BI Norwegian Business School - campus Oslo

GRA 19703

Master Thesis

Thesis Master of Science

Replicating Smart Money - A Derivative-Based Approach

Navn: Jakob Røksund, Mikkel Nymo Foss

Start: 15.01.2020 09.00

Finish: 01.09.2020 12.00

Replicating smart money: a derivative-based approach

Master Thesis

by
Jakob Røksund
Mikkel Nymo Foss
MSc in Finance

Oslo, June 22, 2020
Supervised by Sven Klingler

ABSTRACT

An option strategy, which writes short-dated out-of-the-money put options on the S&P500, is able to replicate the risk and return characteristics of broad hedge fund indices. Further, by extending the Carhart four factor model with this put-writing strategy, we are able to explain the alpha of a factor which goes long low-beta stocks and shorts high-beta stocks. Traditional risk factor models estimate annual alphas in the range 6-7% for hedge funds, and 9% for the betting-against-beta factor. Our results suggest that both hedge funds and betting-against-beta exhibit nonlinear risks which traditional factor models fail to capture. While betting-against-beta suffer during stressed markets, the quality-minus-junk portfolio does not have the same crash risk. Our results suggest that the abnormal returns to BAB is fair compensation for downside risk exposure, while the returns to QMJ remains a puzzle.

Acknowledgements

We extend our gratitude to Sven Klingler for his guidance throughout our thesis. We would also like to thank our fellow classmates, our time at BI Norwegian Business School would not have been the same without you. Finally, we thank each other for a rewarding collaboration.

Contents

List of Abbreviations

APT Arbitrage Pricing Theory

BAB Betting-against-Beta

CAPM Capital Asset Pricing Model

CBOE Chicago Board Options Exchange

DJCS Dow Jones/Credit Suisse

HFRI Hedge Fund Research Inc.

HML High-minus-Low

LIBOR London Interbank Offered Rate

MKT Market

MOM Momentum

OIS Overnight Indexed Swap

QMJ Quality-minus-Junk

SMB Small-minus-Big

List of Figures

List of Tables

1 Introduction

Traditional risk-factor models estimate hedge fund alphas in the range 6-10% (Jurek & Stafford, 2015). With such an impressive track record the attraction of replicating smart money for a fraction of the fee is easy to understand. However, the secretive nature of hedge funds make it difficult to evaluate the trading strategies adopted by these funds. Many academic papers have tried to replicate and explain the impressive track record of hedge funds. Interestingly, AQR, a U.S. based hedge fund, is on the forefront of publishing research on quantitative-based investment strategies.

While traditional factor models have been successful in replicating, and surpassing, the returns of actively managed mutual funds, they have not been able to replicate the returns of hedge funds. Jurek and Stafford (2015) show that a mechanical put-writing strategy, which writes short-dated out-of-the-money put options on the S&P500, outperforms traditional linear factor models in capturing the risk and return characteristics of broad hedge fund indices. The estimated alphas when regressing hedge fund indices on the derivative-based model are not reliably distinguishable from zero. While their overall results hold in our extended sample, we still find significant alpha estimates. However, these strategies outperform traditional models.

Our thesis will research two main questions. The first is:

"Will a strategy which writes out-of-the-money put options on the market exhibit similar risk and return characteristics as broad hedge fund indices?"

This hypothesis is tested by regressing the HFRI Fund Weighted Composite Index and the DJCS Broad Hedge Fund Index on two separate put-writing strategies. We test the null hypothesis that the alpha and beta are jointly equal to zero and one, respectively. We find that writing out-of-the-money put options exhibit similar risk and return characteristics as hedge funds.

Further, we formulate the second research question as:

"Will the same put-writing strategies, combined with traditional factor models, explain the alpha of other factors that exhibit abnormal returns?"

The aforementioned factors that exhibit abnormal returns are in this case betting-against-beta (BAB) and quality-minus-junk (QMJ). We regress these factors on the Carhart (1997) four-factor model and the put-writing strategies, and examine the effect on the alphas. We find that the combination of the Carhart model and a factor which writes far out-of-the-money put options on the S&P500 are able to capture the abnormal returns of BAB. The estimated alpha of QMJ, however, is not affected by the inclusion of the put-writing strategies.

2 Literature Review

While traditional factor models, such as the Capital Asset Pricing Model (CAPM), the Fama-French three factor model, and the Carhart four factor model, have been successful in explaining mutual funds' risk and return characteristics, the same factor models have not been able to explain hedge fund characteristics (Fama & French, 2010). Jurek and Stafford (2015) estimate pre-fee hedge fund alphas for the aforementioned models of 6-10%. Even the asset-based style factor model specifically developed for hedge funds by Fung and Hsieh (2004) estimate an annualized alpha of 5.7%. These results indicate that traditional linear models fail to capture the characteristics of hedge funds, or a market inefficiency which cannot be found in the mutual fund universe (Agarwal & Naik, 2004; Fama & French, 2010; Fung & Hsieh, 2004; Jurek & Stafford, 2015).

The explanation may lie in the strategies adopted by hedge funds. Mutual funds typically face more restrictions in terms of leverage, short-selling, and which asset classes they can invest in compared to hedge funds, which are less restricted (Agarwal & Naik, 2004; Almazan et al., 2004; Pedersen, 2015). Popular hedge fund strategies take full advantage of the financial toolbox. Merger arbitrage, fixed-income arbitrage, global macro, and event-driven strategies all use derivatives, leverage and short-selling in varying degree. In the following we describe some of the most popular strategies' risk and return characteristics.

Many strategies take advantage of arbitrage opportunities. As Pedersen (2015) states, academic arbitrage rarely, if ever, exist in the real world. In the practitioners sense, arbitrage involves buying and selling similar securities at attractive relative prices. It is, however, not riskless, and often involves a cash outlay. Long-short strategies often involve margin requirements and arbitrageurs may face significant losses before the trade converges. Pedersen argues that "arbitrage opportunities arise as compensation for liquidity risk and deal risk in connection with corporate events, convertible bonds, and fixed-income markets" (2015, p.233).

Mitchell and Pulvino (2001) show that risk arbitrage can be replicated by a short position in an out-of-the-money put option on the S&P500. Similarly, Pedersen (2015) argues that arbitrage traders are providing insurance against deal risk, as mergers and other transactions often fall through during market turmoil. Likewise, event-driven funds may focus on distressed companies, or turn-around cases which are also adversely impacted by a deteriorating market sentiment (Pedersen, 2015). Agarwal and Naik (2004) find similar results for the HFR event-driven, event-arbitrage, and restructuring indices. Fung-Hsieh (2002c) show that Fixed Income hedge funds are typically exposed to the yield spread. These funds often buy bonds with low credit ratings and hedge the interest rate exposure by shorting US T-bonds. As credit spreads tend to widen as market conditions deteriorates, these strategies also resemble short put options on the market index. Conversely, the trend-following strategies in the Fung-Hsieh model perform well when markets are distressed (Fung & Hsieh, 2004). Thus, their risk and return profile is similar to a long options strategy. This is because the value of options are increasing in volatility, all else equal.

As a result of these hedge fund strategies, the returns exhibit nonlinear risk exposures. Jurek and Stafford (2015) show that a strategy which writes out-of-the-money put options on the S&P500 is able to replicate the risk and return characteristics of broad hedge fund indices.

They also argue that popular common factor models (such as the Fung-Hsieh model) "explain most of the time series variation, but miss most of the mean, identifying this as alpha" (Jurek & Stafford, 2015, p.2187). Due to this nonlinearity, the mean-variance framework underestimates the tail risk (Agarwal & Naik, 2004).

We extend the work of Jurek and Stafford's put-writing strategy (2015) by combining it with the Carhart (1997) four-factor model to explain the abnormal return of two factors - namely, betting-against-beta (BAB) and quality-minus-junk (QMJ). These factors exhibit significant abnormal returns (Asness et al., 2019; Frazzini and Pedersen, 2014).

Interestingly, quality-minus-junk, betting-against-beta, and the Carhart model, levered by a factor of 1.7, fully explain the abnormal return of Warren Buffett's Berkshire Hathaway (Frazzini et al., 2018). Frazzini and Pedersen (2014) show that the stocks with the lowest 10% beta yields the highest alpha. The BAB factor has statistically significant alphas against both the CAPM, the Fama-French three factor model, and the Carhart model (Frazzini & Pedersen, 2014). The estimated monthly alphas range between 0.73% and 0.55%. Interestingly, they note that the BAB factor would suffer losses when funding liquidity[1] worsens (2014, p.21). This implies that BAB exhibits crash risk, as the TED spread tends to rise when capital markets are stressed. The QMJ factor on the other hand, benefits from flight-to-quality in such market environments. QMJ has statistically significant monthly alphas in the range 0.64% to 1.05%, even when controlling for exposure to the Fama-French and Carhart model (Asness et al., 2019). Asness et al. find that "the primary link between value and momentum returns comes from funding risk" (Asness et al., 2013, p.931). They show that value and momentum has different exposure to funding risk, with value loading negatively.

[1]Funding liquidity is proxied by the TED spread. The TED spread is defined as the difference between the 3-month Eurodollar LIBOR, and the 3-month US Treasury

3 Linear Factor Models

In this section, we introduce the concept of factor models before reviewing the specific models used in our thesis.

Factor models are used in finance to represent "equations that establish links between security returns and their lagged values or exogenous variables" (Fabozzi & Pachamanova, 2016, p.227). These models simplify portfolio optimization in the mean-variance framework by reducing the number of estimates needed. With K factors, one needs $K \times N + K \times (K-1)/2 + K + N$ estimates. For a portfolio with $N = 1000$, using a three-factor model would reduce the number of estimates by 99% (Fabozzi & Pachamanova, 2016). The general form of a linear factor model is

$$r_i = \alpha_i + \beta_{i1} f_1 + ... + \beta_{iK} f_K + \epsilon_i \quad (1)$$

Where,

r_i is the rate of return on security i,

β_{ik} is the factor loading of security i on factor k,

f_k is the factor return on factor k, and

$\alpha_i + \epsilon_i$ is the specific (nonfactor) return on security i, with α_i as the expected return and ϵ_i as a random shock.

The single index model, the simplest factor model, contains a single factor which represent the value-weighted portfolio of all assets. It is generally recognized that a single factor cannot account for the covariance structure of asset returns (Fabozzi & Pachamanova, 2016). While The Arbitrage Pricing Theory (APT) prices securities using no-arbitrage arguments; does not assume a return distribution; and is based on relatively unrestrictive assumptions about investor preferences, it does not propose what the specific factors should be (Fabozzi & Pachamanova, 2016).

Table I. Description of Factors

This table summarizes, and provides a short description of the factors

Factor	Description
MKT	The US equity market excess return. Computed as the value-weighted return of all firms listed on the NYSE, AMEX and NASDAQ
SMB	Denotes the Fama-French Small-minus-Big portfolio
HML	Denotes the Fama-French High-minus-Low portfolio
MOM	Denotes the Fama-French momentum factor.
S&P500	The excess return on the S&P500
SIZE	The Fung-Hsieh size factor is constructed as the Russell 2000 monthly return less the S&P500 monthly return.
TSY	The Fung-Hsieh treasury factor is computed as the change in the US 10-Year Treasury Constant Maturity Rate

Table I –(Continued)

CREDIT	Computed as the change in Moody's Baa yield less the US 10-Year Treasury Constant Maturity Rate
TF-BD	Trend-following bond factor
TF-FX	Trend-following currency factor
TF-COM	Trend-following commodity factor
TF-IR	Trend-following interest rate factor
TF-STK	Trend-following stock factor
BAB	Denotes the Betting-against-beta factor
QMJ	Denotes the Quality-minus-junk factor.

3.1 Carhart Four-Factor Model

The Carhart four-factor model is an APT model developed by Mark Carhart (1997), as an extension of the three-factor model by Eugene Fama and Kenneth French (1993). Carhart added the fourth factor, namely momentum. We apply this model to the hedge fund indices to serve as a benchmark. The regression is as follows:

$$r_{i,t} = \alpha_i + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,MOM}MOM_t + \epsilon_t \tag{2}$$

The first factor (MKT) is the market risk premium ($r_{mkt} - r_f$). Small minus big (SMB) is the size factor and high minus low (HML) is the value premium. These are the original three factors developed by Fama and French (1993). The last factor (MOM) denotes momentum which captures the tendency for stocks to continue rising if it previously has experienced increase and vice versa. The momentum factor originates from Jegadeesh and Titman (1993).

3.2 Fung-Hsieh Nine-Factor model

The Fung-Hsieh nine-factor model is specifically designed to capture the abnormal returns of well-diversified hedge funds. The factors Fung and Hsieh use can be divided into three different groups: trend-following risk factors, equity-oriented risk factors and bond-oriented risk factors. While the most basic trend-following strategy is time-series momentum, hedge funds may apply different approaches. The trend-following strategy chosen by Fung and Hsieh (2001) is identifiable with a large number of hedge funds. They note that this strategy has option-like features as returns tend to be "large and positive during the best and worst performing months of the world equity market" (2001, p. 315). Fung and Hsieh used a "lookback straddle" to model this strategy. A lookback call is the option to buy the underlying at the lowest price during the life of the option, and vice versa for a put option. The combination of a lookback call and a lookback put is the lookback staddle (Fung and Hsieh, 2001). The equity-oriented risk factors are the market- and size factors. These show the exposure hedge funds have to the market, and the spread between large and small cap stocks. The bond-oriented risk factors consists of treasury and credit. They try to capture the main risks of fixed-income hedge funds. Fixed-income hedge funds are typically exposed to interest rate spreads as they tend to buy bonds with low credit quality, and short treasuries to hedge out interest rate risk (Fung and Hsieh, 2002a).

$$r_{i,t} = \alpha_i + \beta_{i,MKT} S\&P500_t + \beta_{i,SIZE} SIZE_t + \\ \beta_{i,TSY} TSY_t + \beta_{i,CREDIT} CREDIT_t + \beta_{i,TFBD} TFBD_t + \beta_{i,TFFX} TFFX_t + \\ \beta_{i,TFCOM} TFCOM_t + \beta_{i,TFIR} TFIR_t + \beta_{i,TFSTK} TFSTK_t + \epsilon_{i,t} \tag{3}$$

The first two factors MKT and $SIZE$ is the equity-oriented risk factors. MKT represent the market factor while $SIZE$ represent the difference between the S&P500 and the Russell 2000 monthly returns. TSY and $CREDIT$ are the bond-oriented risk factors. TSY or treasury is the monthly change in the 10-year treasury constant maturity yield and $CREDIT$ is the change in Moody's Baa yield less the 10-year treasury constant maturity yield. The remaining five factors are the trend following factors. BD, FX, COM, IR and STK represent bonds, currencies, commodities, interest rates and stocks, respectively[2].

3.3 Betting Against Beta

One of the most fundamental assumptions in the CAPM is that people should invest in the portfolio with the highest Sharpe ratio and then lever or de-lever to suit the investor's risk and return preferences. The betting-against-beta (BAB) factor follows the idea that high-beta assets are overpriced as constrained investors are not able to use leverage to obtain their desirable risk and return level. For instance, mutual funds are restricted in leverage (Almazan et al., 2004). Hence, high-beta assets are associated with low alpha (Frazzini and Pedersen, 2014). The factor is therefore compiled of shorting high-beta assets and going long low-beta assets.

3.4 Quality Minus Junk

The quality-minus-junk (QMJ) factor is based on going long high-quality stocks and shorting low-quality (or junk) stocks. Asness, Frazzini, and Pedersen (2019) show that quality has only a moderate impact on prices. Thus, high-quality stocks have high risk-adjusted returns. The authors define quality as characteristics investors should be willing to pay a higher price for. These characteristics are profitability, growth and safety. The factor is constructed by rewriting Gordon's growth model to express a stock's price-book ratio (as shown in Equation (4)). The price-to-book ratio increases linearly in the factor's characteristics (i.e. profitability, growth and safety). The importance of scaling the price by the book ratio is to account for the size of different companies (i.e., make the assets comparable and stationary across time (Asness et al., 2019, p.35)).

$$\frac{P}{B} = \frac{1}{B} \frac{dividend}{required\,return - growth} = \frac{profit/B \cdot dividend/profit}{required\,return - growth}$$

Hence, we have the price-to-book ratio as:

$$\frac{P}{B} = \frac{profitability \cdot payout\,ratio}{required\,return - growth} \tag{4}$$

Profitability is measured as gross profit, margins, earnings, accruals and cash flows. The stock's average rank across these metrics will make up the profitability measure. That is, the average

[2]The factors are retrieved from David Hsieh's data library: faculty.fuqua.duke.edu/ dah7/DataLibrary/TF-FAC.xls

of the individual z-scores:

$$Profitability = z(z_{GPOA} + z_{ROE} + z_{ROA} + z_{CFOA} + z_{GMAR} + z_{ACC}) \quad (5)$$

Profitability is the amount of profit per unit of book value. The metrics are standardized to create Z-scores in order to make them comparable and easily combined. The variables in Equation (5) is: Gross profit over assets (GPOA), return on equity (ROE), return on assets (ROA), cash flow over assets (CFOA), gross margin (GMAR) and the fraction of earnings composed of cash (i.e., less accruals, ACC) (Asness et al., 2019).

Growth is measured using the same metrics as profitability (excluding accruals) over a five-year period. The intuition behind the growth characteristic in quality is that investors should pay a premium for an asset with growing profits. The formula for growth is:

$$Growth = z(z_{\Delta GPOA} + z_{\Delta ROE} + z_{\Delta ROA} + z_{\Delta CFOA} + z_{\Delta GMAR}) \quad (6)$$

Δ denotes the five-year change in each metric of residual income per share, over the lagged denominator (Asness et al., 2019).

Safer assets, i.e. with lower required return, should be priced at a premium. Asness et al. (2019) mention that variables included in required return has not reached a consensus in finance literature. Thus, the factor include both return-based and fundamental-based measures. The formula for safety is:

$$Safety = z(z_{BAB} + z_{LEV} + z_{O} + z_{Z} + z_{EVOL}) \quad (7)$$

From the return-based measure Asness et al. includes betting-against-beta (BAB). The rest of the metrics included in safety stems from the fundamental-based approach. These are low leverage (LEV), low bankruptcy risk (O-score and Z-score[3]) and low ROE volatility (EVOL).

$$Quality = z(Profitability + Growth + Safety) \quad (8)$$

Combining the three quality characteristics returns the quality score.

[3]Ohlson's O-score and Altman's Z-score are models designed to predict bankruptcy or financial distress based on financial data (Ohlson, 1980).

4 Constructing Derivative-Based Factors

In this section, we describe the methodology used to calculate returns to the derivative-based model. The model focuses on the replication of hedge fund returns using put-writing strategies based on the paper "The Cost of Capital for Alternative Investments" by Jurek and Stafford, 2015.

The data sample spans from February 1996 to February 2019. We construct two put-writing strategies with different Z-scores and amount of leverage $[Z,\, L]$.

4.1 Strike Selection

We select options based on rebalancing date, expiration date and strike price - in that order. The rebalancing date is the last trading day of each month. The expiration date is set to the end of the following month or after. As most of the options expire the third Friday of each month, the average time to maturity is seven weeks. We rebalance the portfolio monthly. This is done by buying back the same option after four weeks, or another option with the same strike price and expiration date. Hence, after one month, our position is fully hedged and the average holding period is four weeks. Our strategy is based on writing out-of-the-money put options. To determine how deep out-of-the-money the put options should be, we use Z-scores. Z-scores measure the number of standard deviations the strike price is below the spot price. However, as opposed to keeping the moneyness fixed, such as Agarwal and Naik (2004), we keep the Z-score fixed. Moneyness is 13% and 7% for the $[Z = -2, L = 4]$, and $[Z = -1, L = 2]$ strategies, respectively (measured as the strike/spot ratio). This ensures that the systematic risk is somewhat constant at the rebalancing dates. Equation (9) illustrates the strike selection:

$$K(Z) = S_t \cdot exp(\sigma_{t+1} \cdot Z) \tag{9}$$

S_t denotes the S&P500 spot price at time t, σ_{t+1} denotes the one-month implied volatility of the S&P500 observed at time t. We select the option that has strike price closest to but below the calculated strike price. In the instances where there are no available options with the desired strike price and expiration dates, we postpone writing the option until such an option can be written.

4.2 Amount of Financial Leverage

The writer of the option incurs a liability and must post collateral to cover potential losses. In the case of the put-writing strategy, the highest possible amount one could lose is the option's strike price. A fully unlevered put-writing strategy will therefore need the portfolio's equity to have the same value as the total potential loss or more. We set the margin equal to the maximum potential loss (Jurek and Stafford, 2015). That is, the unlevered asset capital, k_A:

$$k_A = e^{r_{f,t+\tau}} \cdot K(Z) - p_t^{bid}(K(Z), T) \tag{10}$$

In the case of European options (or American which is held until expiration), the initial investment of unlevered capital equals the discounted strike price less the price from selling the option.

$e^{r_{f,t+\tau}}$ is the discounting factor, where τ denotes the exercise date. $r_{f,t+\tau}$ is the risk-free rate corresponding to the period between writing the option and expiration. We use London Interbank Offered Rate (LIBOR) 1-month as the risk-free rate until 2002. From 2002 and onwards we switch to Overnight Indexed Swap (OIS) rate. LIBOR was traditionally used as risk-free rate by derivatives dealers. However, this rate is not completely risk-free and after the financial crisis in 2008 derivatives dealers started the search for another risk-free proxy. Thus, dealers started using OIS rates. That being said, as LIBOR, the OIS rate is not completely risk-free either, but very close (Hull, 2017). Before 2002 we do not have data on the OIS rate, thus we use LIBOR for the first six years of our sample. Leverage constraints are set by the CBOE. By dividing the unlevered capital on leverage, we find the equity capital needed for the investment in the portfolio to comply with the CBOE regulations[4]:

$$k_E = \frac{k_A}{L} \tag{11}$$

In our sample period, both put-writing strategies fully comply with the CBOE margin requirements.

4.3 Computing the returns

The equity capital required combined with the option premium is invested in the risk-free rate every month. This generates the strategy's accrued interest, AI_{t+1}:

$$AI_{t+1} = (k_E(L) + p_t^{bid}(K(Z), T)) \cdot (e^{r_{f,t+1}} - 1) \tag{12}$$

The accrued interest combined with the spread between selling the option at time t and buying back the option at time $t+1$, divided by the equity capital will produce the strategy's monthly return, $r_{p,t+1}$:

$$r_{p,t+1} = \frac{p_t^{bid}(K(Z), T) - p_{t+1}^{ask}(K(Z), T) + AI_{t+1}}{k_E(L)} \tag{13}$$

If no options with the desirable characteristics are available, the equity capital is invested in the risk-free rate. Hence, the return of the months where we do not sell and buy options equals the risk-free rate. For the $[Z = -1, L = 2]$ strategy, this occurs in none of the months, for the $[Z = -2, L = 4]$ strategy, this occurs five times during the 277 months.

[4] The minimum equity capital required by CBOE is calculated as:
min $k_E^{CBOE} = p^{bid}(K, S, T; t) + max(0.1 \cdot K, 0.15 \cdot S - max(0, S - K))$

5 Data

In this section we describe the data sources as well as discuss potential biases inherent to hedge fund return data. Descriptive statistics are presented in Table II.

5.1 Data Sources

Our source of hedge fund return data is the equal-weighted HFRI Fund Weighted Composite Index (HFRI) and the value-weighted Dow Jones/Credit Suisse Broad Hedge Fund Index (DJCS). Both data sets are obtained from Bloomberg and spans from February 1996 to February 2019. Returns are reported as net-of-fee values. To construct pre-fee returns we add back our estimated fee of 3.8%. This is in line with Jurek and Stafford (2015) and corresponds to a "2-and-10" compensation structure where the fund charges a 2% flat fee, and a 10% incentive fee. The "2-and-20" compensation structure is widely used amongst hedge funds. The incentive fee is only activated if the hedge fund realize returns above a pre-set hurdle rate, or high watermark. Hence, the 3.8% fee represent a reality where half of the hedge funds in the indices surpasses the hurdle rate, and half do not (Jurek and Stafford, 2015). Earlier research indicate annual fees in the range 3.34% to 4.26% (French, 2008; Ibbotson et al., 2011).

Factor returns for the Carhart four factor model is obtained from AQR's data library[5]. Their methodology follow that of Fama and French (1993) for the first three factors (MKT, SMB and HML) and Carhart (1997) for the fourth factor, momentum. The trend-following factors for the Fung-Hsieh nine factor model (2002a) are obtained from David Hsieh's data Library[6]. The equity-oriented risk factors and bond-oriented risk factors in the Fung-Hsieh factor model are computed as stipulated in David Hsieh's data library. Historical data for the VIX index is available from the CBOE website. The risk free rates are obtained from Kenneth French' data library[7], while LIBOR and OIS rates are retrieved from Bloomberg. The S&P500 and Russell 2000 data are also from Bloomberg. The option data used to construct the put-writing strategies are from a proprietary data source at BI, while return data for betting-against-beta and quality-minus-junk are obtained from AQR's data library.

5.2 Hedge Fund Biases

Hedge funds are not subject to the same reporting regulations as mutual funds. Therefore, an important aspect of the data set arises, namely biases. It is important to keep these biases in mind as they may distort the reality of hedge fund performance. For instance, the flexibility in hedge fund managers' reporting provides the opportunity to smooth their returns. That is, they only report a fraction of their returns in one period and report the remaining fraction the next period. This is used by hedge funds to mitigate both bad and good surprises and thereby lowering their measured volatility and improving the risk-adjusted returns (Bollen and Pool, 2008). This phenomenon is referred to as "return smoothing" and may bias the data set. With the widespread use of monthly summary statistics (such as, Sharpe ratios and betas), hedge fund managers have incentives to present their returns as both consistent and uncorrelated with

[5] AQR Data Library: aqr.com/Insights/Datasets
[6] David Hsieh Data Library: faculty.fuqua.duke.edu/~dah7/HFRFData.htm
[7] Kenneth French Data Library: mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

the market (Asness et al., 2001). Therefore, there may exist a lagged relationship between the market returns and hedge fund return, leading to an understatement of monthly betas (Asness et al., 2001).

5.2.1 Backfill Bias

Backfill bias is a result of hedge fund reporting rules. As hedge funds do not have to report their returns to a database (only required to report to their investors), backfill bias arises. Reporting the returns to a database can be used to promote the fund, as marketing of hedge funds is not allowed (Pedersen, 2015, p.23). However, when hedge funds decide to report their returns to a database provider, they have to report all of their historical returns (or "backfilling" their performance). Thus, hedge funds choosing to report are likely to be better performing funds, while hedge funds with poor performance will choose not to report (Pedersen, 2015). The historical performance is biased upwards and the risk is biased downward compared to reality (Fung and Hsieh, 2002b).

5.2.2 Survivorship Bias

When observing the returns of indices we do not account for the change in the composition of the indices. That is, HFRI may consist of different hedge funds in 1996 and 2018. This becomes a problem when the indices only includes the hedge funds that operate at the end of the sample period. Hedge funds that experience low performance may cease their operation. Hence, the hedge funds that "survive" are the best performing funds. Another effect that induce survivorship bias is the reporting requirement of hedge funds, or lack thereof. Poor performing hedge funds may stop reporting their returns, and thereby increase the effect of the bias (Pedersen, 2015).

5.2.3 Selection Bias

Selection bias concerns selection criterion of database vendors, such as HFR. For instance, the HFRI Fund Weighted Composite Index has a requirement of minimum $50M assets under management (HFR, 2020). Thus, hedge funds with poor performance may be taken out of the index (as they fall below the requirements of the index) and good performing funds may be included (Fung and Hsieh, 2002b). That being said, reporting regulations of hedge funds also cause a bias pulling in the opposite direction. The best performing hedge funds usually avoid reporting to a database as they value their privacy and do not have to promote their fund. In some cases, the funds are so attractive that their funds are closed to new investors as their capacity is full (Pedersen, 2015; Fung and Hsieh, 2002b). Thus, this bias may have both a negative and positive effect on the observed returns.

5.3 Descriptive Statistics

Table II reports descriptive statistics between February 1996 and February 2019 for hedge fund indices (both pre- and after-fee), and various common risk factors as discussed in Section 3. The pre-fee hedge fund indices realized a higher mean return than the overall equity market, while exhibiting lower volatility and drawdown. While some hedge funds market themselves as equity market-neutral, the equal-weighted HFRI and value-weighted DJCS exhibit CAPM βs of 0.34 and 0.26, respectively. When evaluated using the mean-variance framework, the risk-adjusted returns of hedge fund indices outperform the market. The CAPM alphas are only matched by the put-writing strategies and the BAB factor. However, the Sharpe ratio only takes the first two moments of the distribution into account.

When considering the higher moments of the return series, the non-normality is evident. As shown by the Jarque-Bera test statistic, we reject the null hypothesis of normality for all variables. Additionally, Figure 1 illustrates the similarities between the derivative-based approach and the HFRI index. While the fat left tail is evident for both return series, it is more prominent for the put-writing strategy.

Drawdown is measured as the "cumulative loss since the loss started" (Pedersen, 2015, p.35)[8]. By construction, the put-writing strategies capture downside risk explicitly, i.e., left tail-risk. As the QQ-plot in Figure 1 shows, the hedge fund indices and put-writing strategies have similar tails. The put-writing strategies have more extreme skewness and excess kurtosis than the hedge fund indices (as evident from both Figure 1 and Table II). However, the overall features are similar. The derivative-based approach also match the market exposure of hedge funds, as seen by the CAPM β.

Jurek and Stafford (2015) report a hypothetical "unsmoothed" return series for both hedge fund indices to account for the conditional return smoothing. Table II reports significant autocorrelation, which suggest that return smoothing is present. Jurek and Stafford adjust the returns of August 1998 and October 2008 by assuming the hedge funds only report 50% of their returns these months, and the remainder the subsequent months. However, the authors state that "While there is no direct evidence that these adjustments produce a more accurate description of the true returns to broad hedge fund portfolios, they highlight the sensitivity of inferences regarding the underlying risks to a handful of influential observations" (Jurek and Stafford, 2015, p.2193). Additionally, the authors use quarterly data to "parsimoniously adjust for the effect of return autocorrelation observed at the monthly frequency" (Jurek & Stafford, 2015, p.2193). We do not adjust the time series to reflect the presence of return smoothing, and we use monthly data.

[8]The formula for Maximum Drawdown is: $MDD = \frac{Trough\,Value - Peak\,Value}{Trough\,Value}$

Table II. Summary Statistics (1996 - 2019)

This table reports the excess returns of two hedge fund indices, risk factors, and the two put-writing strategies between February 1996 and February 2019 ($N = 277$). The HFRI Fund Weighted Composite Index (HFRI) and the Dow Jones/Credit Suisse (DJCS) return series are reported both pre-fee, and net-of-fee. HFRI and DJCS are based on data from Hedge Fund Research Inc. and Dow Jones/Credit Suisse, respectively. Pre-fee returns are computed by adding a fee of 3.8%. This corresponds to a 2-and-20% fee-structure where half of the funds surpasses the hurdle rate. Factor returns are based on the Carhart four factor model (Carhart, 1997), the Fung-Hsieh nine factor model (Fung & Hsieh, 2004), and two put-writing strategies as proposed by Jurek and Stafford, 2015. These two strategies differ in how far out of the money they are (Z), and how much leverage which is applied to the strategy (L). QMJ and BAB denote factors developed by AQR. Mean, Volatility, CAPM alphas ($\hat{\alpha}$) and Sharpe-ratios (SR) are reported in annualized terms. Skewness and Kurtosis are estimated based on monthly data. Jarque-Bera (JB) test statistic for normality and associated p-values (P_JB) are based on precomputed values. The CAPM α and β report estimates from a regression of the monthly excess return onto the S&P500. AR(1) reports the coefficient estimate of a first-order autoregressive model and the associated t-statistic. Drawdown measures the largest peak-to-trough return loss for each series. We report drawdown for the full sample (Min), and for the years 1998 (Collapse of Long Term Capital Management) and 2008 (The Financial Crisis).

								CAPM		AR(1)		Drawdown		
Asset	Mean	Vol	Skew	Kurt.	JB	P_{JB}	SR	$\hat{\alpha}$	$\hat{\beta}$	Coeff	*t-stat*	Min	1998	2008
HFRI (pre-fee)	8.7%	6.6%	-0.6	6.00	123.3	0.00	1.32	6.9%	0.34	0.24	4.78	19.1%	11.8%	18.1%
DJCS (pre-fee)	8.6%	6.5%	-0.4	6.87	179.3	0.00	1.34	7.3%	0.26	0.20	4.72	18.6%	14.1%	18.6%
HFRI (after-fee)	4.9%	6.6%	-0.6	6.00	123.3	0.00	0.74	3.1%	0.34	0.24	4.78	23.2%	12.9%	20.4%
DJCS (after-fee)	4.8%	6.5%	-0.4	6.87	179.3	0.00	0.75	3.5%	0.26	0.20	4.72	21.4%	14.9%	20.4%
MKT-RF	7.6%	15.4%	-0.7	4.09	37.1	0.00	0.49	2.1%	1.02	0.07	1.49	54.4%	18.1%	38.8%
SMB	2.1%	11.7%	0.7	10.81	729.5	0.00	0.18	1.7%	0.08	-0.10	-3.61	39.2%	20.6%	6.3%
HML	1.7 %	10.8%	0.2	5.37	66.5	0.00	0.15	2.0%	-0.07	0.15	3.64	40.9%	12.5%	9.0%
MOM	4.5%	17.8%	-1.4	12.78	1199.9	0.00	0.25	6.6%	-0.38	0.06	1.71	57.3%	6.0%	9.0%
FH 1 (SP500)	5.4%	14.9%	-0.7	4.11	34.1	0.00	0.36	0.0%	1.00	0.05	1.11	62.2%	16.3%	40.0%
FH 2 (Size)	-0.8%	11.4%	0.2	7.56	241.0	0.00	-0.07	-1.2%	0.08	-0.14	-4.07	51.5%	27.0%	8.4%
FH 3 (Treasury)	-0.1%	0.9%	0.0	4.34	20.7	0.00	-0.14	-0.2%	0.01	0.06	1.14	5.4%	1.3%	1.8%
FH 4 (Credit)	0.0%	0.7%	1.3	14.04	1481.5	0.00	0.02	0.1%	-0.02	0.32	8.65	4.5%	0.2%	0.5%
FH 5 (TF-BD)	-27.6%	51.2%	1.3	5.43	148.1	0.00	-0.54	-23.2%	-0.83	0.09	1.63	100.0%	42.7%	29.4%

Table II−(Continued)

								CAPM		AR(1)		Drawdown		
Asset	Mean	Vol	Skew	Kurt.	JB	P_{JB}	SR	$\hat{\alpha}$	$\hat{\beta}$	Coeff	*t-stat*	Min	1998	2008
FH 6 (TF-FX)	-10.9%	64.4%	1.2	4.58	92.3	0.00	-0.17	-6.1%	-0.91	0.02	0.39	99.9%	55.4%	53.8%
FH 7 (TF-COM)	-5.3%	49.3%	1.1	4.59	83.6	0.00	-0.11	-2.2%	-0.58	-0.05	-0.80	99.3%	23.2%	33.2%
FH 8 (TF-IR)	-33.2%	88.1%	4.4	31.82	10458.4	0.00	-0.38	-24.2%	-1.68	0.22	6.66	100.0%	44.6%	12.3%
FH 9 (TF-STK)	-60.9%	50.2%	1.6	7.22	316.6	0.00	-1.21	-56.1%	-0.90	0.13	2.20	100.0%	51.3%	52.2%
Put-Writing - [$Z=-1, L=2$]	9.2%	7.7%	-3.4	20.48	4059.2	0.00	1.20	7.0%	0.41	0.06	1.73	22.8%	15.3%	22.8%
Put-Writing - [$Z=-2, L=4$]	9.9%	5.9%	-4.9	38.32	15515.9	0.00	1.69	8.5%	0.27	0.24	9.77	21.7%	13.5%	21.5%
BAB	9.2%	14.2%	-0.4	6.15	1199.9	0.00	0.65	10.7%	-0.29	0.11	3.03	54.9%	19.6%	34.6%
QMJ	5.9%	9.7%	0.2	5.15	121.3	0.00	0.61	8.0%	-0.39	0.24	6.19	28.5%	1.3%	1.3%

Asness et al. (2013) find an interesting relationship between the MOM and HML portfolios and funding liquidity risk. An equal-weighted portfolio of these two factors is "immune to liquidity risk and generates substantial abnormal returns" (Asness et al., 2013, p.931). As seen in Table C.I (see Appendix C), there exists a negative correlation between the momentum- and value portfolio. Similarly to MOM, returns to BAB suffer when funding liquidity risk worsens (Frazzini & Pedersen, 2014), while QMJ does not exhibit this crash risk. Rather, QMJ seems to benefit from a flight-to-quality during stressed markets. The correlation between QMJ and HML is 0.12, significant at the 5% level, while the two factors which exhibit negative exposure to funding risk, BAB and MOM, have a negative correlation of 0.26, significant at the 1% level. Motivated by these results, we augment the Carhart model with our put-writing strategy to capture downside risk explicitly for the QMJ and BAB portfolios. (See Table IV).

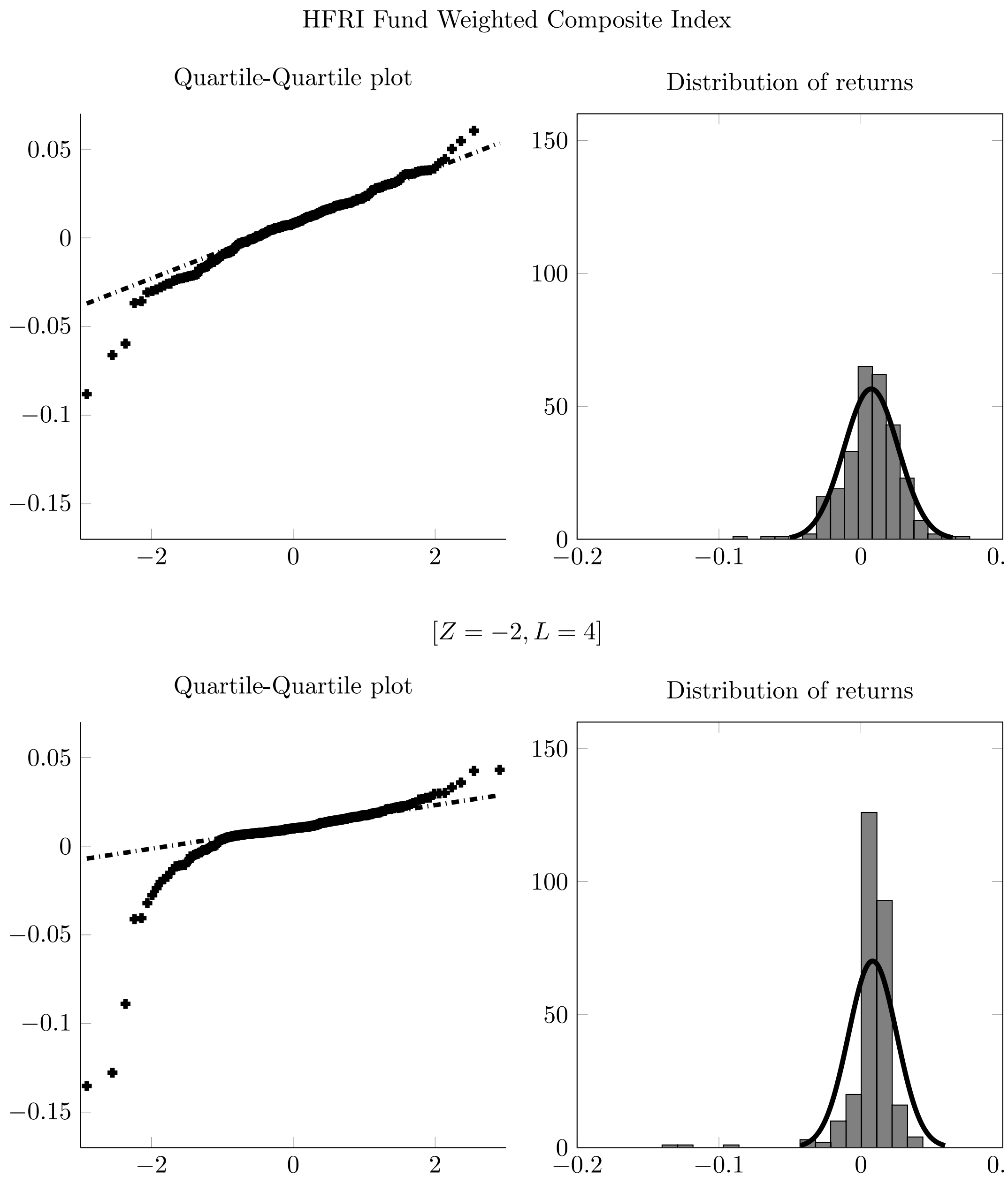

Figure 1. Comparison of Tail-risk in HFRI Fund Weighted Composite Index and a mechanical put-writing strategy

The top panels present the Quartile-Quartile plot and histogram for the HFRI Fund Weighted Composite index in the period February 1996 to February 2019. The bottom panel present the corresponding plots for the $[Z = -2, L = 4]$ strategy. The left panels plot the quartile of the normal distribution on the x-axis, and the empirical distribution on the y-axis. The right panels depicts the empirical probability density function, where the solid line represents the normal distribution.

6 Results and analysis

In this section, we report our results from regressing excess hedge fund returns on the models discussed in Section 3, in addition to the two put-writing strategies. Moreover, we report the results from regressing the AQR factors BAB and QMJ on a combination of linear- and derivative-based factors. When evaluating replicating strategies, we focus on matching downside risk exposure and ability to explain alphas, not ability to explain time series variation.

The put-writing strategies perform better in replicating risk and return characteristics of broad hedge fund indices, as illustrated in Table III and Figure 2. The feasible replicating portfolios track downside risk more accurately, and alpha estimates are significantly reduced. Traditional factor models achieve R^2s in the range 40-75 %, whereas the put-writing strategies only achieve R^2s of 40-46% and 27% for the HFRI and DJCS, respectively. However, as Jurek and Stafford state, "popular common factor models are able to explain the time series variation, but miss most of the mean, identifying this as alpha" (2015, p.2187).

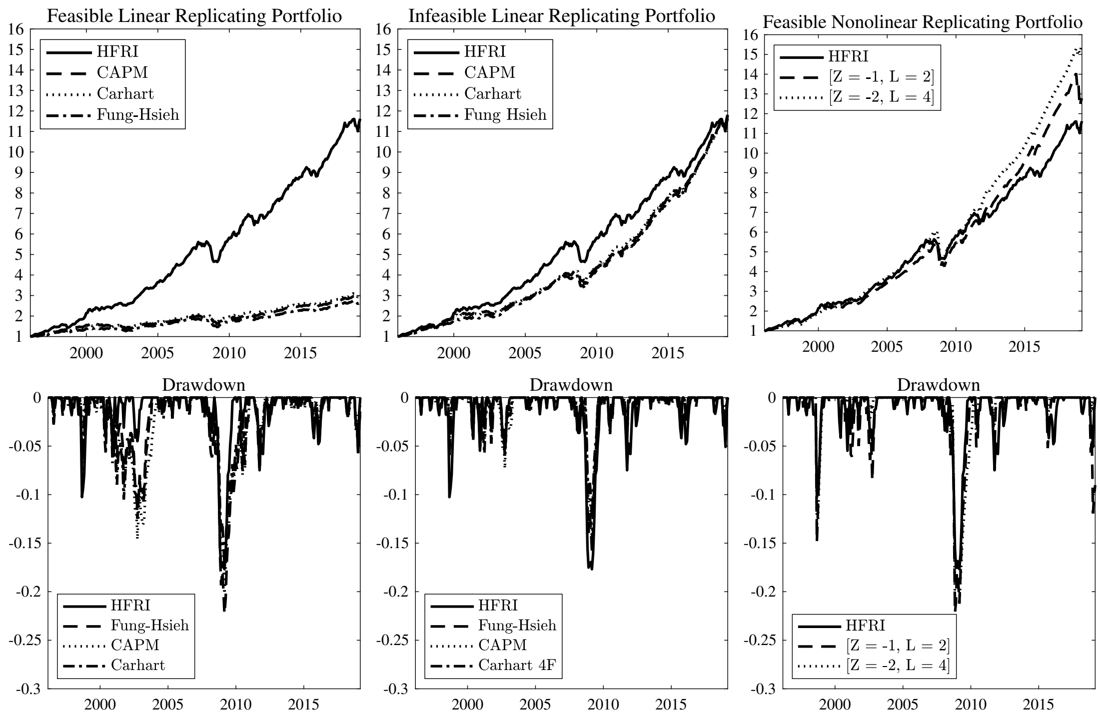

Figure 2. Replicating the risk and return characteristics of the HFRI Fund Weighted Composite Index (January 1996 - February 2019)

The top panels present the cumulative returns of $1 invested in the pre-fee HFRI Fund Weighted Composite Index, as well as CAPM, Carhart, Fung-Hsieh and the two put-writing strategies. The bottom panels displays the corresponding quarterly drawdowns. The top left panel plots the cumulative returns based on fitted values from the CAPM, Carhart and Fung-Hsieh factor models, excluding the estimated intercept. The top middle panel plots the same factors, but includes the estimated intercepts. The top right panel displays the returns from the two put-writing strategies.

The feasible return series in Figure 2 is calculated by subtracting the estimated intercept from the fitted values, as shown in Equation (14).

$$r_{i,t}^{feasible} = \hat{y}_{i,t} - \hat{\alpha}_i \tag{14}$$

The top left panel in Figure 2 illustrates the inadequacy of the traditional linear models' ability to match risk and return characteristics of hedge funds. It becomes clear that the derivative-based approach better captures the average return.

Model specifications (1)-(3) and (6)-(8) in Table III, representing traditional models, estimate annualized hedge fund alphas in the range 5.9-6.7%. These estimates are all statistically significant at the 1%-level. The alphas are also economically significant, exceeding the realized mean excess return of most of the factors, with the exception of BAB (See Table II). Interestingly, when regressing the hedge fund indices on the $[Z = -2, L = 4]$ strategy, we fail to reject the joint hypothesis of zero intercept and unit slope coefficient at the 1% level. While the estimated alphas are notably reduced for the $[Z = -1, L = 2]$ strategy, we reject the joint hypothesis. Hence, the derivative-based approach outperforms the traditional linear factor models in explaining the alpha, as well as matching downside risk exposure in hedge funds. However, our results imply that Jurek and Stafford's (2015) results are not robust to changes in sample size. As Shown in Appendix B.II, we replicate Jurek and Stafford (2015) and fail to reject the null hypothesis of zero intercept and unit slope coefficient for model specifications (4)-(5) and (9)-(10).

The Carhart four-factor model estimates an annualized alpha of 5.9% for the hedge fund indices. The market and size factor is statistically significant at the 1% level for both indices. The positive factor loading on SMB implies that hedge funds are overweight small-caps, relative to the market. However, as shown by Chen and Bassett (2014), an allocation of only 7% to the small portfolio will result in a positive SMB coefficient. The HML and MOM factors are not reliably different from zero or of minimal contribution to the model. The Fung-Hsieh model, which is developed specifically for hedge funds, estimate statistically significant alphas of 7.2% for both HFRI and DJCS. The R^2 is 72.9% for the HFRI and 48.2% for the DJCS. This may be a result of the equal-weighting of the HFRI, whilst the DJCS is value-weighted. Thus, the Fung-Hsieh model performs well in explaining the variation of the typical hedge fund, whilst performing worse in explaining the time series variation of the aggregate hedge fund universe.

Table III. Comparison of Derivative-Based and Linear Factor Hedge Fund Replicating Models (1996-2019)

This table reports the coefficients from ten regressions on excess returns using monthly data between February 1996 and February 2019 ($N = 277$). The dependent variables are monthly excess returns of the HFRI Fund Weighted Composite Index and the DJCS Broad Hedge Fund Index. These are computed as the pre-fee monthly returns less the return of a rolling investment in the 1-month T-bill (retrieved from Kenneth French' data library). Specifications (1)-(5) represents the regression results on the HFRI index, while (6)-(10) displays the results from the DJCS index. Specifications (1) and (6) is the CAPM model with the only factor being market premium (from Kenneth French' data library). (2) and (7) displays the coefficients of the Carhart (1997) four-factor model. The first three factors (RMRF, SMB and HML) stems from the Fama-French (1993) three-factor model with the forth factor, momentum (MOM), added by Carhart (1997). Specifications (3) and (8) display the results of the Fung-Hsieh (2002a) nine-factor model. The market factor in the Fung-Hsieh model is the S&P500. Specifications (4)-(5) and (9)-(10) correspond to the put-writing models computed as a single factor of monthly returns from the [Z, L] put-writing strategies less the return of rolling investments in the 1-month T-bill. These two strategies differ in how far out of the money they are (Z), and how much leverage which is applied to the strategy (L). We report the t-statistics from the OLS in brackets and implement *, ** and *** to represent significance level 10%, 5% and 1%, respectively. Adj. R^2 is the adjusted R^2 from the regressions and adj. R^2 [feasible] is the adjusted R^2 net of the intercept contribution. Finally, we report the p-value of the joint hypothesis test that alpha equals zero and beta equals one when we regress the hedge fund indices onto the feasible replication portfolios.

	HFRI (pre-fee)					DJCS (pre-fee)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept×100	0.50***	0.49***	0.60***	0.27***	0.14	0.55***	0.49***	0.60***	0.38***	0.24**
	[7.67]	[8.46]	[9.24]	[3.08]	[1.38]	[6.34]	[6.07]	[6.94]	[3.75]	[2.28]
RMRF	0.36***	0.33***	0.29***			0.27***	0.29***	0.21***		
	[24.27]	[23.86]	[18.02]			[13.98]	[14.95]	[9.69]		
SMB		0.14***					0.08***			
		[7.82]					[3.18]			
HML		-0.04**					-0.00			
		[-2.02]					[-0.06]			

Table III–*(Continued)*

	HFRI (pre-fee)					DJCS (pre-fee)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
MOM		0.02**					0.10***			
		[1.96]					[6.15]			
SIZE			0.18***					0.12***		
			[9.52]					[4.62]		
TSY			-0.54*					-1.60***		
			[-1.84]					[-4.08]		
CREDIT			-1.78***					-2.48***		
			[-4.38]					[-4.53]		
TF-BD			-0.01					-0.02***		
			[-1.62]					[-2.96]		
TF-FX			0.01**					0.01**		
			[2.02]					[2.34]		
TF-COM			0.00					0.01*		
			[0.58]					[1.75]		
TF-IR			-0.01**					-0.01**		
			[-2.19]					[-2.19]		
TF-STK			0.00					0.01		
			[0.66]					[1.00]		
Put-Writing - [Z=-1, L=2]				0.59***					0.44***	
				[15.46]					[10.30]	
Put-Writing - [Z=-2, L=4]					0.71***					0.58***
					[13.61]					[10.26]
Adj. R^2	68.1%	75.8%	72.9%	46.3%	40.0%	41.3%	51.2%	48.2%	27.6%	27.4%
Adj. R^2 [feasible]	61.1%	69.5%	63.9%	44.2%	39.5%	32.6%	44.9%	39.2%	23.4%	25.7%
p-value ($H_0 : \alpha = 0, \beta = 1$)	0.00	0.00	0.00	0.01	0.31	0.00	0.00	0.00	0.00	0.04

Table IV reports results from regressing the QMJ and BAB portfolios on the Carhart four factor model. Additionally, we extend the Carhart model with two put-writing strategies to serve as a proxy for downside risk. When extending the Carhart model with $[Z = -1, L = 2]$, the estimated monthly alpha of BAB drops by 21 basis points. Controlling for $[Z = -2, L = 4]$, the estimated alpha become insignificant (See model specifications (5) and (6)). The same results are not found for the QMJ portfolio. Specifications (2) and (3) show that the derivative-based strategies have no explanatory power. One possible explanation for this is different exposure to funding liquidity risk. While BAB performs worse when funding liquidity tightens, returns to QMJ does not exhibit this crash risk. On the contrary, QMJ benefits from flight-to-quality during stressed markets. These results suggest that the abnormal returns of BAB represent compensation for downside risk, rather than a market inefficiency.

Interestingly, neither of the put-writing strategies are able to explain the estimated alpha of BAB independently (results are reported in Table A.I, in the Appendix). The adjusted R^2 ranges 0.4% to 3.8% when regressing BAB on put-writing, while ranging 33% to 37% when the strategy is combined with the Carhart model.

These results suggest that the Carhart model is able to explain the time series variation but fails to capture the alpha, while the put-writing strategy has the opposite properties.

Table IV. Regressing Quality-Minus-Junk and Betting-Against-Beta on Derivative-Based Factor Models

This table reports coefficients from regressing monthly excess returns of Quality-Minus-Junk (QMJ) and Betting-Against-Beta (BAB) on the Carhart model, and combinations of the Carhart model and the two put-writing strategies. The data sample spans February 1996 to February 2019 ($N = 277$). Specification (1) and (4) represent the Carhart (1997) four-factor model. Specification (2)-(3) and (5)-(6) reports the results from regressing the AQR factors on the Carhart model augmented with the two put-writing strategies. OLS t-statistics are reported in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. Adj. R^2 is the adjusted goodness-of-fit measure of the linear regression.

	QMJ			BAB		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept ×100	0.70***	0.67***	0.70***	0.72***	0.51***	0.27
	[6.29]	[5.59]	[5.55]	[3.50]	[2.35]	[1.21]
RMRF	-0.32***	-0.34***	-0.32***	-0.15***	-0.31***	-0.32***
	[-11.86]	[-8.22]	[-9.15]	[-3.07]	[-4.03]	[-5.19]
SMB	-0.30***	-0.30***	-0.30***	-0.15**	-0.15**	-0.14**
	[-8.70]	[-8.65]	[-8.67]	[-2.39]	[-2.31]	[-2.33]
HML	-0.01	-0.01	-0.01	0.54***	0.55***	0.55***
	[-0.21]	[-0.18]	[-0.21]	[7.83]	[8.01]	[8.21]
MOM	0.13***	0.13***	0.13***	0.25***	0.25***	0.25***
	[5.52]	[5.54]	[5.51]	[5.83]	[6.00]	[6.05]

Table IV −(Continued)

	QMJ			BAB		
	(1)	(2)	(3)	(4)	(5)	(6)
$[Z=-1, L=2]$		0.06			0.39***	
		[0.74]			[2.66]	
$[Z=-2, L=4]$			0.00			0.67***
			[0.03]			[4.31]
Adj.R^2	57.8%	57.8%	57.7%	33.3%	34.7%	37.3%

Asness et al. (2019) predict that, relative to junk-stocks, high-quality stocks have larger market capitalization and lower market betas. The negative size- and market exposure for the QMJ portfolio is consistent with this theory. While a negative loading on value is consistent with Asness et al. (2019), we do not find a statistically significant loading on HML. The interpretation of the factor loadings on BAB is similar; high-beta stocks tend to be small-cap stocks. Hence, a portfolio which is short high-beta assets load negatively on these factors. While the BAB factor is constructed to be market-neutral (β equal to zero), the ex-ante estimation error causes the realized beta to be negative. Since high-beta assets are associated with low value (Frazzini & Pedersen, 2014), the BAB portfolio's positive loading on HML is natural. The positive loading on momentum may be interpreted as "the winners keep winning", for the assets included in both QMJ and BAB. However, there is no clear economic interpretation regarding the amount of exposure.

7 Conclusion

A mechanical put-writing strategy on the S&P500 captures the pre-fee alpha estimates for the equal-weighted HFRI hedge fund index. While the same result does not hold for the value-weighted DJCS, the estimated alpha is reduced by 3-4% annually, relative to traditional risk factor models. This suggests that the derivative-based approach captures the alpha of a typical hedge fund, while failing to explain the alpha of the aggregate hedge fund universe. It is important to emphasize that the presence of return smoothing and data biases may underestimate the downside risk. We further extend Jurek and Stafford's (2015) research and show that the results are robust to changes in data frequency, while not being robust to changes in sample size. However, the derivative-based approach captures the pre-fee alphas of hedge fund indices much better than the traditional linear models. A novelty in our thesis is that we capture the crash risk of the betting-against-beta portfolio, a popular "smart money" strategy which relates to low-risk, and low-volatility investing. By adding the two derivative-based strategies to the Carhart model, the alpha of the betting-against-beta portfolio is not reliably distinguishable from zero. Relating this finding to BAB's exposure to funding liquidity risk provides a plausible explanation as to why these results cannot be found for the quality-minus-junk portfolio. While betting-against-beta suffer during stressed markets, the quality-minus-junk portfolio does not have the same crash risk. Our results suggest that the abnormal returns to BAB is fair compensation for downside risk exposure, while the returns to QMJ remains a puzzle.

An interesting extension of our work would be to investigate similar exposure to crash risk in other factor portfolios. As the quality-minus-junk portfolio and the put-writing strategies are negatively correlated, it would be interesting to evaluate a combination of the two. However, as the return series are nonlinear, there is need for a portfolio optimization framework which incorporates the higher moments.

Appendix

A Estimating Downside Risk Exposure in Linear Factors

Table A.I. Regressing Asset-based factors on Put-writing

This table reports coefficients from regressing asset-based risk factors on monthly excess returns from two [Z, L] put-writing strategies. These two strategies differ in how far out of the money they are (Z), and how much leverage which is applied to the strategy (L). The data spans February 2012 to February 2019 ($N = 277$). The risk free rate is the 1-month T-bill, r_f, obtained from Kenneth French' data library. SMB and HML denotes the two non-market factors in the Fama-French model (Fama & French, 1993). MOM denotes the fourth factor in the Carhart model (Carhart, 1997; Jegadeesh & Titman, 1993). QMJ and BAB denote the two AQR factors (Asness et al., 2019; Frazzini & Pedersen, 2014). *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

	$[Z = -1, L = 2]$			$[Z = -2, L = 4]$		
	Intercept×100	Coeff	Adj. R^2	Intercept×100	Coeff	Adj. R^2
HML	0.28 [1.42]	-0.19** [-2.20]	1.4%	0.32 [1.54]	-0.22** [-2.01]	1.1%
SMB	-0.02 [-0.08]	0,25*** [2.77]	2.4%	-0.05 [-0.24]	0.28** [2.35]	1.6%
MOM	0,81** [2.55]	-0,57*** [-4.17]	5.6%	0.85** [2.52]	-0.57*** [-3.22]	3.3%
QMJ	0,98*** [6.36]	-0,63*** [-9.62]	24.9%	1.08*** [6.43]	-0.71*** [-8.00]	18.6%
BAB	1,05*** [4.13]	-0,38*** [-3.46]	3.8%	0.93*** [3.42]	-0.21 [-1.42]	0.4%

In Table A.I we report our results from regressing asset-based factors on our two put-writing strategies. The HML factor's estimated alpha is not statistically significant for either model, and exhibits a negative factor loading on both $[Z = -1, L = 2]$, and $[Z = -2, L = 4]$, both statistically significant at the 5% level. However, the models miss most of the time series variation as seen by a low Adj. R^2. The SMB factor's alpha is not statistically significant, while the factor loadings are statistically significant at the 1% and 5% level, for $[Z = -1, L = 2]$ and $[Z = -2, L = 4]$, respectively. The Momentum factor exhibits statistically significant alpha's on the 5% level when regressed on the two put-writing strategies. Additionally, momentum has a statistically significant factor loading on the 1% level. The QMJ factor exhibits statistically significant exposure to both strategies, however, the put-writing strategies are not able to explain the alpha. BAB exhibits a statistically significant negative coefficient when regressed on $[Z = -1, L = 2]$, and a statistically significant alpha, both on the 1% level. However, the Adj. R^2 is relatively low at 3.8%. For $[Z = -2, L = 4]$, the alpha estimate is statistically significant at the 1% level, while the coefficient is not statistically significant. Additionally, the put-writing strategy is able to account for only 0.4% of the time series variation in the BAB factor.

B Replication of Jurek and Stafford (2015)

This appendix presents our results from replicating Jurek and Stafford, 2015. The data sample spans from February 1996, to June 2012. Table B.I reports summary statistics for the factor's excess returns, based on monthly data. Figure B.1 shows the cumulative value of $1 invested in the HFRI, along with the various replicating portfolios. The bottom panels plot the corresponding quarterly drawdown series for the respective return series. Table B.II reports the results from regressing HFRI and DJCS onto factor portfolio returns. We use quarterly data, in accordance with Jurek and Stafford's methodology.

B.1 Our results versus Jurek and Stafford (2015)

While we use the same two hedge fund indices, namely HFRI and DJCS, our results differ in terms of means and volatilites. This may be the result of the use of different risk-free rates. Jurek and Stafford obtain risk-free rates from OptionMetrics zero-coupon yield curve. Whereas we use LIBOR and OIS rates obtained from Bloomberg. Additionally, Jurek and Stafford compute the return of the credit factor (CREDIT) as "the difference between the total return on the Barclays (Lehman) U.S. Credit Bond Index and the return on the 10-year Treasury bond" (Jurek & Stafford, 2015, p.2193). We follow the methodology of Fung and Hsieh and calculate it as the difference between Moody's Baa yield and the 10-year Treasury bond, obtained from the Federal Reserve Bank of St.Louis [9]. We obtain the return series of the Carhart four factor model from AQR[10]. Their methodology follows that of Fama and French (1993). Jurek and Stafford does not state where their corresponding data is obtained from. The Trend-Following factors are obtained from David Hsieh's data library[11]. 1-month T-bills are used as the risk-free rate, obtained from Ken French's data library [12].

Therefore, there are minor differences, but our overall findings are consistent with Jurek and Stafford. The two put-writing strategies perform better in replicating broad hedge fund indices' risk and return characteristics.

[9] Download site for Moody's Baa yield: https://fred.stlouisfed.org/series/DBAA
Download site for 10-year treasury constant maturity yield: https://fred.stlouisfed.org/series/DGS10

[10] AQR Data Library https://www.aqr.com/Insights/Datasets

[11] The factors are retrieved from David Hsieh's data library: faculty.fuqua.duke.edu/~dah7/DataLibrary/

[12] Ken French data library: mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table B.I. Summary Statistics (1996 - 2012)

This table reports the excess returns of the two hedge fund indices, risk factors, and the two put-writing strategies between February 1996 and June 2012 (N = 197). The HFRI Fund Weighted Composite Index (HFRI) and the Dow Jones/Credit Suisse (DJCS) return series are reported both pre-fee, and net-of-fee. HFRI and DJCS are based on data from Hedge Fund Research Inc. and Dow Jones/Credit Suisse, respectively. Pre-fee returns are computed by adding a fee of 3.8%. This corresponds to a 2-and-20% fee-structure where half of the funds surpasses the hurdle rate. Factor returns are based on the Carhart four factor model (Carhart, 1997), the Fung-Hsieh nine factor model (Fung & Hsieh, 2004), and two put-writing strategies as proposed by Jurek and Stafford, 2015. These two strategies differ in how far out of the money they are (Z), and how much leverage which is applied to the strategy (L). Mean, Volatility, CAPM alphas (α) and Sharpe-ratios (SR) are reported in annualized terms. Skewness and Kurtosis are estimated based on monthly data. Jarque-Bera (JB) test statistic for normality and associated p-values (P_JB) are based on precomputed values. The CAPM α and $\hat{\beta}$ report estimates from a regression of the monthly excess return onto the S&P500. AR(1) reports the coefficient estimate of a first-order autoregressive model and the associated t-statistic. Drawdown measures the largest peak-to-trough return loss for each series. We report drawdown for the full sample (Min), and for the years 1998 and 2008.

								CAPM		AR(1)		Drawdown		
Asset	Mean	Vol.	Skew	Kurt.	JB	P_{JB}	SR	$\hat{\alpha}$	$\hat{\beta}$	Coeff	*t-stat*	Min.	1998	2008
HFRI (pre-fee)	9.18%	7.42%	-0.64	5.28	55.9	0.00	1.24	8.09%	0.35	0.26	4.08	-11.8%	-18.1%	-19.1%
DJCS (pre-fee)	9.23%	7.34%	-0.40	5.77	68.0	0.00	1.26	8.39%	0.27	0.22	3.87	-14.0%	-18.6%	-18.6%
HFRI (after-fee)	5.38%	7.42%	-0.64	5.28	55.9	0.00	0.72	4.29%	0.35	0.26	4.08	-12.9%	-20.4%	-23.2%
DJCS (after-fee)	5.43%	7.34%	-0.40	5.77	68.0	0.00	0.74	4.59%	0.27	0.22	3.87	-14.9%	-20.7%	-21.4%
MKT-RF	5.25%	16.75%	-0.63	3.66	16.6	0.00	0.31	2.04%	1.02	0.12	1.92	-18.1%	-38.8%	-54.4%
SMB	3.05%	12.82%	0.75	10.25	449.6	0.00	0.24	2.84%	0.07	-0.08	-2.45	-20.6%	-6.3%	-39.1%
HML	2.78%	11.83%	0.07	4.99	32.8	0.00	0.23	3.01%	-0.07	0.14	2.91	-12.5%	-9.0%	-40.9%
MOM	5.48%	19.97%	-1.46	11.26	629.9	0.00	0.27	6.78%	-0.41	0.08	1.75	-6.0%	-9.0%	-57.3%
FH 1 (SP500)	3.15%	16.24%	-0.58	3.66	14.4	0.01	0.19	0.00%	1.00	0.09	1.56	-16.3%	-40.0%	-62.2%
FH 2 (Size)	-0.89%	12.35%	0.17	7.35	156.6	0.00	-0.07	-1.08%	0.06	-0.12	-2.96	-27.0%	-8.4%	-51.5%
FH 3 (Treasury)	-0.24%	0.96%	0.05	4.01	8.5	0.02	-0.25	-0.28%	0.01	0.07	1.04	-1.3%	-1.8%	5.3%
FH 4 (Credit)	0.10%	0.81%	1.27	12.62	813.1	0.00	0.12	0.17%	-0.02	0.34	7.42	-0.2%	-0.4%	-3.7%
FH 5 (TF-BD)	-21.60%	52.47%	1.43	5.86	134.0	0.00	-0.41	-19.04%	-0.81	0.09	1.44	-42.7%	-29.4%	-99.8%
FH 6 (TF-FX)	-2.44%	64.73%	1.09	4.25	52.1	0.00	-0.04	0.47%	-0.92	0.01	0.21	-55.4%	-53.7%	-97.4%
FH 7 (TF-COM)	-1.14%	48.42%	1.12	5.00	74.0	0.00	-0.02	0.50%	-0.52	-0.04	-0.60	-23.2%	-33.2%	-96.8%
FH 8 (TF-IR)	10.11%	96.36%	4.32	28.76	6057.6	0.00	0.10	15.35%	-1.66	0.20	4.80	-44.6%	-12.3%	-98.4%
FH 9 (TF-STK)	-66.36%	49.01%	1.44	6.58	173.5	0.00	-1.35	-63.68%	-0.85	0.21	2.71	-51.3%	-52.2%	-100.0%
Put-Writing - [Z=-1, L=2]	9.64%	8.45%	-3.18	18.40	2278.4	0.00	1.14	8.3%	0.42	0.1	2.32	-15.3%	-22.8%	-22.8%
Put-Writing - [Z=-2, L=4]	10.27%	6.84%	-4.42	29.89	6575.7	0.00	1.50	9.35%	0.29	0.26	7.94	-13.5%	-21.5%	-21.7%

Table B.II. Comparison of Derivative-Based and Linear Factor Hedge Fund Replicating Models (1996-2012)

This table reports the coefficients from ten regressions on excess returns using quarterly data between February 1996 and June 2012 ($N = 66$). The dependent variables are quarterly excess returns of the HFRI Fund Weighted Composite Index and the DJCS Broad Hedge Fund Index. These are computed as the pre-fee quarterly returns less the return of a rolling investment in the 1-month T-bill (retrieved from Kenneth French' data library). Specifications (1)-(5) represents the regression results on the HFRI index, while (6)-(10) displays the results from the DJCS index. Specifications (1) and (6) is the CAPM model with the only factor being market premium (computed as S&P500 less the risk free rate). (2) and (7) displays the coefficients of the Carhart (1997) four-factor model. The first three factors (RMRF, SMB and HML) stems from the Fama-French (1993) three-factor model with the forth factor, momentum (MOM), added by Carhart (1997). Specifications (3) and (8) displays the results of the Fung-Hsieh (2002a) nine-factor model. The market factor in the Fung-Hsieh model is the S&P500. Specifications (4)-(5) and (9)-(10) correspond to the put-writing models computed as a single factor of quarterly returns from the [Z, L] put-writing strategies less the returns of rolling investments in the 1-month T-bill. These two strategies differ in how far out of the money they are (Z), and how much leverage which is applied to the strategy (L). We report t-statistics from the OLS in brackets and implement *, ** and *** to represent significance level 10%, 5% and 1%, respectively. Adj. R^2 is the adjusted R^2 from the regressions and Adj. R^2 [feasible] is the adjusted R^2 net of the intercept contribution. Finally, we report the p-value of the joint hypothesis test that alpha equals zero and beta equals one when we regress the hedge fund indices onto the feasible replication portfolios.

	HFRI (pre-fee)					DJCS (pre-fee)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept×100	1.76***	1.61***	2.44***	0.37	0.19	1.89***	1.57***	2.59***	0.82*	0.55
	[6.09]	[6.05]	[6.28]	[0.88]	[0.41]	[5.10]	[4.26]	[5.51]	[1.74]	[1.14]
RMRF	0.41***	0.38***	0.29***			0.32***	0.34***	0.19***		
	[13.49]	[12.32]	[6.55]			[8.18]	[8.04]	[3.52]		
SMB		0.23***					0.13			
		[4.16]					[1.64]			
HML		-0.04					0.06			
		[1.08]					[1.13]			
MOM		0.05*					0.11***			
		[1.74]					[2.82]			
SIZE			0.15**					0.06		
			[2.24]					[0.80]		
TSY			0.87					-1.08		
			[0.98]					[-1.00]		

Table B.II–*(Continued)*

	HFRI (pre-fee)					DJCS (pre-fee)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CREDIT			-1.65					-3.38***		
			[-1.55]					[-2.63]		
TF-BD			-0.00					-0.03***		
			[-0.15]					[-2.03]		
TF-FX			0.01					0.02		
			[1.23]					[1.31]		
TF-COM			-0.01					-0.01		
			[-0.69]					[-0.48]		
TF-IR			-0.01					-0.01		
			[-1.39]					[-1.56]		
TF-STK			0.01					0.03		
			[0.84]					[1.50]		
Put-Writing - [Z=-1, L=2]				0.81***					0.63***	0.69***
				[9.37]					[6.47]	[6.55]
Put-Writing - [Z=-2, L=4]					0.82***					
					[8.10]					
Adj. R^2	73.6%	79.5%	73.9%	57.2%	49.9%	50.3%	54.9%	56.6%	38.6%	39.2%
Adj. R^2 [feasible]	57.9%	67.4%	46.9%	56.5%	49.7%	29.7%	42.6%	23.2%	34.7%	37.4%
p-value ($H_0 : \alpha = 0, \beta = 1$)	0.00	0.00	0.00	0.60	0.89	0.00	0.00	0.00	0.14	0.40

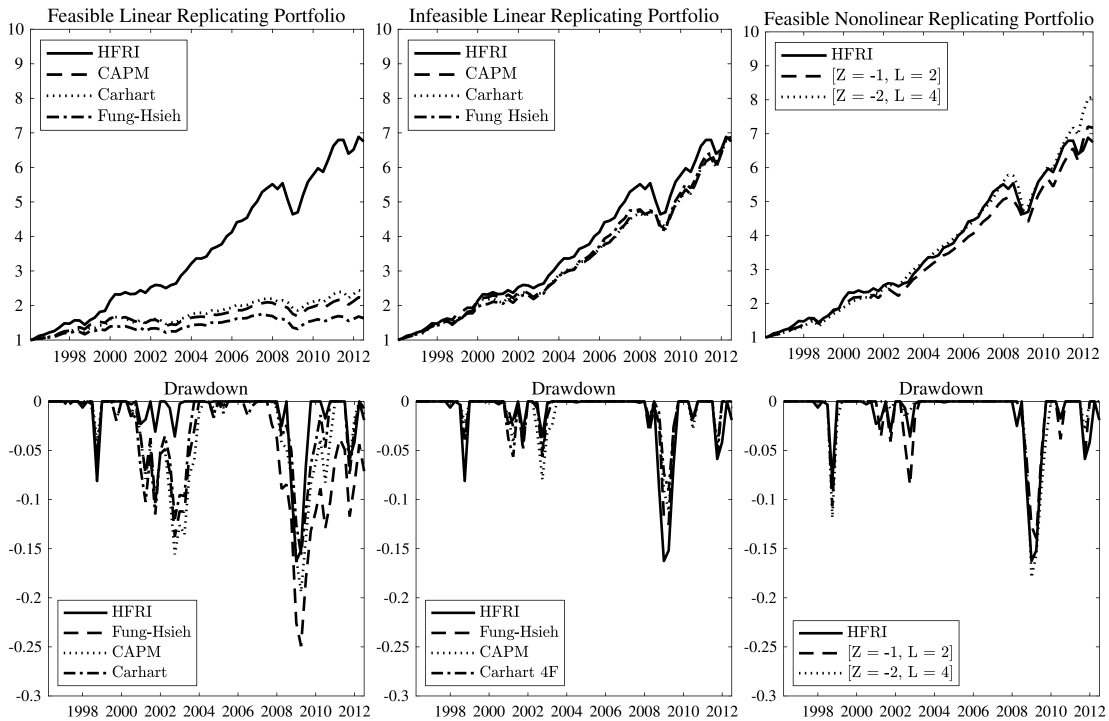

Figure B.1. Replicating the risk and return characteristics of the HFRI Fund Weighted Composite Index (January 1996 - June 2012)

The top panels displays the cumulative returns of $1 invested in the pre-fee HFRI Fund Weighted Composite Index, as well as CAPM, Carhart, Fung-Hsieh and the two put-writing strategies. The bottom panels displays the corresponding quarterly drawdowns. The top left panel plots the cumulative returns based on fitted values from the CAPM, Carhart and Fung-Hsieh factor models, excluding the estimated intercept. The top middle panel plots the same factors, but includes the estimated intercepts. The top right panel displays the returns from the two put-writing strategies.

C Correlation Matrix

Table C.I. Correlation Matrix

This table reports correlation coefficients on monthly excess returns between our two put-writing strategies and various asset factor returns. The data spans February 1996 to February 2019 ($N = 277$). We use the 1-month T-bill (retrieved from Kenneth French' data library). Correlation is calculated as $\rho(A, B) = \frac{Cov(A,B)}{\sigma_A \sigma_B}$. Specifications (1)-(2) denote the two [Z,L] put-writing strategies. (3)-(6) denote the Carhart four factor model (Carhart, 1997). Specifications (7)-(8) correspond to factors developed by AQR. (Asness et al., 2019; Frazzini & Pedersen, 2014) (9)-(15) denote the Fung-Hsieh model (Fung & Hsieh, 2001)

Asset	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) $[Z = -1, L = 2]$	1.00														
(2) $[Z = -2, L = 4]$	0.92	1.00													
(3) HML	-0.13	-0.12	1.00												
(4) SMB	0.16	0.14	-0.28	1.00											
(5) MOM	-0.24	-0.19	-0.21	0.08	1.00										
(6) MKTRF	0.79	0.67	-0.15	0.24	-0.28	1.00									
(7) QMJ	-0.50	-0.43	0.12	-0.46	0.35	-0.66	1.00								
(8) BAB	-0.20	-0.09	0.41	-0.26	0.26	-0.35	0.42	1.00							
(9) TF-BD	-0.26	-0.28	-0.09	-0.05	0.04	-0.24	0.19	-0.07	1.00						
(10) TF-FX	-0.24	-0.28	0.02	0.00	0.15	-0.2	0.15	0.03	0.37	1.00					
(11) TF-COM	-0.18	-0.21	-0.04	-0.06	0.18	-0.18	0.13	0.00	0.19	0.32	1.00				
(12) TF-IR	-0.32	-0.36	0.00	-0.08	0.03	-0.29	0.18	-0.11	0.19	0.22	0.23	1.00			
(13) TF-STK	-0.51	-0.51	0.08	-0.11	0.02	-0.27	0.21	-0.01	0.25	0.26	0.18	0.33	1.00		
(14) Treasury	0.16	0.19	0.02	0.18	-0.2	0.26	-0.26	-0.08	-0.3	-0.15	-0.11	-0.09	-0.14	1.00	
(15) Credit	-0.49	-0.52	0.01	-0.24	0.32	-0.48	0.49	0.03	0.26	0.29	0.18	0.39	0.34	-0.54	1.00

References

Agarwal, V., & Naik, N. Y. (2004). Risks and portfolio decisions involving hedge funds. *The Review of Financial Studies*, *17*(1), 63–98.

Almazan, A., Brown, K. C., Carlson, M., & Chapman, D. A. (2004). Why constrain your mutual fund manager? *Journal of Financial Economics*, *73*(2), 289–321.

Asness, C. S., Frazzini, A., & Pedersen, L. H. (2019). Quality minus junk. *Review of Accounting Studies*, *24*(1), 34–112.

Asness, C. S., Krail, R. J., & Liew, J. M. (2001). Do hedge funds hedge? *The journal of portfolio management*, *28*(1), 6–19.

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. *The Journal of Finance*, *68*(3), 929–985.

Bollen, N. P., & Pool, V. K. (2008). Conditional return smoothing in the hedge fund industry. *Journal of Financial and Quantitative Analysis*, *43*(2), 267–298.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, *52*(1), 57–82.

Chen, H.-l., & Bassett, G. (2014). What does βsmb$>$ 0 really mean? *Journal of Financial Research*, *37*(4), 543–552.

Fabozzi, F. J., & Pachamanova, D. A. (2016). *Portfolio construction and analytics*. John Wiley & Sons.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of*.

Fama, E. F., & French, K. R. (2010). Luck versus skill in the cross-section of mutual fund returns. *The journal of finance*, *65*(5), 1915–1947.

Frazzini, A., Kabiller, D., & Pedersen, L. H. (2018). Buffett's alpha. *Financial Analysts Journal*, *74*(4), 35–55.

Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, *111*(1), 1–25.

French, K. R. (2008). Presidential address: The cost of active investing. *The Journal of Finance*, *63*(4), 1537–1573.

Fung, W., & Hsieh, D. A. (2001). The risk in hedge fund strategies: Theory and evidence from trend followers. *The review of financial studies*, *14*(2), 313–341.

Fung, W., & Hsieh, D. A. (2002a). Asset-based style factors for hedge funds. *Financial Analysts Journal*, *58*(5), 16–27.

Fung, W., & Hsieh, D. A. (2002b). Hedge-fund benchmarks: Information content and biases. *Financial Analysts Journal*, *58*(1), 22–34.

Fung, W., & Hsieh, D. A. (2002c). Risk in fixed-income hedge fund styles. *The Journal of Fixed Income*, *12*(2), 6–27.

Fung, W., & Hsieh, D. A. (2004). Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal*, *60*(5), 65–80.

HFR. (2020). *HFRI Indices - Index Descriptions*. Retrieved May 15, 2020, from https://www.hedgefundresearch.com/hfri-indices-index-descriptions

Hull, J. C. (2017). *Options, futures, and other derivatives, global edition*. (9th ed..).

Ibbotson, R. G., Chen, P., & Zhu, K. X. (2011). The ABCs of hedge funds: Alphas, betas, and costs. *Financial Analysts Journal*, *67*(1), 15–25.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, *48*(1), 65–91.

Jurek, J. W., & Stafford, E. (2015). The cost of capital for alternative investments. *The Journal of Finance*, *70*(5), 2185–2226.

Mitchell, M., & Pulvino, T. (2001). Characteristics of risk and return in risk arbitrage. *the Journal of Finance*, *56*(6), 2135–2175.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of accounting research*, 109–131.

Pedersen, L. H. (2015). Efficiently inefficient : How smart money invests and market prices are determined. *Princeton*, Princeton University Press.