

**HEDGE FUND REPLICATION STRATEGIES:
THE GLOBAL MACRO CASE**

by

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Abstract

This paper performs and analyzes hedge fund replication strategies using liquid exchange-traded instruments to build linear multi-factor models (“clones”) that mimic Hedge Funds returns. First, we follow Hasanhodzic and Lo (2006) six-factor model, using Barclay Hedge Indexes monthly returns for the period of January 1997 to August 2017 on seventeen hedge fund strategies. Next, we introduce variations and new propositions to the model in order to obtain closer risk-return characteristics, focusing on one particular hedge fund strategy: Global Macro. Finally, we use these results to base our conclusion and propose applications for this method.

Our findings promote the use of shorter month period in rolling-windows approach and monthly rebalancing strategy for a faster reaction and adaptation to market conditions. Also, it suggests the addition of a strategic-specific factor to obtain better expected-return replications. These findings are particularly relevant to institutional investors that need diversification and could benefit from this asset class exposure, but many times are restricted from investing in hedge funds due to their high fee structure, illiquidity, and opaque tactics.

Keywords: Replication Strategies; Multi-Factor Models; Hedge Funds Clones; Global Macro Strategy and Linear Regression.

Dedication

I would like to dedicate my thesis to my family, who has supported me for both completing the program and living in Canada. I would also like to dedicate my thesis to many friends, who have supported me throughout the MSc program.

Veronica Zhang

I would like to dedicate this work to my husband, Bernardo Miranda, for his patience, impermissible support, and inspiration. I would also like to thank my parents, Pedro and Nizzi Ferreira, for their unconditional support and guidance.

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1. Introduction

Since the critical turning point of the subprime crisis on March 6th of 2009, when S&P 500 Index hit its rock-bottom low at 666.8, US stocks are undergoing one of the longest bull markets in history. The average bull market lasts roughly five years¹, but this current run is close to completing its ninth year. In a successful attempt to remedy the economic turmoil and bring the economy back to a growth track, the FED quantitative easing program flooded the markets with cheap speculative money and compressed spreads to historically low figures. These factors combined created a particularly challenging equity market, pushing equity active management strategies to an out of favor lasting phase.

The combination of low-interest rates and the population ageing phenomenon created a big demand for high yield products and pressured big institutional investors, specifically pension plans portfolios, to expand their equities exposure and embrace alternative investments as desirable asset classes. Although private investment classes such as Real Estate, Private Equity, and Infrastructure Equity are becoming increasingly common and gaining market share of pensions' portfolios, hedge funds absolute return strategies have effectively lost market share in these portfolios.

For the last decade the hedge fund industry failed to generate excess market returns despite its expensive fee structure, typically two percent management fee² and twenty percent performance fees³. Also, because of the lack of transparency and

¹ October 16, 2017, "Bull Market Conditions Driving Flows to Passive." MFS Investment Management, US Equity Blog.

² Calculated over the amount under management (AUM).

³ Performance fee is calculated by: $\{(Fund\ return - Fund\ Benchmark) * 20\% * AUM\}$

regulation on these instruments many renowned investors and finance academics insist that alpha⁴ at the levels hedge funds claimed is a myth.

A robust replication strategy⁵ could be the answer for those institutional investors that search for an additional low correlation asset-class without forswear transparency and liquidity. Additionally, in recent years, passive managers have launched thousands of new products in response to the inflow of investor capital. In the United States, there are now more indices tracking various asset classes than there are publicly traded stocks. This creates an extra incentive for replication strategies as they are now cheaper and more feasible.

Due to their complex risk exposures, hedge fund returns yield complementary sources of risk premium to a portfolio and are considered a desirable low-correlation asset-class. Hasanhodzic and Lo (2006) brought the idea of using a multi-factor model to regress 1610 hedge funds' returns on selected risk factors and determine the explanatory power of common risk factors for hedge funds components. This paper applies the intuition of this study on a data set of Barclay Hedge⁶ Indices extending from January of 1997 to August of 2017. We start with the construction of fixed-weight and rolling-windows clones with the same factor-model specification used by Hasanhodzic and Lo (2006) in our data sample.

Moreover, we focused on the Global Macro strategy for two main reasons, first because of its outstanding performance during the 2008 crisis and second because of the

⁴ Alpha represents the value that a portfolio manager adds to or subtracts from a fund's return. In other words, alpha is the return on an investment that is not a result of general movement in the greater market (Source: Investopedia).

⁵ A strategy that copy a hedge fund, or a hedge fund index, risk-return characteristics.

⁶ Barclay Hedge (<https://www.barclayhedge.com/about.html>)

myth and frenzy behind this segment that has among its practitioners' all-time market celebrities such as George Soros and Ray Dalio.

Our findings advocate for a 12-month rolling-windows approach, shorter than the 24-months rolling-windows from Hasanhodzic and Lo (2006), data input and a monthly rebalance strategy for a faster reaction and adaptation to market conditions, diverging from the fixed-weight preference in Hasanhodzic and Lo (2006). Also, it suggests the addition of a strategic-specific factor to obtain better expected-return replications, in the case of Global Macro we found this factor to be the Emerging Market Credit Spread. Our results also show a big difference in the replications behavior before and after the subprime crisis turning point, with the later period favoring our enhanced replication strategy that is able to outperform the index while maintaining a lower volatility compared to Global Macro Index.

2. Literature Review

2.1 Linear Factor Model

Linear multi-factor models have been key techniques in the study of the mutual and hedge fund returns⁷. The original capital asset pricing model (CAPM) introduced by Sharpe (1964) used a single factor model (represented as β) to calculate the expected return of a given asset by identifying its risk related to the market (r_m).

$$\bar{R}_i = r_f + \beta(r_m - r_f), \text{ where } r_f \text{ is the risk free return}$$

Sharpe (1992) used an asset-class factor model to implement style analysis that allowed for investors to achieve their investment goals in a cost-effective manner. In such factor model as shown below, each factor \bar{F}_{ti} represents the returns on an asset class, and the sensitivities of the factor, which is b_{in} , are required to sum to 1.

$$\bar{R}_i = [b_{i1} \bar{F}_1 + b_{i2} \bar{F}_2 + \dots + b_{in} \bar{F}_n] + \bar{e}$$

Later Fama & French (1993) model went one step further by adding two extra factors to the original Sharpe equation: SMB (small minus large) and HML (high minus low book to market ratios) factors. In the same year, Jagadeesh & Titman (1993) presented an additional factor: the momentum factor, a portfolio that is long in past winners and short in past losers at equivalent dollar-amount (zero net-value portfolio). Next, Carhart (1997) used a combination of these works and published a paper with a four-factor model.

2.2 Linear Regression Application on Hedge Funds Clone Strategy

In Hasanhodzic and Lo (2006), the paper used monthly returns data from 1610 individual hedge funds in the TASS database, with returns dating from 1986 to 2005, to

⁷ Dimitrios Stafylas (2017)

estimate strategy clones using liquid tradable instruments. The returns were decomposed using a six-factors (tradable assets represented as β) linear regressions models and the output provided estimated betas β^* , that were then used as proxy-weights to build a clone-portfolio that should replicate the original returns of that particular fund. The beta estimations determined by these linear regressions from individual funds were then grouped into 13 different hedge fund strategies and used as asset-classes weights to compose one clone portfolio for each strategy. This implementation was done both in fixed-weight and in rolling-windows data approach.

For rolling-windows, Hasanhodzic and Lo (2006) used 24-months for each month t from $t-24$ to $t-1$ to estimate monthly beta coefficients. In this study, it is stated that although the fixed-weighted method reduces rebalancing efforts to zero, it has the drawback of a look-ahead bias⁸. On the other hand, the rolling-windows method had a credible practical application using only previous months' information, but it had possibly costly rebalancing needs. In both cases, on average the clones' performance was well below that of the actual hedge funds.

According to Amenc, Martellini, Meyfredi & Ziemann (2010), due to the difficulty of selecting representative factors and conducting robust replications with respect to these factors, using non-linear models does not necessarily enhance the replication accuracy. Also, this later study confirmed the initial findings of Hasanhodzic and Lo (2006) that the linear model replication results on average in underperforming clones.

⁸ When you use current data to estimate something in the past, you incur a look-ahead bias, a bias created using information or data in a study or simulation that would not have been known or available during the period being analyzed. This will usually lead to inaccurate results in the study or simulation.

Given the data limitation, we were only able to access to index data and not individual funds data, and the flexibility of the hedge funds' strategies, there is no single "best-fit" model that would best mimic the hedge fund returns. The latest study on the replication of the hedge fund returns done by Michael S. O'Doherty (2017) applied a decision-theoretic⁹ framework and used hedge fund indexes rather than individual hedge funds' returns, which intends to determine the optimal combination of factor models.

Based on the empirical findings of Dimitrios Giannikis (2011), different risk factors affect the returns of different hedge fund indices, and there are different asymmetric/nonlinear risk exposures of hedge funds to different risk factors. Additionally, the study of Dimitrios Stafylas (2017) gives evidence that the macroeconomic risk took a significant part in explaining the hedge fund performance.

2.3 Focus of this paper

Inspired mainly by the study of Hasanhodzic and Lo (2006) and empowered by the other papers cited in this literature review, this publication proposes hedge fund replication strategies with model calibration and implementation focusing on one specific hedge fund strategy.

Based on our research¹⁰ and personal experience, we are confident that focusing on a single strategy will emerge in a more applicable replication method and improved outcomes compared to the cited previous studies. The data used in this paper range from 1997 to 2017, including many macroeconomic big events such as the Asian Debt Crisis (1997), the Russian Default (1998), the Dotcom Bubble (early 2000's), the Subprime

⁹ Decision theory bring together psychology, statistics, philosophy and mathematics to analyse the decision-making process. Decision theory is applied to a wide variety of areas such as game theory, auctions, evolution and marketing. (Source: Investopedia)

¹⁰ Dimitrios Giannikis (2011)

Crisis (2008) and the European Debt Crisis (late 2009 to 2012). Therefore, it seemed particularly opportune to conduct a study in Global Macro strategy.

3. Data, Methodology, and Model

3.1 Data

We based our project on the hedge fund indexes data from Barclay Hedge and the market data from Bloomberg terminal. The time-period of the data ranges from January 1997 to August 2017 on a monthly basis. Our time-period includes several significant financial events and enables us to deepen our analysis by focusing on the Global Macro strategy.

There are limitations in our data, as indexes aggregate the intellectual factors which play critical parts in most hedge funds. In addition, the factors we selected can be biased, as there are certain factors we may not take into our model to do the analysis. Despite these limitations, our study is still sufficient to provide insightful thoughts as well as the inspiration for professional practice.

3.2 Hedge Fund Indexes

In this paper, we applied monthly returns of hedge fund indexes of the Barclay Hedge database of 17 different strategies¹¹: Convertible Arbitrage, Distressed Securities, Emerging Markets, Equity Long Bias, Equity Long/Short, Equity Market Neutral, European Equities, Event Driven, Fixed Income Arbitrage, Fund of Funds, Global Macro, Healthcare & Biotechnology, Merger Arbitrage, Multi Strategy, Pacific Rim Equities and Technology.

¹¹ For the detailing on each strategy refer to Appendix A.

3.3 Original Factors

Following Hasanhodzic and Lo (2006), this study initially applies the following factors¹² as tentative explainable variables for the seventeen Barclay Hedge Indexes monthly returns: 1) Market proxy: S&P 500; 2) Bond Returns: Bloomberg Barclays Aa Corporate Total Return Index Value Unhedged USD; 3) USD Dollar: U.S Dollar Index (USDIX); 4) VIX: Chicago Board Options Exchange SPX Volatility Index; 5) Commodity: S&P GSCI Total Return CME; and 6) Credit Spread: US Corporate Baa and 10-year US Treasury spread.

3.4 Methodology and Model

The methodology of this study is solely based on the linear regression model. Following the guidelines of Hasanhodzic and Lo (2006), we used the 6-factor linear regression to decompose the returns of different hedge fund indexes and obtained betas based on our inputs.

Regression equation:

$$R_{it} = \alpha_i + \beta_{i1} RiskFactor1_t + \beta_{i2} RiskFactor2_t + \dots + \beta_{ik} RiskFactorK_t$$

Then we generated two models for the clones: 1) Fixed-weight clone 2) Rolling-windows clone to get the expected returns for the hedge funds of different strategies. More details on these models in the following sections 3.5 and 3.6.

$$E[R_{it}] = \alpha_i + \beta_{i1} E[RiskFactor1_t] + \beta_{i2} E[RiskFactor2_t] + \dots + \beta_{ik} E[RiskFactorK_t]$$

In order to run statistic tests in Exhibit 3.7.1 and Exhibit 3.7.2 below we ran an unconstraint regression.

¹² For the intuition behind each original factor refer to Appendix B.

Exhibit 3.7.1 Multifactor Linear Regression (unconstrained) Model with Betas Statistics (Six Factors case). MATLAB Results obtained by regressing the selected risk factors on the hedge fund returns of different strategies.

	Credit		Dollar		Market		Bond		Vix		Commodity	
	t-Stat	P-value	t-Stat	P-value								
Convertible Arbitrage	-9.17	0.00	0.05	0.96	-2.45	0.01	6.71	0.00	-1.63	0.11	4.10	0.00
Distress Securities	-9.25	0.00	-0.23	0.82	-0.10	0.92	1.54	0.13	-3.19	0.00	4.61	0.00
Emerging Market	-7.29	0.00	-0.54	0.59	3.96	0.00	-0.61	0.54	-3.89	0.00	4.35	0.00
Long Bias	-7.21	0.00	-1.68	0.09	5.64	0.00	-2.63	0.01	-6.76	0.00	4.81	0.00
Long /Short	-4.32	0.00	0.25	0.80	3.79	0.00	-1.30	0.20	-4.27	0.00	4.33	0.00
European	-4.42	0.00	1.77	0.08	1.86	0.06	0.36	0.72	-2.64	0.01	2.77	0.01
Event Driven	-8.15	0.00	-0.82	0.41	2.26	0.02	-0.06	0.95	-4.52	0.00	4.34	0.00
Fixed Income Arb.	-8.48	0.00	1.73	0.08	1.00	0.32	2.79	0.01	0.96	0.34	5.94	0.00
Fund of Funds	-6.53	0.00	1.04	0.30	2.13	0.03	1.31	0.19	-3.17	0.00	6.26	0.00
Global Macro	-0.66	0.51	0.07	0.95	2.30	0.02	1.99	0.05	-2.90	0.00	3.89	0.00
Health & Biotech	-3.29	0.00	0.42	0.68	3.36	0.00	-1.82	0.07	-3.06	0.00	2.47	0.01
Merger Arb.	-4.52	0.00	0.61	0.54	2.34	0.02	0.54	0.59	-3.57	0.00	3.09	0.00
Multi Strategy	-7.97	0.00	0.65	0.52	-1.39	0.17	5.40	0.00	-3.23	0.00	5.54	0.00
Pacific Rim Equities*	-3.65	0.00	-0.62	0.54	1.25	0.21	-0.96	0.34	-2.77	0.01	2.61	0.01
Technology*	-3.48	0.00	0.57	0.57	4.77	0.00	-3.11	0.00	-4.61	0.00	2.64	0.01
Equity Market Neutral	1.41	0.16	0.98	0.33	-1.03	0.30	1.69	0.09	-2.40	0.02	3.38	0.00
Hedge Fund	-7.49	0.00	-0.64	0.52	3.89	0.00	-0.04	0.97	-5.61	0.00	6.09	0.00

According to the beta coefficients as the results of the regression model, we can find out that the significance of different risk factors based on the t-statistics and P-value. For instance, looking at the elevated figures for the t-statistics and low figures of p-values, the risk factors of market, bond returns, VIX and commodity are obviously significant in the Global Macro Strategy, which means that these factors contribute the most to the returns of this particular strategy. However, this is only the statistics view, we will further elaborate the factors in more details later in this study.

Exhibit 3.7.2 Multifactor Linear Regression (unconstrained) Model with Betas Statistics (Seven Factors case)

	Credit Spread		Dollar Index		SP500 Market		Aa Bond		Vix		Commodity		EM-T Spread	
	t-Stat	P-value	t-Stat	P-value	t-Stat	P-value	t-Stat	P-value	t-Stat	P-value	t-Stat	P-value	t-Stat	P-value
Conv. Arbitrage	6.40	0.00	0.39	0.70	2.58	0.01	6.65	0.00	0.02	0.98	3.52	0.00	-3.89	0.00
Distress	5.81	0.00	0.28	0.78	0.20	0.84	1.28	0.20	0.74	0.46	3.88	0.00	-5.94	0.00
Emerging Market	2.72	0.01	0.26	0.79	4.58	0.00	1.35	0.18	0.16	0.87	3.45	0.00	10.3	0.00
Long Bias	3.34	0.00	1.18	0.24	6.17	0.00	3.40	0.00	3.82	0.00	4.01	0.00	-7.71	0.00
Long /Short	1.17	0.24	0.80	0.42	3.97	0.00	1.75	0.08	1.78	0.08	3.58	0.00	-6.02	0.00
European	2.00	0.05	2.19	0.03	1.86	0.06	0.12	0.91	0.83	0.41	2.14	0.03	-4.17	0.00
Event Driven	4.05	0.00	0.17	0.86	2.44	0.02	0.58	0.56	1.31	0.19	3.47	0.00	-8.48	0.00
Fixed Income	6.20	0.00	2.00	0.05	0.98	0.33	2.66	0.01	2.01	0.05	5.48	0.00	-2.79	0.01
Fund of Funds	3.33	0.00	1.61	0.11	2.18	0.03	1.04	0.30	0.78	0.43	5.63	0.00	-5.76	0.00
Global Macro	1.09	0.28	0.38	0.71	0.02	2.30	0.07	1.82	0.19	-1.32	3.35	0.00	-3.50	0.00
Health & Biotech	1.59	0.11	0.67	0.51	3.37	0.00	2.01	0.05	1.73	0.08	2.01	0.05	-2.76	0.01
Merger Arb.	1.78	0.08	1.07	0.28	2.37	0.02	0.26	0.79	1.45	0.15	2.38	0.02	-4.93	0.00
Multi Strategy	5.03	0.00	1.09	0.28	1.52	0.13	5.33	0.00	1.21	0.23	4.93	0.00	-4.68	0.00
Pacific Rim	2.09	0.04	0.41	0.68	1.23	0.22	1.11	0.27	1.61	0.11	2.21	0.03	-2.38	0.02
Technology*	1.13	0.26	0.96	0.34	4.87	0.00	3.46	0.00	2.67	0.01	2.00	0.05	-4.22	0.00
Market Neutral	2.21	0.03	1.16	0.25	1.07	0.29	1.58	0.12	1.41	0.16	3.02	0.00	-2.01	0.05
Hedge Fund	3.41	0.00	0.02	0.98	4.29	0.00	0.55	0.58	2.47	0.01	5.43	0.00	-8.40	0.00

The factor of Emerging Markets Credit Spread is statistically significant, again high t-stat and low p-value figures, as we included this factor into our model as shown in Exhibit 3.7.2. The inclusion of this factor also enhanced our clone returns as demonstrated later.

3.5 Fixed-weight clone

Fixed-weights clones use the entire data sample to run a single regression and estimate one set of weights that will be implemented in the clone portfolio, in this case, the rebalancing is done daily only to adjust the portfolio back to its original weight composition, but it should not impose too much rebalancing costs since it should be small corrections on deviations from the original configuration. We used MATLAB to run the linear regressions, constraining the beta coefficients to sum to one and eliminating alphas

(intercepts). Since we are evaluating indexes and not specific funds, the human factor is not as material and the elimination of alpha in our regression model does not result in a relevant loss because of the aggregation effect of the indexes.

In our model the least squares algorithm R^*_{it} was applied using the factors' means to fit the mean of the indexes. Later, we used the resulted estimated betas as the representative weights for each factor and constructed each clone portfolio accordingly. The constructed clone will have the returns that are equivalent to the fitted values $E[R^*_{it}]$.

$$R^*_{it} = \beta^*_{i1} SP_t + \beta^*_{i2} Bond_t + \beta^*_{i3} VIX_t + \beta^*_{i4} CMTDY_t + \beta^*_i CREDIT_t$$

$$E[R^*_{it}] = \alpha_i + \beta_{i1} E[SP_t] + \beta_{i2} E[Bond_t] + \beta_{i3} E[VIX_t] + \beta_{i4} E[CMTDY_t] + \beta_i [CREDIT_t]$$

3.6 Rolling-windows clone

Rolling-windows clones use the data sample from a particular month-period to run monthly regression and estimate a set of weights per month that will then be implemented in the clone portfolio, the rebalancing in this case can be done monthly (or sparser periodicity) to adjust the portfolio to the new set of weights, this case should impose higher rebalancing costs compared to the fixed-weight clone strategy, since the weights may diverge a lot from month to month.

Initially, we opted for 24-months rolling-windows following Hasanhodzic and Lo (2006), that is, for each month t , we used the rolling-windows of 24-months from month $t-24$ to $t-1$ to estimate the same regression as R_{it-k} .

The beta coefficients are indexed by both the k (period) and i (risk factors) and the estimated betas β^* are applied as weights to determine the returns of the constructed clones R^*_{it-k} .

$$R_{it-k} = \beta_{i1} SP_{t-k} + \beta_{i2} Bond_{t-k} + \beta_{i3} VIX_{t-k} + \beta_{i4} CMTDY_{t-k} + \beta_i CREDIT_{t-k} + \varepsilon_{it-k}$$

Subject to $1 = \beta_{i1} + \beta_{i2} + \beta_{i3} + \beta_{i4} + \beta_i, k = 1, \dots, 24$

$$R^*_{it-k} = \beta^*_{i1} SP_{t-k} + \beta^*_{i2} Bond_{t-k} + \beta^*_{i3} VIX_{t-k} + \beta^*_{i4} CMTDY_{t-k} + \beta^*_i CREDIT_{t-k} + \varepsilon_{it-k}$$

An important aspect, also described in Hasanhodzic and Lo (2006), is that fixed-weight clones incur a clear look-ahead bias, since it uses the entire data sample to build its portfolios. While rolling-windows estimations generates monthly rebalancing asset-allocation weights for its clone-portfolios, controlling for biases and replicating features of active management.

3.7 Rolling-windows calibration

After replicating Hasanhodzic and Lo (2006) models, we implemented a sensitivity analysis on the rolling-windows model, relaxing the input parameter attempting to improve the model replication capacity. The results appointed for an optimal 12-months rolling-windows period.

$$R_{it-k} = \beta_{i1} SP_{t-k} + \beta_{i2} Bond_{t-k} + \beta_{i3} VIX_{t-k} + \beta_{i4} CMTDY_{t-k} + \beta_i CREDIT_{t-k} + \varepsilon_{it-k}$$

$$\text{Subject to } 1 = \beta_{i1} + \beta_{i2} + \beta_{i3} + \beta_{i4} + \beta_i, k=1, \dots, 12$$

$$R^{**}_{it-k} = \beta^{**}_{i1} SP_{t-k} + \beta^{**}_{i2} Bond_{t-k} + \beta^{**}_{i3} VIX_{t-k} + \beta^{**}_{i4} CMTDY_{t-k} + \beta^{**}_i CREDIT_{t-k} + \varepsilon_{it-k}$$

Although the smaller rolling-windows period is subject to greater estimation errors, market fast reaction imposes the need for this shorter window frame. In this stage, we also relaxed the original factors by replacing and withdrawing each one of them. Later, we tested for an additional strategy-specific factor to close the estimation gap and improve the strategy-specific clone quality and accuracy. The results and intuitions behind each model parameter will be further elaborated in the following chapter¹³ of this study.

¹³ Chapter 4 Results, Model Calibration and Implications

4. Results, Model Calibration and Implications

Following Hasanhodzic and Lo (2006), we implemented two linear regression models to perform a decomposition of each hedge fund strategy's returns. We then based our clone models on the results we got from the decomposition. For each model, we calculated the mean returns and the standard deviation to have the insightful information about our clone risk-return results and how they compared to the indexes. The statistical measure of R-squared as shown on Exhibit 4.1 indicates the percentage of each particular Barclay Index movements can be explained by each clone with different approach.

Exhibit 4.1 Summary of R-squared and F-test - (unconstrained model)

	Fixed Weight			12-months Rolling Window			24-months Rolling Window		
	R Squared	Adjusted R Squared	F-test	R Squared	Adjusted R Squared	F-test	R Squared	Adjusted R Squared	F-test
Conv. Arb.	0.472	0.459	36.0	0.285	0.282	93.2	0.323	0.320	106.0
Distressed*	0.471	0.457	35.7	0.343	0.340	122.0	0.469	0.467	196.0
Emer. Markets	0.455	0.442	33.6	0.515	0.513	249.0	0.545	0.542	265.0
Long Bias*	0.570	0.559	53.2	0.671	0.670	478.0	0.720	0.719	572.0
Long/Short	0.359	0.343	22.5	0.347	0.344	124.0	0.363	0.360	127.0
European*	0.223	0.203	11.5	0.104	0.101	27.3	0.138	0.134	35.6
Event Driven	0.481	0.468	37.2	0.401	0.398	157.0	0.473	0.471	200.0
Fixed Income Arb.	0.391	0.376	25.8	0.237	0.233	72.6	0.312	0.309	101.0
Fund of Funds	0.428	0.413	30.0	0.384	0.381	146.0	0.442	0.440	176.0
Global Macro	0.238	0.219	12.5	0.246	0.243	76.3	0.208	0.205	58.5
Health & Biotech*	0.221	0.201	11.4	0.076	0.072	19.1	0.080	0.076	19.2
Merger Arb. *	0.290	0.272	16.4	0.208	0.205	61.6	0.193	0.190	53.2
Multi Strategy	0.478	0.465	36.7	0.342	0.339	122.0	0.381	0.379	137.0
Pacific Rim*	0.204	0.184	10.3	0.140	0.137	38.2	0.130	0.126	233.1
Technology*	0.321	0.305	19.0	0.361	0.358	132.0	0.330	0.327	109.0
Market Neutral	0.085	0.062	3.7	0.049	0.044	11.9	0.036	0.032	8.4
Hedge Fund*	0.548	0.537	48.7	0.546	0.544	281.0	0.601	0.599	334.0

For example, the R-squared for the Global Macro strategy is the highest for the rolling window of 12 months approach indicates the Barclay index of Global Macro strategy is explained better by the clones, which used the rolling window of 12 months approach compared with other approaches. The statistical results of R-squared and F-test after incorporating the factor of Emerging Market Credit Spread is displayed on Exhibit 4.2.

Exhibit 4.2 Summary of R-squared and F-test with Emerging Market Credit Spread- (unconstrained model)

	Fixed Weight			12-months Rolling Window with EM Credit Spread			24-months Rolling Window with EM Credit Spread		
	R Squared	Adjusted R Squared	F-test	R Squared	Adjusted R Squared	F-test	R Squared	Adjusted R Squared	F-test
Conv. Arb.	0.472	0.459	36.0	0.260	0.257	82.3	0.322	0.319	105.0
Distressed*	0.471	0.457	35.7	0.302	0.299	101.0	0.473	0.471	199.0
Emer. Markets	0.455	0.442	33.6	0.505	0.503	239.0	0.578	0.576	304.0
Long Bias*	0.570	0.559	53.2	0.632	0.630	402.0	0.712	0.711	549.0
Long/Short	0.359	0.343	22.5	0.315	0.312	108.0	0.340	0.337	114.0
European*	0.223	0.203	11.5	0.084	0.081	21.8	0.107	0.103	26.5
Event Driven	0.481	0.468	37.2	0.425	0.423	173.0	0.484	0.481	208.0
Fixed Income Arb.	0.391	0.376	25.8	0.230	0.227	69.8	0.322	0.319	106.0
Fund of Macro	0.428	0.413	30.0	0.351	0.348	126.0	0.437	0.434	172.0
Global Macro	0.238	0.219	12.5	0.248	0.245	77.1	0.202	0.198	56.2
Health & Biotech*	0.221	0.201	11.4	0.040	0.036	9.8	0.046	0.042	10.7
Merger Arb. *	0.290	0.272	16.4	0.185	0.182	53.2	0.191	0.188	52.5
Multi Strategy	0.478	0.465	36.7	0.295	0.292	97.9	0.382	0.379	137.0
Pacific Rim*	0.204	0.184	10.3	0.135	0.131	36.4	0.132	0.129	33.9
Technology*	0.321	0.305	19.0	0.264	0.260	83.7	0.278	0.274	85.3
Market Neutral	0.085	0.062	3.7	0.060	0.056	14.9	0.038	0.034	8.8
Hedge Fund*	0.548	0.537	48.7	0.516	0.514	250.0	0.594	0.592	324.0

Meanwhile, we also applied the autocorrelation of lag one into our model to assess the illiquidity risks as discussed in the study of Getmansky, Lo and Makarov that the autocorrelation can be used to measure the illiquidity risk of the hedge funds (2004). As different strategies have different rebalancing requirements, the clones perform differently for different strategies and the performance of different types of clones also varies. By using the approach of 24-months rolling-windows, most of the autocorrelation of lag one decreased, which indicates a slightly declined liquidity risk due to the liquidity improves under the embedded rebalancing requirements of the rolling window.

Exhibit 4.2 Summary of lag one autocorrelation for both models

	$\rho_1(\%)$ fixed-weight	$\rho_1(\%)$ 24-moth rolling-windows
Convertible Arbitrage	24.9%	23.0%
Distress Securities*	24.4%	24.5%
Emerging Market	19.8%	21.7%
Long Bias*	13.5%	12.9%
Long /Short	10.0%	-2.3%
European*	12.6%	10.6%
Event Driven	19.4%	18.2%
Fixed Income Arb.	16.3%	27.7%
Fund of Funds	15.4%	18.0%
Global Macro	2.9%	10.0%
Health & Biotech*	10.3%	9.6%
Merger Arbitrage*	5.3%	20.5%
Multi Strategy	18.6%	23.2%
Pacific Rim Equities*	16.6%	7.2%
Technology*	4.8%	3.8%
Equity Market Neutral	-1.0%	-16.9%
Hedge Fund	16.2%	15.6%

* Strategy not present in Hasanhodzic and Lo (2006) paper.

Exhibit 4.3 Summary of 1 dollar invested accumulated return for 24-months rolling-windows monthly rebalancing clone portfolios, fixed-weight clone portfolios and Barclay Hedge Indexes. The clones were obtained by linear regressions of monthly returns of Barclay Hedge Indexes from January 1997 to August 2017 on six factors: S&P 500 total return, Barclays Aa Corporate Total Return Index, the US Dollar Index return, Credit Spread: US Corporate Baa - 10-year US Treasury, the first-difference of the CBOE Volatility Index (VIX), and the Goldman Sachs Commodity Index (GSCI) total return.

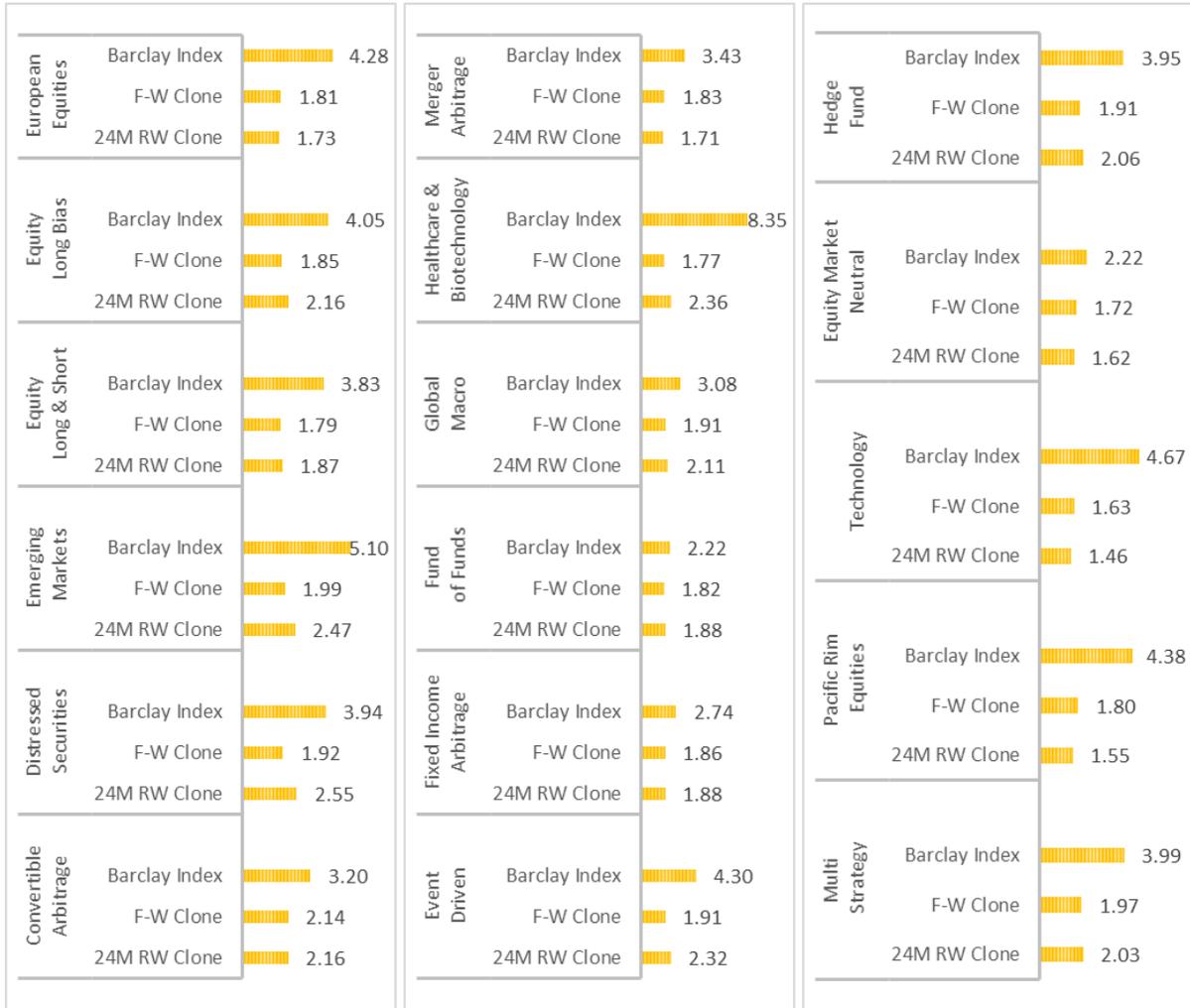
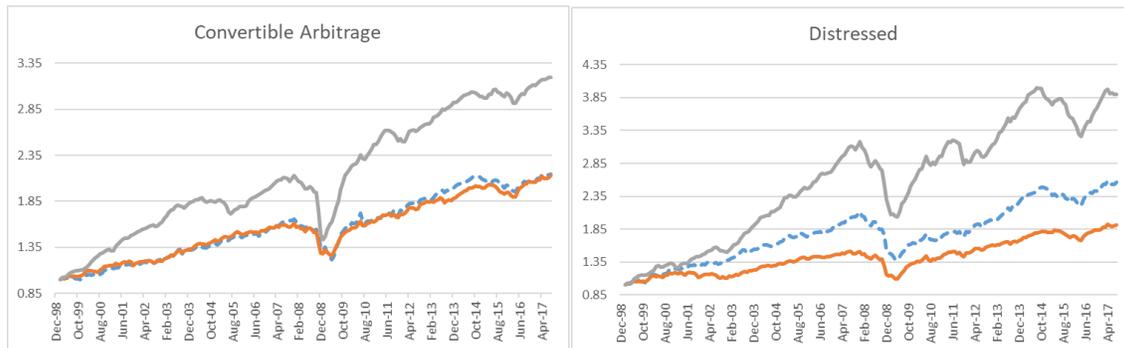
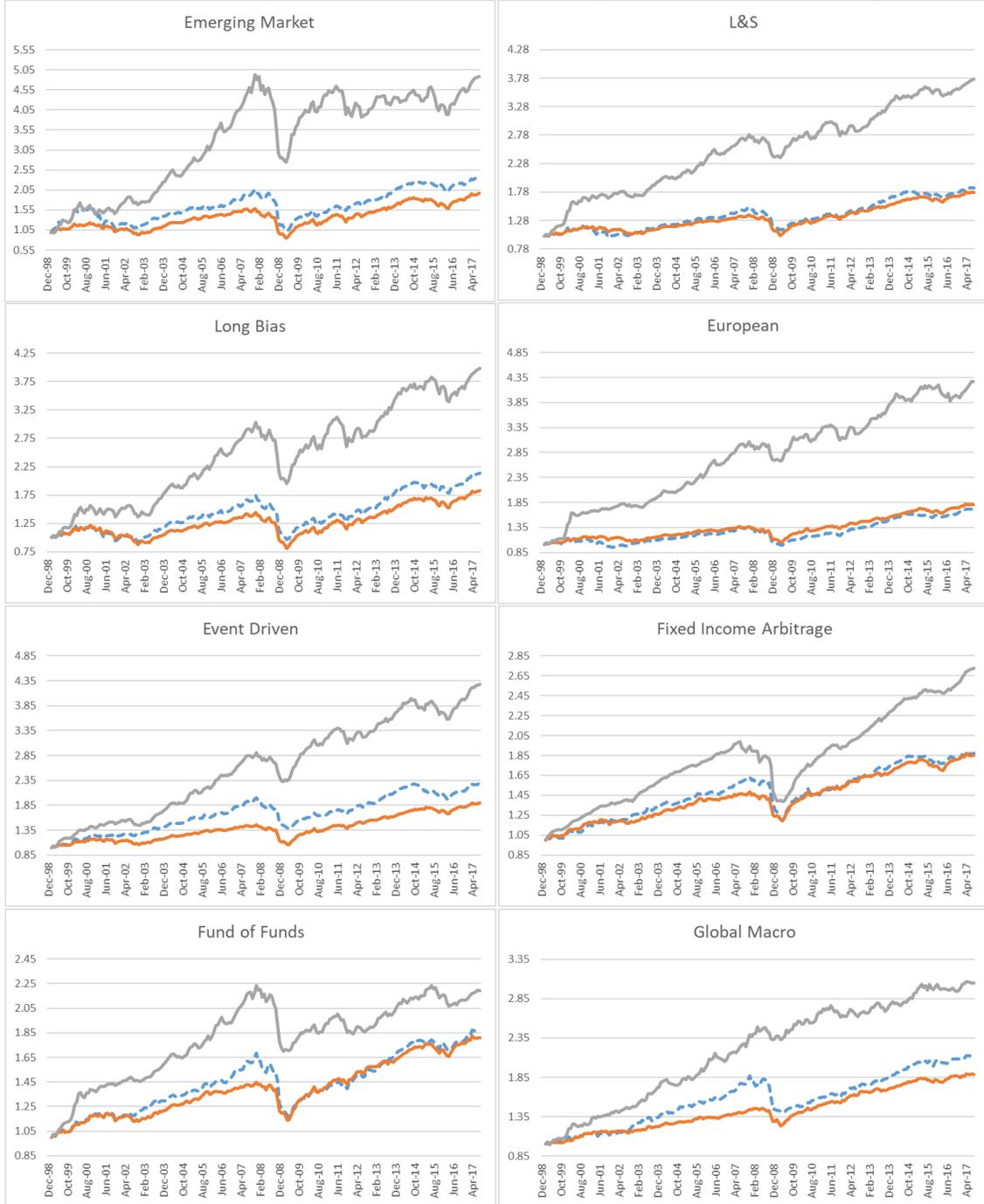
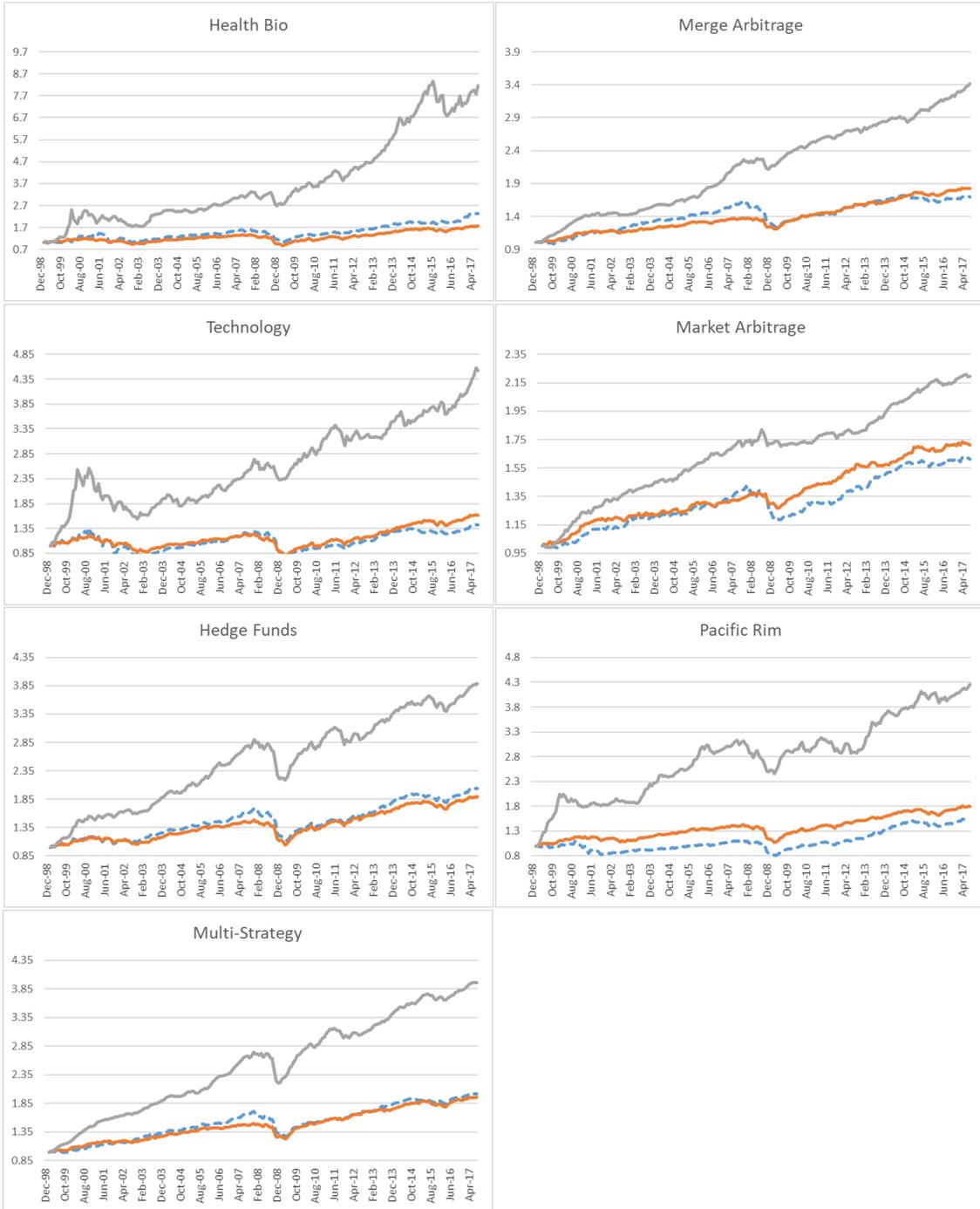


Exhibit 4.4 Individual charts of the same data displayed in the summary of Exhibit 4.2



--- 24-Months Rolling-Window Clone — Fixed-Weight Clone — Barclay Hedge Index





 24-Months Rolling-Windows Clone
 Fixed-Weight Clone
 Barclay Hedge Index

Exhibit 4.5 Clones' Statistics & Tracking Errors (Data sample from January 1998 to August 2017)

Strategy	24-months Rolling-Window					Fixed-Weight		
	E(R) Index	STD Index	E(R) R-W	STD R-W	Tracking Error RW	E(R) F-W	STD F-W	Tracking Error FW
Conv. Arb.	6.7%	6.3%	4.4%	5.4%	5.6%	4.3%	5.0%	4.8%
Distressed*	7.9%	6.9%	5.4%	6.6%	5.4%	3.7%	5.8%	5.3%
Emer. Markets	10.0%	12.4%	5.8%	12.5%	9.1%	4.4%	10.5%	8.0%
Long Bias*	8.4%	10.5%	4.8%	10.5%	5.9%	3.9%	10.0%	5.2%
Long/Short	7.7%	6.4%	3.6%	6.4%	5.8%	3.3%	5.4%	5.0%
European*	8.4%	7.1%	3.2%	6.2%	7.6%	3.4%	4.7%	6.4%
Event Driven	8.3%	6.0%	4.8%	6.2%	4.9%	3.7%	5.7%	4.5%
Fixed Income Arb.	5.7%	5.0%	3.5%	4.8%	4.6%	3.5%	4.1%	4.1%
Fund of Funds	4.5%	5.1%	3.6%	5.6%	4.4%	3.4%	4.5%	4.0%
Global Macro	6.3%	5.1%	4.2%	5.5%	5.6%	3.6%	3.7%	4.8%
Health & Biotech*	13.3%	15.6%	5.4%	11.2%	16.6%	3.5%	8.3%	14.2%
Merger Arb. *	6.9%	3.1%	3.0%	4.0%	4.0%	3.3%	3.3%	3.5%
Multi Strategy	7.8%	4.4%	4.0%	4.7%	4.1%	3.8%	4.1%	3.7%
Pacific Rim*	8.6%	8.5%	2.7%	7.2%	9.1%	3.4%	5.3%	7.6%
Technology*	9.4%	12.1%	2.7%	11.5%	11.1%	3.0%	8.4%	9.7%
Market Neutral	4.4%	2.8%	2.7%	3.8%	4.3%	3.0%	2.8%	3.8%
Hedge Fund*	7.9%	6.6%	4.2%	6.9%	4.6%	3.7%	6.2%	4.1%
Average	7.8%	7.3%	4.0%	7.0%	6.6%	3.6%	5.8%	5.8%

*Strategy not present in Hasanhodzic and Lo (2006) paper.

Although the data source and time-period were quite distinct, the quality of the replications obtained by the 24-months rolling-windows clones was similar to the 24-months rolling-windows clones of the original study conducted by Hasanhodzic and Lo (2006). Nevertheless, in our opinion this replication is not of enough quality to justify the strategy, considering that current market conditions provide investors with much lower returns and, as demonstrated by Exhibit 4.4, the clones underperform the indexes by a very significant amount.

Regarding the fixed-weight linear clones, in our time-frame and data, the results obtained were similar to those of the 24-months rolling-windows linear clones, diverging the findings from Hasanhodzic and Lo (2006). Our interpretation is that the sub-prime

crisis brought a structural break point¹⁴ in our data set; consequently, our entire-period regressions do not provide as precise weights as the original Hasanhodzic and Lo (2006) study.

As mentioned before because fixed-weight clones incur from look-ahead bias and will not react in changes to market conditions, we believe that rolling-windows estimations are more applicable, as it generates monthly rebalancing asset-allocation weights for its clone-portfolios, controlling for biases and replicating features of active management. Also, this model will avoid issues related to possible structural breaks that may occur.

4.1 Other periods rolling-windows

After this exercise, we started to conduct experimentation in order to calibrate this original 24-months rolling-windows model. The first effort was changing the periodicity of the rebalancing of the rolling-windows portfolios to more sparse periods. The results were the deterioration of the clones' ability to replicate the original trends observed by the indexes, therefore we continued to use monthly rebalancing. Next, we attempt for different timespan in the rolling-windows linear regressions, again periods larger than 24-months resulted in a deterioration of the clones, so we decided to test smaller periods.

For most strategies, the autocorrelations for the fixed-weight clones are the highest and the 12-months rolling-windows clones are the lowest. These results indicate that the liquidity risk decreases using a smaller timespan in the rolling-windows model (see Exhibit 4.1.1 below).

¹⁴ When the data have a dramatic event that changes the dynamics of the time-series behaviour and one single linear model cannot successfully fit the entire period with a single regression equation.

Considering the accumulated returns and observing the charts below, the 12-months rolling-windows results were an impressive improvement from the original 24-months period, yielding higher returns for all strategies. On the other hand, this new method had a deterioration in tracking error metric and showed a larger volatility (see Exhibit 4.1.2 and 4.1.3 below).

4.1.1 Summary of lag one autocorrelation for the three models

	$\rho_1(\%)$ fixed-weight	$\rho_1(\%)$ 24-months R-W	$\rho_1(\%)$ 12-moths R-W
Convertible Arbitrage	24.9%	23.0%	3.4%
Distress Securities	24.4%	24.5%	14.2%
Emerging Market	19.8%	21.7%	15.7%
Long Bias	13.5%	12.9%	5.5%
Long /Short	10.0%	-2.3%	-5.5%
European	12.6%	10.6%	2.3%
Event Driven	19.4%	18.2%	8.7%
Fixed Income Arb.	16.3%	27.7%	14.0%
Fund of Funds	15.4%	18.0%	6.8%
Global Macro	2.9%	10.0%	8.9%
Health & Biotech	10.3%	9.6%	-2.9%
Merger Arb.	5.3%	20.5%	11.7%
Multi Strategy	18.6%	23.2%	14.1%
Pacific Rim Equities*	16.6%	7.2%	21.2%
Technology*	4.8%	3.8%	4.4%
Equity Market Neutral	-1.0%	-16.9%	-17.1%
Hedge Fund	16.2%	15.6%	8.9%

Exhibit 4.1.2 Summary of 1 dollar invested accumulated return for 12-months rolling-windows monthly rebalancing clone portfolios, fixed-weight clone portfolios and Barclay Hedge Indexes. From January 1997 to August 2017 on the same six factors.

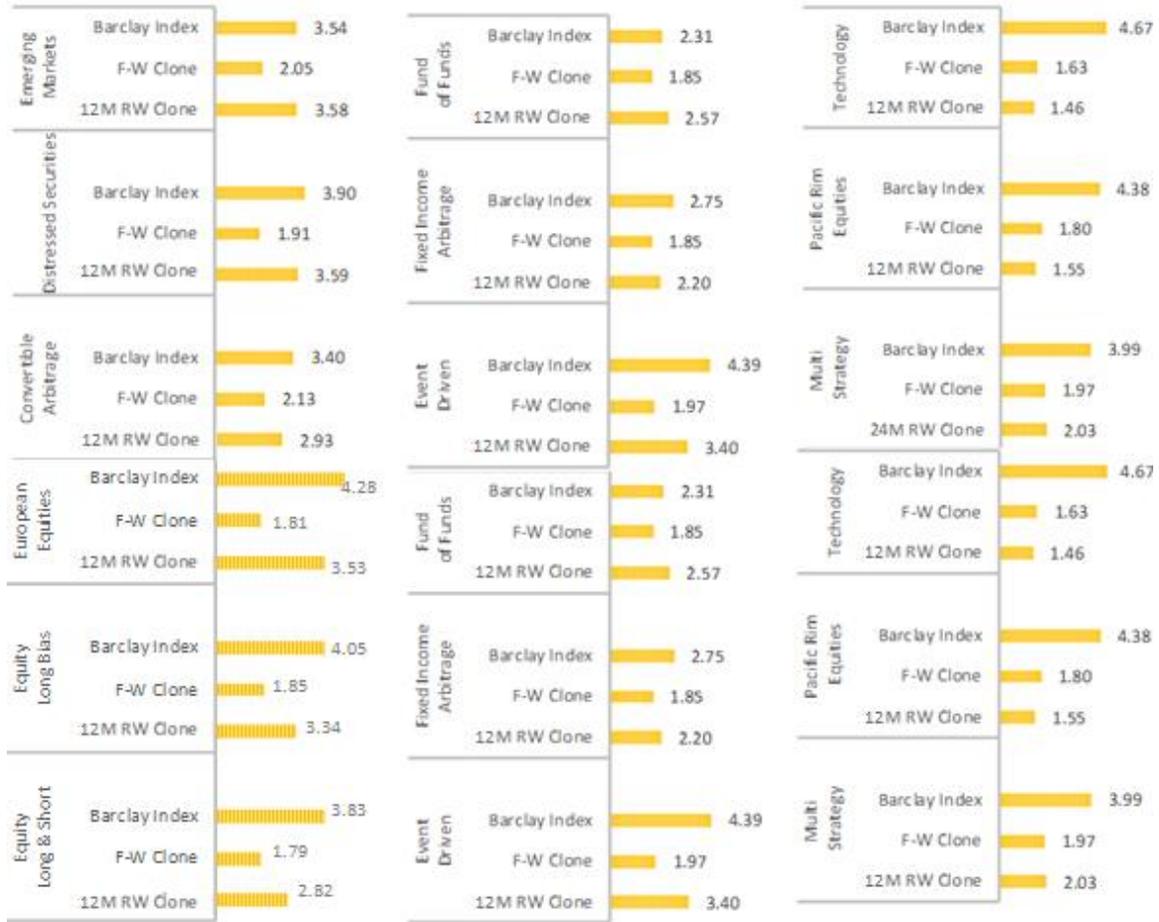
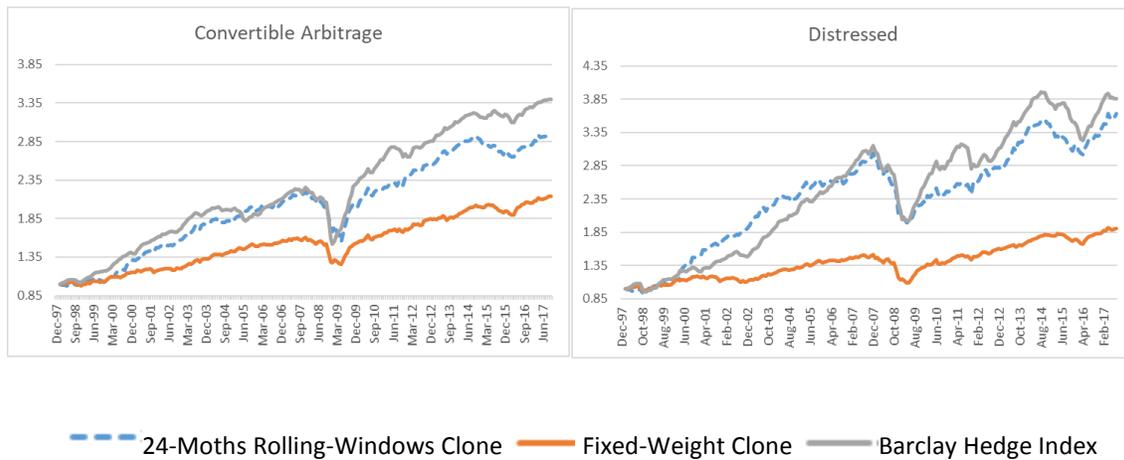
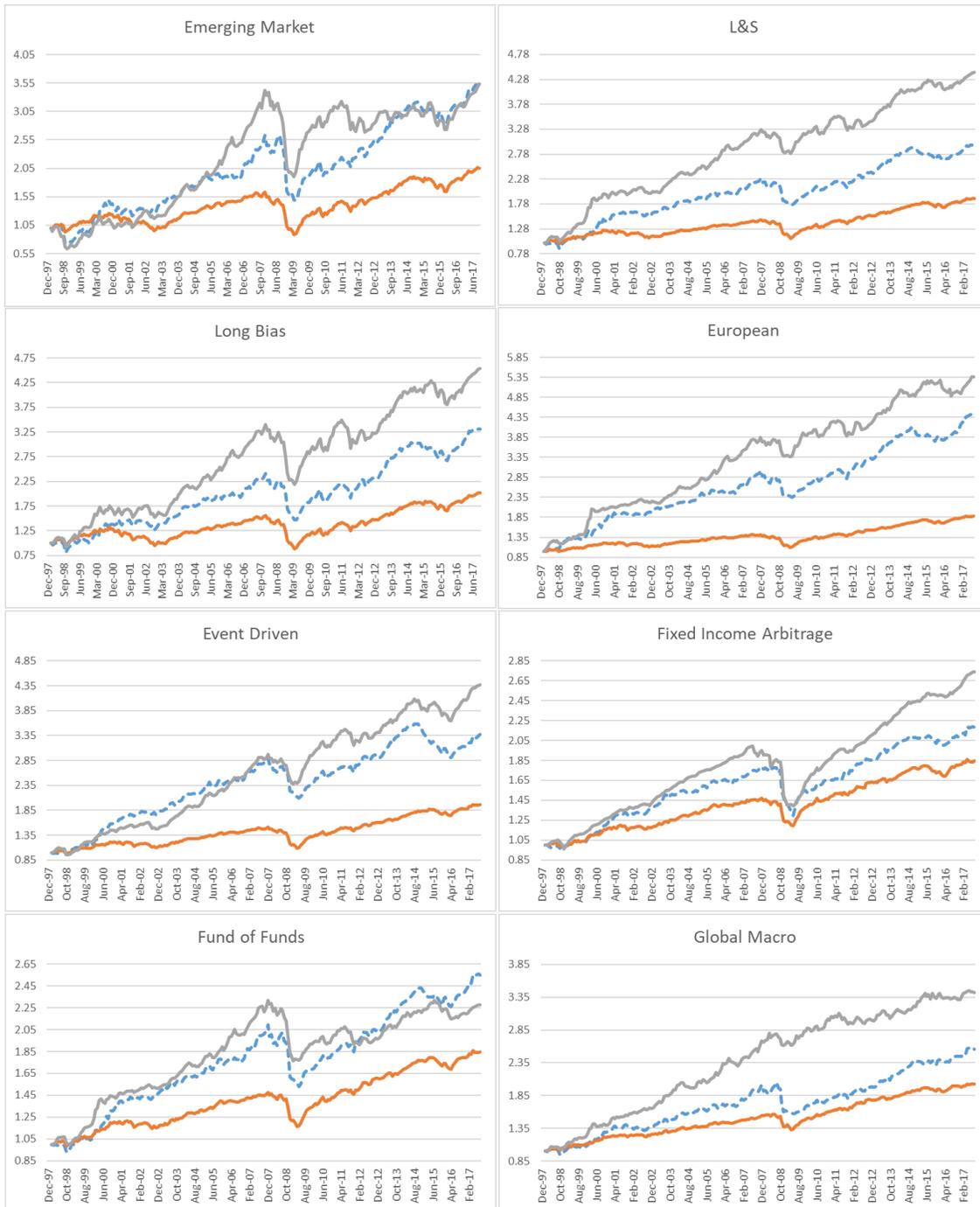
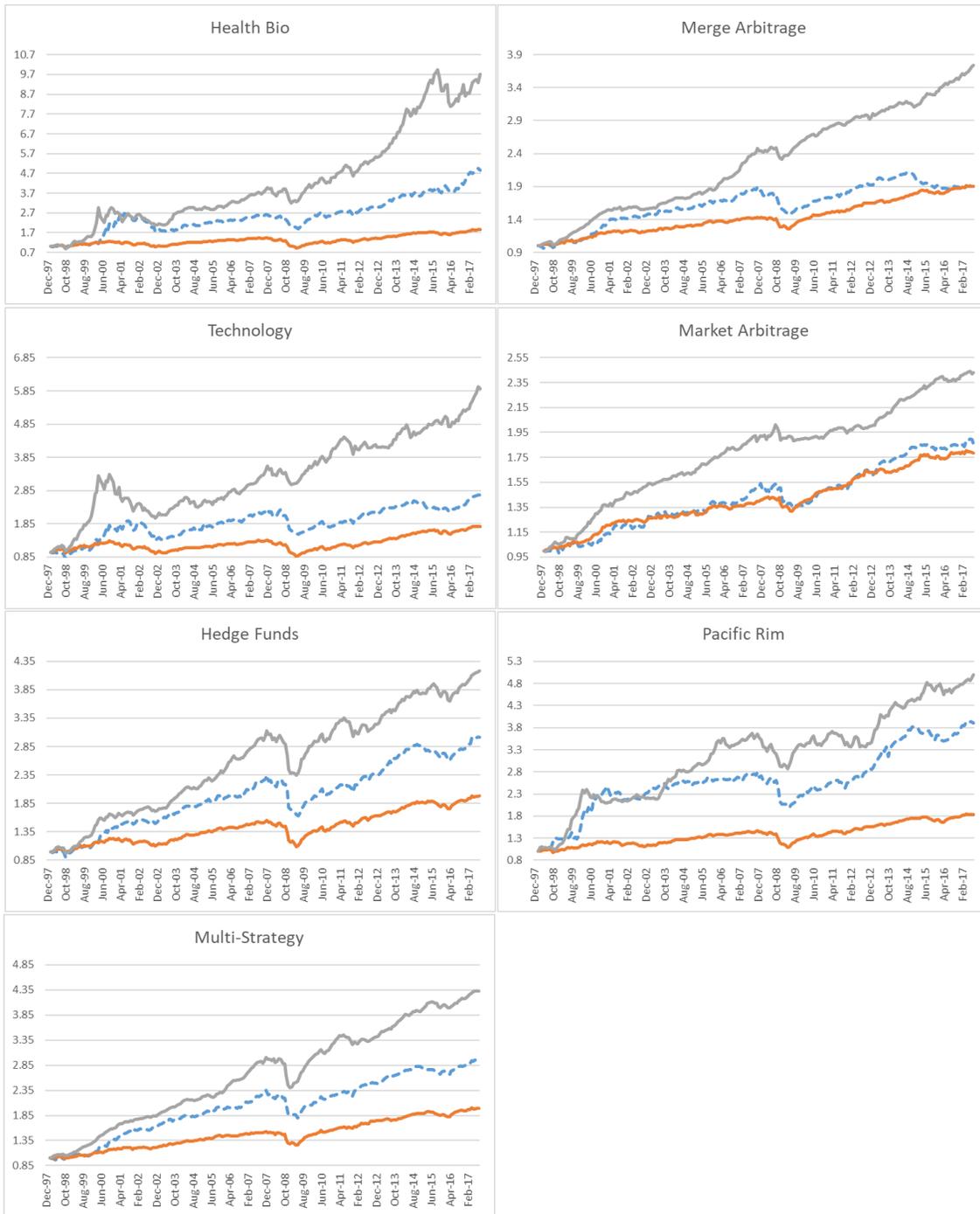


Exhibit 4.1.3 Individual charts of the same data displayed in the summary of Exhibit 4.1.2





- - - 24-Months Rolling-Window Clone
 — Fixed-Weight Clone
 — Barclay Hedge Index



--- 24-Months Rolling-Windows Clone — Fixed-Weight Clone — Barclay Hedge Index

*Exhibit 4.1.4 Clones' Statistics & Tracking Errors with 24-months and 12-months RW
(Data sample from January 1998 to August 2017)*

Conv. Arb.	E(R) Index	STD Index	12-months Rolling-Window			24-months Rolling-Window		
			E(R) R-W	STD R-W	Tracking Error RW	E(R) R-W	STD R-W	Tracking Error RW
Covert. Arb.	6.7%	6.3%	6.0%	6.5%	6.1%	4.4%	5.4%	5.6%
Distressed*	8.0%	6.9%	7.4%	7.7%	6.5%	5.4%	6.6%	5.4%
Emer. Markets	10.0%	12.4%	9.6%	12.8%	9.7%	5.8%	12.5%	9.1%
Long Bias*	8.4%	10.5%	7.3%	10.9%	6.7%	4.8%	10.5%	5.9%
Long/Short	7.7%	6.4%	6.0%	7.3%	6.5%	3.6%	6.4%	5.8%
European*	8.4%	7.1%	7.3%	7.5%	8.3%	3.2%	6.2%	7.6%
Event Driven	8.3%	6.0%	6.7%	7.3%	5.8%	4.8%	6.2%	4.9%
FI Arb.	5.7%	5.0%	4.5%	5.4%	5.2%	3.5%	4.8%	4.6%
Fund of Funds	4.5%	5.1%	5.4%	6.1%	5.0%	3.6%	5.6%	4.4%
Global Macro	6.3%	5.1%	5.2%	6.5%	6.1%	4.2%	5.5%	5.6%
Health & Biotech*	13.3%	15.6%	9.4%	14.6%	19.8%	5.4%	11.2%	16.6%
Merger Arb. *	6.9%	3.1%	3.4%	4.8%	4.5%	3.0%	4.0%	4.0%
Multi Strategy	7.8%	4.4%	5.9%	5.4%	4.5%	4.0%	4.7%	4.1%
Pacific Rim*	8.6%	8.5%	6.7%	10.0%	9.9%	2.7%	7.2%	9.1%
Technology*	9.4%	12.1%	6.5%	12.6%	11.5%	2.7%	11.5%	11.1%
Market Neutral	4.4%	2.8%	3.2%	4.4%	4.7%	2.7%	3.8%	4.3%
Hedge Fund*	7.9%	6.6%	6.3%	7.5%	5.3%	4.2%	6.9%	4.6%
Average	7.8%	7.3%	6.3%	8.1%	7.4%	4.0%	7.0%	6.6%

*Strategy not present in Hasanhodzic and Lo (2006) paper.

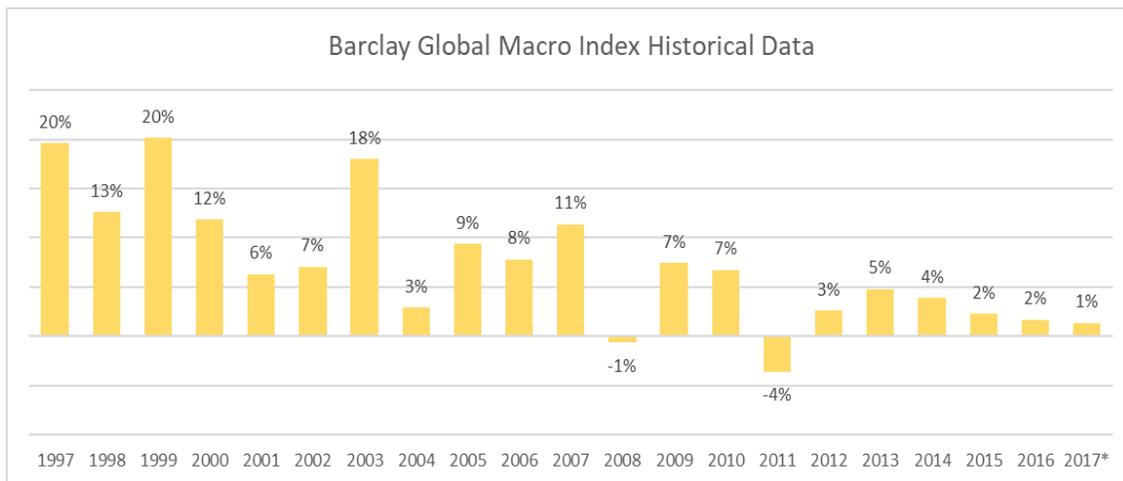
Looking at the exhibits above, although there was a deterioration in the tracking error metrics, the improvement in expected returns was expressive and seems like a reasonable trade-off and an overall improvement in the model to change 24-months for 12-months rolling-windows. Though the new clones present larger volatilities (STD = annualized standard deviation), these figures are very similar to the index volatilities, so an investor should be somewhat comfortable with this level of risk. Because many strategies are quite specific¹⁵ we did not expect all clones to show consistently accurate replications. In our point of view to further calibrate the model, it is imperative to understand the specific strategy and research specific additional factors relevant to that strategy. Therefore, we decided to choose one Global Macro strategy for a more in-depth model building.

¹⁵ Refer to Appendix A. Strategy Definitions for the detailing of strategies.

5. Global Macro Strategy - A Study Case

The reasoning behind our focus in Global Macro hedge fund strategy replication is mainly its capacity of preserving capital through a low correlation with the main indexes of variable income and fixed income, its mandate is the broadest hedge funds and has no formal definition due to its opportunistic nature. Another convenient fact is that this strategy can be used on very large amounts under management as it focuses in very liquid markets, with an emphasis in currency trading usually.

Exhibit 5.1 Yearly Returns of the Barclay Hedge Macro Index from 1997 to August 2017.



Typically, a Global Macro manager aims to obtain positive absolute return adjusted to a certain level of risk under any market circumstances. For this, it takes positions directional (bearish or bullish) or non-directional with or without financial leverage and using any instrument, whether liquid or derivative in the foreign exchange markets, interest rates, variable income, commodities and exceptionally risk capital. The main source of return generation is the analysis of situations of macroeconomic disequilibrium fundamental in any international market.

The Exhibit 5.3 below shows the detailing of the 12-month rolling-windows monthly rebalance strategy obtained by the 6 factors regression; it is quite intuitive to see how this process was able to capture the managers' insights in an opportune and consistent system. Global Macro strategy had a superior comparative performance to most asset classes in downturn years and in our 12-months rolling-windows strategy you can see the translation from the managers knowledge into our model as the disinvestment in S&P 500 starts around 2008's first quarter, before the S&P vast drawdown, and most of the portfolio market share is taken by Aa Corporate Total Return Index.

Exhibit 5.2 Yearly Returns of the Clone 12-months rolling-windows with the 6-factor model

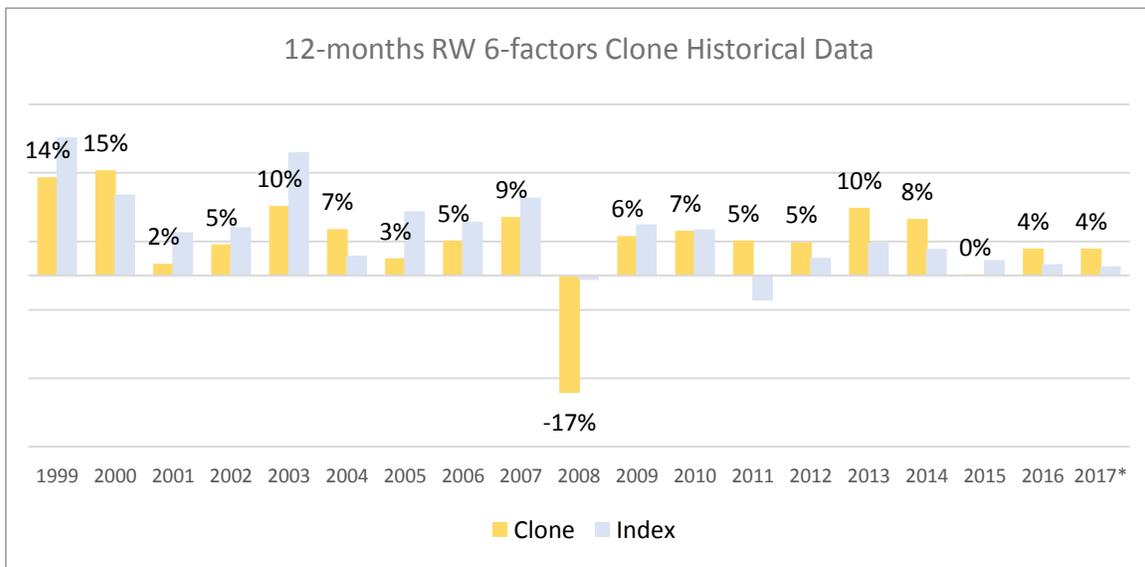
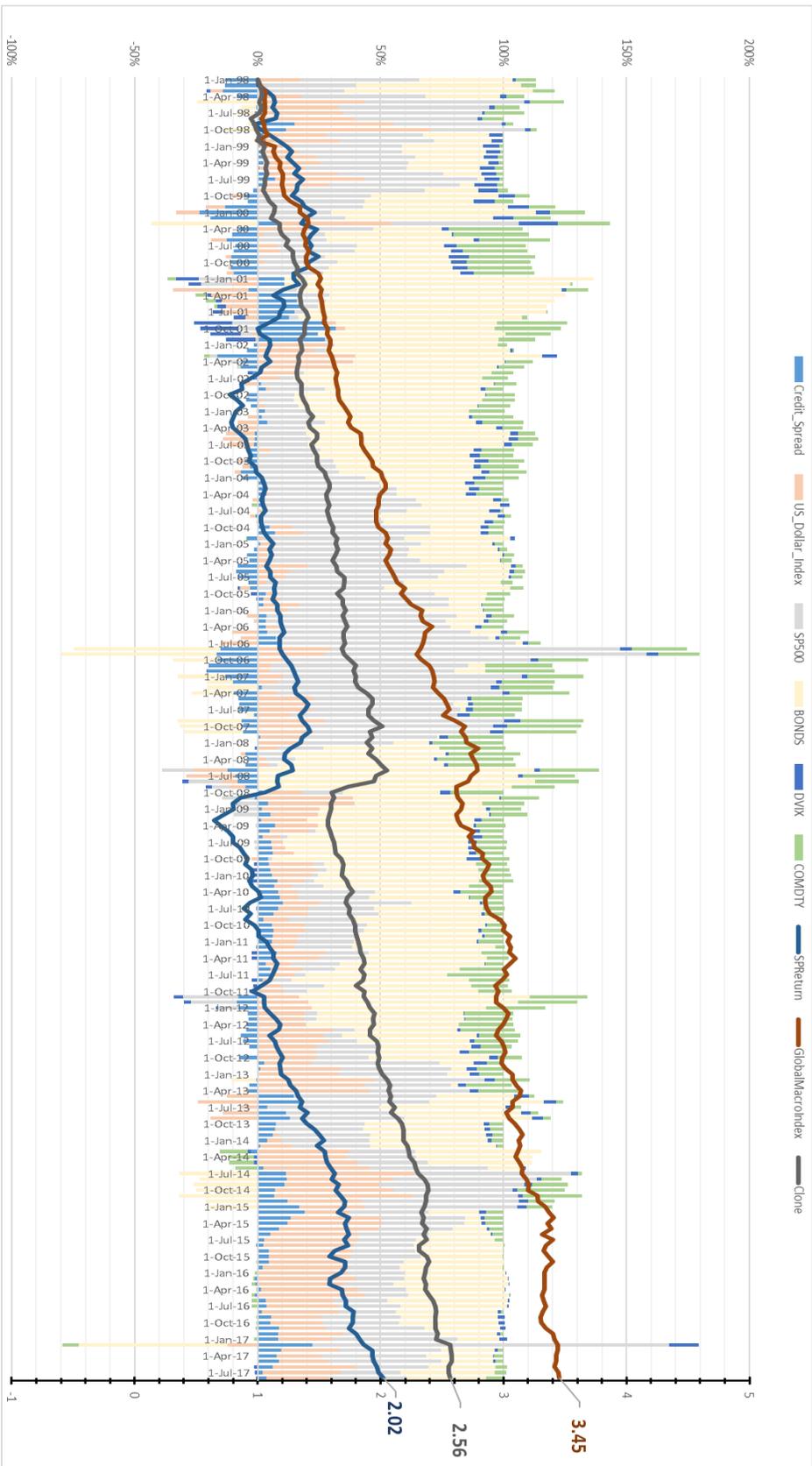


Exhibit 5.3 Summary of 1 dollar invested accumulated return for 12 months rolling-window monthly rebalancing portfolios and fixed-weight portfolios. Obtained by linear regressions of monthly returns of hedge funds in the Barclay Hedge Indexes from January 1999 to August 2017 on six factors: S&P 500 total return, AA Bond Index return, the US Dollar Index return, the spread between the US Aggregate Long Credit BAA Bond Index and the Treasury Long Index, the first-difference of the CBOE Volatility Index (VIX), and the Goldman Sachs Commodity Index (GSCI).



5.1 Factor selection

George Soros, one of the most famous investors of all times is adept at Global Macro strategy. Three of his most successful trades of all his track-record related to macro international critic turning points and took the form of currency bets: He shorted the Pound in 1992, profiting from the fall of the European Exchange Rate Mechanism; he successfully shorted the Malaysian Baht in the Asian financial crisis of 1997; and most recently in 2013 and 2014, he shorted the Yen taking profits out of president Abe's quantitative easing program the deteriorated Japan's currency¹⁶.

Although the Dollar Index provides a decent proxy for currency trades, because of its composition, we thought that this original six-factors-model was missing the Emerging Markets specific-effect. Currently, the Dollar Index is calculated by factoring in the exchange rates of six major world currencies the Euro (EUR), roughly 8% weight, Japanese yen (JPY), roughly 14% weight, Pound sterling (GBP), roughly 12% weight, Canadian dollar (CAD), roughly 9% weight, Swedish krona (SEK), roughly 4% weight and Swiss franc (CHF), roughly 4% weight¹⁷.

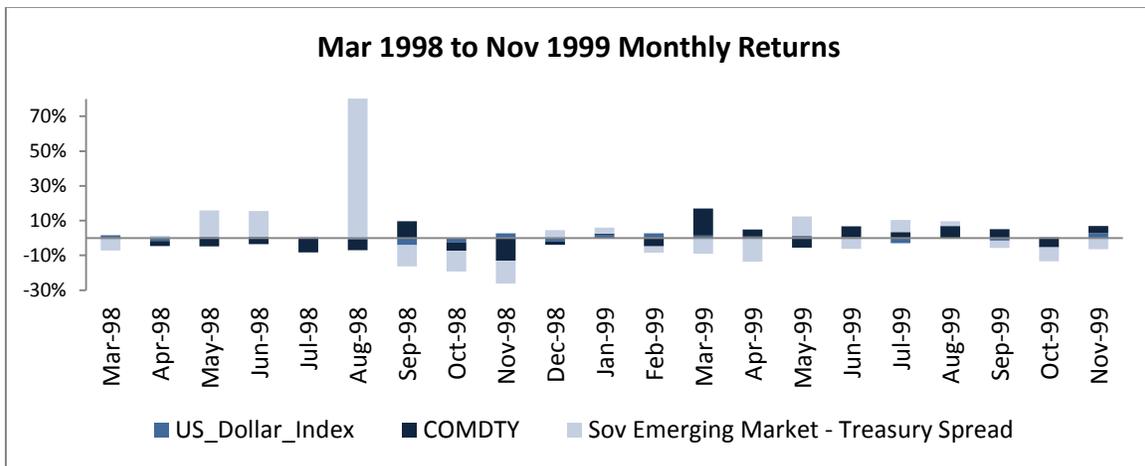
The commodity factor also brings some indirect exposure to Emerging Markets trends, but the commodity market affects the emerging market countries much more than it is affected by them, so it is not heavily influenced by idiosyncratic risk and overall risk aversion. To better capture the Emerging Market specific-effect in a consistent and extremely liquid manner we turned to the sovereign debt market of Emerging Markets countries. The debt market is the best thermometer for these countries because of its liquidity and size liquidity, far superior to its stock exchanges.

¹⁶ Wikipedia December 2017

¹⁷ Investopedia December 2017

Also, the debt market has a contamination effect that helps the replication strategy to better absorb global market opportunities. As an example, when Russia defaulted in 1998, the Brazilian currency suffered a strong speculation attack that reflected in Brazilian sovereign debt instantly and with high intensity, the Dollar Index and Commodity index did not get affected in the same speed and intensity as the Emerging Market debt index.

Exhibit 5.1.1 Monthly Returns of Dollar Index, Commodity, and Emerging Market - Treasury



For those reasons, we opted for the J.P. Morgan EMBI Diversified Sovereign Spread (JPEIDISP) Index, that captures the spread return results from the yield difference between emerging markets debt and US treasuries and has more than twenty years of track-record. The results obtained after the addition of this seventh factor was almost imperceptible in the fixed-weight regression model, but in the 12-months rolling-windows monthly-rebalancing model clones, it significantly improved the quality of the returns replication.

Exhibit 5.1.2 Summary of 1 dollar invested accumulated return for 12 months rolling-window monthly rebalancing portfolios, fixed-weight portfolios and Barclay Hedge Indexes. Obtained by linear regressions of monthly returns of hedge funds in the Barclay Hedge Indexes from January 1999 to August 2017 on seven factors: S&P 500 total return, AA Bond Index return, the US Dollar Index return, the spread between the US Aggregate Long Credit BAA Bond Index and the Treasury Long Index, the first-difference of the CBOE Volatility Index (VIX), the Goldman Sachs Commodity Index (GSCI) total return, and the J.P. Morgan EMBI Diversified Sovereign Spread (JPEIDISP) Index

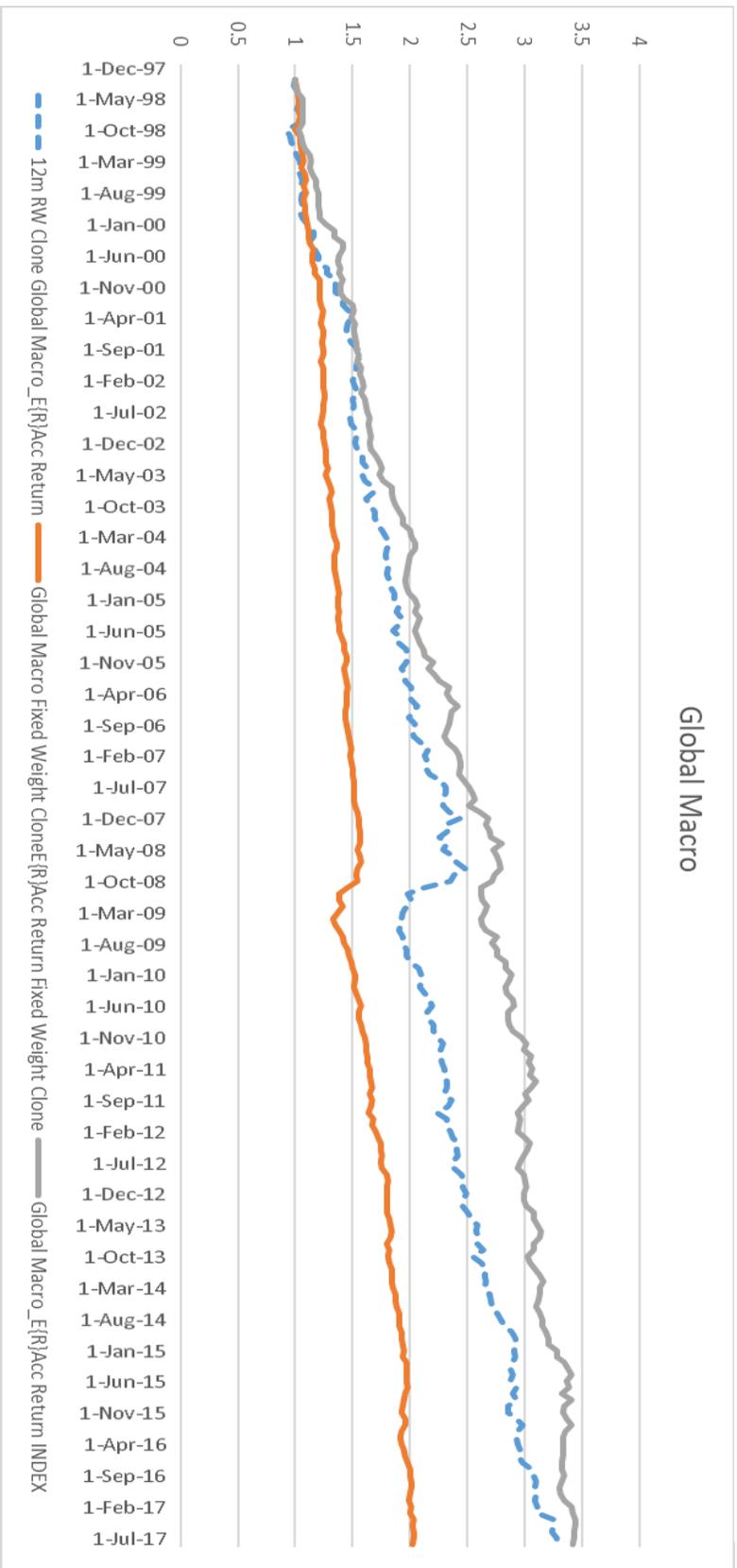


Exhibit 5.1.3 Summary of 1 dollar invested accumulated return for 12 months rolling-window monthly rebalancing portfolios and fixed-weight portfolios. Obtained by linear regressions of monthly returns of hedge funds in the Barclay Hedge Indexes from January 1999 to August 2017 on six factors: S&P 500 total return, AA Bond Index return, the US Dollar Index return, the spread between the US Aggregate Long Credit BAA Bond Index and the Treasury Long Index, the first-difference of the CBOE Volatility Index (VIX), and the Goldman Sachs Commodity Index (GSCI) total return and the J.P. Morgan EMBI Diversified Sovereign Spread (JPEIDISP) Index.

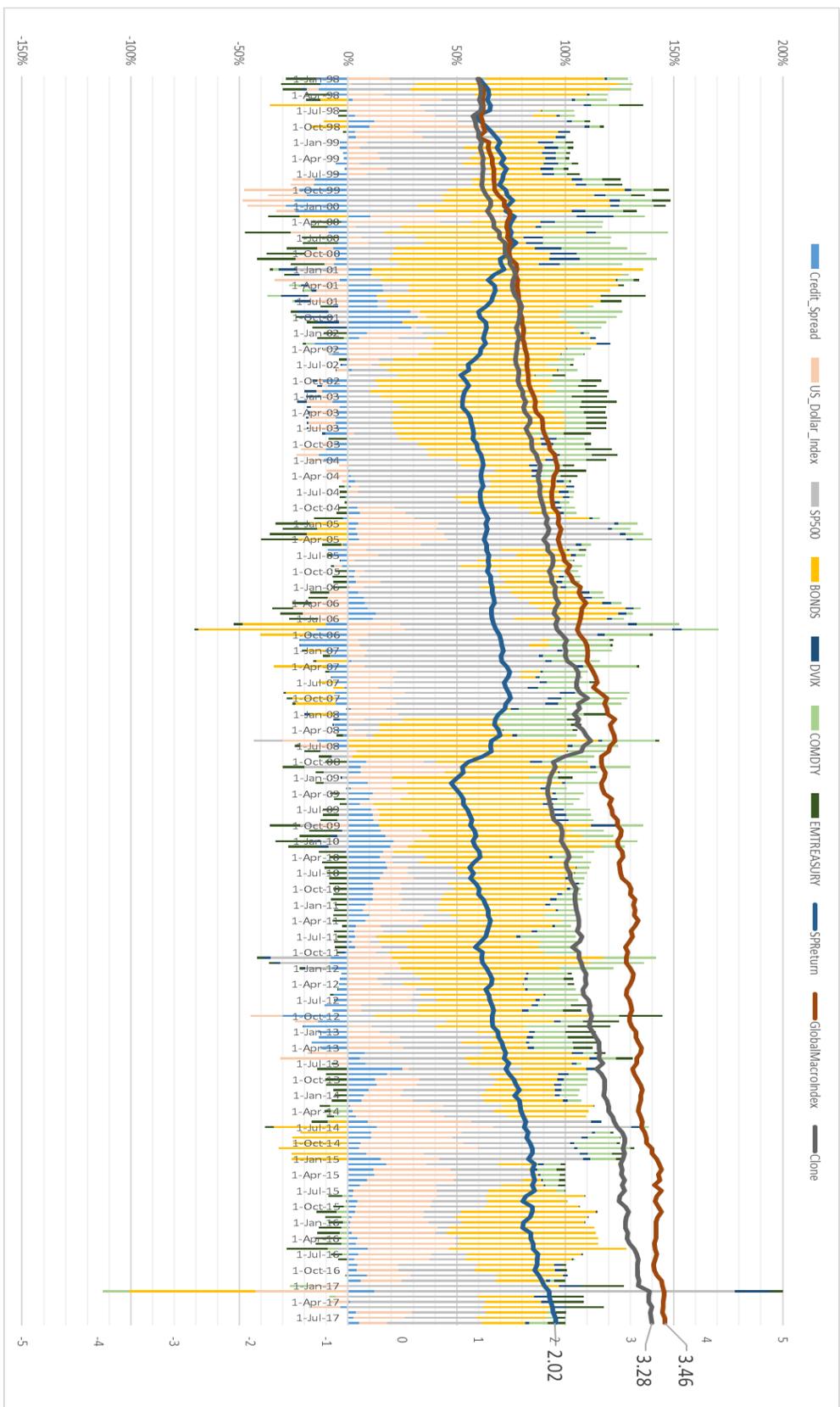
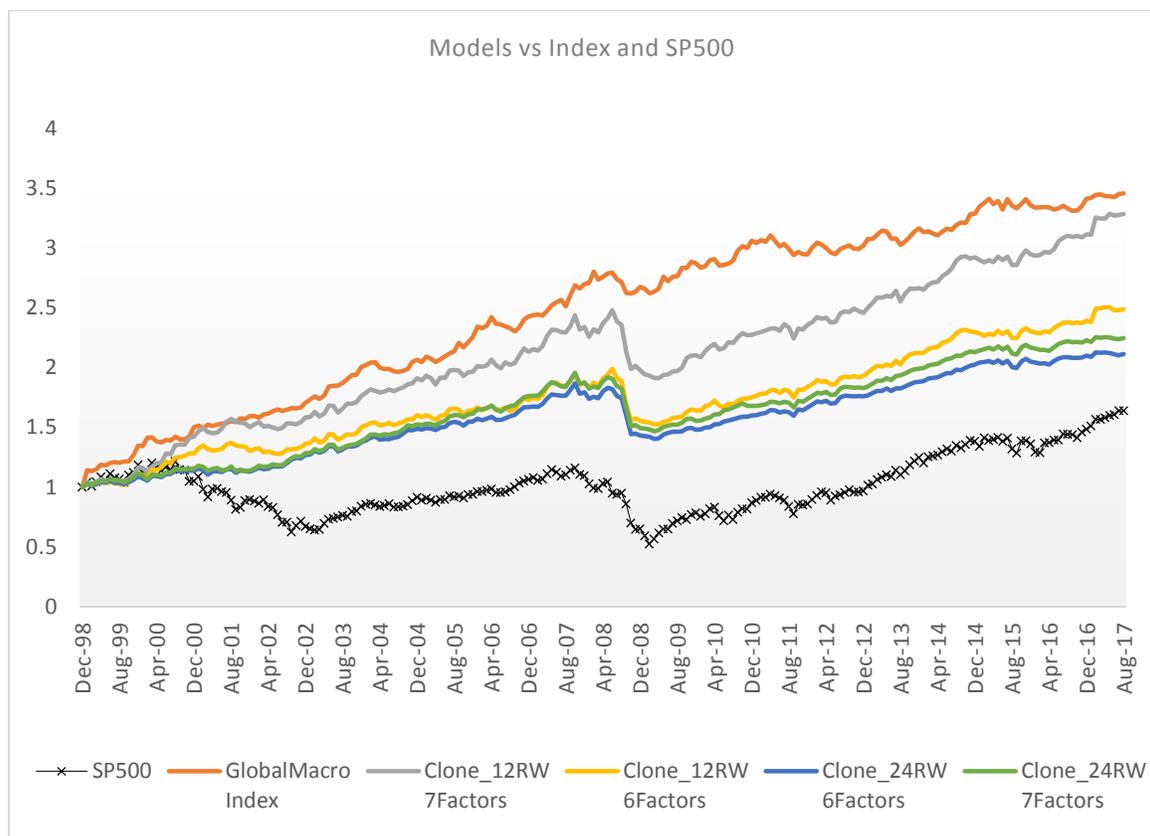


Exhibit 5.1.4 Summary table of Global Macro Clones, Barclay Hedge GM Index and the S&P 500 Index from during their overlapping time-series – December 1998 to 2017

	SP500	Global Macro Index	Clone 12RW 7Factors	Clone 12RW 6Factors	Clone 24RW 6Factors	Clone 24RW 7Factors
E[R] 12-M RoR	2.1%	6.0%	6.2%	4.9%	4.0%	4.3%
STD 12-M RoR	18.2%	5.5%	7.9%	7.4%	6.9%	7.1%
Tracking Error	-	-	6.2%	6.1%	5.6%	5.7%
Smallest 12m RoR	-64%	-7%	-24%	-25%	-26%	-26%
Largest 12m RoR	39%	30%	29%	22%	13%	14%
# of Negative 12M RoR	65	31	21	28	23	24

Exhibit 5.1.5 Chart of Global Macro Clones, Barclay Hedge GM Index and the S&P 500 Index from during their overlapping time-series – From December 1998 to August 2017



As mentioned before, our understanding is that the sub-prime crisis brought a structural break point to our data set. For this reason, we decided to take a closer look at our after-subprime-rock-bottom numbers. The results on Exhibits 5.1.6 and 5.1.7 indicate twofold: 1) The clones have embedded the features of Global Macro Strategy, which have been demonstrated by the weight dynamics (shown by the color shades on the

graph). As can be seen from the graph, the blue shade (represents the weight allocating in SP500) got almost vanished on July of 2008, which is prior to the financial crisis. As the Global Macro Strategy features in betting on the big event, the quick response of the clone to the market indicated by the weights shows a good replication. 2) The clones outperformed the Global Macro Barclay Hedge Index by more than 3% p.a. while maintaining a lower standard deviation, a lower worst 12-months rolling-windows drawdown and less 12-months rolling-windows negative returns.

Exhibit 5.1.6 Chart of \$1-dollar investment in Global Macro Clones, Barclay Hedge GM Index and the S&P 500 Index from during their overlapping time-series – From October 2009 to August 2017

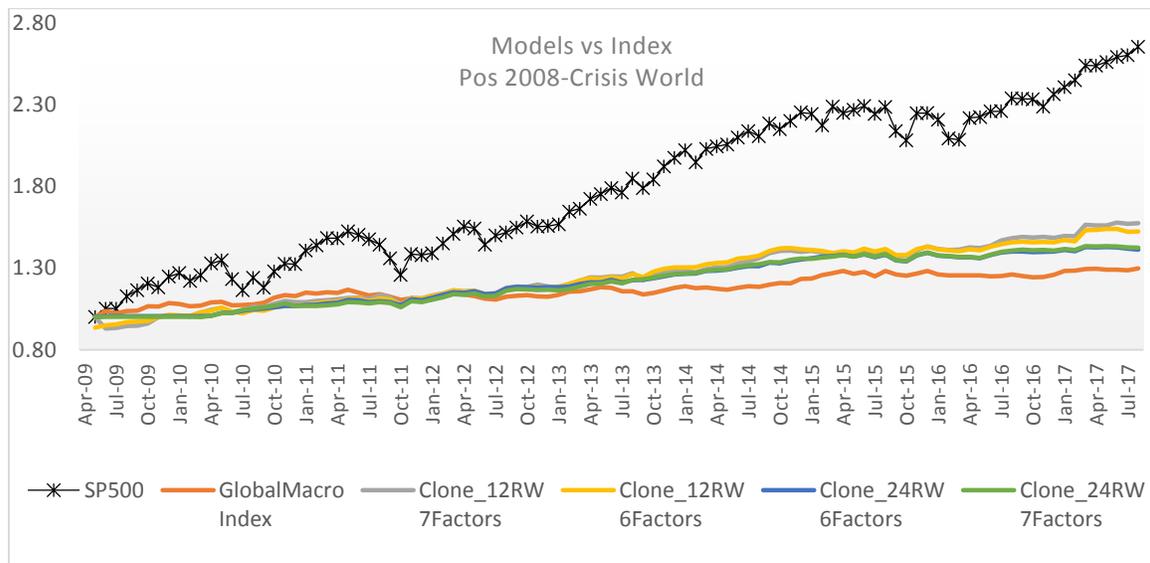
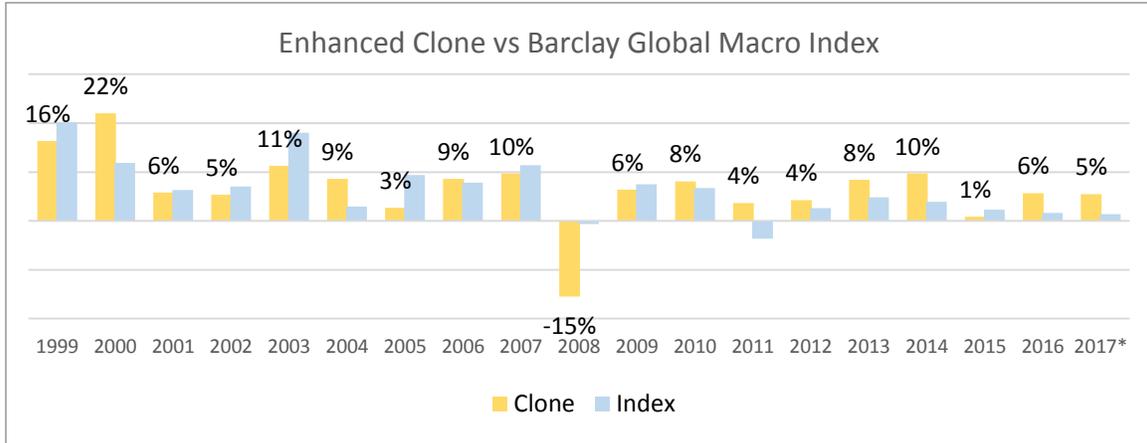


Exhibit 5.1.7 Summary table of Global Macro Clones, Barclay Hedge GM Index and the S&P 500 Index from during their overlapping time-series – March 2009 to August 2017

	SP500	Global Macro Index	Clone 12RW 7 Factors	Clone 12RW 6 Factors	Clone 24RW 6 Factors	Clone 24RW 7 Factors
E[R] 12-M RoR	10.2%	2.6%	6.0%	5.6%	4.6%	4.7%
STD 12-M RoR	7.8%	3.1%	3.0%	2.9%	2.4%	2.5%
Tracking Error	-	-	4.2%	4.4%	3.3%	3.4%
Smallest 12m RoR	-9.3%	-3.8%	-2.3%	-2.8%	-1.0%	-0.9%
Largest 12m RoR	15.3%	8.9%	12.58%	12.1%	9.8%	9.7%
#of Negative 12M RoR	12	22	3	3	4	5

Exhibit 5.1.8 Yearly Returns of the Clone 12-months rolling-windows with the 7-factor model January 1999 to August 2017



We believe that the massive liquidity increases after quantitative easing programs and the flatter yield curve and its compressed spreads are stealing performance from complex models and expensive fee structures and benefiting our clones' semi-passive strategy. Another relevant observation is that the clones of this study do not account for any transactional or operational costs, but considering the available indices trackers in the market and the competitive costs that a large institutional client have access to, we believe that this over performance is more than enough to absorb these costs.

6. Conclusion

The linear regression model is a simple but meaningful tool that enables us to quickly study the fund performance by decomposing the returns, especially for the funds that have exposures to different and broad risk factors. As pointed out by Hasanhodzic and Lo (2006), the factor-model method is a process of reverse-engineering of a hedge fund strategy, in a way, profiting from the intellectual efforts embedded to the funds that compose an index.

We based our study on the paper of Hasanhodzic and Lo (2006) and applied the same methodology with the updated data to examine the performance of the hedge fund. Hasanhodzic and Lo (2006) concluded that a fixed-weight model yields a better historical performance compared to a rolling-windows model. While our conclusion analyzing a different data set is the opposite, our results led us to the conclusion that the fixed-weight method yields a similar historical performance as the rolling-windows of 24 months most of the time (10 out of 17 strategies).

The 12-months rolling-windows approach shows a better replication for most strategies, yielding closer results to the indexes. The discrepancy between our conclusion and the conclusion from Hasanhodzic and Lo (2006) might have resulted from the differences in the dataset, as our data includes several critical financial events that require a more frequent rebalance with an asset-class allocation review, which is embedded in the rolling-windows model.

Although the results from the rolling window of 12-months approach show improvement, investors still need to carefully assess each strategy and make experimentations to the model in order to improve it before applying the replication

method in practice. In our study, motivated by the paper of Hasanhodzic and Lo (2006), we incorporated a new factor that we believe was missing in the original model and it is very relevant to the Global Macro strategy: The Emerging Market Debt Credit Spread. The improved model returned an enhanced back-testing performance, which brought us further interesting findings: 1) The linear regression does not fully replicate the hedge fund performance, but mimics the hedge fund strategies to a reasonable degree, especially when the model expands the universe of factors by including a proper strategy-specific risk factor; 2) the rolling window of 12-months approach combined with the strategy-specific factor returns an even more practical way of replicating the Global Macro Strategy; 3) considering the enhanced model back-testing performance our Global Macro clone could still outperform the index and it could prove to be more beneficial to the investors because of its semi-passive features, even if we account for transaction costs and operational fees.

There are certain boundaries to our study, especially because linear regressions multi-factor models do not fully capture the performance of the hedge fund strategies as there are also uncaptured non-linear factors in hedge funds returns. The study done by Dimitrios Giannikis (2011) has proven that there are different non-linear risk exposures of hedge funds to different risk factors, and this nonlinearity appears to the different risk factors rather than the market. By ignoring the presence of non-linearity associated with non-linear risk-factors will result in “misleading conclusion about ‘alpha’ and about the risk exposures of hedge funds.”¹⁸ Therefore, a further study should be conducted to incorporate the non-linear factors to the model. Other Improvements that should be

¹⁸ Dimitrios Giannikis (2011)

considered in an extension of this study are: 1) The implementation of a cap for a maximum amount of leverage to guarantee the feasibility of the strategy implementation; 2) Attempt for an implementation strategy using available ETFs and account for all operational costs.

Appendices

Appendix A

1. Strategy Definitions

1.1 Barclay Hedge Indexes

The following is a list of category descriptions taken directly from Barclay Hedge documentation, that define the criteria used by Barclay Hedge in assigning funds in their database to one of the 17 possible categories. In their documentation it is also highlighted for each strategy that only funds that provide net returns are included in the index calculation.

1.2 Barclay Convertible Arbitrage Index

Barclay Convertible Arbitrage Index

This strategy is identified by hedge investing in the convertible securities of a company. A typical investment is to be long the convertible bond and short the common stock of the same company. Positions are designed to generate profits from the fixed income security as well as the short sale of stock, while protecting principal from market moves.

1.3 Barclay Distressed Securities Index

Barclay Distressed Securities Index

Fund managers in this non-traditional strategy invest in the debt, equity or trade claims of companies in financial distress or already in default. The securities of companies in distressed or defaulted situations typically trade at substantial discounts to par value due to difficulties in analyzing a proper value for such securities, lack of street coverage, or simply an inability on behalf of traditional investors to accurately value such claims or direct their legal interests during restructuring proceedings.

1.4 Barclay Emerging Markets Index

Barclay Emerging Markets Index

This strategy involves equity or fixed income investing in emerging markets around the world. Because many emerging markets do not allow short selling, nor offer viable futures or other derivative products with which to hedge, emerging market investing often employs a long-only strategy.

1.5 Barclay Equity Long Bias Index

Barclay Equity Long Bias Index

Equity Long/Short managers are typically considered long-biased when the average net long exposure of their portfolio is greater than 35%.

1.6 Barclay Equity Long/Short Index

Barclay Equity Long/Short Index

This directional strategy involves equity-oriented investing on both the long and short sides of the market. The objective is not to be market neutral. Managers have the ability to shift from value to growth, from small to medium to large capitalization stocks, and from a net long position to a net short position. Managers may use futures and options to hedge. The focus may be regional or sector specific.

1.7 Barclay Equity Market Neutral Index

Barclay Equity Market Neutral Index

This investment strategy is designed to exploit equity market inefficiencies and usually involves being simultaneously long and short matched equity portfolios of the same size within a country. Market neutral portfolios are designed to be either beta or currency neutral, or both. Well-designed portfolios typically control for industry, sector, market capitalization, and other exposures. Leverage is often applied to enhance returns.

1.8 Barclay European Equities Index

Barclay European Equities Index

This directional strategy involves equity-oriented investing on both the long and short sides of the market. The objective is not to be market neutral. Managers have the ability to shift from value to growth, from small to medium to large capitalization stocks, and from a net long position to a net short position. Managers may use futures and options to hedge. The focus is regional and includes only funds that have a minimum portfolio allocation of 90% to the countries of Western Europe including the U.K. The index is simply the arithmetic average of the net returns of all funds within the category that have reported that month.

1.9 Barclay Event Driven Index

Barclay Event Driven Index

This strategy is defined as 'special situations' investing designed to capture price movement generated by a significant pending corporate event such as a merger, corporate restructuring, liquidation, bankruptcy or reorganization.

1.10 Barclay Fixed Income Arbitrage Index

Barclay Fixed Income Arbitrage Index

The fixed income arbitrageur aims to profit from price anomalies between related interest rate securities. Most managers trade globally with a goal of generating steady returns with low volatility. This category includes interest rate swap arbitrage, US and non-US government bond arbitrage and forward yield curve arbitrage.

1.11 Barclay Fund of Funds Index

Barclay Fund of Funds Index

The Barclay Fund of Funds Index is a measure of the average return of all FoFs in the Barclay database. The index is simply the arithmetic average of the net returns of all the FoFs that have reported that month.

1.12 Barclay Global Macro Index

Barclay Global Macro Index

Global Macro managers carry long and short positions in any of the world's major capital or derivative markets. These positions reflect their views on overall market direction as influenced by major economic trends and or events. The portfolios of these funds can include stocks, bonds, currencies, and commodities in the form of cash or derivatives instruments. Most funds invest globally in both developed and emerging markets.

1.13 Barclay Healthcare & Biotechnology Index

Barclay Healthcare & Biotechnology Index

This directional strategy involves equity-oriented investing on both the long and short sides of the market. The objective is not to be market neutral. Managers have the ability to shift from value to growth, from small to medium to large capitalization stocks, and from a net long position to a net short position. Managers may use futures and options to hedge. The focus is sector specific and concentrates on the Healthcare & Biotechnology sectors. The index is simply the arithmetic average of the net returns of all funds within the category that have reported that month.

1.14 Barclay Merger Arbitrage Index

Barclay Merger Arbitrage Index

Merger Arbitrage funds typically invest simultaneously long and short in the companies involved in a merger or acquisition. Risk arbitrageurs are typically long the stock of the company being acquired and short the stock of the acquirer. By shorting the stock of the acquirer, the manager hedges out market risk, and isolates his exposure to the outcome of the announced deal.

1.15 Barclay Multi Strategy Index

Barclay Multi Strategy Index

Multi-Strategy funds are characterized by their ability to dynamically allocate capital among strategies falling within several traditional hedge fund disciplines. The use of many strategies, and the ability to reallocate capital between them in response to market opportunities, means that such funds are not easily assigned to any traditional category.

1.16 Barclay Pacific Rim Equities Index

Barclay Pacific Rim Equities Index

This directional strategy involves equity-oriented investing on both the long and short sides of the market. The objective is not to be market neutral. Managers have the ability to shift from value to growth, from small to medium to large capitalization stocks, and from a net long position to a net short position. Managers may use futures and options to hedge. The focus is regional and includes only funds that have a minimum portfolio allocation of 90% to the countries of the Pacific Rim including Japan and Australia. The index is simply the arithmetic average of the net returns of all funds within the category that have reported that month.

1.17 Barclay Technology Index

Barclay Technology Index

This directional strategy involves equity-oriented investing on both the long and short sides of the market. The objective is not to be market neutral. Managers have the ability to shift from value to growth, from small to medium to large capitalization stocks, and from a net long position to a net short position. Managers may use futures and options to hedge. The focus is sector specific and concentrates on the Technology sector. The index is simply the arithmetic average of the net returns of all funds within the category that have reported that month.

Appendix B

Following Hasanhodzic and Lo (2006), this study initially applies the following factors: 1) Market proxy: S&P 500; 2) Bond Returns: Bloomberg Barclays Aa Corporate Total Return Index Value Unhedged USD; 3) USD Dollar: U.S Dollar Index (USDIX); 4) VIX: Chicago Board Options Exchange SPX Volatility Index; 5) Commodity: S&P GSCI Total Return CME; and 6) Credit Spread: US Corporate Baa and 10-year US Treasury spread.

The intuition behind these risk factors are twofold: 1) Representative: They are perceived as a reasonably broad cross-section of risk exposures for the typical hedge fund; 2) Liquidity: The chosen factors can be easily realized by the relatively liquid instruments that will make the constructed clones easy to be implemented. Nonetheless, there are forward contracts and futures contracts for each factor such as the forward contracts for U.S. Dollar index and futures contracts for the stock and bond indexes as well as the commodity index. Also, the OTC market for variance and volatility swaps grows rapidly.

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