01)	(-0.87)
Sharpe Ratio		0.28	0.10		0.38	0.00
Info Ratio		0.43	0.03		0.34	-0.10
Skewness		0.35	-0.28		0.13	0.41
Attrition Rate		6.39%			8.37%	
Mean Adj. R^2		0.737			0.125	

Panel B: Year 2005 to 2012

Year	"Cloneable" Funds, Top R^2 Quartile			"Non-Cloneable" Funds, Btm R^2 Quartile		
	Adj. R^2	Annual Return		Adj. R^2	Annual Return	
		Hedge Funds	Clones		Hedge Funds	Clones
2005	0.815	9.25	11.32	0.215	7.00	6.26
2006	0.816	18.63	19.59	0.203	10.68	8.76
2007	0.824	16.89	15.16	0.196	11.76	6.64
2008	0.850	-26.66	-25.68	0.243	-4.10	-8.20
2009	0.925	38.31	29.74	0.237	7.69	0.55
2010	0.887	11.42	17.31	0.233	9.78	1.69
2011	0.913	-10.16	-7.79	0.263	-4.43	-0.06
2012	0.859	9.50	13.23	0.236	0.61	3.20
End Value		1.68	1.81		1.44	1.19
Monthly Return		0.62	0.72		0.39***	0.19*
(t-stat)		(1.58)	(1.61)		(2.74)	(1.98)
α		0.01	0.08		0.19*	-0.05
(t-stat)		(0.05)	(0.52)		(1.73)	(-0.73)
Sharpe Ratio		0.12	0.13		0.18	0.05
Info Ratio		0.01	0.06		0.20	-0.09
Skewness		-0.62	-0.68		-0.01	-1.50
Attrition Rate		12.53%			18.55%	
Mean Adj. R^2		0.861			0.228	

Table XI: Cloneable and Non-Cloneable Funds - Portfolio Comparisons, Quintiles, 1999-2012

Annual returns and cumulative risk-adjusted performances of portfolios 1999-2012 formed on the basis of LASSO Adj. R2. Portfolios of hedge funds and clones are formed as December 31, 1998, and rebalanced annually for funds in the top and bottom quintile of LASSO Adj. R2. End value is as of December 31, 2012. Skewness reports the mean skewness of out-of-sample portfolio net returns for one year predicting window. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

	"Cloneable" Funds, Top R^2 Quintile			"Non-Cloneable" Funds, Btm R^2 Quintile		
Year	Adj. R^2	Annual Return		Adj. R^2	Annual Return	
		Hedge Funds	Clones		Hedge Funds	Clones
1999	0.783	34.81	20.90	0.073	0.81	2.98
2000	0.736	6.18	-4.20	0.105	12.00	4.77
2001	0.721	0.27	-7.91	0.106	11.35	3.69
2002	0.721	-4.07	-6.78	0.095	8.22	2.24
2003	0.787	35.22	23.09	0.135	18.04	0.49
2004	0.824	13.52	20.19	0.130	6.60	2.99
2005	0.835	9.96	11.70	0.189	6.82	6.01
2006	0.839	17.02	18.89	0.175	10.25	8.04
2007	0.846	17.35	15.88	0.173	11.67	6.45
2008	0.869	-27.19	-25.67	0.214	-4.12	-6.91
2009	0.936	38.85	29.90	0.201	6.42	0.20
2010	0.903	11.22	17.93	0.201	9.48	1.30
2011	0.927	-10.34	-8.38	0.224	-4.56	0.42
2012	0.879	9.46	13.53	0.203	0.68	3.16
End Value		3.52	2.68		2.42	1.41
Monthly Return		0.82***	0.67**		0.54***	0.21***
(t-stat)		(2.93)	(2.19)		(4.53)	(4.20)
α		0.15	0.00		0.16	-0.05
(t-stat)		(1.32)	(-0.06)		(1.62)	(-1.15)
Sharpe Ratio		0.17	0.12		0.23	0.03
Info Ratio		0.11	0.00		0.14	-0.10
Skewness		-0.43	-0.60		-0.24	-1.63
Attrition Rate	9.93%			14.65%		
Mean Adj. R^2	0.829			0.159		

Table XII: Cloneable and Non-Cloneable Funds - Portfolio Comparisons, Quintiles, 1999-2004 and 2005-2012

Annual returns and cumulative risk-adjusted performances of portfolios 1999-2012 formed on the basis of LASSO Adj. R2. Portfolios of hedge funds and clones are formed as December 31, 1998, and rebalanced annually for funds in the top and bottom quintile of LASSO Adj. R2. End value is as of December 31, 2012. Skewness reports the mean skewness of out-of-sample portfolio net returns for one year predicting window. Panel A reports the comparisons of performances 1999-2004. Panel B reports the comparisons of performances 2005-2012. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table XII: Cloneable and Non-Cloneable Funds - Portfolio Comparisons, Quintiles, 1999-2004 and 2005-2012 (Cont.)

Panel A: Year 1999 to 2004

Year	"Cloneable" Funds, Top R^2 Quintile			"Non-Cloneable" Funds, Btm R^2 Quintile		
	Adj. R^2	Annual Return		Adj. R^2	Annual Return	
		Hedge Funds	Clones		Hedge Funds	Clones
1999	0.783	34.81	20.90	0.073	0.81	2.98
2000	0.736	6.18	-4.20	0.105	12.00	4.77
2001	0.721	0.27	-7.91	0.106	11.35	3.69
2002	0.721	-4.07	-6.78	0.095	8.22	2.24
2003	0.787	35.22	23.09	0.135	18.04	0.49
2004	0.824	13.52	20.19	0.130	6.60	2.99
End Value		2.11	1.47		1.71	1.18
Monthly Return		1.09***	0.59		0.76***	0.23***
(t-stat)		(3.00)	(1.59)		(3.74)	(9.41)
α		0.49***	0.05		0.27*	-0.02
(t-stat)		(3.81)	(0.50)		(1.71)	(-1.06)
Sharpe Ratio		0.27	0.11		0.30	-0.05
Info Ratio		0.44	0.06		0.21	-0.12
Skewness		0.34	-0.23		-0.56	0.10
Attrition Rate		6.60%			8.12%	
Mean Adj. R^2		0.762			0.108	

Panel B: Year 2005 to 2012

Year	"Cloneable" Funds, Top R^2 Quintile			"Non-Cloneable" Funds, Btm R^2 Quintile		
	Adj. R^2	Annual Return		Adj. R^2	Annual Return	
		Hedge Funds	Clones		Hedge Funds	Clones
2005	0.835	9.96	11.70	0.189	6.82	6.01
2006	0.839	17.02	18.89	0.175	10.25	8.04
2007	0.846	17.35	15.88	0.173	11.67	6.45
2008	0.869	-27.19	-25.67	0.214	-4.12	-6.91
2009	0.936	38.85	29.90	0.201	6.42	0.20
2010	0.903	11.22	17.93	0.201	9.48	1.30
2011	0.927	-10.34	-8.38	0.224	-4.56	0.42
2012	0.879	9.46	13.53	0.203	0.68	3.16
End Value		1.67	1.82		1.41	1.19
Monthly Return		0.61	0.73		0.37***	0.19**
(t-stat)		(1.51)	(1.60)		(2.66)	(2.21)
α		-0.02	0.07		0.19*	-0.04
(t-stat)		(-0.12)	(0.46)		(1.67)	(-0.60)
Sharpe Ratio		0.12	0.13		0.16	0.05
Info Ratio		-0.01	0.05		0.20	-0.07
Skewness		-0.63	-0.69		0.00	-1.27
Attrition Rate		12.43%			19.54%	
Mean Adj. R^2		0.879			0.197	

Appendix A: Gross returns adjustments for ETFs and hedge funds

Given the fact that Bloomberg only provides net returns for individual hedge funds (net-of-fees, i.e. net of performance and management fees), and Morningstar provides net returns for ETFs (net of management fee), it would be less accurate to import the net returns into our matching model. So as to provide the real return series, we make adjustments to net asset returns and transfer them into estimated gross returns for both hedge funds and ETFs.

We estimate the gross returns for ETFs by adding back the reported management fees from Morningstar:

$$Gross\_ETF_{i,t} = Net\_ETF_{i,t} + \frac{Management\_Fee_{i,t}}{12}, \qquad \text{(A1)}$$

where $Net\_ETF_{i,t}$ is the reported net-of-fee ETF return from Morningstar, and $Management\_Fee_{i,t}$ is the specific ETF management fee.

We adopt the following steps to estimate the gross hedge fund return. We collect the fund management fees from Bloomberg for every individual hedge fund and add them back to the net hedge fund returns. We then adjust for the performance fees using LIBOR as the hurdle rate, collecting LIBOR returns from January 1997 to December 2012 from British Bankers' Association. We use the following equation to calculate the gross hedge fund returns[100]:

$$Gross\_Ret_{i,t} = \left\{ \begin{array}{ll} Net\_Ret_{i,t} + \dfrac{Management\_Fee_{i,t}}{12}, & \text{if } Net\_Ret_{i,t} \leq LIBOR_t \\ \dfrac{Net\_Ret_{i,t} - LIBOR_t}{1 - Performance\_Fee_{i,t}} + \dfrac{Management\_Fee_{i,t}}{12} + LIBOR_t, & \text{otherwise} \end{array} \right\}, \qquad \text{(A2)}$$

[100] We do not adjust for the "high water mark" provision here, since we do not have reliable information regarding to the cash flow of individual hedge fund, nor a complete data on assets under management for every hedge fund.

where $Net\_Ret_{i,t}$ is the reported net-of-fee hedge fund return from Bloomberg, $Management\_Fee_{i,t}$ is the fund manager stated management fee, and $Performance\_Fee_{i,t}$ is the fund manager stated performance fee.

Appendix B: Calculating Fung and Hsieh (2004) alpha

While Fung and Hsieh (2004) specify the seven factor model, the updated specification on David Hsieh's web site[101] includes eight tradable po rtfolio factors such that

$$r_i - r_f = \alpha_i + \beta_{i1} SP500 + \beta_{i2} EM + \beta_{i3} 10Year + \beta_{i4} SizeSpread + \\ + \beta_{i5} CreditSpread + \beta_{i6} BondTrend + \beta_{i7} ComTrend + \beta_{i8} FxTrend + \varepsilon_i, \quad \text{(FH)}$$

where r_i is the monthly return of fund i, r_f is a risk free rate proxied by the monthly return of the 30-day U.S. Treasury bill. *SP500* is the market risk premium proxied by the S&P 500 index return minus the risk free rate. *EM* is the MSCI Emerging Market index return minus the risk free rate. *10Year* is the monthly excess return of a 10-year U.S. treasury bond, proxied by the 10-year U.S. Treasury bond portfolio return from the Center for Research in Security Prices (CRSP), minus the risk free rate. *SizeSpread* is an equity-based risk factor, the Russell 2000 Index return minus the S&P 500 Index return. *CreditSpread* is a fixed income-based risk factor, calculated as the total return on the Citi BBB corporate bond index minus the total return on the Fama U.S. Treasury bond portfolio as per CRSP. Both portfolios are comprised of bonds with maturities of 10 years or more. *BondTrend*, *ComTrend*, and *FxTrend* are excess returns on trend following factors constructed of look-back straddles on futures contracts of bonds, commodities, and currencies, respectively. All factors are therefore arbitrage (zero cost) portfolios. All returns and yields data are from Bloomberg, while trend-following risk factors are courtesy of David Hsieh's website.

[101] See http://faculty.fuqua.duke.edu/~dah7/HFData.htm.

IV. Essay 3: Hedge Fund Market Exposures: Beta Return and Beta Risk[102]

Jun Duanmu and Alexey Malakhov

A. Abstract

In this study, hedge fund excess returns are decomposed into alpha and beta return components and a strong monotonic mean reversal pattern in out-of-sample performance of portfolios sorted by beta returns is documented. Two types of hedge fund managers are identified: Multi-active Managers and Risk-writing Managers. Risk-writing Managers generate returns through excessive risk taking and exhibit the greatest total risk and beta risk among hedge fund managers. Multi-active Managers actively manage their risk factor positions that are reflective of their beliefs, continuously search for market opportunities and effectively adjust their beta positions to reflect their evolving market expectations. The superior performance of the bottom quartile beta return portfolio is mainly driven by Multi-active Managers.

JEL Classification: G11, G23

Keywords: hedge funds, alpha, beta return, beta risk, market timing, performance measurement, performance prediction

B. Introduction

Hedge fund industry is considered one of the most unique alternative investment asset classes and has experienced a tremendous growth in recent years.[103] Actively managed by fund managers, hedge funds often target to generate positive returns[104] regardless of market

[102] We would like to thank Pu Liu, Timothy Yeager, seminar participants at University of Arkansas for their helpful comments and suggestions.

[103] More than $2.94 trillion in global investments currently under management according to Hedge Fund Research, Inc. April 20, 2015 press release.

[104] Ackermann, McEnally, and Ravenscraft (1999), Brown, Goetzmann, and Ibbotson (1999), Fung, Hsieh, Naik, and Ramdorai (2008), Jagannathan, Malakhov, and Novikov (2010), Titman and Tiu (2011), Bali, Brown, and Cagalayan (2012), Duanmu, Malakhov, and McCumber (2014) document positive risk adjusted performance among hedge funds.

conditions. Hedge fund managers are granted the discretionary power and broad flexibility to manage assets with a variety of complicated strategies. Derivative securities, leverage, and short sales are heavily employed to achieve the absolute returns that are uncorrelated with the market.

Hedge fund researchers commonly consider alpha, the constant in a regression specified by a performance evaluation factor model, as a proxy for performance due to active management. However, with an improperly specified model, alpha is only a relative measure of the fund performance as it is sensitive to benchmark factor specifications[105], which questions whether alpha reliably encompasses all relevant information about hedge fund performance.[106] In addition, in the absence of disclosure requirement, hedge fund trading strategies and portfolio holdings are generally unobservable. This raises difficulties in performance attribution analysis and thus makes true factor risk exposures hard to quantify, which ultimately leads to an insufficient segregation of performance attributable to active management (selection) and to market timing activity (style).[107] Moreover, it is questionable whether hedge fund returns are truly isolated from market movement[108] with extant literature documenting that hedge fund

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[105] See, for example, Roll (1978).

[106] Duanmu, Malakhov, and McCumber (2014) find that alpha active managers do not generate significant out-of-sample alpha. However, Kosowski, Naik, and Teo (2007) and Jagannathan, Malakhov, and Novikov (2010) find alpha t-statistics to be predictive of future performance.

[107] Sharpe (1992) develop style analysis approach, which constructs a replicating portfolio by relying on constrained beta coefficients from a linear regression on a set of relevant factors. However, the approach relies only on traditional equity and bond risk exposure styles. Given more complicated nature of alternative risk exposures undertaken by hedge funds, such approach might be inadequate to accurately quantify the performance attribution. Fung and Hsieh (1997) find five dominant investment styles in addition to Sharpe (1992) factors which in together explain around only 40% of hedge fund return variations.

[108] For example, John H. Cochrane observes: "As I look across the hedge fund universe, 90% of what I see is not "picking assets to exploit information not reflected in prices," it is "taking exposure to factors that managers understand and can trade better than clients." (John H. Cochrane's "Hedge Funds" lecture notes at http://faculty.chicagobooth.edu/john.cochrane/teaching/35150_advanced_investments/hedge_notes_and_questions.pdf)

returns are exposed to systematic risk factors.[109] For example, Fung, Hsieh, Naik, and Ramadorai (2008) find that 78% of the funds in their sample did not deliver alpha, instead exhibiting 'beta only' pattern. In addition, Patton (2009) find that one quarter of the hedge funds which claim 'market neutral' strategy exhibit significant exposure to market risk. Bali, Brown and Cagalayan (2012) have shown that hedge funds with greater exposures to systematic risk demonstrate higher risk adjusted performance. In contrast, Titman and Tiu (2011) argue that successful managers hedge away systematic risk exposure and thus exhibit low R^2 in multifactor regressions.[110] In addition, Sun, Wang, and Zheng (2012) find hedge fund managers who pursue unique investment strategies deliver superior performance.

A distinct feature of hedge funds is their dynamic management styles. Many fund managers actively vary their exposures to risk factors according to the macroeconomic conditions and the state of the financial markets.[111] In other words, market timing ability is considered an important factor when evaluating the performance of hedge fund manager. It's been demonstrated in the literature that the hedge fund managers attempt to time the market and those with superior market timing ability are able to generate positive risk-adjusted performance.[112] For example, Cao, Chen, Liang, and Lo (2013) examine the market liquidity timing ability of fund managers and find that managers time market liquidity through adjusting their portfolios' market exposures as aggregate liquidity conditions change. Instead of focusing

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[109] See, for example, Asness, Krail, and Liew (2001), Pattern (2009), Fung, Hsieh, Pattern and Ramadorai (2010), Duanmu, McCumber, and Malakhov (2014), Duanmu, Li, and Malakhov (2014).

[110] Though, Bollen (2013) find higher probability of failure for zero-R^2 funds.

[111] See, for example, Avarmov, Kosowski, Naik, and Teo (2011), Bali, Brown, and Cagalayan (2011), Avramov, Barras, and Kosowski (2013),

[112] See, for example, Fung, Xu, and Yau (2002), Agarwal, and Naik (2000, 2004), Chen and Liang (2007), Chen (2007), Bollen and Whaley (2009), Avramov, Kosowski, Naik, and Teo (2011), Cai and Liang (2012a, 2012b).

on liquidity timing, Duanmu, Malakhov, and McCumber (2014) develop a measure of hedge fund overall beta activity and find that top beta active managers deliver superior out-of-sample performance compared to top alpha active managers.

In reality, market timing could take place in different forms. For some managers, they attempt to time the market, form market expectations precisely and incorporate their beliefs into factor exposures, as state of financial market changes, they profit from their ex-ante anticipatory factor loadings. This attempt to time the market might be signaled by hedge fund temporary inferior beta returns given the fact that even the most prescient managers are not able to precisely time a broad set of macroeconomic factors[113], and the success of the timing should be captured by their ex-post realized beta return increments. Even in the absences of short term alpha production, it is possible for such manager to deliver superior returns if he executes the later most profitable strategies. We define this type of market timing as pure market timing. The efficacy of pure market timing solely depends on the precise and accurate forecast formed by the managers.

On the other hand, without heavy reliance on the accuracy of market expectations, managers continuously form different strategic market beliefs, incorporate those strategies into corresponding factors and at meanwhile actively manage their market exposures. Managers profit from their ex-ante positions should economic conditions change in favor of their exposures. If ex-ante positions do not pay off, managers immediately switch to other investment opportunities. In this sense, managers are pursuing more of a market testing strategy rather than pure market timing. Such managers would be detected by consistent short-term alphas and

[113] Duanmu, Malakhov and McCumber (2014) find that managers who take anticipatory bets on mean reversing factors in the future are is captured by their less profitable preceding beta positions.

contemporaneous unprofitable beta positions which is a signal of market timing attempt. We define this type of market timing as active market testing, in which managers ability to actively manage the factor exposures is the determinant of validity of such strategy.

It is therefore important to evaluate both the alpha and beta management in a consolidated context. This objective could be accomplished by, first, a properly specified asset pricing model that accounts for the unique nature of hedge fund risk exposures[114], and second, a decomposition of the hedge fund return into alpha and beta return and following performance evaluation process as well as factor related risk measurement regarding selection skill through alpha management, pure market timing ability through beta management and active market testing through proper interactions between alpha and beta management.

In this paper, we modify Duanmu, Li and Malakhov (2014) approach that allows a comprehensive coverage of all potential alternative risk factors through tradable liquid portfolios, proxied by Exchange Traded Funds (ETF) to decompose the hedge fund return into alpha (selection) and beta return (style).[115] We evaluate alpha and betas for non-overlapping two year periods and calculate beta returns as the sum of the product of beta and its corresponding factor. Like Bali, Brown, and Caglayan (2012) and Duanmu, Malakhov and McCumber (2014), we do not attempt to capture timing with respect to any specific factor, instead we focus on overall activity. That is, we construct an aggregate measure of activity across all factors in an unconditional performance attribution model. We sort alpha and beta return into equal weight

[114] In addition, hedge fund strategies generate option-like returns. Traditional asset pricing model using benchmark asset indices have difficulties explaining them. See, for example, Fung and Hsieh (2001).
[115] Duanmu, Li and Malakhov (2014) approach is not an equilibrium model of performance evaluation, and instead relies on risk based factor models that approximate the true set of hedge fund risk factors. The accuracy of the model relies on the availability of different types of ETFs that cover a majority of investment categories.

quartile portfolios and examine the out-of-sample portfolio performances. We find that with well specified factor model, top alpha managers deliver significant superior out-of-sample performance that persists as long as three years. We find a strong and persistent mean reversal pattern in portfolios sorted by beta return. Consistent with Duanmu, Malakhov and McCumber (2014), bottom beta return portfolio delivers superior risk-adjusted performance with relatively high attrition, which can be interpreted as beta return only captures the market timing attempt but not pure market timing ability.

We further examine the interactions between alpha and beta return to provide a comprehensive view of alpha and beta management. In addition to out-of-sample portfolio analysis, we go beyond Bali, Brown and Cagalayan (2012)[116] and calculate direct factor risk exposures, cross covariance and total beta risk[117] for each hedge fund in both preceding and post windows in order to better examine the dynamic and segregated market risk pursued by specific managers. We form the portfolio based upon the interaction between top alpha quartile and bottom beta return quartile which represents the group of managers possess active market testing ability. With low beta return being indicative of market timing attempt and top alpha as a proxy for positive active management, the interacting portfolio presents the managers who continuously form different strategic market beliefs, incorporate those strategies into corresponding factors and at meanwhile actively manage their market exposures. We name those active market testing managers *Multi-active Managers*. Market timing attempt together with active factor exposure management grant *Multi-active Managers* the ability to deliver significant risk-adjusted performance, and they are the driving force behind superior performance of low

[116] Bali, Brown and Cagalayan (2012) considers the overall systematic risk which is the difference of the total fund risk minus the idiosyncratic risk from a factor regression.
[117] Total beta risk is the sum of direct factor risk and cross covariance term, which captures the overall risk of managers' market exposures.

beta return portfolio. We find *Multi-active Managers* exhibit the highest risk exposures to direct factors, while generating large negative cross covariance through their active management which leads to an acceptable level of total beta risk.[118] Moreover, we provide evidence that *Multi-active Managers* continuously search for market opportunities and are able to generate overall positive beta returns through their position reallocations. Consistent with Agarwal, Daniel and Naik (2009) we find *Multi-active Managers* are aware of their abilities and charge greater incentive fees to separate themselves from other managers.

Another interaction which is between low alpha and inferior beta return is considered in this study. Arguably, this interaction represents the group of managers who attempt to time the market and are lack of required skill to manage their positions. In addition, since the average hedge fund excess return is the sum of alpha and beta return determined by the regression, the interaction of bottom quartile alpha and bottom quartile beta return is thus a subset of bottom quartile of excess return and identifies the funds with the lowest contemporaneous reported returns, which provides an ideal sample set to empirically test Buraschi, Kosowski and Sritakul (2014) finding of changing endogenous risk taking preference with respect to fund position relative to high water mark. Managers with inferior contemporaneous performances have higher incentives to take risk so as to generate returns above the high water mark to reap potential performance fees. We define this group as *Risk-writing Managers*. Unsurprisingly, *Risk-writing Managers* exhibit the greatest total risk and beta risk in both pre and post portfolio formation period, and generate returns through excessive risk taking which leads to a higher attrition rate compared with other funds. In addition, we show that *Risk-writing Managers* possess

[118] Lo (2008) calculate the sum of covariances between returns and portfolio weights as a measure to capture the forecast power in the managers' dynamic investment choices. Conceptually similar to Lo (2008), we use the cross covariance term to measure the effectiveness of managers' active risk management.

incapability to form new market beliefs as economic condition changes and fail to readjust their beta positions on a timely manner.

The contributions in this paper come in threefold: first, with a properly specified pricing model which accounts for alternative risk factors taken by fund managers with tradable ETFs, we extend Sharpe (1992) and Fung and Hsieh (1997) style analysis and decompose hedge fund returns into alpha and beta return.[119] This approach explores a new dimension of return-based analysis, and allows us to identify managers generating persistent alpha and to evaluate the managerial effectiveness on beta management. Second, we define another strand of market timing activity as active market testing. Based on simple interaction between alpha and beta return, we are able to identify managers with superior active market testing ability and provide evidence that such managers continuously form market expectations, invest in factors according to their beliefs and actively manage the risk exposures related to their positions. We confirm the current literature that beta return is indicative of market timing attempt and suggest that market timing ability should be captured through multi-dimension approach.[120] Finally, instead of focusing on overall systematic risk[121], we calculate the direct factor risk, cross covariance and total beta risk, which provide a useful insight to examine hedge fund market exposures on a separated basis, and concludes that active market testing comes in a form with high direct factor exposures and active risk management signaled by large and negative cross covariance.

[119] We differ from Fung and Hsieh (1997) in a way that our methodology allows us to incorporate all potential alternative risk factors pursued by fund managers and applies to the whole universe of hedge fund strategies.
[120] See, for example, Duanmu. Malakhov, and McCumber (2014).
[121] See, for example, Bali, Brown and Cagalayan (2012).

The remainder of the paper constructs as follows. Section 2 describes the data and presents summary statistics. In section 3, we outline the regression methodology and the out-of-sample portfolio constructions. Section 4 presents the empirical finding and section 5 concludes.

C. Data

In this study we utilize hedge fund data from Bloomberg[122] for the period 2003-2013, which includes 11,159 unique hedge funds, with 3,409 active hedge funds in the end of sample period and 7,750 inactive hedge funds.[123] The data are comprehensive, including fund returns net of management and performance fees, assets under management, manager information, and fund characteristics. To minimize survivorship bias, the sample includes all funds reporting during our sample period, including those that are acquired, liquidated, or chose to stop reporting. We partially offset the effects of backfill bias by eliminating the first 24 months of reported returns.[124]

Table I reports summary statistics of fund excess returns, fee structures, and investor liquidity measures. As medians are better measures of typical funds in our database, we find that the typical fund has a 1.5% management fee, a 20% incentive fee on all profits over an investor's high water mark,[125] a $250,000 minimum initial investment, and a 30 day redemption period.

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[122] Bloomberg is the most common platform used by both hedge funds, who utilize news, analysis, research, and trading tools, and accredited investors, who use Bloomberg data to research hedge funds, private equity firms, and other alternative investment vehicles. Bloomberg aggregates data on live and dead funds inclusive of fund and parent company descriptions, manager and contact information, total assets under management, fees, past performance, and management style.

[123] We do not include funds of hedge funds in our sample.

[124] The 24 month backfill correction is in line with results in Jagannathan, Malakhov, and Novikov (2010) and Titman and Tiu (2011) suggesting dropping the first 25 and 27 months of returns.

[125] High water marks are investor relevant, that is, an investor will not be charged incentive fees until profits accrue over a previous high, net of flows. Thus, not all investors are charged incentive fees in any given year; it is partially determined by when the investor capital was employed by the fund manager. An investor whose fund shares are worth more this year than last

Unsurprisingly, active funds display higher monthly excess returns[126], a positive 0.66% monthly excess return against -0.06% for inactive hedge funds, and higher assets under management. Interestingly, however, we do not observe a noticeable difference regarding investor liquidity measures, both active funds and inactive funds have similar lockup period and total redemption period.

Following Duanmu, Li and Malakhov (2014), we collect ETF data from Morningstar. We construct our sample period from 2003 to 2013 with out-of-sample portfolio starting in 2005. Duanmu, Li and Malakhov (2014) find that their methodology provides significant increase in accuracy when a sufficiently-large-enough number of ETFs are present.[127] We manually check the description of each ETF, and we exclude all ETFs that are not passively managed index tracking funds, as well as hedge-fund-style-index tracking ETFs; this leaves us with 937 unique ETFs that are used in this study. Figure I reports the number of ETFs used for each two year window starting from 2003.

D. Research Methodology

1. Style and Selection Analysis with ETFs

We modify Duanmu, Li and Malakhov (2014)[128] approach to decompose the style and selection attributions from hedge fund excess return. The regression is based on 24 month window. Consistent with DLM's approach, we first conduct cluster analysis to reduce the number of ETF factors prior to the regression analysis, which serves the purpose to minimize the

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will be charged incentive fees. An investor who suffered a loss previously will not pay incentive fees until previous losses are regained.

[126] Excess return is defined as the difference between reported hedge fund net of fee return and the contemporaneous risk free rate proxied by the 30-day U.S. Treasury Bill monthly return.

[127] Duanmu, Li and Malakhov (2014) identifies 100 ETFs as a cutoff point, and split their out-of-sample test period into 1999-2004 and 2005-2012. In this study, we have more than 100 ETFs available in each window across our sample period.

[128] Henceforth, DLM for Duanmu, Li and Malakhov (2014)

multicollinearity issue presented in the ETF factor set. We then calculate the SDI measure proposed by Sun, Wang and Zheng (2012) for each identified cluster.[129] Following DLM, we set the number of clusters ranging from 1 to 100 and iteratively run cluster analysis for a hundred times and use those most centered ETFs for the following regression analysis.

We employ the factor selection model, 'LASSO'[130], which identifies an optimal set of factors with non-zero coefficients subject to the constraint that the sum of the absolute value of the coefficients is lower than a certain threshold. We run LASSO regression using LAR algorithm, which considers all potential path of the threshold and is computationally efficient.[131] We repeat this regression one hundred times for each individual hedge fund with one hundred set of ETF factors determined by the previous cluster analysis and select the model with the lowest SBC score. In regression analysis, our methodology deviates slightly from DLM's approach, we add a constant term in the regression to capture the selection effect, and we use net of fee excess returns instead of gross of fee excess returns as we aim to evaluate the performance attribution. We record the resultant constant term (alpha), regression determined coefficients (beta), and the corresponding ETFs (corresponding factor) for each hedge fund in each window.

The baseline model for LASSO regression is as follows:

$$r_{i,net} - r_f = \alpha + \beta_1(ETF_1 - r_f) + \beta_2(ETF_2 - r_f) + ... + \beta_{100}(ETF_{100} - r_f) + \varepsilon_i \qquad [M]$$

Where $r_{i,net}$ is the net of fee monthly return for fund I, and r_f is the risk free rate proxied by the 30-day U.S. Treasury Bill monthly return. α is the constant term from the regression which

[129] Sun, Wang and Zheng (2012) construct SDI, a distance measure which provides the distance away from the center of each cluster for each individual entity; SDI is one minus the correlation of the individual asset return with the mean return of all asset in the same cluster. Lower SDI indicates a more centered position.
[130] 'LASSO' (Least absolute shrinkage and selection operator) is developed by Tibshirani (1996)
[131] 'LAR' (least angle regression) is developed by Hastie, Johnstone, and Tibshirani (2004)

proxies for the selection factor that is driven by manager's true skill. We do not restrict beta coefficients to be positive or add up to one, as imposing such restrictions would dampen the intuition that hedge funds are free to short-selling and leveraging.[132]

For each regression window, we then calculate the beta return for any given fund, which is simply the sum of the product of regression determined coefficient and corresponding excess factor return[133]:

$$BetaReturn_i = \sum_j \beta_j * ETF_j \qquad (1)$$

For every single hedge fund in the regression window, we calculate the corresponding beta return, the excess return which is the arithmetic average of the hedge fund net of fee excess return, and alpha which is the constant term computed from the regression analysis. Thus, we decompose the excess return into selection and style, with alpha measuring the true managerial skills and beta return quantifying how much overweighting and/or underweighting a set of particular risk factors and the resultant factor return relative to the risk free rate, a proxy for the benchmark, would contribute to the total portfolio performance.

2. Out-of-Sample Portfolio Construction

In this study, we consider out-of-sample portfolio performance analysis to evaluate the efficacy of hedge fund excess return, alpha and beta return, and to demonstrate how the prior relative positions of these three variables would affect fund future performance. We concentrate our analysis on out-of-sample portfolio tests for several reasons. First, our alpha and beta return

[132] This approach is consistent with Duanmu, Li and Malakhov (2014), while slightly deviates from Sharpe (1992) style analysis, in which coefficients are restricted to be positive and sum to one, as mutual funds are leverage-free and short-free.
[133] This is equivalent to the observed average excess return, less of observed alpha from the base model [M].

measures rely on non-dynamic estimates of alpha and beta coefficients from the baseline regression [M], as the model assumes static estimated coefficients over two year window. We mitigate this problem by considering out-of-sample performance of portfolios of funds sorted according to alpha and beta return. Second, by considering all funds up until the moment of their disappearance from the database, we minimize any effects of survivorship bias, as funds drop out of our sample set constantly. Third, out-of-sample portfolio comparisons allow us to evaluate risk-adjusted performance over long periods of time and interpret results in terms of economic significance.

Hedge funds are sorted into equal-weight quartile[134] portfolios based on lagged two-year average excess return, as well as previous 24-month regression determined alpha and beta return. Each equal-weight quartile portfolio is initially formed on December 31, 2004, with the actual out-of-sample performance tracked starting from 2005. We invest the same dollar amount into each fund within a portfolio in the beginning, and follow its performance until December 31, 2013, rebalancing it once a year based on updated rankings with respect to individual variables.[135] When a portfolio fund disappears from the database, we redistribute the remaining capital in the fund equally amongst surviving portfolio funds.[136] We then calculate end dollar values based upon a $1 initial investment, mean excess monthly returns, Sharpe ratios, Fung and Hsieh (2004) alphas[137], information ratios, average annual attrition rates and average in-sample

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[134] We also test quintile portfolio for robustness, results are qualitatively similar.
[135] Excess return, alpha and beta return are based on immediately preceding two two-year windows. Additional out-of-sample portfolio analysis with two year and three year rebalancing are defined and reported in later sections.
[136] This is somewhat conservative as it is possible that a fund simply choses to stop reporting to the database, which is likely for well performing funds that are no longer accepting new investor flows. However, without returns data we obviously cannot keep the fund in the portfolio.
[137] Fung and Hsieh (2004) model is: $r_i – r_{f =} \alpha_i + \beta_{i1}\, SP500 + \beta_{i2}\, EM + \beta_{i3} 10Year + \beta_{i4} SizeSpread + \beta_{i5} CreditSpread + \beta_{i6}\, BondTrend + \beta_{i7} ComTrend + \beta_{i8} FxTrend + \varepsilon_i$. While Fung and Hsieh (2004) specify the seven factor model, the updated specification on David

LASSO R^2 for each time series of monthly portfolio returns from January 2005 until December 2013.[138]

E. Empirical Results

1. Pure Alpha Funds

In LASSO factor selection model with constant term, for some hedge funds, no ETF factor is selected by our methodology. In this case, we are unable to quantify their market exposures. This could be due to the reason that spanning the space of hedge fund risk factors with all available ETFs might not fully capture the entire investment opportunity set, which results in unexplained and unmatched returns for some hedge funds. Second, for those types of hedge funds that are truly 'market neutral', it is reasonable to expect them isolated from market exposures. Their value-added is solely driven by selection skill. In either case, for those hedge funds not matched with any ETF factor, we define them as pure alpha funds. Table II reports the out-of-sample portfolio performance for pure alpha funds with annual rebalancing. The portfolio of pure alpha funds delivers positive risk-adjusted performance with a positively significant excess return, Sharpe ratio of 0.19, and a monthly alpha of 0.19% at 10% significant level. However, pure alpha fund portfolio has an attrition rate of 17.60%.

2. Summary Statistics of Excess Return, Alpha and Beta Return

We then calculate the summary statistics of excess return, alpha and beta return in quartiles by excluding pure alpha funds and report the results in table III. Hedge funds with the

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Hsieh's web site at http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm includes eight factors. Other papers utilizing the Fung and Hsieh (2004) model include Kosowski, Naik, and Teo (2007), Fung, Hsieh, Naik, and Ramadorai (2008), Jagannathan, Malakhov, and Novikov (2010), and Avramov, Kosowski, Naik, and Teo (2011), among others.

[138] A drawback of relying on a single long term time series for each portfolio is that we can calculate *t*-statistic and evaluate statistical significance only for mean monthly returns and long term Fung and Hsieh (2004) alphas.

highest measures comprise quartile 1 and funds with the lowest comprise quartile 4. In total, the average excess return for quartile 1 is 1.75% compared with -0.81% for quartile 4; the mean alpha in quartile 1 is 1.29% and that in quartile 4 is -1.01%; Funds in quartile 1 generate 1.16% beta return while that of quartile 4 is -0.46%.

3. Out-of-Sample Portfolio Comparisons with Annual Rebalance

Table IV presents the results of out-of-sample performance for portfolios sorted by excess return, alpha and beta return in quartiles. For excess return quartile portfolios, bottom quartile portfolio generates the highest end value and monthly excess return associated with the highest attrition rate. However, none of the quartile portfolios delivers significant risk-adjusted performance, with positive but insignificant alpha. This is consistent with Buraschi, Kosowski and Sritakul (2014) finding. Managers with current inferior returns below high water mark have stronger incentive to take risk and higher risk taking is associated with higher potential return. When accounting for the risk taken by the managers, superior risk-adjusted performance should not be expected. On the other hand, excessive risking taking would impose managers to a risky position and leads to a higher probability of failure, which is partially confirmed by the 20.05% attrition rate we find here. We then examine the difference in performance between top quartile and bottom quartile excess return portfolio by implementing the strategy of 'long bottom short top'.[139] This strategy provides positive return with only 0.05% incremental in return and the alpha is close to zero.

Panel B reports the performance of quartile portfolios ranked by alpha. Top quartile alpha funds deliver strong risk-adjusted performance with 0.56% monthly excess return, Sharpe ratio of 0.22 and alpha of 0.31% at 1% significant level. The rest of the quartile portfolios fail to

[139] For internal consistency in table reporting, all difference tests are designed as Q1-Q4, which is long top portfolio and short bottom portfolio.

deliver significant results. The intuition behind this finding is that hedge fund managers should either be able to generate alpha or nothing. The attrition rate for top alpha portfolio is only 7.99%, the second lowest across all portfolios, which is consistent with the finding of Fung, Hsieh, Naik, and Ramadorai (2008) that alpha producing funds are less likely to liquidate than funds that do not deliver alpha. The 'long top short bottom' strategy generates a significant return of 0.18%, however, the Fung and Hsieh (2004) alpha for the long short strategy is positive but insignificant. We also notice that top quartile alpha portfolio has the lowest average in-sample LASSO R^2 of 0.51, which is consistent with the intuition that strong alpha should not be explained by the risk factors. Titman and Tiu (2011) argue that successful managers hedge away systematic risk exposure and thus exhibit low R^2 in multifactor regression. However, our result here is inconclusive to justify their full statement but only partially confirms their finding on low R^2 being a predictive measure of future performance.

Out-of-sample portfolios sorted by beta return yield very interesting and persistent result as reported in Panel C. We find a strong monotonic relationship among the four quartile portfolios. In other words, a noticeable mean reversal pattern is found. Top quartile beta return portfolio delivers the weakest performance in every manner, while bottom quartile beta return portfolio generates the strongest result both in nominal and risk-adjusted basis. Q4 (bottom quartile) portfolio has the highest excess return with 1% significant level, followed by those of Q3 and Q2 portfolios, while Q1 (top quartile) has the lowest excess return which is insignificantly different from zero. For risk-adjusted performance, same patterns are found. We observe that Sharpe ratio, information ratio and Fung and Hsieh (2004) alpha decrease and become insignificant when moving from Q4 to Q1. However, low beta return portfolio has higher attrition rate compared with the rest quartiles. The ‘long bottom short top’[140] strategy delivers a significant alpha of 0.60%, Sharpe ratio of 0.17 and significant average return of 0.51%.

Duanmu, Malakhov and McCumber (2014) develop SBS (scaled beta success) measure to evaluate how well the manager chose beta positions relative to the range between the best and worst performing factors and find that bottom SBS portfolio dominates the top SBS portfolio in risk-adjusted basis. They argue that managers who make factor related bets that are less profitable contemporaneously but that become profitable in the future are captured by SBS measure. However, given the fact that bottom quartile beta return portfolio possesses the highest attrition rate, we argue that there could be two types of managers that would be captured by our beta return measure. For the first type of managers, they form their market expectations and aim to pursue the strategies that best reflect their opinions. They are willing to take contrarian type of investments while recognizing the risk associated with their positions. Those managers are aware of what they are doing and are able to incorporate both market timing and market testing into their management. The superior out-of-sample performance should be mainly driven by those managers. The second type of manager is unconscious of their strategies and form vague market expectations. Consistent with Buraschi, Kosowski and Sritakul (2014), when encountering with inferior beta returns, they alter their endogenous risk taking preference, choose to increase their beta exposures, engage in higher beta risk and wish to generate positive market returns in the following period. Higher beta risk is associated with higher chance of failure, which is reflected in the highest attrition rate for the bottom quartile portfolio compared with those of others.

[140] For internal consistency in table reporting, all difference tests are designed as Q1-Q4, which is long top portfolio and short bottom portfolio.

4. Persistence of Excess Return, Alpha and Beta Return

We further examine the persistence of the excess return, alpha and beta return measures by comparing the out-of-sample performance of quartile portfolios formed on these three measures with lower rebalancing frequency. We calculate the out-of-sample portfolio performance with two year rebalancing and three year rebalancing. Given the mean reversal pattern we find for quartile portfolios sorted by beta return, we decide to employ two different trading strategies that would help identify the level of persistence in our portfolio design with multi-year rebalancing. The first strategy we consider is *Buy and Hold*, which is a self-explanatory strategy. For the two year rebalancing test, we form the portfolios in quartile based on our measures calculated from previous 24 month window and hold the portfolios for the following two years and rebalance with the updated metrics every two year across our sample period. Same technique applies to three-year rebalancing portfolios. *Buy and Hold* strategy is in favor of portfolios with mean-reverting assets, which passively assigns higher weights on assets which increase in value and lower weights on assets that decrease in value. We then consider the second strategy, *Constant Mix*, which rebalances the portfolio to its target weights on a periodic basis. For the two year rebalancing test, we form the equal-weight portfolios on the basis of excess return, alpha, and beta return and hold them for one year. At the end of the first year, we cash out our positions, redistribute the capital amongst the surviving funds on an equal-weight basis and hold the portfolio for another year.[141] *Constant Mix* strategy rebalances the portfolio to equal weights on annual basis, thus provide no bias towards mean-reverting assets. As long as the mean reversal pattern persists, we expect portfolios using *Buy and Hold* strategy outperform those with *Constant Mix* Strategy.

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[141] For three year rebalancing test, we rebalance the portfolio to equal weights annually and reconstruct the portfolio every three year using updated measures.

The results for the quartile portfolios sorted by excess return, alpha and beta return with two year rebalancing are presented in Table V. With two year rebalancing, we observe qualitatively similar portfolio performance as those with annual rebalancing. Bottom quartile excess return portfolio outperforms the other quartiles and generates stronger performance if two year rebalancing frequency is considered. Top alpha portfolio still delivers positive and significant risk-adjusted performance, however, with slightly lower average monthly excess return of 0.54% and Fung and Hsieh (2004) alpha 0.28% compared with 0.58% for excess return and 0.31% for alpha with annual rebalancing.[142] Consistent with previous finding, managers are either able to deliver alpha or nothing, supported by the insignificant results for the other quartile portfolio sorted by alpha. In addition, based on the results, we find that our alpha measure persists at least for the following two years, with strongest results using annual rebalancing and weaker but still significant performance using two year rebalancing frequency. Panel C presents the beta return quartile portfolio performance. Strong mean reversal pattern persists with two year rebalancing, bottom quartile produces the highest mean excess return of 0.81% and the highest Fung and Hsieh (2004) alpha of 0.57% across all portfolios[143] as well as those rebalanced annually. Consistent with previous finding, bottom beta return portfolio has a relatively high attrition rate of 14%.[144] The 'long bottom short top' strategy produces average monthly return of 0.61% and alpha of 0.74%, both are significant at 5% level.[145] On average, portfolios implementing *Buy and Hold* strategy outperforms those employing *Constant Mix* strategy. For

[142] 0.54% for excess return and 0.28% for alpha under *Buy and Hold* strategy; 0.49% for excess return and 0.23% for alpha under *Constant Mix* strategy; all results are significant at 10% at least.
[143] 0.76% for mean excess return and 0.52% for alpha under *Constant Mix* strategy. Bottom quartile beta return portfolio delivers the highest risk-adjusted performance compared with all the other quartile portfolios based on excess return, alpha and beta return measures.
[144] Quartile 4 (bottom quartile beta return) has the second highest attrition rate compared with other beta return portfolios, quartile 3 has the highest attrition of 14.19%.
[145] Mean return of 0.59% and alpha of 0.72% under *Constant Mix* strategy.

beta return quartile portfolios, *Buy and Hold* bottom quartile portfolio generates 0.05% incremental in average monthly return against *Constant Mix* strategy, as well as improved alpha of 0.57% against 0.52% and a slight increase in alpha t statistics. Those increments are the highest across all the beta return quartile portfolio, which indicates that bottom beta return quartile benefits from the mean-reverting biased *Buy and Hold* strategy, and the mean reversal pattern persists for the following two years. Together with the finding of stronger risk-adjusted performance for the bottom beta return portfolio compared with annual rebalanced portfolios, we confirm the existence of mean reversal and conclude the persistence of this pattern to be at least two years in regards of our beta return measure.

Table VI reports the out-of-sample portfolio performance with three year rebalancing. Interestingly, we find momentum pattern in portfolios sorted by previous excess returns on a three year rebalancing basis. Top quartile generates the highest monthly excess return followed by quartile 2 and quartile 3, with quartile 4 (bottom quartile) producing the lowest out-of-sample return. The difference in mean excess return between top and bottom quartile is 0.47% significant at 5% level. However, none of the quartile excess return portfolios is able to generate significant Fung and Hsieh (2004) alpha in the out-of-sample test. Top alpha portfolio produces superior risk-adjusted performance, while the difference of performance among the rest three quartiles is still indistinguishable. The ‘long top short bottom’ strategy generates a monthly average return of 0.42% and an alpha of 0.35% both at 1% significant level.[146] For beta return portfolios, mean reversal pattern is deteriorating when considering three year rebalancing frequency. No straight and obvious pattern is found across the quartile portfolios with regard to mean monthly excess return. In addition, no statistically significant difference is observed in the

[146] Mean return of 0.42% and alpha of 0.34% under *Constant Mix* strategy.

‘long bottom short top’ portfolio. However, bottom quartile beta return portfolio is still able to generate superior risk-adjusted performance, with positive and significant average excess return and out-of-sample portfolio alpha at 1% level under both *Buy and hold* and *Constant Mix* strategies. With respect to three year rebalancing frequency, *Constant Mix* strategy outperforms *Buy and Hold* strategy on average, which is considered the evidence of diminishing mean reverting effect.

Based on the empirical results of out-of-sample portfolio performances with annual and multi-year rebalancing, we conclude that our measures of alpha and beta return provide interesting insight of the portfolio performance. The alpha calculated using our methodology serves as a stable indicator that is predictive of future out-of-sample performance. Portfolio formed upon the basis of top quartile alpha delivers superior risk-adjusted performance and persists as long as three years. We find strong and monotonic mean reversal pattern in portfolios sorted by our beta return measure with both annual and two year rebalancing frequency, which leads to the conclusion that hedge funds with inferior previous beta returns are able to generate superior future risk-adjusted performance for at least following two years.

5. Multi-active and Risk-writing Managers

We argue that low beta return portfolio is constituted of two type of managers: The first type of managers are those with adequate ability to incorporate their market beliefs, execute their decisions consistently, manage the risk exposures of their current positions actively and adjust their opinions when necessary; the second type of managers are those with inability to form appropriate market expectations, alter their beta positions that increases their exposures to exchange for better future returns given inferior performance with their current positions, and excessively take unnecessary risks which leads to potential higher probability of failures. We define the first type managers as *Multi-active Managers* and the second type as *Risk-writing Managers.* We then develop a simple methodology to distinguish these managers and examine their out-of-sample performances accordingly. *Multi-active Managers* actively time the market, take corresponding actions while not betting on one single strategy, at mean time, they actively manage their positions with adequate downside protections and possible return enhancements. We expect *Multi-active Managers* produce alpha as well. We define the interaction portfolio between the top quartile alpha and the bottom quartile beta return as our sample portfolio for *Multi-active Managers*. On the other hand, *Risk-writing Managers* possess neither perfect timing ability nor selection skill, which results in lower beta returns and alphas. We then define *Risk-writing Managers* to be the ones with low beta return and inability to generate alpha. We examine the out-of-sample performance of interaction portfolio between bottom beta return and bottom alpha which is representative as *Risk-writing Managers.* [147]

We calculate the out-of-sample performance for *Multi-active Managers* and *Risk-writing Managers*[148] with annual rebalancing and multi-year rebalancing.[149] The results are presented in table VII, VIII and IX.[150] With annual rebalancing, we find that *MM* portfolio outperforms *RM* portfolio in every manner. *MM* portfolio generates a monthly excess return of 0.92% compared with 0.59% by *RM*, a Sharpe ratio of 0.41 against 0.11, and Fung and Hsieh (2004) alpha of 0.69% at 1% significance level compared with an insignificant alpha of 0.26%. In addition, *MM*

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[147] Hedge fund excess return is the sum of alpha and beta return. The interaction of bottom quartile alpha and bottom quartile beta return is a subset of bottom quartile of excess return, which provides an ideal sample to empirically test Buraschi, Kosowski and Sritakul (2014) finding of changing endogenous risk taking preference with respect to fund position relative to high water mark.

[148] Henceforth, *MM* for *Multi-active Managers* and *RM* for *Risk-writing Managers.*

[149] Two year and three year rebalancing are tested, under both *Buy and Hold* and *Constant Mix* strategies.

[150] Hedge funds in *Multi-active Managers* and *Risk-writing Managers* are both subsets of bottom beta return quartile. In table VII, VIII and IX, we report results for three portfolios: bottom beta return quartile, *Multi-active Managers* and *Risk-writing Managers*.

portfolio has an attrition rate of only 8.47%, which the attrition is 25.53% for *RM*. It is clear that the superior performance of bottom quartile beta return portfolio is driven by *Multi-active Managers*, and the attrition is attributed to *Risk-writing Managers.* This finding is consistent with our argument that *Multi-active Managers* possess active management and timing ability[151], while the performance of *Risk-writing Managers* is driven by their excessive risking taking associated with a higher probability of failures.

With two year rebalancing, both *MM* and *RM* portfolios produce superior out-of-sample performances. Though *RM* portfolio has higher average monthly excess return and higher out-of-sample alpha, the statistical significance is weaker. In addition, with respect to risk-adjusted performance, *MM* portfolio delivers a higher Sharpe ratio of 0.32 and a higher information ratio of 0.40, with the lowest attrition rate of 10.30%. We attribute the significant improvement in *RM* to potential survivorship bias. It is reasonable to expect higher returns to come from those surviving hedge funds with excessive risking takings, and those returns are driven by higher risks.[152] When properly adjusted for risks, *RM* portfolio is expected to underperform *MM* portfolio, which is confirmed by our results. Consistent with previous finding, *Buy and Hold* strategy outperforms *Constant Mix,* which suggests the persistence of mean reversal pattern. When portfolios are rebalanced every three year, *MM* portfolio is still able to deliver superior and significant risk-adjusted performance, while *RM* portfolio generates a close to zero average monthly excess return of only 0.03% and a negative but insignificant alpha of -0.04% associated with the highest attrition rate of 27.56% across all portfolios in our sample.

[151] *Multi-active Managers* portfolio has the lowest in-sample LASSO R^2, which is another evidence of possessed active management.

[152] This is consistent with the implication of Buraschi, Kosowski and Sritakul (2014), they argue that managers with inferior contemporaneous returns have more incentive to take risk.

The out-of-sample portfolio test confirms that the superior performance of low beta return portfolio is mainly driven by *Multi-active Managers*, who are able to generate consistent positive risk-adjusted performance that persists as long as three years. On the other hand, *Risk-writing Managers* delivers inferior risk-adjusted performance with the highest attrition rate, which suggest that they generate returns through excessive risk taking.

6. Comparisons of Performance Fee, Management Fee and High Water Mark

In hedge fund industry, the existence of incentive fee structure helps align manager's interest and provides them sufficient motivation to chase outstanding performance.[153] We then investigate the fee structures for managers in our portfolios. Agarwal, Daniel and Naik (2009) examine the role of managerial incentives and discretion in hedge fund performance and find that funds with greater managerial incentives are associated with superior performance. On the other hand, managerial incentives[154] might serve as a signal of superior abilities used by managers to separate themselves from ordinary managers. Since we identify *Individualist Managers* as managers possess active management and timing ability, we expect such funds to charge higher incentive fees. We collect the fund manager stated management fee, performance fee and indicator of provision of high water mark for the funds in our sample. We then examine the difference in incentives for four beta return quartile portfolios, *Multi-active Managers* portfolio and *Risk-writing Managers* portfolio. The summary statistics and difference in mean tests are reported in Table X.[155]

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[153] In addition to incentives, other characteristics are documented to affect fund performance, such as investor liquidity provision, see, for example, Aragon (2007), Agarwal, Daniel, and Naik (2009), liquidity risk, see, for example, Sadka (2010, 2012), and fund age, see, for example, Aggarwal and Jorion (2010).

[154] For example, provision of hurdle rate and high water mark, higher performance fee and management fee.

[155] We calculate and compare risk measures for six portfolios: four quartile portfolios sorted by preceding beta return, *Individualist Managers* portfolio and *Risk-writing Managers* portfolio.

Consistent with Agarwal, Daniel and Naik (2009), we find that *Multi-active Managers* portfolio charges the highest performance compared with *Risk-writing Managers*, as well as the four beta return quartile portfolios and the differences are statistically different at 1% level. In addition, the average fund manager stated management fee is the highest for *Multi-active Managers*, and the differences are statistically different compared with other portfolios except for top quartile beta return funds. *Multi-active Managers* portfolio has the highest percentage of high water mark provision, with 92% of the funds within the portfolio have included provisions for high water mark, and this is statistically different from other portfolios at 1% level.

We conclude that *Multi-active Managers* are aware of their ability, and thus charge higher managerial incentives to distinguish themselves from other managers, which confirms the validity of identification of *Multi-active Managers.*

7. Total Risk, Factor Variance, Cross-Covariance, and Beta Risk

Multi-active Managers actively time the market and produce superior out-of-sample performance. This indicates that *Multi-active Managers* might take certain risk exposures which are reflective of their views of the market movements but at meantime actively manage their exposures. In other words, they do not solely bet on any single specific market factor. However, they hedge their bets with corresponding techniques. On the other hands, *Risk-writing Managers* assume excessive risk and generate inferior risk-adjusted performance. They expose themselves to great amount of market risks and employ no strategy to protect their exposures. Should the market condition change, they are slow to react.

To quantify managers risk exposures, we construct three beta related risk measures defined as follow:

$$FactorVariance_i = \sum_j \beta_j^2 Var(ETF_j) \qquad (2)$$

$$CrossCovariance_i = \sum_{j \neq k} 2\beta_j \beta_k \rho_{j,k} \sigma(ETF_j)\sigma(ETF_j) \qquad (3)$$

$$BetaRisk_i = FactorVariance_i + CrossCovariance_i \qquad (4)$$

Where *FactorVariance* is the sum of the product of squared beta coefficient determined by LASSO regression and the variance of its corresponding variance of selected ETF, which captures the direct factor exposures assumed by the managers. *CrossCovariance* is defined as two times the regress determined coefficient weighted average multiplied by the covariance of all selected ETF pairs. This measure quantifies the managers' efforts to reduce their total market exposures. *BetaRisk* is simply the sum of *FactorVariance* and *CrossCovariance*, which represents the total market exposures taken by fund managers. In addition, we calculate the variance of hedge fund excess return for different portfolio, and define the variance as total risk which represents overall risk exposure for each hedge fund. We report the summary statistics and difference in means test for both pre portfolio formation period and post portfolio formation period in table XI.[156]

We first examine the risk exposures taken by the managers for pre portfolio formation period. We calculate different risk measures based upon the beta coefficients determined by the LASSO regression over the 24 months preceding portfolio formation. As expected, *Risk-writing Managers* have the highest total risk as well as beta risk across all portfolios. We compare the total risk and beta risk of *Risk-writing Managers* with other portfolios and the differences are positive and significant at 1% level in all cases. *Multi-active Managers*, however, have the highest factor exposures, which is consistent with our argument that those managers aim to time the market, incorporate their beliefs of market movements and engage in corresponding risk

[156] We calculate and compare risk measures for six portfolios: four quartile portfolios sorted by preceding beta return, *Individualist Managers* portfolio and *Spontaneous Managers* portfolio.

factors. The cross-covariance for *Multi-active Managers* is negative and the largest in value, which represents a huge decrease in beta risk exposures when combining the factor variance and cross-covariance together. We interpret this finding that *Multi-active Managers* assume intensive factor exposures while actively managing their risk exposures which results in a large negative cross-covariance, and ultimately reduce their beta exposures to an acceptable level.

We then investigate the risk exposures of different portfolios post portfolio formation period.[157] Consistent with Buraschi, Kosowski and Sritakul (2014), *Risk-writing Managers* exhibit the greatest variance of excess return, which is consistent with the statement of excessive risk taking. Those managers with prior inferior performance increase their market risk exposures and bet on future rebound. Using risk measures calculated based on new regression determined beta positions in post 24 month window, we find the difference in means of total risk comparison and beta risk between *RM* portfolio and other portfolios is significant at 1% level except for comparison between *Risk-writing Managers* and top quartile beta return portfolio. *Risk-writing Managers* possess greater total risk but lower beta risk compared with those of top quartile beta return portfolio. However, these differences are not statistically different. In addition, *Risk-writing Managers* now exhibit the highest variance with respect to direct factor exposures, while *Multi-active Managers* decrease their factor variance noticeably during the out-of-sample period. We interpret this find to be consistent with our previous argument that performance of *Risk-writing Managers* is mainly driven by excessive risk taking, and *Multi-active Managers* switch

[157] Our results for post 24 month period are subject to survivorship bias, only funds that survive for the following 24 months are included in the calculation. Calculations using only surviving funds would bring bias the total risk measure downward. Ackerman, McEnally, and Ravenscraft (1999), Liang (2000), and Fung and Hsieh (2000) find dropped funds possess inferior collective performance.

their positions when their market beliefs are justified, which results in a decreased level of market risk exposures.

8. Post Beta Return Correlation and Difference in Beta Return

Multi-active Managers continuously search for investment opportunities as market condition evolves and incorporate their market expectations into their corresponding factor exposures. In other words, *Multi-active Managers* constantly and efficiently adjust their beta positions on a continuous basis. However, *Risk-writing Managers* possess incapability of evaluating market condition which results in either untimely adjustment or impetuous factor switching. We then construct two measures that quantify the degree and the effectiveness of beta position reallocations. Following Duanmu, Malakhov and McCumber (2014), we calculate the forward synthetic beta return, which is the beta return the manager would have realized if he had not changed beta positions from the previous 24 month window.[158] We calculate the correlation between the realized beta returns and the forward synthetic beta returns for each fund for post portfolio formation 24 month window, such that

$$BetaReturnCorrelation_i = Corr(\sum_j \beta_{j,t} ETF_{j,t}, \sum_j \beta_{j,t-1} ETF_{j,t}) \qquad (5)$$

BetaReturnCorrelation measures the degree of beta position reallocation. A higher beta return correlation may be indicative of inadequate beta position reallocation if the manager merely stick with the previous factors and nearly switch factor loadings as market condition changes.

[158] Specifically, we carry forward beta coefficients from the previous two-year window and multiply them by the factor returns from the current window, finally averaging these to create a synthetic return.

In addition, we calculate *FDBR (Forward Difference in Beta Returns)* proposed by Duanmu, Malakhov and McCumber (2014), which is the difference between the realized beta return between forward synthetic beta return, such that

$$FDBR_i = \beta_{j,t} ETF_{j,t} - \beta_{j,t-1} ETF_{j,t} \quad (6)$$

FDBR captures the effectiveness of reallocation of beta positions and measures the fund performance in relation to a ‘change nothing’ strategy. A higher *FDBR* may be indicative of manager skill if ex-ante the manager correctly anticipated changing macroeconomic opportunities; his beta return is higher than it would have been had he not made changes to factor loadings.

Table XII reports the summary statistics of beta return correlation and *FDBR* for portfolios of interest, and the difference in means test is presented by comparing the degree and the effectiveness of beta position reallocation for *Multi-active Managers* and *Risk-writing Managers* against other portfolios. Compared with the rest portfolios, *Multi-active Managers* exhibit the lowest correlation between the realized beta return and forward synthetic beta return of 0.51, and the differences in correlations compared with other managers are significant at 1% level. This provides indirect evidence that *Multi-active Managers* might adjust their beta positions more often than do other managers, which is consistent with our argument that *Multi-active Managers* continuously search for investment opportunities as market condition evolves. On the other hand, we do not observe significant difference on beta return correlation for *Risk-writing Managers* compared with other managers.

In terms of *FDBR, Multi-active Managers* have the highest measure of 0.15% and this number is statistically different from those of other portfolios at 1% level.[159] *Risk-writing*

[159] Except for that of top quartile beta return portfolio, the difference is at 10% significant level.

Managers are the only ones with a negative average *FDBR*, which is significantly lower than those for other portfolios at 1% level. This result confirms our expectation that *Multi-active Managers* are more effective in switching their beta positions, while *Risk-writing Managers* rarely add value to the portfolio performance through beta management. Furthermore, this provides indirect support to our previous findings that the out-of-sample return of *Risk-writing Managers* is mainly driven by excessive risk taking.

F. Conclusion

We modify Duanmu, Li and Malakhov (2014) methodology to decompose hedge fund excess return into alpha, a proxy for selection and beta return, a proxy for style. We sort 24 month preceding hedge fund excess return, regression determined alpha and beta return into equal weight quartile portfolios and examine their out-of-sample performances. We find alpha to be a persistent indicator of future superior risk-adjusted performance which lasts as long as three years. We observe a strong monotonic mean reversal pattern in out-of-sample performances when ranking hedge funds by beta return, and the pattern persists as long as at least two years.

We define two types of managers: *Multi-active Managers*, who properly form market expectations, incorporate beliefs into corresponding market factors, actively manage their market exposures and continuously search for new investment opportunities; and *Risk-writing Managers*, who possess inability to form appropriate market expectations, increase risk exposures impetuously when facing inferior performance, generate returns through excessive risking takings, and fail to adjust market positions as market conditions evolve. We report ample evidence that the superior out-of-sample performance of bottom quartile beta return portfolio is driven by *Multi-active Managers*, and the excessive risk taking by *Risk-writing Managers* results in a higher attrition. We find that *Multi-active Managers* are aware of their abilities and charge higher incentives to distinguish themselves from other managers.

Finally, we confirm that *Risk-writing Managers* exhibit the greatest total risk and beta risk in both period prior to portfolio formation and period post portfolio formation. We find that *Multi-active Managers* actively manage their market position that is reflective of their beliefs which significantly reduces their considerable direct factor risk to a reasonable level of beta risk. In addition, there is an indication that *Multi-active Managers* continuously search for market opportunities and effectively adjust their beta positions to reflect their evolving market expectations.

G. References:

Ackerman, C., R. McEnally, and D. Ravenscraft. 1999. The Performance of Hedge Funds: Risk, Return, and Incentives. Journal of Finance 54: 833–74.

Agarwal, V., N.D. Daniel, and N.Y. Naik. 2009. Role of Managerial Incentives and Discretion in Hedge Fund Performance. Journal of Finance 64: 2221–56.

Agarwal, V., and N.Y. Naik. 2000. On Taking the Alternative Route: Risks, Rewards, and Performance Persistence of Hedge Funds. Journal of Alternative Investments 2: 6–23.

Agarwal, V., and N.Y. Naik. 2004. Risk and Portfolio Decisions Involving Hedge Funds. Review of Financial Studies 17: 63–98.

Aggarwal, R.K., and P. Jorion. 2010. The Performance of Emerging Hedge Funds and Managers. Journal of Financial Economics. 96: 238-56.

Aragon, G. 2007. Share Restriction and Asset Pricing: Evidence from the Hedge Fund Industry. Journal of Financial Economics 83: 33–58.

Asness, C., R. Krail, and J. Liew. 2001. Do Hedge Funds Hedge? Journal of Portfolio Management 28: 6–19.

Avramov, D., L. Barras, and R. Kosowski. 2013. Hedge Fund Return Predictability under the Magnifying Glass. Journal of Financial and Quantitative Analysis. 48: 1057-83.

Avramov, D., R. Kosowski, N.Y. Naik, and M. Teo. 2011. Hedge Funds, Managerial Skill, and Macroeconomic Variables. Journal of Financial Economics 99: 672–92.

Bali, T.G., S.J. Brown, and M.O. Caglayan. 2011. Do Hedge Funds' Exposures to Risk Factors Predict Their Future Returns? Journal of Financial Economics 101: 36–68.

Bali, T.G., S.J. Brown, and M.O. Caglayan. 2012. Systematic Risk and the Cross Section of Hedge Fund Returns. Journal of Financial Economics 106: 114–31.

Baquero, G., J. ter Horst, and M. Verbeek. 2005. Survival, Look-ahead Bias, and Persistence in Hedge Fund Performance. Journal of Financial and Quantitative Analysis. 40: 493-517.

Bollen, N.P.B. 2013. Zero-R2 Hedge Funds and Market Neutrality. Journal of Financial and Quantitative Analysis. 48: 519-47.

Bollen, N.P.B., and R.E. Whaley. 2009. Hedge Fund Risk Dynamics: Implications for Performance Appraisal. Journal of Finance 64: 985–1035.

Brown, S.J., W.N. Goetzmann, and R.G. Ibbotson. 1998. Offshore Hedge Funds: Survival and Performance 1989-1995. Journal of Business. 72: 91-117.

Buraschi, A., R. Kosowski, and W. Sritrakul. 2014. Incentives and Endogenous Risk Taking: A Structural View on Hedge Fund Alphas. Journal of Finance. 69: 2819-70.

Cai, L., and B. Liang. 2012a. On the Dynamics of Hedge Fund Strategies. Journal of Alternative Investments 14: 51–68.

Cai, L., and B. Liang. 2012b. Asset Allocation Dynamics in the Hedge Fund Industry. Journal of Investment Management 10: 35–59.

Cao, C., Y. Chen, B. Liang, and A.W. Lo. 20130. Can Hedge Funds Time Market Liquidity? Journal of Financial Economics. 109: 493-516

Chen, Y. 2007. Timing Ability in the Focus Market of Hedge Funds. Journal of Investment Management 5: 66–98.

Chen, Y., and B. Liang. 2007. Do Market Timing Hedge Funds Time the Market? Journal of Financial and Quantitative Analysis 42: 827–56.

Cremers, K.J.M., and A. Petajisto. 2009. How Active Is Your Fund Manager? A New Measure That Predicts Performance. Review of Financial Studies 22: 3329–65.

Duanmu, J., Y. Li, and A. Malakhov. 2014. In Search of Missing Risk Factors; Hedge Fund Return Replication with ETFs. Working paper.

Duanmu, J., A. Malakhov and W. McCumber. 2014. Beta Active Hedge Fund Management. Working paper.

Efron, B., T. Hastie, I. Johnstone, and R. Tibishirani. 2004. Least Angle Regression. Annals of Statistics. 32: 407-99.

Fung, H.G., X.E. Xu, and J. Yau. 2002. Global Hedge Funds: Risk, Return, and Market Timing. Financial Analysts Journal 58: 19–30.

Fung, W., and D.A. Hsieh. 1997. Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds. Review of Financial Studies 10: 275–302.

Fung, W., and D.A. Hsieh. 2000. Performance Characteristics of Hedge Funds and Commodity Funds: Natural vs. Spurious Biases. Journal of Financial and Quantitative Analysis 35: 291–307.

Fung, W., and D.A. Hsieh. 2001. The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers. Review of Financial Studies 14: 313–41.

Fung, W., and D.A. Hsieh. 2004. Hedge Fund Benchmarks: A Risk-Based Approach. Financial Analysts Journal 60: 65–80.

Fung, W., D.A. Hsieh, N.Y. Naik, and T. Ramadorai. 2008. Hedge Funds: Performance, Risk, and Capital Formation. Journal of Finance 63: 1777–803.

Henriksson, R., and R. Merton. 1981. On Market Timing and Investment Performance II: Statistical Procedures for Evaluating Forecasting Skills. Journal of Business 54: 513–34.

Jagannathan, R., A. Malakhov, and D. Novikov. 2010. Do Hot Hands Exist among Hedge Fund Managers? An Empirical Evaluation. Journal of Finance 65: 217–55.

Kosowski, R., N.Y. Naik, and M. Teo. 2007. Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis. Journal of Financial Economics 84: 229–64.

Liang, B. 2000. Hedge Funds: The Living and the Dead. Journal of Financial and Quantitative Analysis 35: 309–26.

Lo. A. 2008. Where Do Alphas Come From?: A Measure of the Value of Active Investment Management. Journal of Investment Management. 6: 1-29.

Patton, A.J. 2009. Are "Market Neutral" Hedge Funds Really Market Neutral? Review of Financial Studies 22: 2495–530.

Roll, R. 1978. Ambiguity when Performance Is Measured by the Securities Market Line. Journal of Finance 33: 1051–69.

Sadka, R. 2010. Liquidity Risk and the Cross-Section of Hedge-Pund Returns. Journal of Financial Economics 98: 54–71.

Sadka, R. 2012. Hedge-Fund Performance and Liquidity Risk. Journal of Investment Management 10: 60–72.

Sharpe, W.F. 1992. Asset Allocation: Management Style and Performance Management. Journal of Portfolio Management 18: 7–19.

Sun, Z., A. Wang, and L. Zheng. 2012. The Road Less Traveled: Strategy Distinctiveness and Hedge Fund Performance. Review of Financial Studies 25: 96–143.

Tibshirani, R. 1996. Regression Shrinkage and Selection via the Lasso. Journal of the Royal Statistical

Society B 58: 267–88.

Titman, S., and C. Tiu. 2011. Do the Best Hedge Funds Hedge? Review of Financial Studies 24: 123–68.

Figure 1: Number of ETFs Used

Number of ETFs used in the LASSO regressions is reported. ETF data is collected from Morningstar.

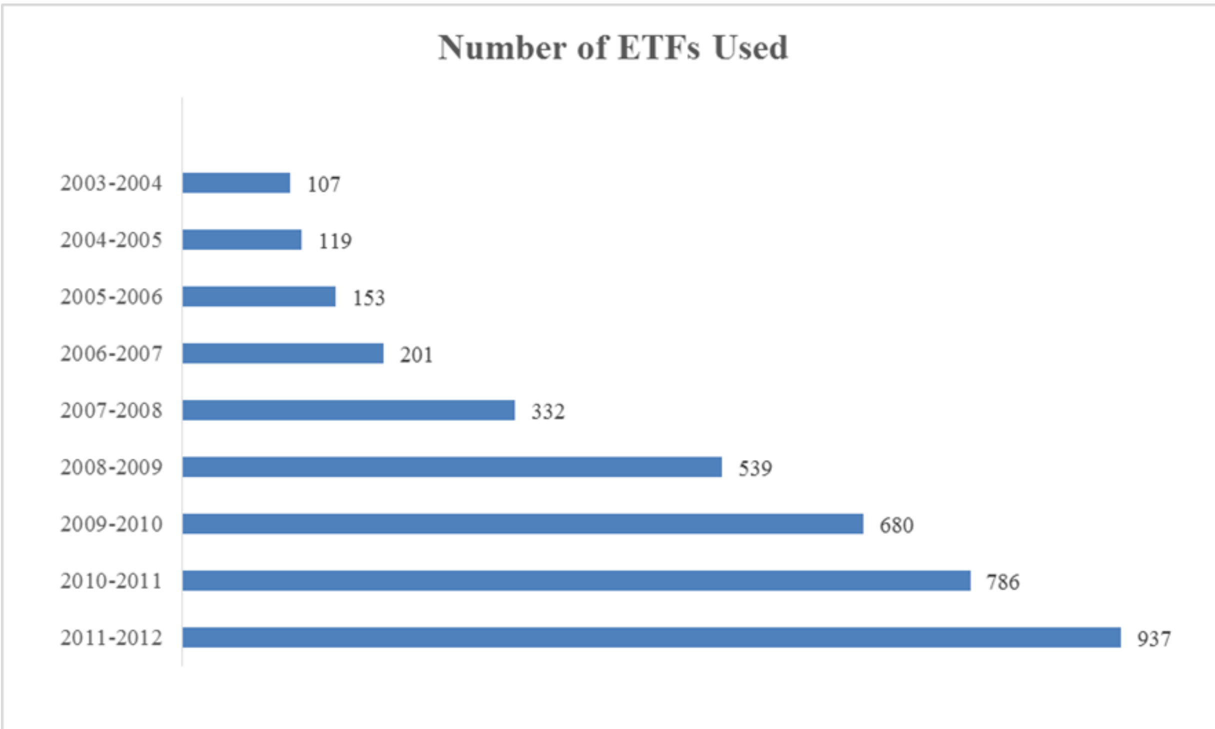

Table I: Summary Statistics of Hedge Funds

Summary statistics of all hedge funds 2003-2013. First 24 monthly observations are dropped to control for backfill bias. Summary statistics of full sample hedge funds, subsample of active hedge funds and subsample of inactive funds are reported.

Table I: Summary Statistics of Hedge Funds (Cont.)

	Full Sample (11,159 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly Excess Return	0.16	0.29	-1.26	1.44	3.49
Assets ($M)	209.82	45.22	3.74	381.20	1,421.19
Min Invest ($M)	1.34	0.25	0.03	1	12.37
Mgmt Fee (%)	1.51	1.5	0.75	2	0.65
Perf Fee (%)	17.06	20	0	20	7.19
Hurdle Rate (%)	0.31	0	0	0	1.60
Lockup Period (days)	73.23	0	0	360	244.55
Redemption Notice (days)	12.67	0	0	45	26.88
Redemption Period (days)	50.68	30	7	90	51.74
Total Redemption (days)	64.44	35	30	120	62.32
	Active Funds (3,409 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly Excess Return	0.66	0.62	-0.17	1.62	1.37
Assets ($M)	246.65	78.06	8.20	634.98	558.83
Min Invest ($M)	1.44	0.25	0.03	1	11.16
Mgmt Fee (%)	1.51	1.5	0.75	2	0.64
Perf Fee (%)	16.78	20	0	20	7.16
Hurdle Rate (%)	0.36	0	0	0	1.65
Lockup Period (days)	77.57	0	0	360	325.20
Redemption Notice (days)	21.30	3	0	60	31.80
Redemption Period (days)	47.65	30	7	90	50.58
Total Redemption (days)	69.83	50	12	150	66.11
	Inactive Funds (7,750 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly Excess Return	-0.06	0.12	-1.69	1.29	4.07
Assets ($M)	193.51	34.93	2.85	285.50	1,666.04
Min Invest ($M)	1.30	0.25	0.03	1	12.87
Mgmt Fee (%)	1.52	1.5	1	2	0.69
Perf Fee (%)	17.19	20	0	20	7.20
Hurdle Rate (%)	0.29	0	0	0	1.57
Lockup Period (days)	71.18	0	0	360	195.08
Redemption Notice (days)	8.87	0	0	30	23.42
Redemption Period (days)	52.10	30	30	90	52.21
Total Redemption (days)	61.91	30	30	120	60.30

Table II: Out-of-Sample Portfolio of Pure Alpha

Portfolios are based upon funds exhibiting zero matches under LASSO regression (Pure Alpha Funds) and rebalanced annually. Portfolios are initiated as of December 31, 2004. End value is as of December 31, 2013; Attrition rate is the average annual rate at which funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio funds. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

	Pure Alpha Funds		
Year	Annual Return	Num of Start Funds	Num of End Funds
2005	5.94	207	187
2006	10.46	195	175
2007	10.33	208	179
2008	-1.47	206	145
2009	4.45	208	170
2010	7.57	198	162
2011	-2.02	281	231
2012	-2.45	251	209
2013	4.60	230	175
End Value		1.43	
Excess Return		0.21**	
(t-stat)		(2.03)	
Sharpe Ratio		0.19	
α		0.13*	
(t-stat)		(1.71)	
Info Ratio		0.17	
Attrition rate		17.60%	

Table III: Summary Statistics of Hedge Fund Excess Return, Alpha and Beta Return

Panel A reports the summary statistics of hedge fund excess return in quartiles. Panel B reports the summary statistics of hedge fund alpha in quartiles. Panel C reports the summary statistics of hedge fund beta return in quartiles. Quartile 1 represents the top quartile of variables of interest, quartile 4 represents the bottom quartile of variables of interest. Mean, median, 10th percentile, 90th percentile and standard deviation of variables of interest for every quartile are reported.

Panel A Quartiles-Excess Return

	Quartile 1 (High)					Quartile 2					Quartile 3					Quartile 4 (Low)				
Year	Mean	Median	10th pct	90th pct	Std	Mean	Median	10th pct	90th pct	Std	Mean	Median	10th pct	90th pct	Std	Mean	Median	10th pct	90th pct	Std
2003-2004	2.72	2.55	2.01	3.64	0.75	1.57	1.54	1.33	1.81	0.18	1.00	1.00	0.79	1.22	0.16	0.22	0.38	-0.24	0.66	0.62
2004-2005	1.70	1.42	0.97	2.98	0.88	0.66	0.65	0.49	0.83	0.13	0.31	0.31	0.17	0.43	0.09	-0.27	-0.13	-0.82	0.10	0.62
2005-2006	1.62	1.30	0.88	2.74	0.97	0.64	0.64	0.50	0.78	0.10	0.31	0.32	0.17	0.44	0.10	-0.23	-0.12	-0.65	0.10	0.44
2006-2007	1.75	1.53	1.19	2.58	0.70	0.86	0.85	0.68	1.06	0.14	0.45	0.45	0.29	0.60	0.11	-0.20	-0.06	-0.76	0.20	0.46
2007-2008	1.26	0.89	0.41	2.50	1.25	-0.10	-0.10	-0.44	0.23	0.24	-0.93	-0.92	-1.27	-0.58	0.24	-2.55	-2.24	-4.39	-1.48	1.18
2008-2009	1.42	1.08	0.69	2.36	1.11	0.33	0.32	0.13	0.54	0.14	-0.21	-0.19	-0.48	0.04	0.19	-1.43	-1.05	-2.69	-0.64	1.03
2009-2010	3.60	3.13	2.28	5.27	1.55	1.61	1.61	1.26	1.98	0.27	0.77	0.75	0.51	1.08	0.21	-0.18	0.04	-0.84	0.36	0.84
2010-2011	1.20	1.00	0.69	1.94	0.63	0.40	0.39	0.22	0.60	0.13	-0.02	-0.01	-0.21	0.14	0.13	-0.83	-0.61	-1.36	-0.31	0.85
2011-2012	0.97	0.78	0.56	1.61	0.54	0.32	0.32	0.18	0.48	0.11	-0.04	-0.03	-0.23	0.12	0.12	-1.00	-0.67	-1.95	-0.34	0.97
Total	1.75	1.32	0.67	3.37	1.30	0.65	0.51	0.13	1.57	0.56	0.12	0.13	-0.61	0.84	0.54	-0.81	-0.50	-2.26	0.19	1.15

Table III: Summary Statistics of Hedge Fund Excess Return, Alpha and Beta Return (Cont.)

Panel B Quartiles-Alpha

	Quartile 1 (High)					Quartile 2					Quartile 3					Quartile 4 (Low)				
Year	Mean	Median	10th pct	90th pct	Std	Mean	Median	10th pct	90th pct	Std	Mean	Median	10th pct	90th pct	Std	Mean	Median	10th pct	90th pct	Std
2003-2004	1.54	1.32	0.98	2.32	0.64	0.67	0.67	0.49	0.86	0.14	0.24	0.23	0.08	0.39	0.12	-0.45	-0.31	-1.13	-0.02	0.49
2004-2005	0.85	0.66	0.38	1.49	0.62	0.14	0.13	-0.01	0.30	0.11	-0.26	-0.26	-0.43	-0.09	0.12	-1.05	-0.88	-1.77	-0.55	0.65
2005-2006	0.83	0.60	0.38	1.52	0.69	0.16	0.15	0.02	0.30	0.10	-0.21	-0.20	-0.37	-0.05	0.11	-0.85	-0.72	-1.25	-0.50	0.45
2006-2007	0.96	0.79	0.51	1.52	0.62	0.27	0.27	0.13	0.42	0.10	-0.08	-0.08	-0.23	0.07	0.11	-0.77	-0.62	-1.35	-0.34	0.47
2007-2008	1.14	0.88	0.52	1.93	0.97	0.20	0.19	0.01	0.40	0.14	-0.28	-0.29	-0.50	-0.08	0.15	-1.34	-1.06	-2.42	-0.63	0.88
2008-2009	1.79	1.40	0.89	3.07	1.21	0.45	0.44	0.21	0.71	0.18	-0.08	-0.06	-0.29	0.11	0.15	-1.16	-0.90	-2.23	-0.44	0.93
2009-2010	2.20	1.87	1.23	3.68	1.06	0.75	0.74	0.49	1.04	0.20	0.18	0.17	-0.05	0.39	0.16	-0.76	-0.53	-1.47	-0.19	0.85
2010-2011	1.10	0.91	0.54	1.77	0.72	0.23	0.21	0.06	0.41	0.13	-0.21	-0.20	-0.41	-0.03	0.14	-1.13	-0.83	-1.88	-0.52	0.92
2011-2012	1.01	0.78	0.53	1.84	0.70	0.27	0.26	0.11	0.44	0.12	-0.14	-0.13	-0.34	0.03	0.13	-1.24	-0.86	-2.31	-0.47	1.14
Total	1.29	1.02	0.52	2.38	0.97	0.35	0.29	0.07	0.73	0.25	-0.10	-0.11	-0.36	0.19	0.21	-1.01	-0.78	-1.87	-0.38	0.87

Table III: Summary Statistics of Hedge Fund Excess Return, Alpha and Beta Return (Cont.)

Panel C Quartiles-Beta Return

	Quartile 1 (High)					Quartile 2					Quartile 3					Quartile 4 (Low)				
Year	Mean	Median	10th pct	90th pct	Std	Mean	Median	10th pct	90th pct	Std	Mean	Median	10th pct	90th pct	Std	Mean	Median	10th pct	90th pct	Std
2003-2004	1.94	1.74	1.34	2.81	0.63	0.99	0.99	0.81	1.19	0.15	0.54	0.54	0.39	0.69	0.11	0.05	0.15	-0.31	0.32	0.38
2004-2005	1.47	1.30	1.02	2.13	0.48	0.75	0.74	0.60	0.93	0.12	0.42	0.42	0.30	0.54	0.09	0.07	0.11	-0.13	0.25	0.20
2005-2006	1.40	1.26	0.89	2.08	0.53	0.63	0.63	0.50	0.78	0.10	0.34	0.34	0.24	0.44	0.07	0.04	0.09	-0.19	0.20	0.20
2006-2007	1.44	1.27	0.97	2.16	0.55	0.69	0.69	0.53	0.85	0.11	0.34	0.34	0.23	0.46	0.09	0.01	0.05	-0.18	0.16	0.17
2007-2008	0.52	0.29	0.11	1.29	0.57	-0.16	-0.15	-0.33	-0.01	0.12	-0.66	-0.65	-0.93	-0.43	0.18	-1.73	-1.52	-2.58	-1.11	0.75
2008-2009	0.45	0.35	0.21	0.73	0.34	0.04	0.03	-0.05	0.14	0.07	-0.23	-0.22	-0.40	-0.10	0.11	-1.14	-0.88	-2.10	-0.51	0.79
2009-2010	2.25	1.99	1.39	3.32	1.04	0.88	0.85	0.62	1.17	0.20	0.36	0.35	0.22	0.52	0.11	-0.06	0.02	-0.32	0.16	0.36
2010-2011	0.89	0.72	0.44	1.52	0.62	0.22	0.21	0.11	0.36	0.09	0.02	0.02	-0.05	0.08	0.05	-0.38	-0.25	-0.80	-0.09	0.39
2011-2012	0.66	0.53	0.33	1.15	0.40	0.17	0.15	0.09	0.27	0.07	0.01	0.01	-0.03	0.05	0.03	-0.48	-0.38	-0.93	-0.12	0.39
Total	1.16	1.01	0.30	2.21	0.87	0.41	0.31	-0.05	0.92	0.39	0.08	0.07	-0.44	0.47	0.36	-0.46	-0.19	-1.47	0.16	0.75

Table IV: Portfolios of Excess Return, Alpha and Beta Return, Annual Rebalancing

Portfolios are formulated based upon quartiles of variables of interest and rebalanced annually. Panel A reports the hedge fund excess return quartile portfolios. Panel B reports the alpha quartile portfolios. Panel C reports the beta return quartile portfolios. Q1 –Q4 represents the hold-top-quartile-short-bottom-quartile strategy. Portfolios are initiated as of December 31, 2004. End value is as of December 31, 2013; Attrition rate is the average annual rate at which funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio funds. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Panel A Excess Return - Annual Rebalancing

	End Value	Attrition Rate	LASSO R^2	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio
Quartile 1 (High)	1.76	6.98%	0.58	0.45 (1.44)	0.14	0.15 (0.89)	0.09
Quartile 2	1.56	10.62%	0.59	0.31 (1.38)	0.13	0.07 (0.71)	0.07
Quartile 3	1.68	14.42%	0.59	0.38* (1.75)	0.17	0.13 (1.38)	0.14
Quartile 4 (Low)	1.88	20.05%	0.56	0.50* (1.76)	0.17	0.20 (1.08)	0.12
Q1-Q4	-	-	-	-0.05 (-0.23)	-0.02	-0.05 (-0.18)	-0.02

Panel B Alpha - Annual Rebalancing

	End Value	Attrition Rate	LASSO R^2	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio
Quartile 1 (High)	2.02	7.79%	0.51	0.56** (2.28)	0.22	0.31*** (2.87)	0.28
Quartile 2	1.59	10.59%	0.58	0.33 (1.49)	0.14	0.07 (0.89)	0.09
Quartile 3	1.69	14.14%	0.62	0.39 (1.63)	0.16	0.10 (1.10)	0.11
Quartile 4 (Low)	1.64	19.51%	0.61	0.38 (1.28)	0.12	0.08 (0.52)	0.05
Q1-Q4	-	-	-	0.18* (1.67)	0.13	0.22 (1.56)	0.17

Table IV: Portfolios of Excess Return, Alpha and Beta Return, Annual Rebalancing (Cont.)

Panel C Beta Return - Annual Rebalancing

	End Value	Attrition Rate	LASSO R^2	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio
Quartile 1 (High)	1.36	11.89%	0.68	0.22 (0.63)	0.06	-0.14 (-0.71)	-0.07
Quartile 2	1.52	12.71%	0.58	0.29 (1.24)	0.12	0.05 (0.46)	0.05
Quartile 3	1.73	13.72%	0.53	0.40* (1.90)	0.18	0.18** (2.14)	0.21
Quartile 4 (Low)	2.43	13.78%	0.54	0.73*** (2.77)	0.27	0.46** (2.49)	0.27
Q1-Q4	-	-	-	-0.51** (-2.14)	-0.17	-0.60** (-2.01)	-0.21

Table V: Portfolios of Excess Return, Alpha and Beta Return, Two-Year Rebalancing

Portfolios are formulated based upon quartiles of variables of interest and rebalanced every two year. Panel A reports the hedge fund excess return quartile portfolios. Panel B reports the alpha quartile portfolios. Panel C reports the beta return quartile portfolios. Q1 – Q4 represents the hold-top-quartile-short-bottom-quartile strategy. Portfolios are initiated as of December 31, 2004. End value is as of December 31, 2013; Attrition rate is the average annual rate at which funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio funds. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table V: Portfolios of Excess Return, Alpha and Beta Return, Two-Year Rebalancing (Cont.)

Panel A Excess Return - 2 year Rebalancing

	Buy and Hold							Constant Mix						
	End Value	Attrition Rate	LASSO R^2	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio	End Value	Attrition Rate	LASSO R^2	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio
Quartile 1 (High)	1.65	9.01%	0.57	0.40 (1.20)	0.12	0.06 (0.36)	0.04	1.57	9.01%	0.57	0.35 (1.06)	0.10	0.02 (0.12)	0.01
Quartile 2	1.54	11.03%	0.58	0.30 (1.34)	0.13	0.05 (0.56)	0.05	1.51	11.03%	0.58	0.28 (1.27)	0.12	0.04 (0.39)	0.04
Quartile 3	1.69	15.26%	0.57	0.38* (1.85)	0.18	0.17* (1.69)	0.17	1.66	15.26%	0.57	0.37* (1.77)	0.17	0.15 (1.56)	0.16
Quartile 4 (Low)	2.21	18.23%	0.54	0.65** (2.33)	0.23	0.38** (2.00)	0.21	2.10	18.23%	0.54	0.60** (2.18)	0.21	0.33* (1.80)	0.19
Q1-Q4	-	-	-	-0.25 (-1.11)	-0.09	-0.31 (-1.04)	-0.11	-	-	-	-0.25 (-1.09)	-0.09	-0.31 (-1.05)	-0.11

Panel B Alpha - 2 year Rebalancing

	Buy and Hold							Constant Mix						
	End Value	Attrition Rate	LASSO R^2	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio	End Value	Attrition Rate	LASSO R^2	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio
Quartile 1 (High)	1.98	9.48%	0.50	0.54** (2.10)	0.20	0.28** (2.48)	0.25	1.87	9.48%	0.50	0.49* (1.90)	0.18	0.23** (2.02)	0.21
Quartile 2	1.59	11.26%	0.57	0.33 (1.49)	0.14	0.08 (0.94)	0.09	1.57	11.26%	0.57	0.31 (1.41)	0.14	0.07 (0.76)	0.08
Quartile 3	1.68	14.72%	0.61	0.38 (1.62)	0.16	0.11 (1.18)	0.12	1.65	14.72%	0.61	0.37 (1.57)	0.15	0.09 (1.05)	0.10
Quartile 4 (Low)	1.86	17.93%	0.60	0.49* (1.70)	0.16	0.20 (1.26)	0.12	1.77	17.93%	0.60	0.44 (1.56)	0.15	0.16 (1.02)	0.10
Q1-Q4	-	-	-	0.05 (0.39)	0.03	0.08 (0.46)	0.05	-	-	-	0.05 (0.37)	0.03	0.07 (0.43)	0.04

Table V: Portfolios of Excess Return, Alpha and Beta Return, Two-Year Rebalancing (Cont.)

Panel C Beta Return - 2 year Rebalancing

	Buy and Hold							Constant Mix						
	End Value	Attrition Rate	LASSO R^2	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio	End Value	Attrition Rate	LASSO R^2	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio
Quartile 1 (High)	1.33	12.47%	0.67	0.21 (0.58)	0.06	-0.17 (-0.90)	-0.09	1.29	12.47%	0.67	0.17 (0.49)	0.05	-0.20 (-1.04)	-0.10
Quartile 2	1.56	12.67%	0.57	0.31 (1.36)	0.13	0.08 (0.72)	0.07	1.50	12.67%	0.57	0.28 (1.22)	0.12	0.04 (0.40)	0.04
Quartile 3	1.76	14.19%	0.52	0.42** (2.00)	0.16	0.21** (2.43)	0.23	1.71	14.19%	0.52	0.39* (1.87)	0.18	0.18** (2.17)	0.20
Quartile 4 (Low)	2.64	14..00%	0.51	0.81*** (3.04)	0.29	0.57*** (2.95)	0.32	2.51	14..00%	0.51	0.76*** (2.89)	0.28	0.52*** (2.77)	0.30
Q1-Q4	-	-	-	-0.61** (-2.40)	-0.19	-0.74** (-2.37)	-0.24	-	-	-	-0.59** (-2.36)	-0.18	-0.72** (-2.34)	-0.24

Table VI: Portfolios of Excess Return, Alpha and Beta Return, Three-Year Rebalancing

Portfolios are formulated based upon quartiles of variables of interest and rebalanced every three year. Panel A reports the hedge fund excess return quartile portfolios. Panel B reports the alpha quartile portfolios. Panel C reports the beta return quartile portfolios. Q1 – Q4 represents the hold-top-quartile-short-bottom-quartile strategy. Portfolios are initiated as of December 31, 2004. End value is as of December 31, 2013; Attrition rate is the average annual rate at which funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio funds. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table VI: Portfolios of Excess Return, Alpha and Beta Return, Three-Year Rebalancing (Cont.)

Panel A Excess Return - 3 year Rebalancing

	Buy and Hold							Constant Mix						
	End Value	Attrition Rate	LASSO R^2	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio	End Value	Attrition Rate	LASSO R^2	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio
Quartile 1 (High)	2.09	8.74%	0.60	0.63* (1.72)	0.17	0.22 (1.43)	0.14	2.20	8.74%	0.60	0.68* (1.79)	0.17	0.26* (1.68)	0.17
Quartile 2	1.61	11.07%	0.57	0.35 (1.47)	0.14	0.08 (0.73)	0.07	1.65	11.07%	0.57	0.37 (1.53)	0.15	0.10 (0.88)	0.09
Quartile 3	1.49	14.17%	0.51	0.26 (1.44)	0.14	0.08 (0.97)	0.09	1.54	14.17%	0.51	0.29 (1.58)	0.15	0.10 (1.32)	0.12
Quartile 4 (Low)	1.35	19.57%	0.46	0.16 (0.96)	0.09	0.01 (0.12)	0.01	1.35	19.57%	0.46	0.17 (0.96)	0.09	0.01 (0.15)	0.01
Q1-Q4	-	-	-	0.47** (2.52)	0.20	0.21 (1.58)	0.16	-	-	-	0.51*** (2.66)	0.21	0.25* (1.82)	0.19

Panel B Alpha - 3 year Rebalancing

	Buy and Hold							Constant Mix						
	End Value	Attrition Rate	LASSO R^2	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio	End Value	Attrition Rate	LASSO R^2	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio
Quartile 1 (High)	2.12	8.40%	0.47	0.60** (2.36)	0.23	0.32*** (2.94)	0.29	2.19	8.40%	0.47	0.64** (2.39)	0.23	0.34*** (3.13)	0.31
Quartile 2	1.54	11.88%	0.54	0.30 (1.34)	0.13	0.05 (0.53)	0.05	1.58	11.88%	0.54	0.33 (1.42)	0.14	0.07 (0.75)	0.07
Quartile 3	1.60	13.64%	0.59	0.33 (1.46)	0.14	0.07 (0.74)	0.07	1.64	13.64%	0.59	0.36 (1.53)	0.15	0.09 (0.98)	0.10
Quartile 4 (Low)	1.35	19.54%	0.56	0.19 (0.72)	0.07	-0.03 (-0.18)	-0.02	1.40	19.54%	0.56	0.22 (0.83)	0.08	-0.00 (-0.02)	-0.00
Q1-Q4	-	-	-	0.42*** (4.27)	0.33	0.35*** (3.01)	0.32	-	-	-	0.42*** (4.40)	0.34	0.34*** (2.99)	0.32

Table VI: Portfolios of Excess Return, Alpha and Beta Return, Three-Year Rebalancing (Cont.)

Panel C Beta Return - 3 year Rebalancing

	Buy and Hold							Constant Mix						
	End Value	Attrition Rate	LASSO R^2	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio	End Value	Attrition Rate	LASSO R^2	Return (t-stat)	Sharpe Ratio	α (t-stat)	Info Ratio
Quartile 1 (High)	1.69	11.34%	0.70	0.44 (1.14)	0.11	0.03 (0.13)	0.01	1.82	11.34%	0.70	0.51 (1.28)	0.12	0.08 (0.45)	0.05
Quartile 2	1.67	13.32%	0.58	0.39 (1.44)	0.14	0.08 (0.76)	0.07	1.68	13.32%	0.58	0.39 (1.44)	0.14	0.08 (0.77)	0.07
Quartile 3	1.58	13.67%	0.47	0.32* (1.70)	0.16	0.12 (1.61)	0.15	1.60	13.67%	0.47	0.32* (1.70)	0.16	0.13* (1.75)	0.16
Quartile 4 (Low)	1.63	14.64%	0.40	0.33*** (2.69)	0.26	0.21*** (3.51)	0.33	1.65	14.64%	0.40	0.35*** (2.71)	0.26	0.22*** (3.79)	0.35
Q1-Q4	-	-	-	0.11 (0.48)	0.04	-0.19 (-1.12)	-0.11	-	-	-	0.17 (0.71)	0.06	-0.14 (-0.84)	-0.09

Table VII: Portfolios of Multi-active and Risk-writing Managers, Annual Rebalancing

Annual returns and cumulative performance of portfolios for bottom quartile beta return, Multi-active Managers, and Risk-writing Managers, previously defined. Portfolios are initiated as of December 31, 2004 and rebalanced annually. End value is as of December 31, 2013. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

	Beta Return			Multi-active Managers			Risk-writing Managers		
Year	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds
2005	6.91	282	261	10.35	81	81	-0.90	48	37
2006	10.25	359	330	11.06	142	136	10.94	17	13
2007	9.20	447	393	10.36	192	176	10.58	36	28
2008	-9.46	527	415	-3.08	193	167	-11.16	70	43
2009	55.69	544	477	56.39	113	98	66.48	193	164
2010	16.71	601	537	22.69	270	255	7.70	108	91
2011	-2.16	659	552	-0.62	139	127	-4.01	114	75
2012	6.08	717	588	7.83	281	252	2.63	93	63
2013	10.40	702	576	10.38	330	289	7.48	91	68
End Value		2.43			2.98			2.05	
Excess Return		0.73***			0.92***			0.59*	
(t-stat)		(2.77)			(3.63)			(1.85)	
Sharpe Ratio		0.27			0.35			0.18	
α		0.46**			0.69***			0.26	
(t-stat)		(2.49)			(3.75)			(0.98)	
Info Ratio		0.27			0.41			0.11	
Attrition rate		13.78%			8.47%			25.53%	
LASSO R^2		0.54			0.49			0.55	

Table VIII: Portfolios of Multi-active and Risk-writing Managers, Two-Year Rebalancing

Annual returns and cumulative performance of portfolios for bottom quartile beta return, Multi-active Managers, and Risk-writing Managers, previously defined. Portfolios are initiated as of December 31, 2004 and rebalanced every two year. End value is as of December 31, 2013. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table VIII: Portfolios of Multi-active and Risk-writing Managers, Two-Year Rebalancing (Cont.)

Panel A 2 year Rebalancing - Buy and Hold

	Beta Return			Multi-active Managers			Risk-writing Managers		
Year	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds
2005	6.91	282	261	10.35	81	81	-0.90	48	37
2006	12.08	261	240	14.77	81	78	8.27	37	29
2007	9.20	447	393	10.36	192	176	10.58	36	28
2008	-4.23	393	306	-7.10	176	136	24.08	28	22
2009	55.69	544	477	56.39	113	98	66.48	193	164
2010	21.16	477	431	17.54	98	88	27.23	164	149
2011	-2.16	659	552	-0.62	139	127	-4.01	114	75
2012	3.36	552	441	8.21	127	110	-4.97	75	53
2013	10.40	702	576	10.38	330	289	7.48	91	68
End Value	2.64			2.83			3.06		
Mean Return	0.81***			0.87***			0.96***		
(t-stat)	(3.04)			(3.34)			(3.00)		
Sharpe Ratio	0.29			0.32			0.29		
α	0.57***			0.64***			0.76**		
(t-stat)	(2.95)			(3.79)			(2.53)		
Info Ratio	0.32			0.40			0.27		
Attrition rate	14.00%			10.30%			22.35%		
LASSO R^2	0.51			0.46			0.53		

Panel B 2 year Rebalancing - Constant Mix

	Beta Return			Multi-active Managers			Risk-writing Managers		
Year	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds
2005	6.91	282	261	10.35	81	81	-0.90	48	37
2006	11.26	261	240	13.31	81	78	7.02	37	29
2007	9.20	447	393	10.36	192	176	10.58	36	28
2008	-5.90	393	306	-9.68	176	136	22.77	28	22
2009	55.69	544	477	56.39	113	98	66.48	193	164
2010	18.27	477	431	14.51	98	88	23.91	164	149
2011	-2.16	659	552	-0.62	139	127	-4.01	114	75
2012	3.23	552	441	8.02	127	110	-4.95	75	53
2013	10.40	702	576	10.38	330	289	7.48	91	68
End Value	2.51			2.64			2.91		
Mean Return	0.76***			0.81***			0.92***		
(t-stat)	(2.89)			(3.12)			(2.90)		
Sharpe Ratio	0.28			0.30			0.28		
α	0.52***			0.58***			0.72**		
(t-stat)	(2.77)			(3.48)			(2.41)		
Info Ratio	0.30			0.37			0.26		
Attrition rate	14.00%			10.30%			22.35%		
LASSO R^2	0.51			0.46			0.53		

Table IX: Portfolios of Multi-active and Risk-writing Managers, Three-Year Rebalancing

Annual returns and cumulative performance of portfolios for bottom quartile beta return, Multi-active Managers, and Risk-writing Managers, previously defined. Portfolios are initiated as of December 31, 2004 and rebalanced every three year. End value is as of December 31, 2013. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table IX: Portfolios of Multi-active and Risk-writing Managers, Three-Year Rebalancing (Cont.)

Panel A 3 year Rebalancing - Buy and Hold

	Beta Return			Multi-active Managers			Risk-writing Managers		
Year	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds
2005	6.91	282	261	10.35	81	81	-0.90	48	37
2006	12.08	261	240	14.77	81	78	8.27	37	29
2007	8.81	240	217	13.45	78	72	9.23	29	23
2008	-9.46	527	415	-3.08	193	167	-11.16	70	43
2009	16.36	415	352	13.82	167	146	5.65	43	33
2010	9.70	352	311	8.60	146	127	11.77	33	29
2011	-2.16	659	552	-0.62	139	127	-4.01	114	75
2012	3.36	552	441	8.21	127	110	-4.97	75	53
2013	6.66	441	343	7.65	110	98	5.05	53	29
End Value		1.63			1.99			1.18	
Mean Return		0.33***			0.52***			0.03	
(t-stat)		(2.69)			(4.35)			(0.24)	
Sharpe Ratio		0.26			0.41			0.02	
α		0.21***			0.41***			-0.04	
(t-stat)		(3.51)			(5.65)			(-0.32)	
Info Ratio		0.33			0.56			-0.03	
Attrition rate		14.64%			9.26%			27.56%	
LASSO R^2		0.40			0.34			0.43	

Panel B 3 year Rebalancing - Constant Mix

	Beta Return			Multi-active Managers			Risk-writing Managers		
Year	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds
2005	6.91	282	261	10.35	81	81	-0.90	48	37
2006	11.26	261	240	13.31	81	78	7.02	37	29
2007	8.46	240	217	12.68	78	72	8.87	29	23
2008	-9.46	527	415	-3.08	193	167	-11.16	70	43
2009	20.50	415	352	19.50	167	146	7.45	43	33
2010	9.29	352	311	8.26	146	127	10.72	33	29
2011	-2.16	659	552	-0.62	139	127	-4.01	114	75
2012	3.23	552	441	8.02	127	110	-4.95	75	53
2013	6.33	441	343	6.96	110	98	4.84	53	29
End Value		1.65			2.03			1.17	
Mean Return		0.35***			0.54***			0.02	
(t-stat)		(2.71)			(4.38)			(0.17)	
Sharpe Ratio		0.26			0.42			0.02	
α		0.22***			0.41***			-0.05	
(t-stat)		(3.79)			(6.22)			(-0.45)	
Info Ratio		0.35			0.60			-0.04	
Attrition rate		14.64%			9.26%			27.56%	
LASSO R^2		0.40			0.34			0.43	

Table X: Comparisons of Performance Fee, Management Fee and High Water Mark

Summary statistics of performance fee, management fee, and high water mark for beta return quartile portfolios, Multi-active Managers, and Risk-writing Managers are reported. Panel A reports the summary statistics of performance fee. Panel B reports the summary statistics of management fee. Panel C reports the summary statistics of high water mark. Quartile 1 represents the top quartile; Quartile 4 represents the bottom quartile; MM is Multi-active Manager; RM is Risk-writing Managers. Test for equal means is performed on selected portfolios. Difference in means and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table X: Comparisons of Performance Fee, Management Fee and High Water Mark (Cont.)

Panel A Performance Fee

	Mean	Median	Min	Max	Std	Q4-Qi	MM-Qi	MM-RM
Quartile 1 (High)	17.39	20	0	50	7.07	0.04 (0.30)	1.21*** (6.44)	- -
Quartile 2	17.61	20	0	50	6.49	0.05 (0.37)	0.99*** (5.63)	- -
Quartile 3	17.62	20	0	50	6.60	0.27* (1.95)	0.98*** (5.51)	- -
Quartile 4 (Low)	17.66	20	0	75	6.59	- -	0.94*** (5.29)	- -
Multi-active Managers	18.60	20	0	75	5.52	- -	- -	- -
Risk-writing Managers	17.33	20	0	33	6.83	- -	- -	1.27*** (4.91)

Panel B Management Fee

	Mean	Median	Min	Max	Std	Q4-Qi	MM-Qi	MM-RM
Quartile 1 (High)	1.50	1.5	0	6	0.74	-0.04*** (-2.94)	0.02 (0.84)	- -
Quartile 2	1.48	1.5	0	6	0.65	-0.02* (-1.81)	0.03* (1.91)	- -
Quartile 3	1.46	1.5	0	6	0.60	-0.00 (-0.29)	0.05*** (3.20)	- -
Quartile 4 (Low)	1.46	1.5	0	6	0.60	- -	0.06*** (3.43)	- -
Multi-active Managers	1.52	1.5	0	6	0.57	- -	- -	- -
Risk-writing Managers	1.47	1.5	0	4	0.70	- -	- -	0.05* (1.72)

Table X: Comparisons of Performance Fee, Management Fee and High Water Mark (Cont.)

Panel C High Water Mark

	Mean	Median	Min	Max	Std	Q4-Qi	MM-Qi	MM-RM
Quartile 1 (High)	0.88	1	0	1	0.33	0.00 (0.66)	0.04*** (4.64)	- -
Quartile 2	0.89	1	0	1	0.32	-0.01 (0.90)	0.03*** (3.57)	- -
Quartile 3	0.89	1	0	1	0.31	-0.01 (-1.30)	0.03*** (3.26)	- -
Quartile 4 (Low)	0.88	1	0	1	0.32	- -	0.04*** (4.19)	- -
Multi-active Managers	0.92	1	0	1	0.27	- -	- -	- -
Risk-writing Managers	0.88	1	0	1	0.32	- -	- -	0.04*** (2.91)

Table XI: Comparisons of Risk Measures, Pre 24-month Window and Post 24-month Window

Summary statistics of risk measures for beta return quartile portfolios, Multi-active Managers, and Risk-writing Managers are reported. Panel A reports the summary statistics of risk measures calculated based upon beta exposures from previous 24-month window. Panel B reports the summary statistics of risk measures calculated based upon beta exposures from post 24-month window. Quartile 1 represents the top quartile; Quartile 4 represents the bottom quartile; MM is Multi-active Managers; RM is Risk-writing Managers. Test for equal means is performed on selected portfolios. Difference in means and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Panel A Pre 24-month Window

	Total Risk	Factor Variance	Cross-Covarianc	Beta Risk	Total Risk Q4-Qi	Total Risk RM-Qi	Total Risk RM-MM	Beta Risk Q4-Qi	Beta Risk RM-Qi	Beta Risk RM-MM
Quartile 1 (High)	43.42	30.29	-7.88	22.42	-11.31***	11.31***	-	-3.30***	10.74***	-
					(-8.17)	(4.28)	-	(-4.30)	(8.02)	-
Quartile 2	19.29	10.84	-2.32	8.52	12.82***	35.44***	-	10.60***	24.64***	-
					(12.11)	(25.15)	-	(16.62)	(30.46)	-
Quartile 3	18.14	10.88	-1.92	8.96	13.97***	36.59***	-	10.16***	24.20***	-
					(13.06)	(25.06)	-	(15.31)	(26.01)	-
Quartile 4 (Low)	32.11	40.46	-21.34	19.12	-	22.63***	-	-	14.04***	-
					-	(8.71)	-	-	(8.50)	-
Multi-active Managers	37.63	64.34	-43.54	20.80	-	-	17.10***	-	-	12.36***
					-	-	(4.56)	-	-	(5.40)
Risk-writing Managers	54.73	41.60	-8.44	33.16	-	-	-	-	-	-
					-	-	-	-	-	-

Table XI: Comparisons of Risk Measures, Pre 24-month Window and Post 24-month Window (Cont.)

Panel B Post 24-month Window

	Total Risk	Factor Variance	Cross-Covarianc	Beta Risk	Total Risk Q4-Qi	Total Risk RM-Qi	Total Risk RM-MM	Beta Risk Q4-Qi	Beta Risk RM-Qi	Beta Risk RM-MM
Quartile 1 (High)	44.53	30.10	-5.91	24.20	-19.81***	4.40	-	-11.36***	-0.38	-
					(-12.83)	(1.18)	-	(-12.92)	(-0.18)	-
Quartile 2	21.58	14.98	-4.02	10.96	3.14***	27.35***	-	1.88***	12.86***	-
					(2.82)	(11.85)	-	(2.74)	(8.82)	-
Quartile 3	18.55	16.92	-7.37	9.55	6.17***	30.38***	-	3.29***	14.27***	-
					(6.19)	(16.30)	-	(5.61)	(13.05)	-
Quartile 4 (Low)	24.72	23.46	-10.63	12.84	-	24.21***	-	-	10.98***	-
					-	(9.24)	-	-	(7.32)	-
Multi-active Managers	23.97	26.23	-14.14	12.09	-	-	24.96***	-	-	11.73***
					-	-	(7.91)	-	-	(6.35)
Risk-writing Managers	48.93	42.02	-18.20	23.82	-	-	-	-	-	-
					-	-	-	-	-	-

Table XII: Comparisons of Post Beta Return Correlations and Difference in Beta Returns

Summary statistics of beta return correlations for beta return quartile portfolios, Multi-active Managers, and Risk-writing Managers are reported. Panel A reports the summary statistics of beta return correlations for post 24-month window. Panel B reports the summary statistics of difference in beta returns for post 24-month window. Quartile 1 represents the top quartile; Quartile 4 represents the bottom quartile; MM is Multi-active Managers; RM is Risk-writing Managers. Test for equal means is performed on selected portfolios. Difference in means and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Table XII: Comparisons of Post Beta Return Correlations and Difference in Beta Returns (Cont.)

Panel A Post 24-month Beta Correlation

	Mean	Median	Min	Max	Std	MM-Qi	MM-RM	RM-Qi
Quartile 1 (High)	0.69	0.86	-0.99	1.00	0.40	-0.18*** (-12.52)	- -	-0.02 (-1.14)
Quartile 2	0.67	0.82	-0.99	1.00	0.38	-0.15*** (-11.03)	- -	0.00 (0.06)
Quartile 3	0.67	0.82	-0.93	1.00	0.37	-0.15*** (-11.19)	- -	0.00 (0.12)
Quartile 4 (Low)	0.58	0.77	-1.00	1.00	0.43	-0.07*** (-4.42)	- -	0.09*** (3.93)
Multi-active Managers	0.51	0.69	-1.00	0.99	0.44	- -	- -	- -
Risk-writing Managers	0.67	0.84	-0.78	1.00	0.38	- -	-0.15*** (-6.29)	- -

Panel B Post 24-month FDBR

	Mean	Median	Min	Max	Std	MM-Qi	MM-RM	RM-Qi
Quartile 1 (High)	0.09	0.02	-6.49	9.30	1.07	0.07* (1.84)	- -	-0.16*** (-2.77)
Quartile 2	0.08	0.05	-5.66	4.40	0.63	0.07*** (2.75)	- -	-0.15*** (-4.18)
Quartile 3	0.04	0.04	-5.09	4.36	0.63	0.11*** (4.37)	- -	-0.11*** (-3.04)
Quartile 4 (Low)	0.05	0.06	-5.76	6.14	0.83	0.10*** (3.32)	- -	-0.12*** (2.66)
Multi-active Managers	0.15	0.13	-5.76	6.14	0.93	- -	- -	- -
Risk-writing Managers	-0.07	0.03	-3.55	5.64	1.08	- -	0.22*** (3.95)	- -

V. Conclusion

In the first essay I define two types of active hedge fund management: alpha active and beta active. I develop measures to identify those successful beta active managers and find that top beta active managers deliver superior risk-adjusted performance compared with alpha active managers. In addition, the beta active measure is the driving factor behind systematic risk and low R^2.

The second essay illustrates that some hedge funds generate returns that are merely compensations for exposures to alternative risk factors. By using ETFs as proxies for alternative risk factors, I employ LAR LASSO selection model and use the regression selected ETF factors to replicate hedge fund returns. I find that the clone portfolio provide similar or better performance for those cloneable hedge funds. However, non-cloneable hedge funds possess unique selection skills which cannot be captured by the methodology, and such funds generate significant risk-adjusted out-of-sample performance.

The third essay decomposes hedge fund excess return into alpha and beta return by using a comprehensive performance evaluation model which captures possible alternative risk factors undertaken by hedge fund managers. I find that alpha determined by this methodology is a persistent indicator of future performance and a strong mean reversal pattern exists in beta return sorted portfolios. In addition, with simple interaction between alpha and beta return, I identify multi-active managers, those who possess unique active market testing ability, and risk-writing managers, those who generate returns through excessive risk taking.