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Active Factor Investing: Hedge Funds versus the Rest of Us

Jun Duanmu
Seattle University

Yongjia Li
Boise State University

Alexey Malakhov
University of Arkansas

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Jun Duanmu*
Seattle University
jduanmu@seattleu.edu

Yongjia Li*
Boise State University
eddyli@boisestate.edu

Alexey Malakhov
University of Arkansas

ABSTRACT

We examine if the success of hedge fund market timing strategies can be replicated. We develop a methodology for creating a portfolio of ETFs to capture risk factor exposures of market timing hedge funds identified using extant market timing measures. We find that the top market timing hedge funds outperform their ETF clone peers and the superior performance cannot be replicated. We show that the irreplicable market timing skills are more profound in certain hedge fund styles. Finally, we provide evidence that the success of market timing strategies is driven by non-cloneable hedge funds that possess managerial skills.

JEL classification: G11, G23

Keywords: hedge funds, market timing, beta management, risk factor exposures, return replication, performance prediction

1. Introduction

Hedge funds experienced tremendous growth in recent years and recorded more than $3 trillion in global investments currently under management.[1] Considered as the apex of actively managed portfolios, hedge funds seek to provide investors absolute performance in low correlation with major asset classes through alpha and beta management. Among which, hedge fund beta management has gained greater attention recently. The extant literature provides ample evidence on hedge fund manager's market timing ability and various market timing measures are constructed to identify successful market timing hedge funds.[2] For example, Chen and Liang (2007) construct a measure for timing return and volatility jointly that relates fund returns to the squared Sharpe ratio of the market portfolio and find evidence of timing ability. Cao, Chen, Liang, and Lo (2013) find strong evidence of hedge fund market liquidity timing ability as aggregate liquidity conditions change. Instead of examining market timing with regard to a single factor, Duanmu, Malakhov, and McCumber (2018) quantify the efficacy of beta active hedge fund management by introducing a measure of the overall beta activity, *BA*. The authors argue that, unlike alpha-active hedge funds whose returns are mainly driven by managerial skills captured by alpha coefficients from a factor model, beta-driven hedge fund performance is also valuable and is predictive of future performance. They define beta active managements as taking directional positions correlated with macroeconomic risk factors and altering factor loadings in anticipation of changing opportunity sets. Relying on regression determined factor coefficient and corresponding risk factors, Duanmu et al. (2018) construct an overall measure of beta activities, *BA*, which captures both contemporaneous and dynamic factor changing success. Portfolios comprised of the most beta active hedge funds produce outstanding long-term risk-adjusted performance, outperforming portfolios comprised of the most alpha active hedge funds.

As hedge funds exhibit exposure to systematic risk factors,[3] it is reasonable to expect that the returns of market timing hedge funds are exposed to specific risk factor exposures. Then it is natural to question if the success of market timing strategies can be replicated by taking corresponding risk factors or such beta management is a true reflection of managerial skills that cannot be cloned otherwise. It falls into an empirical question to examine the replicability of successful market timing hedge funds which builds upon the extant literature on hedge fund return replications.

[1] According to Hedge Fund Research, Inc., the global hedge fund capital is $3.18 trillion (April 17, 2019 press release).
[2] A partial list includes Fung and Hsieh (1997), (2001), (2004), Asness, Krail, and Liew (2001), Agarwal and Naik (2000), (2004), Patton (2009), and Bali et al. (2011), (2012).
[3] See Bali, Brown, and Cagalayan (2011), (2012).

Numerous attempts at cloning hedge fund returns with liquid investment alternatives have been made in academic literature[4] and also among major asset management companies.[5] Ideally, hedge fund clones should alleviate all three major problems with hedge funds by providing transparency and liquidity at much lower costs. However, it is not clear that hedge fund returns can be replicated in the first place, as truly active proprietary fund management strategies could be beyond replication efforts.[6] For example, the S.A.C. Capital Advisors' strategy in trading Elan and Wyeth stocks based on insider tips obviously can't be replicated with any algorithmic approach.[7] But as John H. Cochrane observes, hedge fund returns may be predominantly driven by beta exposures to latent risk factors not readily discernible to average investors:

> *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."*[8]

If hedge fund returns are indeed driven by alternative risk factor exposures,[9] then it is reasonable to presume that it is possible to come up with a procedure for replicating hedge fund returns at a lower cost for all investors with a portfolio of alternative risk factors. The factor approach to hedge fund cloning is being employed by Hasanhodzic and Lo (2007), Amenc, Martellini, Meyfredi, and Ziemann (2010), Giamouridis and Paterlini (2010), and Weber and Peres (2013). There are, however, two problems with prevailing methods. First, only a limited number of potential risk factors[10] are considered. Second, the prevailing focus is on replicating either all individual hedge funds or broad hedge fund indexes without regard to the fact that some hedge fund strategies are, in fact, non-reproducible.

To address the two issues above, we follow Duanmu, Li, and Malakhov (2020) (DLM thereafter) and utilize a methodology that captures the factor-driven component of hedge fund returns and replicates hedge fund returns with tradable investment instruments - exchange-traded funds (ETFs). The methodology builds on return attribution and interprets passive ETFs as proxies for risk factors. DLM argues that passive ETFs deliver return patterns executed formulaically without human discretion, and such rigid formulaic strategies represent reasonable proxies to a multitude of alternative risk factors that investors find attractive from the risk-and-return perspective.[11] This approach greatly expands the coverage of tradable risk factors available for hedge fund replication and allows for proper identification and selection of risk factors relevant for each individual hedge fund.[12] In addition, the DLM methodology provides value in identifying skilled managers of *non-cloneable* hedge funds. If a hedge fund manager has the genuine skill and pursues a unique strategy that cannot be cloned, then such a fund could be viewed as a *non-cloneable* fund.

In this paper, we combine the ideas of cloning beta-driven hedge fund returns (cloneability) and identifying hedge funds with high quality of beta management and market timing activities, by focusing replication efforts on portfolios of hedge funds that are *cloneable* and also display a high degree of market timing measures. This approach allows us to examine if we are able to replicate the returns of the *cloneable* hedge funds that are identified as successful market timers. We construct market timing measures that capture the market return timing, volatility timing, liquidity timing, and the overall management of beta activity. Specifically, these market timing measures are Henriksson and Merton

[4] See, for example, Kat and Palaro (2005), Jaeger and Wagner (2005), Hasanhodzic and Lo (2007), Amenc, Gehin, Martellini, and Meyfredi (2008), Amenc, Martellini, Meyfredi, and Ziemann (2010), Giamouridis and Paterlini (2010), Freed and McMillan (2011), Weber and Peres (2013), and Duanmu, Li, and Malakhov (2020).

[5] For example, Goldman Sachs, Morgan Stanley, Barclays, Credit Suisse, Societe Generale, and BNP Paribus offer hedge fund clone products.

[6] Such strategies are often referred to as 'pure alpha strategies', synonymous with true managerial skill of hedge fund managers.

[7] This strategy is also illegal. See *The Empire of Edge* by P.R. Keefe in The New Yorker (October 13, 2014 issue).

[8] See John H. Cochrane's 'Hedge Funds' lecture notes at http://faculty.chicagobooth.edu/john.cochrane/teaching/35150_advanced_investments/hedge_notes_and_questions.pdf

[9] An example of such a strategy could be writing out-of-the-money put options on the S&P 500 index.

[10] The number of tradable factors varies from six in Hasanhodzic and Lo (2007) to thirty in Weber and Peres (2013).

[11] For example, writing out of the money put options or covered call options on the S&P 500 index, earning returns by exposing investors to an easily quantifiable alternative risk factor. Other examples include volatility put write ETFs, currency carry ETFs, value ETFs, momentum ETFs and so on. Such return patterns are associated with 'passive' or 'smart beta' investment strategies. The difference between 'passive' and 'smart beta' strategies is typically in the degree of sophistication in utilizing exotic risk factors.

[12] The number of U.S. listed passively managed ETFs increases from 34 in 1997 to 1,926 in 2018. ETFs span the space of potential risk factors and provide access to a great variety of alternative investment styles that were previously available only to institutional investors.

(1981) measure which is a directional market return factor (HM thereafter), Chen and Liang (2007) measure which jointly captures the return and volatility timing (CLT thereafter), Cao et al. (2013) market liquidity measure (LIQ thereafter), and Duanmu et al. (2018) overall beta activity measure (DMM thereafter).

Following Duanmu, Li, and Malakhov (2020), we first test the efficacy of the methodology on hedge fund return replication using ETF clone portfolios. Consistent with DLM, we find that the ETF clone portfolios slightly outperform *cloneable* hedge funds. Furthermore, we confirm that hedge fund portfolios formed on selected market timing metrics outperform the Bloomberg peers in the context of raw returns, Sharpe ratio, Fung and Hsieh (2004) alpha and information ratio.[13] The finding indicates that market timing strategies add value to hedge fund management. However, applying the replication methodology to the top market timing hedge funds, we find that the corresponding ETF clone portfolios fail to match the performance of market timing hedge funds. The result suggests that successful market timing hedge funds fall within the *non-cloneable* hedge fund category, and they possess true managerial skills valuable to investors.

We further repeat our analysis on subsets of hedge fund samples classified by hedge fund styles.[14] It is possible that the replication quality as well as the market timing efficacy vary across different hedge fund styles. We show that the irreplicable market timing skills are more profound in Directional Traders and Multiprocess style market timing hedge funds. For Relative Value and Security Selection style market timing hedge funds, the performance between hedge fund portfolio and their clones are comparable. The finding is consistent with our expectation as Directional Traders and Multiprocess hedge funds tend to make timely shifts among risk factor exposures based upon the directional change of capital assets returns.

Finally, we investigate the performance of hedge funds within each market timing hedge fund portfolio by dividing the portfolio into *cloneable* market timing and *non-cloneable* market timing hedge funds. We find that the resulting cloneable market timing hedge funds are dragging down the overall performance of market timing hedge funds. Instead, the *non-cloneable* market timing hedge funds are the driving factors behind the successful market timing strategies. We interpret this result as true market timing ability being irreplicable managerial skills and such managerial skills eventually add value to hedge fund management. Hedge fund managers with genuine market timing skills take positions considering a wide range of possible macroeconomic scenarios. Their timely and dynamic shift across different risk factors in anticipation of changing economic conditions and opportunity sets may not be captured by statically matching the risk factor exposures of hedge funds. On the other hand, although some hedge funds are identified as market timing hedge funds, their returns can be replicated by using ETFs and their performance is not statistically different from the ETF clones. These *cloneable* market timing funds may pursue algorithmic strategies highly correlated with latent risk factors and their returns mostly reflect exposures to these risk factors. Overall, the findings suggest that our cloning methodology is valuable in identifying market timing hedge funds that possess the genuine ability and pursues a truly unique strategy uncorrelated with identifiable risk factors.

The rest of the paper is organized as follows. Section 2 describes the hedge fund and ETF data. Section 3 explains the methodology on how we construct market timing measures and how we construct the replicating portfolios for the out-of-sample test. Section 4 discusses and analyzes the empirical results. Section 5 concludes.

2. Data Description

This study utilizes hedge fund data from Bloomberg[15] from 1994-2018 on 20,073 unique hedge funds.[16] The compiled data is comprehensive with information on fund returns net of management and performance fees, assets under management, manager information, and fund characteristics for live as well as dead hedge funds that were acquired, liquidated, or simply ceased to report. We mitigate the effects of backfill bias by eliminating the first 24 months of

[13] Though hedge fund portfolio formed on HM has slightly lower Sharpe ratio and information ratio than those of the Bloomberg peers.

[14] We follow Agarwal, Daniel and Naik (2009) and reclassify the hedge funds into four consolidated categories: Directional Traders, Relative Value, Security Selection and Multiprocess.

[15] 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.

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

reported returns.[17] Additionally, since four years of data are required to calculate the measure of hedge fund beta activity, *BA*,[18] only funds with inception dates prior to 2007 are considered, which leaves us with 5,523 unique funds that have sufficient longevity to enable our methodology. Finally, in the sample of the 5,523 funds that remain, 2,087 funds are active and 3,436 funds are inactive.

Panel A of Table 1 reports summary statistics on fund returns, fees, investor liquidity, and fund longevity. The typical hedge fund has a median 1.5% management fee, a median 20% incentive fee on all profits over an investor's high-water mark,[19] a $250,000 minimum initial investment, and a thirty-day redemption period. Not surprisingly, active funds exhibit higher median monthly excess returns, larger median assets under management, and greater longevity compared to inactive hedge funds. Inactive funds have longer average redemption and lockup periods. Panel B of Table 1 reports the distribution of characteristics across hedge funds. 85% of all funds have a high-water mark provision, and only 5% impose hurdle rates in addition to high-water marks. 32% of funds are non-U.S. domiciled. Panel C presents the distribution of fund styles. In our sample, we have 28 unique hedge fund styles with the number of hedge funds under each distinction varying dramatically across styles. In order to carry a meaningful analysis of the relationship between cloneability and fund styles, we follow Agarwal, Daniel, and Naik (2009) and reclassify the hedge funds into four consolidated categories: Directional Traders, Relative Value, Security Selection and Multiprocess. The most common consolidated style is Security Selection, which accounts 37% of all hedge funds, while Relative Value is the least common style, accounting for 16% of hedge funds.[20]

We obtain ETF data from Morningstar over the period 1994-2018 on 2,383 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,[21] as well as ETFs that track hedge fund style indexes; this leaves us with 2,286 unique ETFs. Additionally, we require ETFs to have at least 24 monthly observations starting from January each year, and eliminate ETFs with missing information on management fees. Further, since fewer than five ETFs were available prior to 1997, we excluded these years from the analysis. The 1,926 unique passively managed ETFs over the period 1997-2018 that remain are used in the study.

Figure 1 reports the number of ETFs available each year in our sample period. As shown, ETFs experienced significant growth over the sample period; from 34 ETFs in 1997 to 1,926 ETFs in 2018. The increase in the number of ETFs available expands the investment opportunity set dramatically, and consequently, our hedge fund replicating process achieves higher precision in identifying *cloneable* and *non-cloneable* funds towards the later years in our sample period.

Following the hedge fund return replication methodology (DLM),[22] we utilize two years of monthly ETF returns in order to identify the number of latent risk factors and ETFs that provide the best proxies for latent risk factors. Figure 2 reports the actual number of ETFs used for each two-year window. In the early years, relatively few ETFs make the replication procedure less accurate. Following DLM, we restrict our out-of-sample analysis to the period after 2005, where more than 100 ETFs per year are available for the replication procedure.[23]

[17] 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. As a robustness check, we drop the first 12 monthly observations to address the backfill bias, which increases the data availability for our analysis. The results are quantitatively similar, and we decide not to report these results for brevity.
[18] See Section 3 of this paper for the details of the *BA* methodology.
[19] 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.
[20] The reclassification process is illustrated in Appendix C.
[21] Benchmark indexes that retained ETFs track may not be publicly available. Some funds track in-house indexes.
[22] See Section 3 of this paper for the details of the methodology used to replicate hedge fund returns with ETFs.
[23] Specifically, for our in-sample analysis, we employ hedge fund data going back to 1999 and ETF data going back to 2003.

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3. Research Methodology

3.1 Henriksson and Merton (1981) Market Timing Measure

Following Henriksson and Merton (1981), we construct a directional market return timing factor, Max(0, r_M), which is the excess return CRSP stock market value-weighted index over the monthly return of 30-day U.S. Treasury bills. We add the HM directional market return timing factor, Max(0, r_M), to the baseline model [1]. The regression coefficient, HM, measures the ability of hedge fund managers to time the market.

$$r_i - r_f = \alpha_i + \beta_{i1}SP500 + \beta_{i2}EM + \beta_{i3}10Year + \beta_{i4}SizeSpread + \beta_{i5}CreditSpread +$$

$$+ \beta_{i6}BondTrend + \beta_{i7}ComTrend + \beta_{i8}FxTrend + \beta_{i9}Max(0, r_M) + \varepsilon_i. \quad [1]$$

3.2 Chen and Liang (2007) Joint Timing Measure

Chen and Liang (2007) construct a measure for timing return and volatility jointly that relates fund returns to the squared Sharpe ratio of the market portfolio and find evidence of timing ability. We follow Chen and Liang (2007) and calculate hedge fund exposure to the joint return and volatility timing factor, $(r_M/\sigma_M)^2$, where r_M is the excess return of the CRSP stock market value-weighted index over the monthly return of 30-day U.S. Treasury bills and σ_M is the VIX implied volatility index per the Chicago Board Options Exchange. We add this joint return and volatility timing factor to base equation [2] and the regression coefficient captures, CLT, captures the joint timing ability of fund managers.

$$r_i - r_f = \alpha_i + \beta_{i1}SP500 + \beta_{i2}EM + \beta_{i3}10Year + \beta_{i4}SizeSpread + \beta_{i5}CreditSpread +$$

$$+ \beta_{i6}BondTrend + \beta_{i7}ComTrend + \beta_{i8}FxTrend + \beta_{i9}(r_M/\sigma_M)^2 + \varepsilon_i. \quad [2]$$

3.3 Cao, Chen, Liang, and Lo (2013) Liquidity Timing Measure

Cao et al. (2013) provide evidence that hedge fund managers adjust their portfolios' market exposures as aggregate liquidity conditions change and find that liquidity timing funds yield better performance. Following Cao et al. (2013), we construct the liquidity timing factor as $SP500_t(L_{M,t} - \bar{L}_{M,t-1})$ and add it to the baseline model [3]. L_M is the Pastor–Stambaugh (2003) liquidity measure and the regression coefficient LIQ captures manager's ability to time the market liquidity.

$$r_i - r_f = \alpha_i + \beta_{i1}SP500 + \beta_{i2}EM + \beta_{i3}10Year + \beta_{i4}SizeSpread + \beta_{i5}CreditSpread +$$

$$+ \beta_{i6}BondTrend + \beta_{i7}ComTrend + \beta_{i8}FxTrend + \beta_{i9}\mathrm{SP500t}(L_{M,t} - \bar{L}_{M,t-1}) + \varepsilon_i. \quad [3]$$

3.4 Duanmu, Malakhov, and McCumber (2018) Beta Activity

Following Duanmu, Malakhov, and McCumber (2018), we employ a modified Fung and Hsieh (2004) model to construct the measure of a hedge fund's beta activity, *BA*:

$$r_i - r_f = \alpha_i + \beta_{i1}SP500 + \beta_{i2}EM + \beta_{i3}10Year + \beta_{i4}SizeSpread + \beta_{i5}CreditSpread +$$

$$+ \beta_{i6}BondTrend + \beta_{i7}ComTrend + \beta_{i8}FxTrend + \varepsilon_i. \quad [4]$$

Consistent with DMM, we run individual fund regressions [4][24] for every 2-year window, and we roll the 2-year window over the entire sample period. We estimate and record the regression determined beta coefficients to construct the components of *BA* measure and eventually *BA.*

[24] See Appendix A for detailed descriptions of variables.

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We first construct Scaled Beta Success, *SBS*, which captures how well a manager's beta position performs relative to the range between the best and worst performing factors. *SBS* is constructed using equation [5]:

$$SBS_{w,i} = \frac{1}{2}\frac{\beta'_{w,i}\overline{f}_{w} - \min_j\{\overline{f}_{w,j}\}}{\max_j\{\overline{f}_{w,j}\} - \min_j\{\overline{f}_{w,j}\}} + \frac{1}{2}\frac{\beta'_{w-1,i}\overline{f}_{w-1} - \min_j\{\overline{f}_{w-1,j}\}}{\max_j\{\overline{f}_{w-1,j}\} - \min_j\{\overline{f}_{w-1,j}\}}, \qquad [5]$$

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*.

We then compute Difference in Beta Returns, *DBR*, a measure of managers' success in making timely strategic changes in overall factor allocations and such measure is constructed by comparing two-year window realized beta returns to forward and backward looking 'what-if' synthetic beta returns. We compute *FDBR*, Forward Difference in Beta Returns and *RDBR*, Reverse Difference in Beta Returns using equation [6] and [7]:

$$FDBR_{w,i} = \beta'_{w,i}\overline{f}_{w} - \beta'_{w-1,i}\overline{f}_{w}, \qquad [6]$$

$$RDBR_{w,i} = \beta'_{w-1,i}\overline{f}_{w-1} - \beta'_{w,i}\overline{f}_{w-1}, \qquad [7]$$

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*, $\beta_{w-1,i}$ is the vector of factor loadings for fund *i* in window *w-1*, $\bar{f}_{w-1}$ is the vector of average factor returns in window *w-1*.

Generally, *FDBR* captures the profit realized through changing beta positions from the previous window to the current window and measures the relative success in relation to a 'change nothing' strategy. While *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. We then combine *FDBR* and *RDBR* into a normalized *DBR* using equation [8]:

$$DBR_{w,i} = \frac{1}{2}\frac{FDBR_{w,i} - \min_i\{FDBR_{w,i}\}}{\max_i\{FDBR_{w,i}\} - \min_i\{FDBR_{w,i}\}} + \frac{1}{2}\frac{RDBR_{w,i} - \min_i\{RDBR_{w,i}\}}{\max_i\{RDBR_{w,i}\} - \min_i\{RDBR_{w,i}\}}. \qquad [8]$$

Finally, we construct our measure of beta activity, *BA*, as an equally weighted average of two normalized variables, *SBS*, Scaled Beta Success and *DBR*, Difference in Beta Returns.

3.5 Hedge Fund Cloning

Once the market timing metrics and the overall beta activities are quantified, we utilize the cloning methodology proposed in Duanmu, Li, and Malakhov (2020) to replicate hedge fund returns with ETFs and to identify *non-cloneable* hedge funds with genuine managerial skill.

First, we employ the LASSO (least absolute shrinkage and selection operator) factor selection model proposed in Tibshirani (1996). For a given parameter *t*, LASSO regression identifies an optimal set of factors with nonzero coefficients such that:

$$\hat{\beta}_{Lasso} = \arg\min_{\beta} \|\mathbf{r} - \mathbf{X}\beta\|^2, \qquad [9]$$
$$\text{such that } \sum_{j=1}^{m} |\beta_j| \le t.$$

where $\mathbf{r}$ is the vector of hedge fund monthly returns in this paper and $\mathbf{X}$ is the vector of ETF monthly returns. Given a set of factors, LASSO selects the appropriate factors through an optimization approach. Specifically, for a given selection parameter *t*, the sum of absolute values of the beta coefficients is estimated and constrained to be smaller than the parameter *t*. If an explanatory variable reveals little information about the dependent variable, its corresponding beta coefficient will be set to zero. As a result, LASSO regression 'shrinks' the set of factors until the beta coefficients yield the solution of the optimization problem. The degree of 'shrinking' depends on the chosen value of selection parameter *t*, with lower *t* resulting in fewer factors selected. We estimate LASSO solutions across a range of *t* values by using a computationally efficient least angle regression (LAR) modification of the LASSO procedure introduced by Efron, Hastie, Johnstone and Tibshirani (2004). We then use the Bayesian Information Criterion (BIC) as the model selection criterion and select the model with the lowest BIC value.

While the large number of ETFs allows for spanning the space of risk factors, a potential concern is that multicollinearity among ETFs may distort the LASSO procedure, as many ETFs are closely correlated and may expose to similar risk factors.[25] In order to handle collinearity and select factors in a meaningful way, we follow DLM and conduct cluster analysis to reduce the number of ETF factors prior to running LASSO regressions. Specifically, we divide the ETFs into a number of clusters, and 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*:

$$SDI_i = 1 - corr(r_i, \mu_I),$$
$$\text{where } \mu_I = \frac{\sum_{i\in I} r_i}{count(i \in I)}. \qquad [10]$$

The lower the *SDI*, the closer the ETF is from the center of its cluster. We pick the ETF with the lowest *SDI* to proxy all the ETFs in the same cluster, and then include this ETF as a replicating factor in LASSO regression. This approach overcomes multicollinearity among ETFs and minimizes data-mining bias while using all ETFs available. Furthermore, when dividing ETFs into clusters, we follow DLM and assume that the number of clusters could range from 1 to 100, as the number of ETFs changes over time and the 'true' number of clusters is unobservable.[26] We run cluster analysis iteratively for 100 times (1-100) and use the corresponding number of ETFs (each selected ETF locates at the center of its cluster) in LASSO regressions. As a result, each fund has 100 corresponding models after a series of cluster analysis and LASSO regressions. The model with the highest adjusted R^2 is then chosen as the clone model.

The LASSO regression model is as follows:

$$r_{i,gross} - r_f = \beta_1(ETF_1 - r_f) + \beta_2(ETF_2 - r_f) + ... + \beta_{100}(ETF_{100} - r_f) + \varepsilon_i \qquad [11]$$

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. To be consistent with DLM, we use gross hedge fund returns and gross ETF returns, since the factor-driven hedge fund returns would be altered if we use net of fees returns, and the matched ETF risk profile may lead to biased risk exposure estimates.[27] Following a common practice in cloning literature, we suppress the regression intercept.[28] Moreover, we do not restrict beta coefficients to be positive or add up to one since hedge funds can use leverage and take short positions. To quantify the dynamic nature of hedge funds' investment activities, we run the LAR LASSO regression for every hedge fund over a two-year window, rolling annually over the sample period. We

[25] For example, there are multiple ETFs tracking the S&P 500 index.
[26] The maximum number is set to 100 since it represents a sufficiently large set of investment opportunities. Since there are fewer than 100 ETFs for the years before 2003, the maximum number of clusters is set to be the number of ETFs available in those years.
[27] Bloomberg provides only net returns for individual hedge funds (net of performance and management fees) and Morningstar provides net returns for ETFs (net of management fee). 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. Please see Appendix B for details on the gross return adjustments.
[28] See, for example, Hasanhodzic and Lo 2007.

use adjusted R^2 and BIC values from the LAR LASSO regressions to measure the 'overall quality' of the matching procedure. We interpret high adjusted R^2 and low BIC values as indicators of the methodology's success in capturing hedge fund risk factors, and thus the potential for cloning hedge fund returns with ETFs.

Next, to examine whether beta activity represents true managerial skill and whether beta active hedge funds could be replicated, we follow DLM to construct hedge fund clones using the selected ETF factors. For each hedge fund, we take the corresponding ETFs selected through the previous two-year window LASSO regression and their beta coefficients, and construct the hedge fund clone by loading selected ETFs with regression-determined weights:

$$CloneRet_{i,t} = r_{f,t} + \sum_{j=1}^{n} \beta_{j,t-1}(ETF_{j,t} - r_{f,t}), \qquad [12]$$

where $CloneRet_{i,t}$ is the hedge fund clone performance after the matching period, $\beta_{j,t-1}$ is the beta coefficient for ETF j selected from the previous two-year window LASSO regression. We rely on net-of-fees returns for both hedge funds and their ETF matches in out-of-sample analysis as we are interested in comparing future returns from the investors' perspective.

Overall, this cloning procedure allows us to identify *cloneable* and *non-cloneable* hedge funds, defined as the top and bottom in-sample adjusted R^2 matches. On the one hand, if a manager pursues algorithmic strategies highly correlated with risk factors, then we expect success in replicating such *cloneable* fund, as its performance would be driven mostly by factor risk exposures. On the one hand, if a hedge fund manager has the genuine skill and pursues a unique strategy, then we consider such fund as a *non-cloneable* fund which possesses active management skills.

3.6 Out-of-Sample Portfolio Analysis

Our analysis relies on out-of-sample portfolio tests for the following reasons. First, the portfolio approach allows for out-of-sample risk-adjusted performance evaluation of hedge funds and their replicating ETF portfolios over long periods of time. Second, it allows us to explore the impact of hedge fund survivorship bias on replicating ETF portfolios by either immediately rebalancing an ETF clone portfolio after a matched hedge fund disappears from the database, or leaving the ETF clone portfolio unchanged until January 1 of the next year.

Portfolios of *cloneable*, *non-cloneable*, and market timing hedge funds as well as their replicating ETF portfolios are initially formed on January 1, 2005 and rebalanced on January 1 of each subsequent year based on the results from re-estimations of replicating ETF regressions. The same dollar amount is invested in each hedge fund with each annual rebalancing, and returns net-of-fees are computed each month until the sample period ends on December 31, 2018.[29] When a hedge fund disappears, the remaining capital is redistributed equally among the surviving hedge funds in the portfolio. Moreover, when a hedge fund disappears, adjustments to the replicating ETF portfolio are made in the same way that investments in the replicating ETFs are liquidated and redistributed among the surviving ETFs.[30]

Over our sample period, the above procedure produces a time series of 168 monthly returns for hedge fund and replicating ETF portfolios, which is then used to evaluate long-term portfolio performance across diverse economic conditions including the most recent financial crisis of 2008-2009. We calculate end dollar values based upon a $1 initial investment, mean excess monthly returns, Sharpe ratios, Fung and Hsieh (2004) alphas,[31] information ratios, and attrition rates for each time series of monthly portfolio returns from January 2005 until December 2018.

[29] To reflect the possible delay in reporting, we introduce one-month lag and exclude the most recent December return in portfolio formation per Molyboga and L'Ahelec (2016) as a robustness check. The results are quantitatively similar and we decide not to report these results for brevity.
[30] The results may be subject to liquidation bias suggested by Ackermann et al. (1999) as for some of the terminated funds additional return activity may follow the final monthly performance figure recorded in the database. Adjustment for liquidation bias will negatively impact hedge fund portfolio return and favor ETF clone return though such impact might be negligible per Ackermann et al. (1999). Due to data limitation, we are not able to make proper adjustment for liquidation bias.
[31] See DLM for details on Fung and Hsieh (2004) alpha calculation.

4. Empirical Results

4.1 Can Market Timing Strategies be Replicated?

We start our analysis by examining the out-of-sample performance for portfolios of *cloneable* hedge funds and market timing hedge funds, as well as their replicating ETF portfolios.

Table 2 reports the out-of-sample performance over the period 2005 to 2018 for the following hedge fund and clone portfolios: *cloneable hedge funds*, namely, portfolio formed by funds in the top in-sample R^2 quartile of in-sample regressions of hedge fund returns on ETFs, and its corresponding replicating ETF portfolio; *HM hedge funds*, funds in the top Henriksson and Merton (1981) measure quartile, and its corresponding replicating portfolio; *CLT hedge funds*, funds are sorted into the top quartile of Chen and Liang (2007) joint timing measure, and its corresponding replicating portfolio; *LIQ hedge funds*, portfolio of funds in the top quartile of Cao et al. (2013) market liquidity measure, and its corresponding replicating portfolio; *Beta Active hedge funds*, portfolio constructed with funds in the top Duanmu et al. (2018) beta activity measure, and its corresponding replicating portfolio. We also report the performance of *Bloomberg peers* portfolio which includes all hedge funds in our sample. The performance measures include portfolio end value, mean monthly return, Sharpe ratio, alpha, and information ratio.

Consistent with Duanmu, Li, and Malakhov (2020), compared to *cloneable hedge funds*, the ETF clone portfolio delivers better out-of-sample absolute and risk-adjusted performance due to its preferable fee structure. The result confirms the overall efficacy of the DLM methodology in constructing ETF clones whose returns are not statistically significantly different from the returns on their associated hedge fund portfolios. In fact, the clone portfolio yields better performance than cloneable hedge funds.

For market timing activities, we find that hedge fund portfolios formed on selected market timing metrics outperform the Bloomberg peers in the context of raw returns, Sharpe ratio, Fung and Hsieh (2004) alpha and information ratio in most cases.[32] Among which, portfolio constructed based on Duanmu et al. (2018) yields the best out-of-sample performance with the highest Sharpe ratio of 0.19, information ratio of 0.16, and a significant out-of-sample monthly Fung and Hsieh (2004) alpha of 0.19%. The results suggest market timing strategies add value to hedge fund management and hence benefit hedge fund investors. For clone portfolios, we find that the performances are not as desirable as those of market timing hedge funds which they seek to replicate. Though in terms of raw returns, some clone portfolios deliver comparable results. For example, *LIQ* clone portfolio yields 0.34% monthly excess return compared with 0.35% for *LIQ hedge fund* portfolio. Overall, market timing hedge funds dominate its ETF clone portfolios in every aspect of risk-adjusted performance measures such as Sharpe ratio, information ratio, and Fung and Hsieh (2004) alpha. This result indicates that hedge funds with successful market timing might not be replicated by simply matching their risk factor exposures.

4.2 Cloning Market Timing Hedge Funds based on Hedge Fund Styles

It is natural to argue that hedge fund styles play impactful roles in both hedge fund return replication and hedge fund market timing strategies. The replication quality as well as the market timing efficacy might vary across different hedge fund styles. We then repeat our analysis on subsets of hedge fund samples classified by hedge fund styles to study how styles impact our results. In order to get a meaningful number of hedge funds in each style, we follow Agarwal, Daniel, and Naik (2009) and reclassify the hedge funds into four consolidated categories: Directional Traders, Relative Value, Security Selection, and Multiprocess. We compare the performance of the market timing hedge fund portfolio and the clone portfolio in each of the four consolidated styles and report the results in Table 3.

We find that market timing metrics are stronger indicators of superior performance among Directional Traders and Multiprocess hedge funds. For example, the best performing HM and CLT hedge funds are Multiprocess hedge funds and Directional Traders, the top performing LIQ and DMM portfolios are Multiprocess hedge funds with the later records the highest Sharpe ratio and information ratio among all sub-portfolios. However, for these successful market timers, the clone portfolios again fail to match the performances. The finding is consistent with our expectation as

[32] Though hedge fund portfolio formed on HM has slightly lower Sharpe ratio and information ratio than those of the Bloomberg peers.

Directional Traders and Multiprocess hedge funds tend to make timely shifts among risk factor exposures based upon the directional change of capital assets returns and such timely shifts might be viewed as true managerial skills which cannot be replicated by ETF clone portfolios.

Though for Relative Value and Security Selection style market timing hedge funds, the performance between hedge fund portfolio and their clones are comparable. In most cases, clone portfolios deliver better performance than that of the hedge fund portfolios. Unfortunately, this in fact would not benefit investors as Relative Value and Security Selection market timing hedge funds themselves are not generating satisfying performances.

4.3 Market Timing Strategies and Managerial Skills

Prior results suggest the irreplicability of market timing strategies taken by top market timing hedge funds. However, it is reasonable to argue that some of the market timing hedge funds might be cloneable while others are just unclonable. Duanmu, Li, and Malakhov (2020) claim that their methodology provides convincing results among cloneable hedge funds. We then move further and identify the subset of hedge funds that are both successful market timers and cloneable. In other words, we now consider a portfolio that is an intersection of the *cloneable* and the top *HM, CLT, LIQ, and DMM* portfolios. For example, the *Cloneable HM Hedge Funds* is a portfolio of *funds that rank in the t*op quartile of HM measure and are also in the top in-sample R^2 quartile of LASSO regressions of hedge fund returns on ETFs. On the other hand, to further evaluate whether the market timing ability represents irreplicable managerial skills, we also examine the performance of market timing portfolios sorted by selected market timing metrics to the exclusion of high in-sample R^2 funds. For example, the *Non-Cloneable HM Hedge Funds* is a portfolio of funds in the top quartile of HM excluding any funds that are also in the top quarter of in-sample $R^2$of LASSO matching regressions. This resulting portfolio allows us to examine the performance of top HM hedge funds whose returns cannot be replicated.

The results for *cloneable* hedge funds, *non-cloneable* hedge funds, and their corresponding ETF clone portfolios are presented in Table 4. We confirm that the market timing success represents managerial skills that cannot be replicated except for LIQ hedge funds. For example, *cloneable beta active hedge funds* yield a Sharpe ratio of 0.08, an information ratio of -0.07, a statistically insignificant excess return of 0.26%, and -0.12% monthly alpha. The corresponding clone portfolio generates quantitatively similar results. Meanwhile, *non-cloneable beta active hedge funds* produce a Sharpe ratio of 0.20, an information ratio of 0.19, an excess return of 0.33%, and 0.21% monthly alpha which are both statistically significant at 5% or above. Its corresponding clone portfolio fails to replicate the performance. The results imply that the success of beta active market timing strategy is driven by beta active hedge funds which cannot be cloned. We thus conclude this as evidence of irreplicable managerial skill. The result for LIQ hedge funds is mixed. Both *cloneable LIQ hedge funds* and *non-clonebale hedge funds* have similar Sharpe ratio and monthly alpha. Cloneable LIQ hedge funds record higher raw returns but lower information ratio. Moreover, consistent with Duanmu, Li, and Malakhov (2020), we find better replication results when replicating the performance of *cloneable* market timing hedge funds, while the clones generally fail to match the performances for *non-cloneable* market timing hedge funds.

Overall, we interpret the results as true market timing ability being irreplicable managerial skills and such managerial skills eventually add value to investors. The *non-cloneable* market timing hedge funds are the driving factors behind the successful market timing strategies. Hedge fund managers with genuine market timing skills take positions considering a wide range of possible macroeconomic scenarios. Their timely and dynamic shift across different risk factors in anticipation of changing economic conditions and opportunity sets may not be captured by statically matching the risk factor exposures of hedge funds. On the other hand, even though some hedge funds are identified as top market timing hedge funds, their returns might be replicated by using ETFs and their performance is not statistically different from that of the ETF clones. These *cloneable* market timing funds may pursue algorithmic strategies highly correlated with latent risk factors and their returns mostly reflect exposures to these risk factors. Therefore, the findings suggest that our cloning methodology is valuable in identifying market timing hedge funds that possess the genuine ability and pursues truly unique investment strategies uncorrelated with identifiable risk factors.

5. Conclusion

In this paper, we examine if the success of hedge fund market timing strategies can be replicated. We use four extant market timing measures, Henriksson and Merton (1981) measure, Chen and Liang (2007) joint return and volatility measure, Cao et al. (2013) market liquidity measure, and Duanmu, Malakhov, and McCumber (2018) beta activity measure to identify successful market timing hedge funds. Following Duanmu, Li, and Malakhov (2020), we develop a methodology for creating a portfolio of ETFs to capture risk factor exposures of market timing hedge funds. We find that the success of market timing strategies cannot be replicated by taking specific risk factor exposures. In fact, we provide evidence that the success of market timing strategies is driven by non-cloneable hedge funds that possess true managerial skills. Our methodology provides useful structural framework and straightforward methodology which allow investors to identify genuine irreplicable managerial skills.

Appendix A: Variable Descriptions for Modified Fung and Hsieh (2004) Model

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 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 10-year U.S. Treasury bond portfolio monthly return from the Center for Research in Security Prices (CRSP), minus the risk-free rate.

SizeSpread is the Russell 2000 Index return minus the S&P 500 Index return.

CreditSpread is 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.

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. Trend factors are collected from David Hsieh's website.[33]

Appendix B: Gross Returns Adjustments for ETFs And Hedge Funds

Given that Bloomberg provides only net returns for individual hedge funds (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 LASSO 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:

$$Gross\_ETF_{i,t} = Net\_ETF_{i,t} + \frac{Management\_Fee_{i,t}}{12}, \qquad \text{(B1)}$$

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.

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

We employ 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 the monthly return of the 30-day U.S. Treasury bill as the hurdle rate, collecting the Treasury bill returns from January 1997 to December 2018 from the Center for Research in Security Prices. We use the following equation to calculate the gross hedge fund returns:[34]

$$Gross\_Ret_{i,t} = \begin{cases} Net\_Ret_{i,t} + \frac{Management\_Fee_{i,t}}{12}, & if\ Net\_Ret_{i,t} \leq TBill_t \\ \frac{Net\_Ret_{i,t} - TBill_t \times Performance\_Fee_{i,t}}{1 - Performance\_Fee_{i,t}} + \frac{Management\_Fee_{i,t}}{12}, & otherwise \end{cases} \quad \text{(B2)}$$

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 C: Hedge Fund Styles Consolidation

We examine the efficacy of our methodology across broad hedge fund styles, as it is plausible for investment styles of hedge fund managers to play a role in determining how successful the cloning and market timing methodologies would be for individual funds. In our sample, we have 28 unique hedge styles with the number of hedge funds under each distinction varying dramatically across styles. In order to carry a meaningful analysis of the styles and cloning and market timing success, we follow Agarwal, Daniel, and Naik (2009) and reclassify the hedge funds into four consolidated categories: Directional Traders, Relative Value, Security Selection and Multiprocess.[35] The mapping process is reported in Appendix Table C.

[34] 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 or complete data on assets under management for every hedge fund. Our adjustment is consistent with the adjustment formula (B2) in Agarwal, Daniel and Naik (2009), with the exception that we also adjust for management fees. Our approximation addresses only the biggest source of nonlinearity of hedge fund fees and returns, created by hedge funds charging the performance fee once hedge fund returns exceed a hurdle rate. We believe that our approach is justified by our success in replicating hedge performance out of sample.

[35] Hedge funds that fall into "Undisclosed" style are not included in the style analysis.

Table Appendix C: Hedge Fund Style Mapping

This table reports the mapping between the four consolidated styles (Directional Traders, Relative Value, Security Selection and Multiprocess) in Agarwal, Daniel and Naik (2009) and the original hedge fund styles in our sample. Hedge funds that fall into "Undisclosed" style are not included in the style analysis.

Original Hedge Fund Style	Consolidated Style
Currency	Directional Traders
Discretionary	Directional Traders
Discretionary Thematic	Directional Traders
Emerging Market	Directional Traders
Emerging Market Debt	Directional Traders
Macro Diversified	Directional Traders
Short Biased	Directional Traders
Systematic	Directional Traders
Systematic Diversified	Directional Traders
Activist	Multiprocess
Distressed Securities	Multiprocess
Event Driven Diversified	Multiprocess
Fixed Income Diversified	Multiprocess
Multi Strategy	Multiprocess
Special Situation	Multiprocess
Asset-Backed Securities	Relative Value
Cap Structure/Credit Arbitrage	Relative Value
Convertible Arbitrage	Relative Value
Fixed Income Arbitrage	Relative Value
Market Neutral	Relative Value
Merger Arbitrage	Relative Value
Mortgage-Backed	Relative Value
Statistical Arbitrage	Relative Value
Equity Hedge Diversified	Security Selection
Long Biased	Security Selection
Long-Short	Security Selection

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Figure 1: Number of ETFs Available, 1997-2018

Number of ETFs available each year from 1997 to 2018 is reported. ETF data is collected from Morningstar.

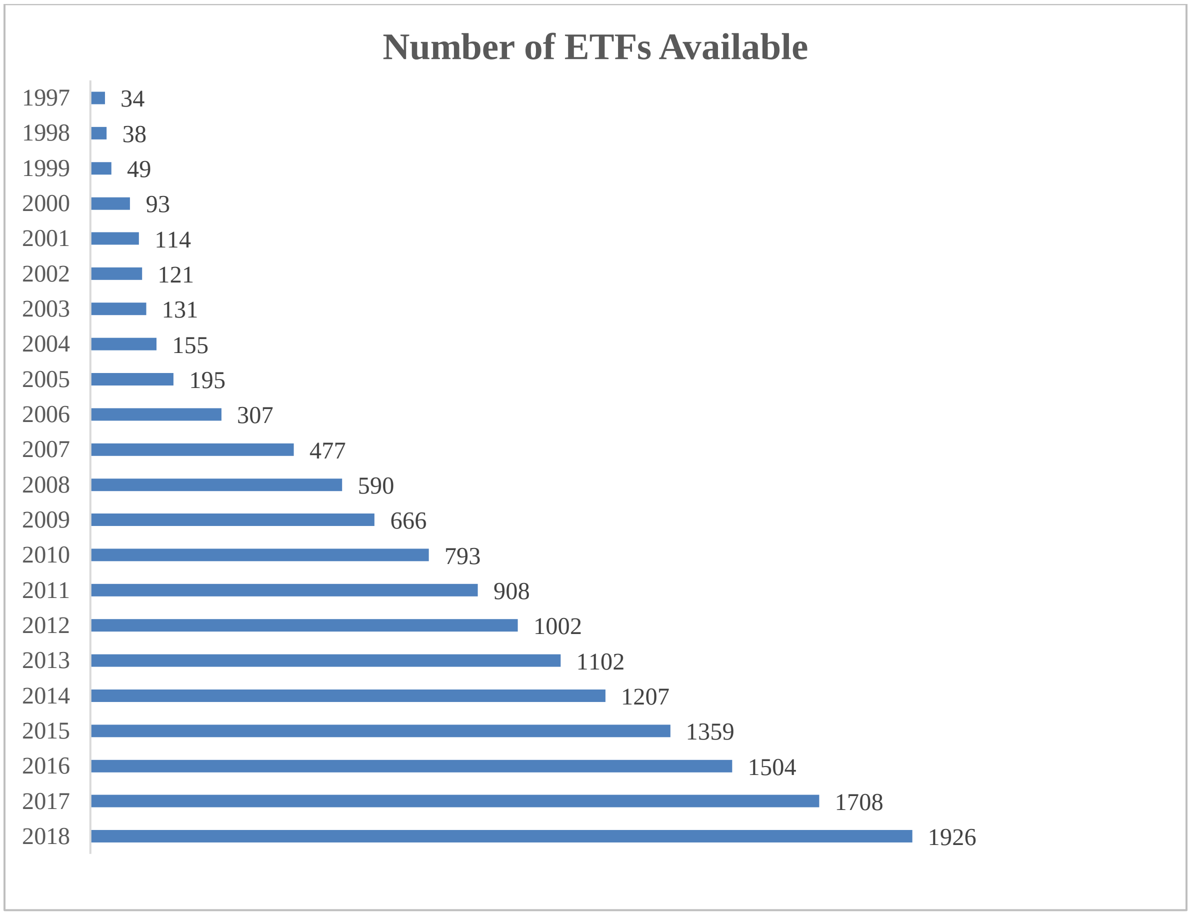

Figure 2: Number of ETFs Used

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

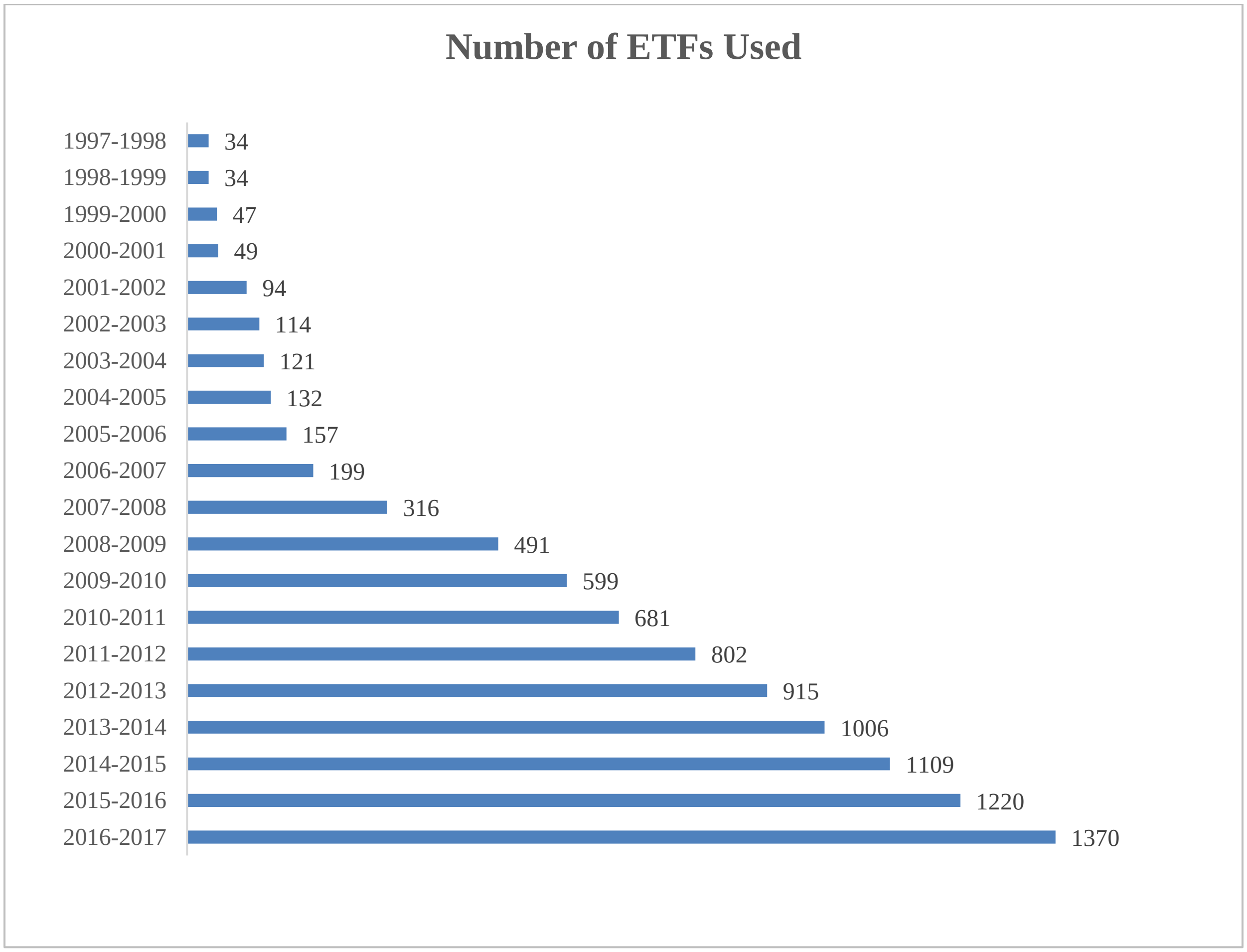

Table 1: Summary Statistics

Summary statistics of all hedge funds 1994-2018. Panel A reports returns, fees, investor liquidity measures, and fund longevity. Panel B reports means of indicator variables for fund characteristics. Panel C reports aggregated fund styles.

Panel A	Full Sample (5,523 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly excess return	0.57	0.56	0.00	1.18	0.61
Assets ($M)	340.85	78.60	8.86	559.48	2,345.75
Min Invest ($M)	1.44	0.25	0.03	1	13.02
Mgmt. Fee (%)	1.50	1.5	0.85	2	0.64
Perf Fee (%)	17.39	20	1	20	6.82
Hurdle Rate (%)	0.32	0	0	0	1.59
Lockup Period (days)	83.68	0	0	360	205.69
Redemption Notice (days)	18.66	0	0	60	30.45
Redemption Period (days)	55.11	30	30	90	55.66
Total Redemption (days)	74.70	60	30	150	68.69
Longevity (months)	130.80	118	82	199	48.44

	Active Funds (2,087 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly excess return	0.59	0.58	0.06	1.14	0.53
Assets ($M)	509.96	117.95	12.62	802.14	3,100.84
Min Invest ($M)	1.53	0.25	0.025	2	7.26
Mgmt. Fee (%)	1.45	1.5	0.75	2	0.61
Perf Fee (%)	17.03	20	5	20	6.74
Hurdle Rate (%)	0.38	0	0	0	1.61
Lockup Period (days)	78.32	0	0	360	189.95
Redemption Notice (days)	26.86	10	0	90	35.01
Redemption Period (days)	54.07	30	30	90	55.66
Total Redemption (days)	82.65	60	30	180	74.43
Longevity (months)	144.38	132	82	228	56.02

	Inactive Funds (3,436 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly excess return	0.56	0.54	-0.02	1.21	0.66
Assets ($M)	239.86	64.51	7.43	430.58	1,738.27
Min Invest ($M)	1.38	0.25	0.025	1	15.47
Mgmt. Fee (%)	1.52	1.5	0.96	2	0.66
Perf Fee (%)	17.60	20	0	20	6.86
Hurdle Rate (%)	0.29	0	0	0	1.57
Lockup Period (days)	86.75	0	0	360	214.16
Redemption Notice (days)	13.68	0	0	45	26.08
Redemption Period (days)	55.73	30	30	90	55.65
Total Redemption (days)	69.97	45	30	135	64.59
Longevity (months)	122.55	112	82	178	41.06

Table 1 cont.: Summary Statistics

Panel B - Indicator	% of Funds		
	Full Sample	Active Funds	Inactive Funds
High Water Mark	0.85	0.84	0.85
Hurdle Rate	0.05	0.06	0.04
Offshore (non-US)	0.32	0.34	0.30
Closed to New Inv	0.06	0.06	0.06
Liquidated	0.33	0.00	0.53
Acquired	0.02	0.00	0.04

Panel C - Fund Styles	% of Funds		
	Full Sample	Active Funds	Inactive Funds
Relative Value	0.16	0.14	0.17
Directional Traders	0.24	0.22	0.26
Security Selection	0.37	0.41	0.34
Multiprocess	0.21	0.23	0.20
Undisclosed	0.02	0.00	0.03

Table 2: Replicating Returns of Cloneable Hedge Funds, Top Market Timing Hedge Funds, and Bloomberg Peers Hedge Funds

This table summarizes the comparisons between hedge fund portfolio and its clone for Cloneable Hedge Funds (DLM), Top HM Market Timing Hedge Funds, Top CLT Joint Timing Hedge Funds, Top LIQ Liquidity Timing Hedge Funds, Top Beta Active Hedge Funds (DMM), and Bloomberg Peers Hedge Funds. Annual returns and cumulative risk-adjusted performances of each hedge fund portfolio and its clone are reported. Portfolios of hedge funds and clones are formed on January 1, 2005, and rebalanced annually. End value is as of December 31, 2018. Attrition rate is the average annual rate at which hedge funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio hedge funds. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

	End Value	Mean Return (t-stat)	Sharpe Ratio	α (t-stat)	Information Ratio	Mean In-Sample R^2	Attrition Rate
Cloneable Hedge Funds, Top Quartile of In-Sample R^2:							
Hedge Fund Portfolio	1.89	0.34 (1.29)	0.10	-0.03 (-0.30)	-0.02	0.84	10.51%
Clone Portfolio	2.29	0.47 (1.59)	0.12	0.01 (0.07)	0.01		
HM Hedge Funds, Top Quartile of Henriksson and Merton (1981) Measure:							
Hedge Fund Portfolio	1.84	0.29 (1.57)	0.12	0.11 (0.93)	0.08	0.53	11.91%
Clone Portfolio	1.58	0.21 (1.00)	0.08	-0.04 (-0.34)	-0.03		
CLT Hedge Funds, Top Quartile of Chen and Liang (2007) Timing Measure:							
Hedge Fund Portfolio	1.90	0.31 (1.65)	0.13	0.14 (1.09)	0.09	0.53	12.81%
Clone Portfolio	1.60	0.22 (1.03)	0.08	-0.03 (-0.29)	-0.02		
LIQ Hedge Funds, Top Quartile of Cao et al. (2013) Liquidity Timing Measure:							
Hedge Fund Portfolio	2.01	0.35* (1.70)	0.13	0.13 (1.30)	0.11	0.54	11.85%
Clone Portfolio	1.94	0.34 (1.55)	0.12	0.01 (0.19)	0.01		
Beta Active Hedge Funds, Top Quartile of Duanmu et. Al. (2018) Measure:							
Hedge Fund Portfolio	2.10	0.36** (2.41)	0.19	0.19* (1.92)	0.16	0.47	12.63%
Clone Portfolio	1.76	0.26* (1.78)	0.14	0.03 (0.44)	0.04		
Bloomberg Peers:							
Hedge Fund Portfolio	1.82	0.28* (1.75)	0.13	0.08 (1.13)	0.09	0.53	11.91%
Clone Portfolio	1.77	0.26 (1.59)	0.12	0.02 (0.35)	0.03		

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Table 3: Replicating Hedge Fund Returns Based on Styles

This table summarizes the comparisons between hedge fund portfolio and its clone for market timing hedge funds including the Top HM Market Timing Hedge Funds (Panel A), Top CLT Joint Timing Hedge Funds (Panel B), Top LIQ Liquidity Timing Hedge Funds (Panel C), and Top Beta Active Hedge Funds (Panel D). Each type of market timing hedge funds is reclassified into four consolidated categories as proposed in Agarwal, Daniel and Naik (2009): Directional Traders, Relative Value, Security Selection and Multiprocess. Annual returns and cumulative risk-adjusted performances of each hedge fund portfolio and its clone are reported. Portfolios of hedge funds and clones are formed on January 1, 2005, and rebalanced annually. End value is as of December 31, 2018. Attrition rate is the average annual rate at which hedge funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio hedge funds. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Panel A - HM Market Timing Hedge Funds

	End Value	Mean Return (t-stat)	Sharpe Ratio	α (t-stat)	Information Ratio	Attrition Rate	Mean Portfolio Size	Mean In-Sample R^2
Directional Traders Style:								
Hedge Fund Portfolio	1.48	0.20 (0.71)	0.05	-0.00 (-0.01)	-0.00	10.96%	28.79	0.79
Clone Portfolio	1.10	0.10 (0.25)	0.02	-0.39* (-1.72)	-0.15			
MultiProcess Style:								
Hedge Fund Portfolio	2.29	0.48 (1.50)	0.12	0.77 (0.12)	0.06	11.86%	22.71	0.81
Clone Portfolio	2.37	0.50 (1.59)	0.12	0.04 (0.32)	0.03			
Relative Value Style:								
Hedge Fund Portfolio	1.34	0.12 (0.52)	0.04	-0.22 (-1.50)	-0.13	16.15%	20.00	0.74
Clone Portfolio	1.68	0.26 (1.08)	0.08	-0.10 (-0.93)	-0.07			
Security Selection Style:								
Hedge Fund Portfolio	2.12	0.44 (1.32)	0.10	-0.00 (-0.01)	-0.00	7.20%	42.57	0.87
Clone Portfolio	2.43	0.57 (1.40)	0.11	-0.05 (-0.37)	-0.03			

Table 3 cont.: Replicating Hedge Fund Returns Based on Styles

Panel B - CLT Joint Timing Hedge Funds

	End Value	Mean Return (t-stat)	Sharpe Ratio	α (t-stat)	Information Ratio	Attrition Rate	Mean Portfolio Size	Mean In-Sample R^2
Directional Traders Style:								
Hedge Fund Portfolio	2.25	0.46 (1.55)	0.12	0.29 (1.34)	0.11	11.60%	28.14	0.79
Clone Portfolio	1.18	0.14 (0.34)	0.03	-0.28 (-1.35)	-0.11			
MultiProcess Style:								
Hedge Fund Portfolio	2.16	0.44 (1.44)	0.11	0.10 (0.62)	0.05	13.76%	23.21	0.81
Clone Portfolio	2.34	0.48 (1.61)	0.12	0.04 (0.36)	0.03			
Relative Value Style:								
Hedge Fund Portfolio	1.20	0.06 (0.24)	0.02	-0.28** (-1.98)	-0.17	14.91%	21.43	0.74
Clone Portfolio	1.64	0.25 (0.99)	0.08	-0.14 (-1.31)	-0.10			
Security Selection Style:								
Hedge Fund Portfolio	1.82	0.36 (1.04)	0.08	-0.08 (-0.53)	-0.04	9.48%	41.43	0.87
Clone Portfolio	2.06	0.48 (1.16)	0.09	-0.11 (-0.66)	-0.05			

Table 3 cont.: Replicating Hedge Fund Returns Based on Styles

Panel C - LIQ Liquidity Timing Hedge Funds

	End Value	Mean Return (t-stat)	Sharpe Ratio	α (t-stat)	Information Ratio	Attrition Rate	Mean Portfolio Size	Mean In-Sample R^2
Directional Traders Style:								
Hedge Fund Portfolio	2.41	0.52 (1.56)	0.12	0.22 (1.08)	0.09	11.65%	27.79	0.80
Clone Portfolio	1.96	0.42 (1.14)	0.09	-0.04 (-0.22)	-0.02			
MultiProcess Style:								
Hedge Fund Portfolio	2.66	0.55* (1.95)	0.15	0.23 (1.41)	0.12	10.46%	20.21	0.81
Clone Portfolio	2.50	0.52* (1.73)	0.13	0.07 (0.50)	0.04			
Relative Value Style:								
Hedge Fund Portfolio	1.79	0.28 (1.36)	0.11	0.05 (0.42)	0.04	11.24%	17.21	0.74
Clone Portfolio	2.14	0.41 (1.64)	0.13	-0.01 (-0.11)	-0.01			
Security Selection Style:								
Hedge Fund Portfolio	2.16	0.45 (1.36)	0.10	0.05 (0.35)	0.03	9.09%	39.00	0.87
Clone Portfolio	2.38	0.54 (1.31)	0.11	0.02 (0.11)	0.01			

Table 3 cont.: Replicating Hedge Fund Returns Based on Styles

Panel D - Beta Active Hedge Funds

	End Value	Mean Return (t-stat)	Sharpe Ratio	α (t-stat)	Information Ratio	Attrition Rate	Mean Portfolio Size	Mean In-Sample R^2
Directional Traders Style:								
Hedge Fund Portfolio	3.15	0.69* (1.92)	0.15	0.37 (1.14)	0.09	11.51%	16.07	0.78
Clone Portfolio	2.06	0.41 (1.36)	0.10	0.12 (0.50)	0.05			
MultiProcess Style:								
Hedge Fund Portfolio	2.27	0.54** (2.08)	0.16	0.26 (1.55)	0.14	8.80%	19.50	0.81
Clone Portfolio	1.87	0.41 (1.57)	0.12	0.00 (0.03)	0.00			
Relative Value Style:								
Hedge Fund Portfolio	1.63	0.23 (1.14)	0.09	-0.02 (-0.12)	-0.01	17.63%	12.07	0.74
Clone Portfolio	1.73	0.27 (1.18)	0.09	-0.12 (-0.73)	-0.06			
Security Selection Style:								
Hedge Fund Portfolio	1.39	0.18 (0.57)	0.04	-0.31 (-1.44)	-0.12	10.43%	29.29	0.87
Clone Portfolio	2.10	0.44 (1.28)	0.10	-0.15 (-0.80)	-0.06			

Table 4: Comparisons of Cloneable and Non-cloneable Hedge Funds within Each Market Timing Hedge Fund Portfolio

This table presents the comparisons between cloneable hedge funds and non-cloneable hedge funds with each market timing hedge fund portfolio. Market timing hedge funds include HM Market Timing Hedge Funds, CLT Joint Timing Hedge Funds, LIQ Liquidity Timing Hedge Funds, and Beta Active Hedge Funds (DMM). Annual returns and cumulative risk-adjusted performances of each hedge fund portfolio and its clone are reported. Portfolios of hedge funds and clones are formed on January 1, 2005, and rebalanced annually. End value is as of December 31, 2018. Attrition rate is the average annual rate at which hedge funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio hedge funds. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

	End Value	Mean Return (t-stat)	Sharpe Ratio	α (t-stat)	Information Ratio	Mean In-Sample R^2	Attrition Rate
Cloneable HM Hedge Funds:							
Hedge Fund Portfolio	2.20	0.45 (1.47)	0.11	0.06 (0.43)	0.03	0.83	9.67%
Clone Portfolio	2.28	0.51 (1.37)	0.11	-0.03 (-0.28)	-0.02		
Non-Cloneable HM Hedge Funds:							
Hedge Fund Portfolio	1.81	0.28* (1.72)	0.13	0.16 (1.28)	0.11	0.43	12.69%
Clone Portfolio	1.46	0.15 (0.89)	0.07	-0.02 (-0.20)	-0.02		
Cloneable CLT Hedge Funds:							
Hedge Fund Portfolio	2.10	0.42 (1.38)	0.11	0.05 (0.34)	0.03	0.83	11.05%
Clone Portfolio	2.14	0.48 (1.27)	0.10	-0.04 (-0.28)	-0.02		
Non-Cloneable CLT Hedge Funds:							
Hedge Fund Portfolio	1.82	0.28* (1.70)	0.13	0.16 (1.29)	0.11	0.43	13.39%
Clone Portfolio	1.44	0.14 (0.84)	0.06	-0.02 (-0.23)	-0.02		
Cloneable LIQ Hedge Funds:							
Hedge Fund Portfolio	2.28	0.47 (1.56)	0.12	0.11 (0.83)	0.07	0.83	10.25%
Clone Portfolio	2.27	0.50 (1.40)	0.11	-0.00 (-0.01)	-0.00		
Non-Cloneable LIQ Hedge Funds:							
Hedge Fund Portfolio	1.83	0.29 (1.61)	0.12	0.11 (1.23)	0.10	0.44	12.24%
Clone Portfolio	1.74	0.26 (1.48)	0.11	-0.00 (-0.01)	-0.00		
Cloneable Beta Active Hedge Funds							
Hedge Fund Portfolio	1.66	0.26 (1.01)	0.08	-0.12 (-0.85)	-0.07	0.83	12.11%
Clone Portfolio	2.03	0.39 (1.37)	0.11	-0.08 (-0.58)	-0.05		
Non-Cloneable Beta Active Hedge Funds:							
Hedge Fund Portfolio	2.01	0.33*** (2.60)	0.20	0.21** (2.30)	0.19	0.39	12.90%
Clone Portfolio	1.62	0.20* (1.80)	0.14	0.05 (0.82)	0.07		