Hedge Funds With(out) Edge*

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Abstract

I propose a new benchmark to evaluate hedge fund performance: the returns to shorting CBOE Volatility Index (VIX) futures. The informativeness of this benchmark leads to a new methodology that is able to predict hedge fund performance. Specifically, it separates hedge funds, ex-ante, into one group that delivers higher sharpe ratios and *positive* skewness (SR of 0.52 and Skew of 4.30) while the other group has lower sharpe ratios and *negative* skewness (SR of 0.15 and Skew of -0.83), out-of-sample (OOS). I refer to the former group as those hedge funds with edge, in contrast to the latter group as those hedge funds that are without edge. This approach cannot be explained or replicated by previously known methods. Lastly, I show that my empirical findings can be explained by a model that features traders with extrapolative expectations.

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1 Introduction

Are hedge funds adding value to investors' portfolios? At the end of 2021, hedge funds represent nearly one third (32%) of the \$13.32 trillion global alternatives market assets under management (AUM) with a compound annual growth rate of 5.8% since 2015 according to Prequin[1]. The outsized amount of capital, within the alternatives market, that has flowed toward hedge funds has sparked a vast body of research work that studies hedge fund performance. One of the most important stylized facts that has been documented in the literature is that hedge fund returns can be characterized by concave payoffs (i.e. average gains are smaller relative to the average losses) with high Sharpe Ratios (SR) and significant negative skewness.

The central message of this article is that the stylized fact that depicts hedge fund performance as offering return streams with high SRs at the expense of negative skewness is incomplete. Instead, this monolithic interpretation of hedge funds can be improved upon by showing how we can split hedge funds into two groups: one group of hedge funds that add value to investors' portfolios (high SR and positive skewness) and those that do not add value (low SR and negative skewness). To my knowledge, this paper provides the first ex-ante classification of hedge funds that is able to separate hedge funds into two distinct groups (based on both SR and skewness) and reliably predict out-of-sample (OOS) hedge fund performance. One group is represented by hedge funds with higher SRs and positive skewness in contrast to the other group that has lower SRs and negative skewness. I refer to the former as hedge funds that have edge versus those in the latter that do not possess edge.[2]

After more than 50 years of research work on active management since Jensen (1968), the problem of fund manager performance evaluation and prediction remains controversial. To date, hedge fund investors (allocators) still rely too heavily on the use of SRs first introduced by Sharpe (1966).[3] The SR is only informative about the distribution of returns insofar

[1] Alternatives includes Private Equity, Hedge Funds, Infrastructure, Private Debt, Real Estate and Natural Resources.

[2] Building off of the seminal work of Kelly Jr. (1956), MacLean et al. (2011) define edge on page 5 in a gambling context as the expected gain per trial (i.e. edge $= p - (1-p) = 2p - 1$, where one wins $+1$ with probability p and loses -1 with probability $(1-p)$). In principle, if edge is directly observable and it is deemed to be zero then the respective bet should also be zero. I apply this same concept of edge to financial markets. Since the edge of a trading strategy is inherently unobservable (i.e. we do not know the objective probability of a gain, let alone the average gain / loss), I instead rely on the following heuristic which I argue proxies for the edge of a trading strategy: A high SR with positive skewness. Since it is well documented that hedge fund returns follow a non-normal distribution that is negatively skewed, the SR is not a sufficient statistic to indicate whether a hedge fund has edge (i.e. returns with a positive expected value). Hence, I argue that it is more accurate to rely on both a higher SR and positive skewness as indicative of a hedge fund with edge.

[3] https://www.institutionalinvestor.com/article/b1p62z599ns4pd/The-Sharpe-Ratio-Broke-Investors-

as returns are normally distributed and thus can be fully characterized by the mean and variance. Ingersoll et al. (2007) demonstrate how this creates the following moral hazard problem. In order to maximize assets under management (AUM), hedge fund managers exploit investors' overreliance on SRs by implementing investment strategies that produce high SRs that are significantly negatively skewed which exposes investors to unforeseen crash risk. Even though this moral hazard problem is well understood, there remains no agreed upon benchmark, in the same spirit as the first one proposed by Jensen (1968), that is able to distinguish which hedge funds would make investors better (or worse) off. More precisely, the hedge fund literature has not yet produced a measure or methodology that can separate hedge funds that are distinct in terms of *both* SR and skewness, ex-ante.

To bridge this gap in the literature, I undertake the following two steps. In the first step I propose the following benchmark for hedge fund performance evaluation: the returns from shorting CBOE Volatility Index (VIX) futures at the short-end of the VIX futures curve. This simple trading strategy is an ideal benchmark for hedge fund performance based on the following novel economic insight: The slope dynamics at the short-end of the VIX futures term structure is especially informative as to the time-varying level of risk premia in financial assets more generally. Given that the slope dynamics of the VIX futures curve account for the vast majority of the returns from shorting near-dated VIX futures (Johnson, 2017), we can better evaluate hedge funds by using this benchmark since the objective of a hedge fund is to harvest returns (i.e. observable risk premia). In addition to this core economic insight, the short VIX strategy is tradeable and requires no skill to implement, thereby making it a feasible investment alternative to hedge fund investors.[4] Moreover, the Short VIX has the same return profile (high SR and negative skewness) that hedge funds are known for and investors have been conditioned to expect of hedge fund performance.[5] Hence, it is conceivable that the only difference that remains between the Short VIX benchmark and hedge fund performance is the hedge fund manager's investment ability. With that, the Short VIX satisfies the definition of an Otherwise Equivalent (OE) benchmark defined by Aragon and Ferson (2006). The second step I take to bridge the gap in the literature is to classify hedge funds into two groups, ex-ante, using the parameter estimates from the null

Brains

[4]There exists an exchange traded fund (ETF) called the ProShares Short VIX Short-Term Futures under the ticker symbol: SVXY. This ETF measures the returns of a portfolio of VIX futures contracts with a weighted average maturity of one month. The portfolio is formed by rolling positions between first- and second-dated VIX futures contracts at a daily frequency. The inception date of this ETF was October 3, 2011.

[5]It is important to also recognize that the Short VIX has the highest SR and least negative skewness compared to other alternatives that are often considered to replicate hedge fund performance such as shorting an at-the-money (ATM) straddle or out-of-the-money (OTM) put written on the S&P 500.

hypothesis in my first step. By classifying hedge funds, I am able to predict OOS, hedge funds with superior returns (based on SR and skewness) relative to the remaining hedge funds in the sample.

At a more fundamental level, the Short VIX strategy exploits a defining property of the short-end of the VIX futures term structure: Most of the time the VIX futures term structure is in contango (upward sloping), while on occassion the VIX term structure inverts during periods of market turbulence and elevated risk premia amongst financial market assets.[6] Given that the Short VIX is directly impacted by this term structure dynamic, it provides a window into observing time-varying risk premia. In the context of hedge fund performance evaluation, this benchmark can be viewed as akin to some fund manager who has no ability to determine whether a particular VIX futures contract (or any security, more generally) is mispriced. At the same time, this fund manager does recognize that the VIX term structure is upward sloping, unconditionally. Accordingly, the fund manager shorts VIX futures contracts indiscriminately and experiences large losses on occassion. Clearly, investors should not be paying fees for this type of return profile (i.e. high SR and negative skewness) which they can easily generate themselves. Hence, it provides a floor by which hedge fund managers can be measured against.

This paper is divided into three main parts: (i) documenting the empirical relationship between hedge fund returns and the Short VIX benchmark; (ii) motivating a classification approach to predict hedge fund performance that is supported by the robust empirical evidence; and (iii) simulation evidence from the Barberis et al. (2015) X-CAPM model, at the trader-level, that provides an economic explanation of the empirical findings. Specifically, I begin by detailing the hedge fund data and cleaning methodology used in this paper along with the construction of the Short VIX trading strategy and null hypothesis. I then provide evidence that hedge fund returns can be explained by the benchmark at the index- and fund-level both cross-sectionally and in the time series. Moreover, I show that the benchmark Short VIX strategy is able to replicate hedge fund returns more closely than previously known hedge fund predictors such as the Jurek and Stafford (2015) OTM Short S&P 500 Put strategy and the Fung and Hsieh (2001) FH8 model. Subsequent to this, I present the market timing results, with respect to the Short VIX. After having established this set of performance evaluation results, I move onto the second part of the paper which concerns economic significance of using the Short VIX benchmark. In particular, I motivate a classification approach that is informed by the null hypothesis. This methodology produces an

[6] This might reflect the fact that investors face more uncertainty further out into the future. Alternatively, it might also be a manifestation of differences in the Variance Risk Premium (VRP) across maturities. It remains an active area of research as to what drives the shape of the VIX term structure.

investment rule that allows me to form two OOS equal-weighted hedge fund portfolios: one with a higher SR and positive skewness versus the other portfolio with a lower SR and negative skewness. In the third and final part of the paper, I provide simulation evidence from the Barberis et al. (2015) X-CAPM model, at the trader-level, that is able to explain the main empirical finding that is counterintuitive given the prevailing interpretation of hedge fund returns.

This article contributes to the vast literature on hedge fund performance evaluation by proposing a new benchmark that we can use to explain and replicate hedge fund returns in the cross-section and time-series. A partial list of the hedge fund literature that attempts to explain hedge fund performance both in the cross-section and time-series includes Agarwal et al. (2017a, 2018); Agarwal and Jorion (2010); Agarwal and Naik (2004); Agarwal et al. (2017b); Avramov et al. (2013, 2011); Bali et al. (2014, 2021); Black (2006); Fung and Hsieh (2001, 2002, 2004); Fung et al. (2008); Jagannathan et al. (2010); Joenvaara et al. (2021); Jurek and Stafford (2015); Kelly and Jiang (2012); Kosowski et al. (2007). A leading example that is most closely related to this study is Jurek and Stafford (2015) who show that hedge fund returns at the index-level can be closely replicated by writing an OTM S&P 500 put option. They explain this empirical finding by arguing that it suggests hedge fund investors are compensated for holding concentrated portfolios that are exposed to market crashes. This argument is the leading explanation as to why hedge fund returns exhibit relatively high excess returns with significant negative skewness.[7] In another study that is related to this paper, researchers have linked macroeconomic variables (i.e. VIX) to hedge fund performance. Avramov et al. (2011) argue that hedge fund managers should be evaluated based on the credit spread and the VIX in order to determine whether a manager has skill. In particular, they exploit the predictability inherent in these macroeconomic variables to form portfolios of hedge funds. [8] In sum, it is well documented that tail risk and market

[7]Agarwal et al. (2017b) construct a tail risk measure in order to determine the extent to which systematic tail risk can explain hedge fund performance. They conclude that tail risk is important in explaining both the cross-section and time-series variation of returns produced by equity-focused hedge funds. Kelly and Jiang (2012) also find that the main driver underlying hedge fund returns is their exposure to downside tail risk.

[8]Black (2006) shows how hedge fund investors would benefit from adding a small position in VIX futures to their portfolio of hedge funds in order to reduce overall volatility and negative skewness. Avramov et al. (2013) use the VIX as a proxy for market uncertainty to predict hedge fund returns. Agarwal et al. (2017a) use a lookback straddle option strategy written on the VIX to determine whether market uncertainty about stock market volatility can account for hedge fund performance. The authors find that their option-based strategy has a significant negative risk premium which is largest during the 2008 financial crisis. It is important to note the difference between using the spot VIX index as opposed to VIX futures. The returns to using the VIX futures are largely determined by the slope of the VIX term structure in contrast to the spot VIX which is a reflection of the level of the S&P 500's implied volatility. The slope of the VIX term structure has much more stability compared to the level of the VIX. It is this property of stability that the Short VIX futures strategy inherits that leads to a trading strategy with a high SR and negative skewness

uncertainty are important drivers of the variation in hedge fund returns. The pervasiveness of this finding is what has led to it becoming a stylized fact of the hedge fund literature. However, none of these papers have used a Short VIX futures strategy to explain hedge fund returns cross-sectionally and predict hedge fund performance in the time-series.

This article also contributes to the performance evaluation literature that addresses the market timing bias inherent in the intercept originally highlighted by Jensen (1968). Specifically, this study offers a new classification approach based on the parameters estimated from the null hypothesis that is able to separate and predict OOS a portfolio of hedge funds with higher SRs and positive skewness from a portfolio with lower SRs and negative skewness. The methodology is motivated by the ubiquity of negative market timing hedge funds in the sample. Several classic studies have revisited Jensen (1968) by proposing a revised estimate of the intercept to account for the estimation issue regarding market timing bias Ferson and Schadt (1996); Grinblatt and Titman (1989); Henriksson and Merton (1981); Jensen (1972); Treynor and Mazuy (1966). Jensen (1972); Treynor and Mazuy (1966) add a quadratic term in the market factor to account for market timing bias whereas Henriksson and Merton (1981) add the payoff to a call option on the market factor. In a theoretical study, Grinblatt and Titman (1989) show that Jensen's alpha is a positive weighting measure akin to Treynor and Mazuy (1966) that is unaffected by market timing and does not require data on portfolio holdings. Lastly, Ferson and Schadt (1996) motivate a revised alpha by using conditioning information that accounts for time-varying returns and volatilities. Their conditional model is used to extend Henriksson and Merton (1981); Treynor and Mazuy (1966). In sum, this body of work shows that by controlling for the market timing bias we get more accurate intercepts that reflect security selection of the fund manager. To my knowledge, this is the first study to classify hedge funds based on the parameter estimates that is able to separate hedge fund performance with respect to two groups, ex-ante: (i) higher SRs and positive skewness; and (ii) lower SRs and negative skewness. In contrast to entirely removing the market timing bias, I instead remove negative market timers that load positively on the Short VIX strategy. By approaching the problem this way, we are left with a more attractive set of investment opportunities in hedge funds, given that a rational investor would prefer a portfolio that delivers a higer SR and positive skewness in comparison to a portfolio that offers a lower SR and negative skewness. This is an important contribution which makes clear that while as a group hedge funds are indistinguishable from shorting VIX futures, there is significant heterogeneity that can be teased out to the benefit of investors. In other words, investors do not have to settle for higher risk-adjusted returns by exposing themselves to downside risk in markets.

(reminscent of hedge fund returns).

In addition to the fund manager performance evaluation literature, this study contributes to the literature that studies the VIX term structure and the VRP (Bakshi and Kapadia, 2003; Coval and Shumway, 2001; Johnson, 2017). Most closely related, Cheng (2019) examines the VIX futures premium which he defines as the expected dollar loss associated with a long position in the nearest-dated VIX futures contract over the contract's life. His main finding is that this premium either stays flat or declines predictably when ex-ante measures of risk are increasing. He attributes this to a decrease in hedging demand as hedgers monetize their positions. I contribute to this literature by applying a closely related measure, the Short VIX strategy, in its ability to explain and predict hedge fund returns. The aim is to shed light on a key market participant (hedge funds) by leveraging the rich information encoded in the VIX term structure.

The remainder of the paper is organized as follows. In Section 2 the Short VIX benchmark measure is detailed along with the data and hypothesis tested in the paper. Section 3 displays the empirical evidence regarding the benchmark's efficacy in explaining hedge fund returns in the time series and cross-section. Section 4 goes on to show the market timing evidence with respect to the benchmark. The hedge fund classification is presented in Section 5. Section 6 applies the classification methodology by constructing hedge fund portfolios with and without edge to document economic significance of the paper. Section 7 provides simulation evidence from the Barberis et al. (2015) X-CAPM model conditioned at the investor level. Lastly, Section 8 concludes.

2 Data, Short VIX Measure and Null Hypothesis

This section provides an overview of the data used in the paper, the methodology used to to clean the commercial hedge fund data of biases that have been previously documented in the hedge fund literature[9], in addition to the construction of the benchmark Short VIX trading strategy. Subsequent to this, I detail the null hypothesis.

2.1 Data

The data used in this paper is from the following sources: i) Bloomberg, ii) the Hedge Fund Research (HFR) Database, (iii) the Lipper Hedge Fund Commercial Database (TASS), (iv) OptionMetrics (v) the Fung and Hsieh (2001) trend-following factors[10], (vi) Kenneth

[9]See Chapter 1 of Pedersen (2015) for a summary of the main biases present in hedge fund data.

[10]I thank David Hsieh for providing this data on his website (http://people.duke.edu/ dah7/DataLibrary/TF-Fac.xls)

French's Online Data Library[11] and (vii) the Federal Reserve Bank of St. Louis (FRED). From Bloomberg, I collect end-of-month spot Foreign Exchange (FX) rates (with USD as the base currency), daily closing prices of the S&P 500, Russell 2000 index, MSCI Emerging Market index, CBOE VIX Spot and Futures (second- and third-nearest-dated contract) from May 1, 2004[12] to December 31, 2022. I exclude the front month VIX futures contract to ensure that the strategy is realistic in its implementation and avoids the risk associated with liquidation prior to expiration.

From the HFR Database, I collect the HFR 500 Composite Index end of month Net Asset Values (NAVs) from January 2005 (the start date of the database) to December 2022. The HFR 500 Composite Index consists of the largest funds that report to HFR Database that are open to new investments and offer quarterly liquidity or better. The HFRI 500 is a representative and broadly diversified benchmark for the hedge fund industry. The HFRI 500 Composite is equally weighted across its constituents and is comprised of the following hedge fund strategies: (i) Equity Hedge, (ii) Event-Driven, (iii) Macro, (iv) Relative Value and (v) Emerging Markets. In addition, I collect the monthly NAVs for these 5 subindices. From FRED, I collect the 10-year treasury constant maturity yield and the Moody's Baa yield to construct the Bond Market Factor and Credit Spread Factor, respectively as part of the Fung-Hsieh eight-factor model (Fung and Hsieh, 2001, 2002, 2004) (FH8). From Kenneth French's website, I collect the Fama and French (2015) five factors (FF5) in addition to the risk-free rate, all at a monthly frequency.

I collect panel data, at a monthly frequency, from the TASS data from May 2004 to December 2022. This represents 22,269 unique hedge funds of which 3,790 survived (18,479 died) over the sample period, which in total is a sample size of 1,598,051 hedge fund month observations. The primary categories of the hedge fund strategies are: (i) Convertible Arbitrage, (ii) Dedicated Short Bias, (iii) Emerging Markets, (iv) Equity Market Neutral, (v) Event-Driven, (vi) Fixed Income Arbitrage, (vii) Fund of Funds, (viii) Global Macro, (ix) Long-Short Equity Hedge, (x) Managed Futures, (xi) Multi-Strategy, (xii) Options Strategy, (xiii) Other and (xiv) Undefined. No dedicated Short Bias hedge fund survives over the sample period. In addition, nearly two thirds (64%) of all hedge funds are represented by three categories: Fund of Funds (31.5%), Long-Short Equity (20.9%) and Multi-Strategy (11.5%). This over-representation declines to 55% of those that survive. Table 1 provides the unique hedge fund counts for the cleaned database by primary category for all, survived and dead hedge funds. The strategy composition of the cleaned database is consistent with the orig-

[11] I thank Kenneth French for providing this data on his website, (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

[12] The first trading date of the CBOE VIX futures occurred on March 26, 2004.

inal database (i.e. top three categories represent 73.1% vs. 64%). To provide more colour, Figure 1 displays the total number of hedge funds (and the percentage that survive) over the sample period for the cleaned database. The number of hedge funds is hump-shaped with its peak at 2,425 unique funds in April 2011 with a steady decline afterwards. The number of survived hedge funds over the entire sample period represents 7% of the total number of reporting hedge funds.

It is important to note the limitations of using data reported in commercial hedge fund databases which is neatly summarized in Chapter 1 of Pedersen (2015). In essence, hedge fund data suffers from various biases due to the fact that reporting to hedge fund databases is voluntary. To remedy this, I have chosen the most widely studied hedge fund database, the Lipper Trading Advisor Selection System Database (hereafter TASS)[13], accessed in February 2023. I perform several screens on the data that are standard in the literature.

I first exclude all observations with missing returns or Assets under Management (AUM). I restrict the sample to those funds that have at least US$5 mm in AUM at some point during the sample period and report net-of-fee returns with a minimum of 36 consecutive monthly observations consistent with Couts et al. (2020). The AUM restriction mitigates the impact of small funds. All funds with AUM whose base currency is foreign-denominated is converted to USD using end-of-month spot rates from Bloomberg. 51% of my sample consists of USD denominated hedge funds. Also consistent with Couts et al. (2020), I exclude hedge funds whose primary strategy is classified as "Undefined" or "Other." I remove backfill bias by adopting the method proposed by Jorion and Schwarz (2019) to identify backfilled observations. Survivorship bias is addressed by using both "dead" and "alive" hedge funds included in the TASS database. Lastly, I address the smoothing bias present in hedge fund returns by implementing the recent 3-step methodology proposed by Couts et al. (2020) which builds off of the 1-step methodology introduced by Getmansky et al. (2004). The 3-step methodology removes autocorrelation in returns at the fund- and strategy-level. I follow the convention in the hedge fund literature by estimating an MA(2) process which is used to unsmooth reported hedge fund returns.

The final cleaned TASS panel data used for the fund-level empirical work is reduced to 334,354 hedge fund month observations. This represents 4,078 unique hedge funds of which 811 survived (3,267 died). Nearly 90% of the final set of unique hedge funds is spanned by

[13]Joenväärä et al. (2021) review seven commercial hedge fund databases and find that TASS is the most widely used commercial database in academic research (79% of 92 papers reviewed used TASS) since it offers one of the highest quality datasets in terms of coverage and lack of survivorship bias after 1994. I have chosen the TASS database given that the primary scope of this paper is to shed more light on the main stylized fact that has been documented in the hedge fund literature: average hedge fund returns can be represented by a concave payoff (positive risk-adjusted returns with significant negative skewness).

three countries, with respect to the fund's base currency: U.S. Dollar (63%), Euro (20%) and Swiss Franc (4%). All monthly returns used in this study are in excess of the one-month risk-free rate, unless stated otherwise.

I use option price data from OptionMetrics to construct the out-of-the-money (OTM) S&P 500 Put-Writing strategy. The sample period is from May 2004 to December 2021 at a daily frequency. The sample ends in December 2021 due to data not yet being available for 2022. I build the OTM put-writing measure using the same methodology as Jurek and Stafford (2015) with one modification. Instead of writing S&P 500 (SPX) put options at fixed Z-Scores, I instead choose the option with a fixed moneyness and expiration. Specifically, I choose the option whose delta is closest to the upper bound of the following range: $\Delta^{\text{put}} \in [-0.4, -0.2)$ as in Koijen et al. (2018) with a maturity that is closest to one month to expiration. The final strategy assumes leverage of two times unleveraged asset capital and produces a highly similar return profile with Jurek and Stafford (2015), in terms of SR and skewness.

2.2 Short VIX Measure

Here, I detail the construction of the benchmark used in this paper to test the null hypothesis. The benchmark is an investment strategy that shorts VIX futures contracts with monthly rollovers. A Short VIX strategy with monthly rollovers[14] is an ideal benchmark for hedge fund returns since it is one of the best windows into time-varying risk premia (detailed in the next subsection) in addition to also being accessible to any investor given that it requires no skill to implement. Moreover, this strategy offers a hedge fund-like return profile (i.e. high SR with significant negative skewness). The most common benchmark that's used to replicate hedge fund returns is with the Fung and Hsieh (2001) FH8 model or with writing S&P 500 put options (Jurek and Stafford, 2015). The practical advantage of instead using the Short VIX strategy to replicate hedge fund returns is its simplicity relative to options. The Short VIX strategy only requires an investor to choose along one dimension (maturity) as opposed to options which are spanned by two dimensions (strike price and maturity).

At a more fundamental level, VIX futures prices reflect a risk premium for exposure to downside risks driven by hedging demand (Cheng, 2019). The following states the VIX by its

[14] Monthly rollovers are captured by computing monthly roll-adjusted returns based on constant exposure to one contract of the second nearest-dated CBOE VIX futures contract. Daily log roll-adjusted returns are summed within each month to produce the Short VIX monthly return series.

theoretical construct as in Johnson (2017) in addition to the current CBOE discretization:

$$
\begin{aligned}
\mathrm{VIX}^2_{T,t} &\equiv \frac{2e^{rT}}{T}\left\{\int_0^{F_t}\frac{1}{K^2}\mathrm{Put}_t\left(K;t+T\right)dK+\int_{F_t}^{\infty}\frac{1}{K^2}\mathrm{Call}_t\left(K;t+T\right)dK\right\} \\
\hat{\mathrm{VIX}}^2_{T,t} &\equiv \frac{2e^{rT}}{T}\sum_{K_i}\frac{\Delta K_i}{K_i^2}\mathrm{Option}_t\left(K_i;t+T\right)-\frac{1}{T}\left(\frac{F}{K_0}-1\right)^2,
\end{aligned} \tag{1}
$$

where r represents the risk-free rate to expiration, F_t is the S&P 500 forward price at time t expiring at time $t+T$, $\mathrm{Put}_t\left(K;t+T\right)$ and $\mathrm{Call}_t\left(K;t+T\right)$ are time t option prices with a strike price of K and expiration of $t+T$. In the discretized VIX calculation, T is the time to expiration measured in years, $\mathrm{Option}_t\left(K_i;t+T\right)$ represents the midpoint of the bid-ask spread for each option with strike K_i, K_0 is the first strike equal to or otherwise immediately below the option-implied forward price, F, ΔK_i is the midpoint between strike prices at either side of K_i which is the strike price of the i^{th} OTM option (i.e. a call option if $K_i > K_0$, and vice versa).[15]

There are two important takeaways from Equation 1. First, the option weights ($\frac{1}{K^2}$) indicate that more weight is placed on put options relative to call options in the VIX calculation. This is why the VIX is widely known as a useful measure of downside risk in the S&P 500. Second, the VIX calculation helps reveal the informativeness of using a trading strategy based on VIX futures prices. The VIX and its derivatives (i.e. VIX futures) reflect the distribution of implied volatility across moneyness. In contrast, a trading strategy that writes an OTM S&P 500 put option as in Jurek and Stafford (2015), reflects a single point estimate of implied volatility. It follows that the Short VIX measure better reflects all of the variation in implied volatility. Hence, the Short VIX trading strategy provides a new window for us to observe time-varying expected returns, since implied volatility is itself a function of both changes in investors' expectations and risk preferences.

Figure 2 displays the cumulative log monthly returns generated from the benchmark strategy of shorting second-dated constant maturity VIX futures at a monthly frequency. The returns to this strategy are impressive with a Sharpe Ratio (SR) of 0.95 and cumulative returns of 920% over the full sample period from May 2004 to December 2022. The strong positive returns come with significant tail risks (negative skewness of -1.29) which is clearly indicated in the substantial drawdowns in two periods: (i) Around the 2008 Financial Crisis from June 2007 to March 2009 investors would have lost 158% applying this strategy; and (ii) At the beginning of the COVID-19 Global Pandemic from January 2020 to March 2020 investors would have lost 97%. Of course, the large magnitude of each drawdown reflects

[15] For further details on the CBOE VIX calculation please see https://cdn.cboe.com/api/global/us_indices/governance/Volatility_Index_Methodology_Cboe_Volatility_Index.pdf.

the Short VIX's annualized volatility of 52%.

It is important to understand what underpins the return profile of the Short VIX strategy. The vast majority of the time, the VIX term structure (or futures curve) is upward sloping[16] due to dealers' hedging demand of longer-term VIX futures to hedge equity market downside risk (Cheng, 2019). The presence of these market participants results in a highly liquid VIX futures market. Hence, an investor can collect the roll yield by shorting a longer-dated contract (i.e. 2 months from now) and holding it for one-month as the contract falls in value. The investor can liquidate the contract and repeat this process by buying the new second dated contract. The main risk is that a material and unforeseen market event occurs (i.e. COVID-19), in which case the VIX spikes upward leading the VIX futures curve to invert or shift upward. In this scenario, the investor who's shorted VIX futures suffers large losses. In the presence of significant hedging demand, these episodes are rare. It is this dynamic that results in the Short VIX trading strategy's return profile: high SR and negative skewness.

2.3 Why is the Short VIX Strategy an Ideal Benchmark?

This subsection provides the economic rationale as to why a strategy that shorts VIX futures is an ideal benchmark for evaluating hedge fund returns.

Risk premia are not constant. Ferson and Schadt (1996) argue that a managed portfolio (i.e. a hedge fund strategy) should be evaluated based on publicly observable measures that reflect this return predictability. The only way we can determine whether a hedge fund manager has edge in financial markets is if we find outperformance relative to a simple (and tradeable) publicly observable measure that incorporates all relevant return predictability. The following provides my argument outlining why I believe the short VIX benchmark provides one of the best windows into observing time-varying risk premia.

2.3.1 SDF Decomposition

I begin with a decomposition of the stochastic discount factor (SDF).[17]

[16] At a daily frequency, 83% of the time, from May 2004 to December 2022, the nearest dated VIX futures contract is cheaper than the second nearest dated contract.

[17] This decomposition closely follows the same decomposition outlined in an unpublished manuscript, "Asset prices and financial markets," by Stefan Nagel and Ian Martin.

Let,

$$
\begin{aligned}
P(X) &= \sum_{s=1}^{S} \pi(s) M(s) X(s), \text{ prices under objective probabilities} \\
P(X) &= \sum_{s=1}^{S} \tilde{\pi}(s) \tilde{M}(s) X(s), \text{ prices under investors' subjective probabilities,}
\end{aligned}
\tag{2}
$$

where X represents the assets' cash flows (or payoffs), $\pi(s)$ and $\tilde{\pi}(s)$ represent the likelihood of state s under the objective measure (observed by the econometrician) and subjective measure (observed by the investor), respectively. To be clear, any variable with a tilde is under the subjective measure. Lastly, the SDF, $M(s)$, represents the desirability of the cash flow in state s.

It follows that,

$$
M(s) = \tilde{M}(s)\frac{\tilde{\pi}(s)}{\pi(s)} \text{ and } \frac{1}{R_f} = \sum_{s=1}^{S} \pi(s) M(s) = \sum_{s=1}^{S} \tilde{\pi}(s) \tilde{M}(s), \tag{3}
$$

where R_f is the gross riskless rate, whereby a risk-free asset is assumed to exist.

With that, we can now better detail the variation of the SDF around its mean:

$$
\begin{aligned}
M(s) - \frac{1}{R_f} =& \tilde{M}(s)\frac{\tilde{\pi}(s)}{\pi(s)} - \frac{1}{R_f} \\
=& \tilde{M}(s)\frac{\tilde{\pi}(s)}{\pi(s)} - \frac{1}{R_f} + \frac{1}{R_f} - \frac{1}{R_f} + \tilde{M}(s) - \tilde{M}(s) + \frac{\tilde{\pi}(s)}{\pi(s)}\frac{1}{R_f} - \frac{\tilde{\pi}(s)}{\pi(s)}\frac{1}{R_f} \\
=& \frac{\tilde{\pi}(s)}{\pi(s)}\frac{1}{R_f} - \frac{1}{R_f} + \tilde{M}(s) - \frac{1}{R_f} + \tilde{M}(s)\frac{\tilde{\pi}(s)}{\pi(s)} - \frac{\tilde{\pi}(s)}{\pi(s)}\frac{1}{R_f} - \tilde{M}(s) + \frac{1}{R_f} \\
=& \left[\frac{\tilde{\pi}(s)}{\pi(s)} - 1\right]\frac{1}{R_f} + \left[\tilde{M}(s) - \frac{1}{R_f}\right] + \left[\frac{\tilde{\pi}(s)}{\pi(s)} - 1\right]\left[\tilde{M}(s) - \frac{1}{R_f}\right]
\end{aligned}
\tag{4}
$$

Equation 4 highlights that the SDF that the econometrician observes is comprised of both belief distortions and risk preferences. Said differently, observable time-varying risk premia contains both variation in beliefs and risk preferences.

I now ask the following question, when does Equation 4 experience it's highest levels? That is, when are observable risk premia especially large? In light of Equation 4, the answer is clear. Risk premia are largest when both (i) investor beliefs are most optimistic about the payoffs and risk of the asset and (ii) investors are more risk-averse. Having answered this question we can now identify an asset under certain conditions that satisfy these criteria in order to infer periods when risk premia are most elevated.

At first glance, satisfying the two criteria mentioned in the previous paragraph might seem counter to one another with a traditional asset. In particular, a traditional asset whose current investor base is over-represented by optimists would naturally coincide with investors who are also less risk averse, leaving the net result on risk premia indeterminate. Given that we have not yet developed an agreed upon methodology to separate investor beliefs from risk preferences, it might seem especially futile then to be able to identify an asset whose beliefs and risk preferences have the same directional impact on risk premia. However, I argue that these two criteria can easily be satisfied with a hedging asset that is prone to *extreme* pricing dynamics (i.e. VIX futures).

In a seminal article, Miller (1977) argues that the price of a security that is hard to short-sell will reflect the beliefs of the optimists, to the extent that there is disagreement regarding the prospects of the respective security. I extend the reasoning of Miller (1977) by considering that this argument not only applies to the cross-section of securities (or assets) but also to the time-series. That is, there are periods of time which make it particularly difficult to short-sell an asset. In that vein, near-dated VIX futures contracts are especially risky (i.e. difficult) to short when the VIX term structure begins to invert. It has been documented that during an inversion of the VIX term structure, there is a tendency for the inversion to become more pronounced during a significant market dislocation (Cheng, 2019; Johnson, 2017). Given that the VIX is bounded below by zero, investors who are shorting near-dated VIX futures contracts during a VIX term structure inversion face the potential to lose multiples of whatever gains they made prior to the inversion. Hence, the VIX term structure dynamics make it difficult to short VIX futures contracts during an inversion. It follows that during an inversion, near-dated VIX futures contracts will reflect the beliefs of optimists regarding VIX payoffs. Moreover, these inversions tend to occur during periods of heightened market stress (i.e. when investors are more risk-averse).[18] Given that VIX futures are often used as a hedging asset, it seems reasonable to assume that risk-averse investors will crowd into this hedging asset during these times. All together, near-dated VIX futures contracts during a VIX term structure inversion, provide us a window into estimating risk premia when they are largest. By applying the same logic, we can also infer periods when risk premia are lowest. That is, when the VIX term structure is steeply in contango. This

[18] The argument by Miller (1977) is based on the premise that there exist disagreement with respect to the prospects of the security. A period when the VIX term structure is negatively sloped is a time when investors are in greater disagreement with eachother surrounding the prospects of the level of the VIX. Martin and Papadimitriou (2022) build a model featuring agents with heterogenous beliefs whereby they produce a VIX term structure that increases in backwardation as disagreement rises amongst investors.

would coincide with a period in which investors are both (i) excessively pessimistic regarding VIX payoffs and (ii) least risk averse. It is in this sense that makes the short VIX strategy an ideal benchmark for hedge funds given it's ability to reflect the greatest variation in risk premia (i.e. risk premia at both it's minimum and maximum levels).[19]

A strategy that shorts near-dated VIX futures each month will experience it's largest losses during a VIX term structure inversion (i.e. when risk premia are most pronounced). The short VIX strategy experiences it's worst (best) returns when risk premia are highest (lowest). Arguably, the modus operandi of any hedge fund is to harvest risk premia. It follows that hedge funds should stand to have their largest returns when risk premia are greatest. Hence, hedge funds with edge should generate returns that are inversely correlated with the short VIX benchmark.

2.4 The Relationship between Short VIX, Short Put and S&P 500 Returns

At this point, I illustrate how the Short VIX returns relate to two important determinants of hedge fund returns: the S&P 500 index and the OTM S&P 500 Put-Writing Strategy from Jurek and Stafford (2015). Figure 3 plots the Short VIX returns next to the S&P 500 and the Short Put returns. Panels A and C present scatterplots of the respective time series in relation to the Short VIX from May 2004 to December 2022. Panel B and D plot the predicted Short VIX returns as a fractional polynomial of the S&P 500 and Short Put returns, respectively, with 95% confidence bands. All four panels show the concavity inherent in the Short VIX returns. The Short VIX earns more modest gains when either the S&P 500 or the Short Put have high positive returns. In contrast, the Short VIX incurs relatively steep losses when the S&P 500 or the Short Put experience large negative returns. Ex-ante, the relationship between the Short VIX and the S&P 500 is not surprising. However, it is interesting to note that the Short Put is a concave function of Short VIX returns. This additional negative convexity (or concavity) is a key feature of the majority of hedge fund returns that we would miss if we simply used the Short Put strategy returns as our benchmark.

Table 2 illustrates the same point as Figure 3 numerically. That is, it displays the results

[19] The previous paragraph emphasized that we need to identify a hedging asset with extreme pricing dynamics. Miller (1977) highlights how the price of a security with increased visibility will reflect the beliefs of a smaller proportion of the investor population. In other words, as the salience of an asset increases, the prices of that asset will be determined by the more extreme ends of the distribution of investor beliefs. Given the relative importance placed on the level of the VIX by market participants and the financial press, it seems reasonable to argue that VIX futures are one of the most salient assets in comparison to some other alternative substitute.

of a univariate spanning test of Short VIX returns on the S&P 500 and OTM S&P 500 Put-Writing Strategy returns, respectively, from May 2004 to December 2022. The intuition behind a spanning test is that it shows us statistically whether there is a measure that has significant variation over and above a highly related measure. I follow the same methodology and interpretation of my results as in Koijen et al. (2018) who also use spanning tests to evaluate predictors next to one another. The spanning test works as follows. We conduct two regressions. In both regressions, we expect a highly significant coefficient. In the first regression, we regress the variable of interest on an alternative measure. In the second regression, we run the reverse regression. The variable of interest subsumes the alternative measure if in the first regression we estimate a statistically significant intercept, in contrast to the second regression where we observe an intercept with no significance. This is evidence that the variable of interest has variation over and above the variation in the alternative measure.

Panel A displays the results of the following univariate time series regressions of the Short VIX returns on the S&P 500 and OTM Put-Writing Strategy, respectively.

$$\begin{aligned} \text{Short VIX Returns}_t &= \alpha + \beta\,(\text{S\&P 500}_t) + \epsilon_t \\ \text{Short VIX Returns}_t &= \alpha + \beta\,(\text{OTM Short S\&P 500 Put}_t) + \epsilon_t \end{aligned} \tag{5}$$

Panel B displays the following reverse univariate regressions,

$$\begin{aligned} \text{S\&P 500}_t &= \alpha + \beta\,(\text{Short VIX Returns}_t) + \epsilon_t \\ \text{OTM Short S\&P 500 Put}_t &= \alpha + \beta\,(\text{Short VIX Returns}_t) + \epsilon_t \end{aligned} \tag{6}$$

Panel A reports an intercept and coefficient that are both statistically significant at the 1% level with an R^2 of 61% for the S&P 500 regression. The OTM Put-Writing regression displays an intercept that is statistically significant at the 10% level with a highly significant coefficient and high R^2 of 56%. In Panel B, the intercepts for both the S&P 500 and OTM Put-Writing Strategy are no longer statistically significant at any conventional level whereas the coefficients remain highly significant at the 1% level. This spanning test of the S&P 500 confirms what was depicted visually in Figure 3. That is, while the S&P 500 and Short Put are both highly correlated with the Short VIX returns (correlation of 0.78 and 0.75, respectively)[20], there is important variation *unique* to Short VIX returns that cannot be captured by the S&P 500 or the Short Put strategy. The Short VIX subsumes the return variation of the S&P 500 at the 1% level and the Short Put at the 10% level. Hence, neither of these two measures can be used as a substitute for the Short VIX if we want a benchmark that more closely reflects hedge funds' concave payoff profile.

2.5 Null Hypothesis

The previous subsection presents preliminary evidence that the Short VIX strategy subsumes two prevailing determinants of hedge fund returns: the S&P 500 and the OTM Short S&P 500 Put strategy. The Short VIX strategy reflects the full distribution of implied volatility as a function of option strike prices. It is for this very reason that it is able to capture additional variation beyond the Short Put strategy, which is often used to replicate hedge fund returns. It stands to reason that the Short VIX strategy has the potential to better explain and predict hedge fund returns so long as that additional variation has incremental explanatory power with respect to hedge fund performance. With that, I test the following linear regression which informs the Null Hypothesis (H_0),

$$\text{HF Returns}_t = \alpha + \beta \text{Short VIX Returns}_t + \varepsilon_t, \quad \text{H}_0 : \alpha \leq 0 \;\; \& \;\; \beta > 0 \tag{7}$$

where t corresponds to a monthly frequency, α represents the return variation left unexplained by the Short VIX returns, β represents the hedge funds' loading on the Short VIX strategy.

The linear one-factor model of Equation 7 can be viewed as a potential alternative to other leading models used to replicate hedge fund returns in the cross-section and time-series (Agarwal et al., 2017a; Fung and Hsieh, 2001; Jurek and Stafford, 2015). The main benefit of the null lies in its simplicity and ease to implement that a naive investor could use to achieve hedge fund-like performance at minimal cost or ability. The null hypothesis is to be interpreted in the following way: hedge fund returns can be fully explained by positive exposure to the Short VIX strategy benchmark.

3 Short VIX Strategy: A Benchmark for Hedge Fund Returns

In this section, I provide empirical evidence that documents the fact that the Short VIX strategy explains the majority of the variation in hedge fund returns both cross-sectionally

[20]Since this is a univariate time-series regression, the R^2 represents the squared correlation coefficient.

and in the time series.

3.1 Hedge Fund Returns and Hedge Fund Replicators

Table 3 displays the summary statistics (annualized) for hedge fund returns and leading candidates to replicate hedge fund returns from January 2005 to December 2022. This includes the HFRI 500 Index, TASS equal-weighted portfolio, Short FH Stock Index Lookback Straddle (PTFSSTK), FH8 model, OTM S&P 500 Put-Writing Strategy and Short VIX strategy. The HFRI 500 provides a useful hedge fund benchmark given that it is widely used in research (see Jurek and Stafford (2015)) as a measure of aggregate hedge fund performance. Over the sample period, the HFRI 500 has a SR of 0.61 with negative skewness of -1.18, thus highlighting the concave payoff profile often associated with hedge fund returns. It is reassuring to see that an equal-weighted hedge fund portfolio constructed from the cleaned TASS data is highly correlated (0.97) with the HFRI 500 index. The TASS data has a lower SR of 0.21 which is a direct result of applying the Couts et al. (2020) 3-step unsmoothing method that has increased volatilities significantly while leaving the mean unchanged. The HFRI mean return which is double the mean return of the TASS data reflects the selection bias inherent in the HFRI 500 Composite. This selection bias is by construction, in that HFRI 500 index represents the largest funds that choose to report to the HFR database. The PTFSSTK, FH8, Short Put and Short VIX represent four potential substitutes that an investor could use to replicate hedge fund returns. The SRs range from 0.03 (FH8) to 0.91 (Short VIX) with skewness ranging between -2.44 (PTFSSTK) to -1.26 (Short VIX) and correlations from 0.40 (PTFSSTK) to 0.74 (Short Put). The Short VIX strategy has second highest correlation (0.72) with the HFRI 500 and more importantly has a highly similar return profile with respect to SR and skewness. In particular, the Short VIX displays a SR of 0.91 and skewness of -1.26 compared to the HFRI 500 which has a SR of 0.61 and skewness of -1.18. The clearest alternative to using the Short VIX would be to use the Short Put. While it has a similar SR of 0.85, it has significantly more negative skewness of -2.26. A benchmark is more attractive if it mirrors the fund under evaluation as an investment. Table 3 provides additional evidence indicating that the Short VIX is a more promising benchmark for hedge fund returns compared to the OTM Put-Writing Strategy given that it offers a return profile (SR and skewness) that is most similar to hedge fund returns.

In a recent survey of the hedge fund literature Getmansky et al. (2015) review the well documented empirical evidence that shows hedge fund returns tend to display excess risk-adjusted returns (i.e. positive and significant alphas) where risk is accounted for by using linear factor models such as Fama and French (1992). Table 4 presents the alphas with their

Newey and West (1987) t-statistics (in parentheses) from monthly time series regressions, from January 2005 to December 2022, of hedge fund returns and their substitutes on four models: (i) the CAPM (market factor from Fama and French (1992)), (ii) FF3 (Fama and French, 1992), (iii) FF5 (Fama and French, 2015), and (iv) FF5 (Fama and French, 2015) + MOM (Carhart, 1997). The HFRI 500 has a CAPM, FF3, FF5, FF5 + MOM alpha of 1.2% per annum that are all insignificant at the 10% level. The TASS equal-weighted hedge fund portfolio has alphas that are significant at the 10% level for the CAPM and FF3 models. The FF5 and FF5 + MOM alphas are not significant at the 10% level. This lack of strong statistical significance is likely the result of the Couts et al. (2020) 3-step unsmoothing whose methodology is primarily motivated to more accurately measure risk factors of illiquid assets. The PTFSSTK straddle has a CAPM, FF3, FF5 alpha of 34% per annum that are all significant at the 5% level. Its FF5 + MOM alpha is significant at the 10% level. None of the alphas with respect to FH8 model returns are significant. The Short S&P 500 Put has a CAPM, FF3, FF5 and FF5 + MOM alpha of 3.6% per annum that are significant at the 5% level, except the FF5 and FF5 + MOM alpha which are significant at the 10% level. Lastly, the Short VIX strategy has a CAPM, FF3, FF5 and FF5 + MOM alpha of 25% per annum that are all significant at the 1% level. Table 4 provides evidence that is largely consistent with the hedge fund literature in reporting positive and significant factor model alphas. Importantly, the Short VIX strategy has the strongest statistical evidence, among other leading hedge fund replicators, that shows it has additional return variation over and above traditional linear factor models from asset pricing.

Table 5 displays the results of a spanning test of Short VIX returns on the HFRI 500 Index, TASS equal-weighted portfolio, Short Stock Index Lookback Straddle (PTFSSTK) and the FH8 portfolio returns. I follow the same methodology and interpretation as in Table 2. Panel A displays the results of a univariate time series regression of the Short VIX returns on each of the hedge fund variables. Panel B displays the reverse regression. I first discuss the results regarding the hedge fund variables: (i) HFRI 500 and (ii) TASS. In Panel A, the coefficients are both significant at the 1% level, whereas the intercept is significant at the 5% and 1% level for the HFRI 500 Index and TASS data, respectively. In Panel B, the coefficients remain significant at the 1% level. The alpha is not significant at the 10% level for HFRI 500 in contrast to the alpha being significant at the 5% level for the TASS data. The R^2 is 52% and 53% for HFRI 500 and TASS, respectively. This evidence suggests that the Short VIX subsumes the hedge fund variation, at the 5% level, at an aggregate level based on the HFRI 500. However, it fails to subsume the TASS data at the 10% level. Regarding the two potential hedge fund replicators (PTFSSTK and FH8), the coefficients are significant at the 1% level in both panels. The alphas in panel A are significant at the 5%

and 1% level for PTFSSTK and FH8, respectively, whereas in panel B, the PTFSSTK alpha is no longer significant at the 10% level whereas the FH8 model alpha is not significant at the 5% level. This evidence suggests that the Short VIX subsumes the return variation of the Fung and Hsieh (2001) short lookback straddle at the 5% level and Fung and Hsieh (2001) FH8 model at the 10% level. All together, these spanning test provide additional evidence that supports the conclusion that the Short VIX captures additional variation that is both relevant to hedge funds at an aggregate level and return variation that leading replicators fail to capture.

3.2 Short VIX as a Replicator of Hedge Funds at the Index and Fund-Level

In the previous subsection, the Short VIX strategy has been shown to closely resemble aggregate hedge fund returns and outperform leading hedge fund replicators offered in the hedge fund literature. It is reasonable to question whether this is largely a result of two notable periods (i.e. 2008 Financial Crisis and 2020 COVID-19 Market Crash) during the sample period that might be affecting the results. After all, the Short VIX experienced its most pronounced drawdowns during these two market episodes, as noted previously. Figure 4 lays to rest this concern by clearly showing that the average hedge fund (as captured by the HFRI 500 Index) has a large, positive and stable exposure to a Short VIX futures strategy. Figure 4 plots the rolling 36-month correlations between the HFRI 500 Composite Index and the Short VIX strategy returns from December 2007 to December 2022. The average correlation is 0.73 ranging between 0.51 and 0.89. The most striking feature of this high correlation is its stability over time. Ex-ante, we might expect that correlations of most strategies to tend towards 1 during a crisis as liquidity dries up and investors seek safe haven assets. While the correlations between the Short VIX and hedge fund composite index do spike during crises (i.e. 2008 Financial Crisis and March 2020 COVID-19 crash), the correlations have a tendency to remain high before and after these crisis periods. The empirical success of the Short VIX is not simply a consequence of these two market outlier events.

The evidence presented thus far has documented the informativeness of the Short VIX benchmark in explaining hedge fund returns at an aggregate level, I now shift my attention to examining its relationship with hedge fund returns at the fund-level by hedge fund strategy type. Panel A of Table 6 displays the panel regression results of spanning the TASS data by primary category (i.e. hedge fund strategy) on the Short VIX returns, with hedge fund, year fixed effects and clustered standard errors at the fund level. The regression specification is as follows,

$$r_t^i = \alpha + a^i + b_t + \beta \text{ShortVIX}_t + \varepsilon_t^i, \tag{8}$$

where r_t^i is the hedge fund excess return, a^i is a hedge fund-specific fixed effect, b_t are year fixed effects, α is unexplained return variation, ShortVIX_t is the Short VIX monthly return and β is the coefficient of interest that measures how well the Short VIX explains returns. The sample period is May 2004 to December 2022 at a monthly frequency.

The most important takeaway from Table 6 is that across all strategies the null hypothesis ($\alpha \leq 0$ and $\beta > 0$) is not rejected at any conventional level of statistical significance. The full panel has a coefficient value of 0.149 (t-statistic of 77.41) and an alpha of 0.03% per month (t-statistic of 0.84). The large magnitude of the t-statistic on the coefficient value of the Short VIX is the result of very little variation in unobservable time-varying fixed effects which results in relatively small standard errors. All hedge fund strategies (except for Managed Futures) have a highly significant loading on the Short VIX strategy at the 1% level. Dedicated Short Bias is the only strategy with a negative loading which is intuitive since Dedicated Short Bias performs well from asset prices falling. This tends to occur during a market crash when the Short VIXstrategy suffers losses from either the VIX futures curve shifting upwards or inverting. Dedicated Short Bias, Equity Market Neutral, Fund of Funds, Multi-Strategy and the Options Strategy have insignificant alphas at the 10% level, indicating that the Short VIX fully explains their return variation. Emerging Markets, Event Driven and L/S Equity Hedge have alphas that are significant at the 10%, while the remaining 4/12 (Convertible Arbitrage, Fixed Income Arbitrage, Global Macro and Managed Futures) alphas are significant at the 5% level. With the exception of Managed Futures, the alphas are all at least one order of magnitude smaller relative to their coefficient values on the Short VIX, with an average R^2 of 19% that ranges between 4% and 38%. Table 6 provides strong evidence that suggest the Short VIX strategy explains the majority of return variation at the individual hedge fund level across a diverse universe of hedge fund strategies.

Table 6 Panel B performs the same panel regression test as in Table 6 Panel A, except the Short VIX benchmark is replaced with the OTM Short Put Strategy. The key takeaway from this set of results is that the Short Put which is viewed as an important determinant and useful replicator of hedge fund returns in the literature is not able to account for as much variation as the Short VIX at the hedge fund level. More specifically, Table 6 Panel B shows that across all strategies the null hypothesis is rejected at the 1% level when we use the OTM Put strategy as the benchmark (an alpha of 0.2% per month with a t-statistic of 5.24). Panels A and B share highly significant coefficient values that are positive across all strategies. In sum, the Short VIX strategy is better able, relative to leading hedge fund replicators, to account for hedge fund variation at both the index-level and individual fund-level.

3.3 Does Exposure to the Short VIX Predict Hedge Fund Performance?

Table 7 reports the results of Fama and MacBeth (1973) regressions whereby I first estimate rolling 5-year (60 month) regressions of individual hedge fund returns on the Short VIX returns to estimate the factor loadings. Subsequent to this, I regress the one-year ahead $(t+1)$ returns on the factor loadings estimated at time t. Prior to estimation, I dropped any hedge funds that did not have a minimum return history of 5 years. Accounting for the initial estimation window, the sample period runs from May 2010 to December 2022. I report the results by hedge fund strategy. The key takeaway from Table 7 is that I find positive exposure to the Short VIX strategy weakly predicts higher returns (across all strategies) with a coefficient of 0.005 that is statistically significant at the 10% level and an R^2 of 2.0%. This is a reflection of the following strategies which are significant at the 10% level: Event Driven, Long/Short Equity Hedge, Multi-Strategy and the Options Strategy. The remaining 8 out of 12 hedge fund strategies do not have any significant loading on the Short VIX at the 10% level. All together, this evidence indicates that increased positive exposure, over the past five years, to the Short VIX strategy weakly predicts higher one-year ahead hedge fund returns, in aggregate. While we know from Table 6 that return variation is largely explained by the Short VIX at the strategy level, Table 7 tells us that this positive exposure tends not to predict higher one-year ahead returns at the fund-level by strategy type.

4 Market Timing with respect to the Short VIX Strategy

After having established in the previous section that hedge funds have significant exposure to the Short VIX strategy, it is natural to investigate if this exposure varies across different market regimes. That is, do hedge funds have the same loading on the Short VIX strategy regardless of whether the Shortort VIX is experiencing its best or worst returns? This section answers this question and in doing so test whether hedge funds exhibit market timing, or lack thereof.[21]

[21] It is important to note that I specifically narrow the scope of this paper to market timing as opposed to volatility timing given that the benchmark is based on returns to the Short VIX strategy which has a high degree of correlation with the market factor (0.77). The scope would change to volatility timing if the

4.1 Are Hedge Funds Short VIX during Major Market Dislocations?

Figure 5 displays the coefficient estimates from two sets of regressions for all hedge funds by primary strategy. I first calculate the bottom and top quartiles of Short VIX returns. I then run a panel regression of hedge fund returns during those periods for which the Short VIX returns fall in either the top (red bars) or bottom (blue bars) quartiles. I refer to the bottom quartile of Short VIX returns as periods of market dislocation whereas the top quartile is referred to as a period of market calm. The motivation for this approach is that the largest drawdowns of the Short VIX returns coincide with the two largest market dislocations (2008 Financial Crisis and February-March 2020 COVID-19 Crash). This is represented by the bottom quartile of Short VIX returns. There are two important takeaways from Figure 5. First, hedge fund exposure to the Short VIX during periods of market dislocation (blue bars) is larger in absolute magnitude relative to periods of market calm (red bars) for all hedge fund strategies, except for Managed Futures. The Q1 coeffient is over 3x larger than the Q4 coefficient for all hedge funds and is significant at the 1% level. Second, the Q1 coefficient is highly significant for the majority of strategies in sharp contrast to the Q4 coefficient which is insignificant at the 10% level for four of the 12 strategies. Specifically, the Q1 coefficient is highly significant at the 1% level for all strategies except for Managed Futures (significant at 5% level), in contrast to the Q4 coefficients which are not significant for Convertible Arbitrage, Dedicated Short Bias, Fixed-Income Arbitrage and Global Macro. This second finding is consistent with a Short put payoff profile whereby the underlying is the Short VIX strategy. That is, the Short put is linear as the returns to the underling become more negative, whereas the payoff profile is flat for high positive returns to the underlying. This is further evidenced by the fact that the R^2 for the Q1 regressions exceed those of the Q4 regressions for all but Global Macro and Managed Futures with an average differential of 12%. This is the initial market timing evidence that suggest that hedge funds tend to be more exposed to the Short VIX strategy at the worst possible time. Hedge funds have significant exposure to left tail risk in the Short VIX. This is consistent with the hedge fund literature (Agarwal and Naik, 2004; Mitchell and Pulvino, 2001) that has suggested that high risk-adjusted returns (based on linear factor models) of hedge funds can be explained by their exposure to crash risk.

benchmark was instead the VIX Index.

4.2 Traditional Market Timing Tests

In this section, I perform the classic market timing tests of Henriksson and Merton (1981) and Treynor and Mazuy (1966) with Short VIX substituted for the market portfolio. Table 8 reports the panel regression results (with standard errors clustered at the fund level) by strategy type for both models. In Panel A, I follow the Henriksson and Merton (1981) test by estimating the following regression with hedge fund and year fixed effects,

$$r_{j,t+1} = \gamma_j + \lambda_j r_{\text{Short VIX},t+1} + a_j \text{Max}\left(r_{\text{Short VIX},t+1}, 0\right) + b_t + \varepsilon_{t+1}, \tag{9}$$

where the coefficient a_j measures the hedge fund manager's market timing ability.

In Panel B, I test Treynor and Mazuy (1966) by estimating the following panel regression with hedge fund and year fixed effects:

$$r_{j,t+1} = \gamma_j + \lambda_j r_{\text{Short VIX},t+1} + a_j r^2_{\text{Short VIX},t+1} + b_t + \varepsilon_{t+1}, \tag{10}$$

where the coefficient a_j measures the hedge fund manager's market timing ability.

Table 8 shows that both models yield similar market timing results. 8 of the 12 strategies display a *negative* market timing coefficient (a_j) that is highly significant at the 1% level. Across all strategies the market timing coefficient is -0.053 and -0.059 with t-statistics of -25 and -20 for Panel A and B, respectively. The three strategies that show no market timing significance are: Dedicated Short Bias, Equity Market Neutral, Global Macro and Managed Futures. This result is intuitive since Dedicated Short Bias, Global Macro and Managed Futures are all set up to benefit from market dislocations when the Short VIX strategy suffers large losses. Moreover, hedge funds that employ a Equity Market Neutral strategy are by definition supposed to have no significant exposure to the underlying market, which is highly related to the Short VIX strategy. Overall, the estimation results from this set of classic market timing tests clearly indicates that hedge funds at the strategy level and in aggregate are negative market timers with respect to the Short VIX strategy.

5 Identifying Hedge Funds With(out) Edge

This section offers a new and simple approach, informed by the null hypothesis, to distinguish those hedge funds with higher SRs and positive skewness from those hedge funds with lower SRs and negative skewness.

The previous section documented robust evidence that hedge funds over the sample period from May 2004 to December 2022 display negative market timing at the strategy level. This evidence is consistent with Fung et al. (2002). The broader hedge fund literature surveyed by Getmansky et al. (2015) shows mixed evidence as to hedge funds' market timing abilities. The evidence of positive market timing that Getmansky et al. (2015) highlight tends to be conditioned on some identifying variable or an extension of the classic market timing tests of Henriksson and Merton (1981) and Treynor and Mazuy (1966) as in Chen and Liang (2007) who use the squared SR of the market portfolio. As per a conditioning variable, Aragon (2005) finds positive market timing amongst fund of funds that hold the most liquid portfolios. The majority of studies that document positive market timing with respect to hedge funds use samples that end before the financial crisis. Hedge fund studies that include the financial crisis offer more mixed results.

The utility in separating hedge funds with and without edge is motivated by the research question at the outset of this paper as to whether hedge funds add value to investors' portfolios. I argue that investors would strictly prefer a portfolio that offers a higher SR and positive skewness compared to a portfolio with a lower SR and negative skewness. Said differently, a portfolio with a higher SR and positive skewness adds value to an investor's portfolio. My reasoning is based on the seminal work of Kraus and Litzenberger (1976) who show that investors have a preference for positive skewness that is priced. Harvey and Siddique (2000) focus on conditional skewness instead and find that it is also priced with a risk premium of 3.6% per year. In particular, portfolios with high skewness earn lower expected returns. Hence, a portfolio that offers higher risk-adjusted returns with positive skewness should be strictly preferred.

To help illustrate the skewness of the underlying benchmark (Short VIX strategy), Figure 6 displays the monthly returns (in panel A) of the strategy of shorting one second-dated VIX futures contract with monthly rollovers. Panel B displays the same strategy returns with one modification. I have replaced all negative monthly returns with zero to present the payoff of a call option in which the underlying is the Short VIX strategy. The skewness of each monthly return series is shown in the top left hand corner. There is one important takeaway from this figure. The Short VIX strategy exhibits significant negative skewness which is solely due to the sharp negative returns during the 2008 Financial Crisis and the COVID-19 stock market crash from February to March 2020. The previous section provided evidence that hedge funds have relatively larger exposures to extreme losses (bottom quartile returns) of the Short VIX strategy compared to the highest gains (top quartile returns). This is evidence of negative market timing. The approach undertaken in this section offers us a way to remove hedge funds that are negative market timers and the respective negative skewness associated with their returns. In doing so, this methodology identifies hedge funds that exhibit returns that look more similar to the returns in Figure 6 panel B with positive skewness.

Recall the Null Hypothesis stated in Equation 7: $\mathrm{H}_0 : \alpha \leq 0 \;\;\&\;\; \beta > 0$. To separate hedge funds with respect to edge, I simply identify those hedge funds that either reject or do not reject the null hypothesis. I identify hedge funds that reject the null hypothesis ($\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$) as those *with* edge. In contrast, I identify hedge funds that fail to reject the null hypothesis ($\hat{\alpha} \leq 0$ & / or $\hat{\beta} > 0$) as those *without* edge. This approach gives us a simple and direct way to identify those hedge funds that exhibit negative market timing and load positively on the Short VIX strategy. In doing so, we reduce the market timing bias from this group of hedge funds. This new approach produces a differentiated return profile that is more attractive to a hedge fund allocator who is already well-diversified. It is important to note that this approach is useful insofar as we have a meaningful hedge fund return benchmark whereby most hedge funds have significant exposure to it. The evidence presented thus far has confirmed that this necessary condition is satisfied. With that, this new methodology produces a new investment (or allocation) rule that rewards those hedge funds with a positive market timing bias. Instead of using Jensen's alpha, $\hat{\alpha}_j > 0$ from Jensen (1968), with the Short VIX in place of the market factor, we can instead use ($\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$) as our allocation rule for those hedge funds that have edge (i.e. add value) versus those hedge funds without edge.

The final important takeaway from this approach is that it provides us with a testable implication: Hedge funds that reject the null hypothesis ($\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$) should offer higher SRs and *positive* skewness in contrast to hedge funds which fail to reject the null hypothesis whose returns should exhibit lower SRs and *negative* skewness. This testable implication is a consequence of the investment rule removing hedge funds with negative market timing and positive loadings to the Short VIX which itself has significant negative skewness. The modification of the market timing bias caused by this methodology is what results in separation with respect to the sign of skewness. Higher SRs follow from the fact that $\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$ represents a sufficiently high bar for hedge funds given that it requires average hedge fund returns to more than offset the contribution from a high SR benchmark such as the Short VIX strategy.

5.1 How does this new approach compare with previous studies?

There have been several classic studies that have highlighted the estimation issue of Jensen's alpha with respect to market timing bias. These same studies have proposed alternative measures to address the bias by building on the seminal work of Jensen (1968). I compare my approach with the most related and widely cited studies' methodologies used to address the same issue.

Table 9 displays the main regression equation along with the bias-adjusted alpha tested in each respective study. The final row of the table displays the proposed methodology in this study to separate hedge funds with edge from those without edge.

Treynor and Mazuy (1966) and Jensen (1972) propose related empirical approaches in order to estimate an unbiased intercept. That is, they both propose a quadratic regression with respect to the market factor. The main difference between the two studies is the measurement of the market factor whereby Jensen (1972) derives a measure based on a model that relies on an unobservable de-meaned market factor, π_t. The main drawback to using a quadratic regression for performance identification is that the intercepts the econometrician is left with have too little variation. In particular, while you achieve an unbiased estimate of alpha, you are removing both good and bad market timing. Given that positive market timing generates positive skewness in returns, this methodology cannot separate portfolios into those with higher (lower) SRs and positive (negative) skewness. Henriksson and Merton (1981) suffers from the same criticisim where the quadratic term in the market factor is substituted for a call option on the market factor.

Lastly, Ferson and Schadt (1996) offer a different motivation for a revised measure of Jensen's alpha. They argue that performance evaluation needs to account for conditioning information given that expected returns and risks are time-varying. It follows that an unconditional approach is inappropriate in this environment. The main weakness of incorporating conditioning information is that it relies on the econometrician accounting for the full information set relevant for evaluating the respective managed portfolios. Again, this approach leaves us with intercepts that have too little variation in the following sense. In our context, it is reasonable to argue that the relevant conditioning information for the Short VIX is with respect to the shape of the VIX term structure. The shape of the VIX term structure can be measured by the carry of VIX at the short-end (i.e. between the 1st and 2nd dated VIX futures contracts, Carry $= C_t = \frac{F_{1,t} - F_{2,t}}{F1,t}$ as per Koijen et al. (2018)). VIX carry is negative the vast majority of the time with infrequent periods that are positive (i.e. 2008 Financial Crisis and COVID-19 February to March 2020). Simply put, VIX carry is significantly positively skewed (skew of 1.81). The conditioning information in this case (VIX carry) reflects market timing given that the change in sign of carry coincides with periods of market turbulence leading to losses in the Short VIX strategy. It follows that by removing this conditioning information, the econometrician is removing variation that coincides with funds that are able to capitalize on these abnormal periods where returns are skewed. Hence, this approach is unable to separate portfolios in terms of both SR and skewness.

6 Portfolio Returns

In this section, I display the main empirical results of the paper that concern economic significance. The results in this section are an application of the novel approach proposed in the previous section. To be clear, I refer to hedge funds with "edge" as those hedge funds that satisfy the investment rule (i.e. reject the null hypothesis), $\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$, in contrast to hedge funds without "edge" as those which do not satisfy the investment rule (i.e. fail to reject the null hypothesis), $\hat{\alpha} \leq 0$ & / or $\hat{\beta} > 0$.

Figure 7 presents two panels that differ with respect to the benchmark used. Panel A is based on the main specification using the Short VIX strategy returns, whereas Panel B instead uses the OTM Short S&P 500 Put strategy returns. Both panels display the out-of-sample (OOS) cumulative returns of an equal-weighted portfolio of hedge funds that meet the proposed investment rule, $\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$ (blue line). For comparison, equal-weighted portfolios are also formed for all hedge funds (grey line) and hedge funds that do not meet the investment rule, $\hat{\alpha} \leq 0$ & / or $\hat{\beta} > 0$ (red line). The parameters are estimated by 3-year rolling regressions. The equal-weighted portfolios are formed by an annual rebalancing that takes place each December. The three portfolios' cumulative returns are scaled to have the same volatility as the portfolio with all hedge funds (grey line). The SR and skewness for the three portfolios is provided in the bottom right (panel A) and top left (panel B) hand portion of the subfigures. The main result of the paper is documented in this figure: Hedge funds that meet the new investment rule $\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$ (blue line) add value to an investors portfolio by offering higher SRs and more importantly positive skewness. Put simply, these hedge funds have edge in financial markets. In Panel A, hedge funds with edge (without edge) earn a SR of 0.52 (versus 0.15) and have positive skewness of 4.30 (versus -0.83). In Panel B, hedge funds with edge (without edge) earn a SR of 0.25 (versus 0.16) and have positive skewness of 1.14 (versus -0.73). This result shows that hedge funds are clearly not a monolith and can be separated into two distinct groups, ex-ante, with an annual rebalancing based on 3-year rolling regressions. It is especially interesting to note that the hedge funds that do not meet the investment rule (red line) are almost indistinguishable from the entire hedge fund universe (grey line). This negative skewness that appears in the cross-section of hedge fund returns, unconditionally, is why hedge fund returns have been characterized as equivalent to writing OTM put options on the S&P 500. This figure tells us that this characterization is incomplete. Importantly, this characterization only represents one of two groups (based on the sign of skewness) of hedge funds. With this new evidence and ex-ante classification of hedge funds, it seems clear that investors will eschew the former in favor of the latter group with positive skewness. In sum, the testable implication that was generated from the identification strategy is confirmed in the data given the portfolio separation with respect to skewness. Lastly, Figure 7 provides additional confirmation that there is considerably more economic significance when we span hedge fund returns using the Short VIX strategy (Panel A) in comparison to the OTM Short S&P 500 Put strategy (Panel B). In Panel A, the difference in SR and skewness between hedge funds with and without edge is 0.37 and 5.13, respectively. In Panel B, the difference in SR and skewness between hedge funds with and without edge is 0.09 and 1.87, respectively. This is consistent with the previous evidence presented in the study that shows the Short VIX is able to explain the vast majority of hedge fund returns at the fund-level in sharp contrast to the OTM Short Put strategy. This is likely a manifestation of the fact that VIX futures reflect the full distribution across moneyness of implied volatility as opposed to the Short Put which reflects a point estimate of implied volatility.

The following figure further illustrates the difference between selecting hedge funds based on the Short VIX versus OTM Short Put rolling regressions. Figure 8 builds two portfolios that are both equal risk-weighted between a hedge fund portfolio and the corresponding benchmark. That is, the blue line represents the cumulative returns to a portfolio that is comprised of a 50% weight to the Short VIX strategy returns and a 50% weight to the hedge funds with edge portfolio based on the Short VIX regression (Figure 7 Panel A). The red line are the cumulative returns based on the same construction except the Short VIX strategy returns are replaced with the Short Put strategy returns (i.e. Short Put returns in addition to the portfolio in Figure 7 Panel B). In sum, the Short VIX combination portfolio offers a SR of 0.97 and skewness of 2.27 in comparison to the Short Put combination portfolio that has a SR of 0.71 and skewness of -0.46. Interestingly, the correlation is extremely low at 0.01 between the Short VIX strategy returns and the Hedge fund portfolio formed on the Short VIX rolling regressions. Figure 8 highlights the benefit of adding a portfolio with positive skewness and a relatively high SR to a portfolio with significant negative skewness.

Figure 9 displays the cumulative returns of equal-weighted portfolios as in Figure 7. The only difference is that the investment rule is based on four alternatives: Panel A refers to Jensen (1968), Panel B refers to Treynor and Mazuy (1966), Panel C refers to Henriksson and Merton (1981) and Panel D refers to Ferson and Schadt (1996). Each regression that is estimated is based on the Short VIX strategy. The main takeaway from this set of results is that all four of the portfolios' cumulative returns, that meet the alternative investment rule (i.e. a positive intercept), display highly similar return profiles. Specifically, they offer higher SRs with negative skewness. In contrast to Figure 7 there is better separation between the portfolios that satisfy and do not satisfy the respective investment rule. However, this is not particularly useful to an investor since you cannot form a long/short portfolio of hedge funds.

With that, an investor would be better off by following the proposed $\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$ investment rule in Figure 7 compared to any one of the alternatives in Figure 9. The remainder of this section further investigates the investment rule based on the Short VIX as the benchmark (Panel A), unless stated otherwise.

To shed more light on the informativeness of the proposed investment rule that separates hedge funds in terms of the sign of skewness, Figure 10 displays the percentage of hedge funds that meet the criterion (blue line) next to its component parts (the grey line corresponds to funds with a positive intercept and the red line refers to hedge funds with a non-positive loading on the Short VIX strategy). The left hand vertical axis corresponds to the grey line whereas the right vertical axis refers to the red and blue line. On average, 38% of hedge funds have a positive intercept which is consistent with the significant negative market timing amongst the panel of hedge funds documented previously. In sharp contrast, only 3% of hedge funds have a negative loading, on average over the sample period. As a consequence, 2% of hedge funds satisfy the investment rule, on average. There is no clear trend among the parameters over the sample period.

The next step in better understanding the new investment rule is detailing its portfolio composition. Figure 11 exhibits the annual portfolio turnover (%) which represents the number of hedge funds that are invested and (or) redeemed each year based on satisfying the proposed investment rule. The average annual turnover is relatively low at 2%. This statistic suggests that hedge funds that meet the investment rule tend to have performance that persists and is sustainable. This characteristic is consistent with the notion of unobserved alpha which represents fund manager skill (or edge).

Table 10 displays the details regarding the portfolio composition of each hedge fund portfolio exhibited in Figure 7 Panel A whereby the investment rule is the proposed $\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$ criterion. Panel A lists the primary hedge fund strategy (percentage of hedge fund months) by investment portfolio. Panel B displays key portfolio characteristics: AUM (USD mm), Fund Age (Years), Average Monthly Number of Funds, and the top three currency denominations (percent representation) within each portfolio. Panel A shows that the majority (74.2%) of fund strategies for the entire hedge fund universe is comprised of Fund of Funds (34.7%), Long/Short Equity Hedge (26.5%) and Multi-Strategy (13.0%). This composition changes to the top three hedge fund strategies now represented by Global Macro (37.1%), Fund of Funds (15.1%) and Long/Short Equity Hedge (11.2%) for those hedge funds satisfying the investment rule. This accounts for 63% of the hedge fund months indicating that there is more diverse representation of differing hedge fund styles in this portfolio. For instance, Global Macro's representation increases by 32.6% which increases the skewness of the portfolio given that global macro strategies tend to outperform during periods of market stress. Lastly, the hedge funds that fail to meet the investment criterion are largely represented by Fund of Funds (35.2%), Long/Short Equity Hedge (26.8%) and Multi-Strategy (13.1%) thereby representing 75% of the total portfolio. This portfolio is highly similar to the entire hedge fund universe. Focusing our attention on Panel B, funds that meet the investment rule tend to be larger ($US 916 mm) in comparison to all hedge funds ($US 237 mm) and those that do not satisfy the rule ($US 225 mm). Fund age of 11 years does not differ signficantly across the three portfolios. Given the relatively high bar of the investment rule, only 29 funds, on average, are held in the portfolio monthly in comparison to 1,158 that do not meet the criteria and 1,187 funds in the entire universe. Finally, the top three countries represented with respect to currency denomination (USD, Euro and Swiss France) is the same for all three portfolios with minor discrepancies. These three currencies represent nearly 90% of the portfolio.

In the previous section, I proposed an approach to classify hedge funds ex-ante into one group with edge and another without edge. The classification was largely motivated by the robust evidence that showed negative market timing is pervasive across the hedge fund universe. Table 11 revisits market timing by re-examining the market timing results for those hedge funds that satisfy the investment rule. Specifically, I test the market timing model of Henriksson and Merton (1981) on the universe of hedge funds that satisfy the $\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$ criterion (Panel A) whereas I restrict the sample to those hedge funds that satisfy a positive intercept as in Jensen (1968) (Panel B). The investment parameters for both rules are estimated based on the 3 year rolling regressions with annual rebalancings of returns on the Short VIX strategy. Most notably, in Panel A, the new investment rule eliminates negative market timers for all hedge fund strategies except for Managed Futures which displays negative market timing at the 1% level. Fixed Income Arbitrage now displays *positive* market timing that is significant at the 1% level. In Panel B, Long/Short Equity now displays positive market timing that is significant at the 1% level. However, Panel B confirms that the market timing bias is largely unchanged in comparison to Table 8. In short, Table 11 confirms that the new approach does in fact lead to a reduction in negative market timing across hedge fund strategies.

The difference in market timing results between the two panels in Table 11 highlights the important role of the coefficient's sign in the null hypothesis. In other words, by only focusing on the intercept from performance evaluation regressions, we are throwing away valuable information that can be used to further improve performance evaluation. Figures 12, 13, 14, 15 make this point visually by displaying hedge fund returns as a fractional polynomial of the Short VIX returns with 95% confidence bands as the grey shaded region. The intuition behind displaying these figures is to further showcase the payoff profiles of hedge fund returns and how those payoff profiles change after being filtered by either the intercept or proposed investment rule. For all four figures, the left hand side refers to all hedge funds, the center refers to those hedge funds that have a positive intercept (akin to Jensen's α) and the right hand side figure are those hedge funds that have been identified as having edge. Since the parameters have been estimated over a 3-year rolling window, the sample period, which accounts for the initial estimation window, for all figures is as before: May 2008 to December 2022.

Figure 12 displays the results across all strategies (i.e. the full panel of hedge fund returns). As shown previously, all hedge fund returns are a concave function reminiscent of a Short Put payoff whereby the underlying is the Short VIX, which is itself concave. Hedge funds with a positive intercept now display concavity that is more pronounced with a slight levelling off at the left most tail of Short VIX returns. The payoff profile changes dramatically when we shift our attention towards the right most subfigure. Hedge funds classified as those with edge have a payoff profile reminiscent of Long Straddle which benefits from positive exposure to volatility. This is the significant positive skewness that distinguishes this portfolio. Figures 13, 14, 15 perform the same exercise with hedge fund returns at the strategy-level. The majority of strategies display the same pattern of payoff profiles: Selecting hedge funds based on a positive intercept has little to no effect on the payoff profile, whereas selecting hedge funds by those that reject the null hypothesis ends up dramatically altering the payoff profile into one that is attractive to a highly-diversified hedge fund investor.

The discussion up until this point has centered on SRs and skewness as useful summary statistics in order to characterize hedge fund performance. However, Ingersoll et al. (2007) show how SRs can be manipulated in order for a fund manager to attract more capital. They derive the following Manipulation-Proof Performance Measure (MPPM),

$$\hat{\Theta} \equiv \frac{1}{(1-\rho)\Delta t} \ln \left(\frac{1}{T} \sum_{t=1}^{T} \left[(1+r_t)\,(1+r_{ft}) \right]^{1-\rho} \right), \tag{11}$$

where $\hat{\Theta}$ measures the portfolios excess risk-adjusted return. ρ represents relative risk aversion, T denotes the total number of observations, Δt is the time step necessary to annualize observations (i.e. 1/12 for monthly observations). r_t represents the unannualized hedge fund return and r_{ft} represents the unannualized riskless rate.

Ingersoll et al. (2007) show that if the benchmark portfolio's return follows a lognormal distribution, then we can infer relative risk aversion from the following,

$$\rho = \frac{\ln\left[\mathbb{E}\left(1+\tilde{r}_b\right)\right] - \ln(1+r_f)}{\operatorname{Var}\left[\ln\left(1+\tilde{r}_b\right)\right]}, \tag{12}$$

where in our case the benchmark return, $\tilde{r}_b$ corresponds to the Short VIX strategy. Using the Short VIX data over the full sample period from April 2004 to December 2021, the estimate of ρ is equal to 1.18. Given that the Short VIX log monthly returns have significant negative skewness, it is clear that the returns are not lognormally distributed. Ingersoll et al. (2007) note that historically ρ is between 2 and 4 for the CRSP value-weighted market portfolio.

Table 12 displays the results of the MPPM calculated using the Short VIX benchmark and the three equal-weighted portfolios from Figure 7: All, $\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$, and Jensen (1968) $\hat{\alpha} > 0$ hedge funds. The MPPM results are reported row by row with respect to the following levels of relative risk aversion: 1.18, 2, 3 and 4. In addition to providing the point estimate of MPPM, the differenc (Δ) between the equal weighted hedge fund portfolio MPPM and the Short VIX MPPM is listed. Lastly, the equivalent risk-free rate is reported for ρ equal to 3. The equivalent risk-free rate (i.e. the certainty equivalent compound excess return) is computed by,

$$\text{Equivalent Risk-Free Rate} = \exp\left[\ln\left(1 + \bar{r}_{ft}\right) + \hat{\Theta}\Delta t\right] \tag{13}$$

Table 12 shows that hedge funds that satisfy the proposed investment rule display higher MPPMs compared to an equal weighted portfolio of all hedge funds or those selected by Jensen's alpha (Jensen, 1968). Importantly, these hedge funds with edge outperform the Short VIX benchmark for all values of ρ except for the lowest level of risk aversion of 1.18. As noted previously, since the Short VIX returns are not symmetric around zero due to the negative skewness found in the data, this level of risk aversion is likely understated and thus not a fair comparison. It is interesting to note how the outperformance, relative to the benchmark, of the hedge funds with edge grows as risk aversion grows (1.18 to 4) from -22.04% to 139.63%. This is an important characteristic which is desirable to risk averse investors that's likely driven by the portfolios' positive skewness. In contrast, the all hedge fund and Jensen's alpha portfolios both underperform at an increasing rate as risk aversion grows. Finally, the equivalent annualized risk-free rate (computed based on a risk aversion of 3) for hedge funds with edge is 5.1% compared to -0.3 and 1.2% for all and Jensen's alpha hedge funds, respectively. The benchmark Short VIX strategy earns the lowest rate of -43.7% which is indicative of the significant negative skewness associated with the benchmark as noted by Ingersoll et al. (2007).

The last part of this section investigates the predictability of hedge fund returns inherent in the Short VIX strategy benchmark in addition to the investment rule. A natural question to address is whether we can simply use the historical distribution of hedge fund returns to predict hedge fund performance going forward, instead of using the information from regressing hedge fund returns on the Short VIX returns. To address this concern, I employ the methodology from Goyal and Welch (2008). That is, I compute their out-of-sample R^2 measure,

$$R^2_{\text{OOS}} = 1 - \frac{\sum \epsilon_t^2}{\sum u_t^2}, \tag{14}$$

where ϵ_t is the error when Short VIX is used to forecast hedge fund returns and u_t is the error when the historical mean hedge fund return is used to forecast hedge fund returns.

Table 13 presents the predictive rolling regressions for different horizons from one-month to 3 years. For each forecast horizon, I estimate a rolling 3-year regression (with Newey and West (1987) standard errors) of hedge fund returns, at the individual hedge fund level, on the lagged Short VIX. The lag of the Short VIX is based on the forecast horizon (i.e. 1 month horizon corresponds to a one month lag of the Short VIX). All parameter estimates and statistics (R^2 and R^2_{OOS}) are averaged across all hedge funds. The most important takeaway from Table 13 is that the OOS R^2 is positive for every forecast horizon. This is robust evidence that shows that we would be worse off if we only used the historical mean of hedge fund returns as a predictor of hedge fund performance. Said differently, the Short VIX strategy returns add additional information that helps predict hedge fund performance. This is consistent with the strong economic significance that reports the ability to successfully separate hedge funds with edge from those without edge using the parameter estimates from Short VIX regressions.

I also exaimine whether the proposed investment rule (in comparison to Jensen's alpha) can predict whether a hedge fund will rank in the top quartile one year ahead. Table 14 reports these results, by strategy type, which are estimated via running probit regressions (with standard errors clustered at the fund level) of an indicator variable for top quartile returns within a given month on an indicator of whether a hedge fund satisfies either the new investment rule or Jensen's alpha with the Short VIX taking the place of the market factor. The results represent average marginal effects for ease of interpretation. The main takeaway from this table is that hedge funds that satisfy the new investment rule are 7.8% more likely to end up as a top quartile hedge fund one year hence. In comparison, hedge funds identified by Jensen's alpha are 3.8% more likely to be identified as a top quartile hedge fund. Both results are significant at the 1% level. Jensen's alpha results are driven by an increased probability for three strategies that are significant: Fund of Funds, Multi-Strategy and the Options Strategy. In comparison, hedge funds within the new investment rule portfolio have an increased probability that is significant for Event-Driven, Fund of Funds, Multi-Strategy and and the Options Strategy. In sum, hedge funds with edge are two times more likely to be identified as a top quartile hedge fund one year from now relative to those identified by Jensen's alpha.

7 Simulation Evidence

The previous section documented the main empirical finding of this paper: By adopting the novel yet simple methodology that removes negative market timing hedge funds, we can form two equal-weighted hedge fund portfolios that offer starkly different return profiles. One portfolio has a higher SR and positive skewness while the other has a lower SR and negative skewness. This new empirical finding may seem counterintuitive in light of the prevailing hedge fund evidence and consensus interpretation regarding hedge fund returns and crash risk (i.e. Jurek and Stafford (2015)). That is, how is it possible for investors to earn higher risk-adjusted returns (i.e. proxied by higher SRs) while at the same time also be compensated for exposure to crash risk (i.e. positive skewness)? The hedge fund literature would suggest that higher SRs come at the expense of increased exposure to tail events (negative skewness). In this section, I explain this seemingly counterintuitive empirical result by examining the simulation evidence of the Barberis et al. (2015) X-CAPM model at the investor-level.

Barberis et al. (2015) build a continuous time heterogeneous agent consumption-based model (i.e. the X-CAPM) that is capable of reproducing many of the observed stylized facts of stock market prices and returns. As it relates to this paper, their model economy features two types of infinitely-lived traders who maximize expected lifetime utility: (i) traders who form beliefs about expected returns by extrapolating past price changes in the stock market; and (ii) rational traders who have correct beliefs about future price changes. In contrast to their study which examines stock market phenomena at the aggregate-level, I am instead interested in return phenomena at the trader-level. To link their model to the scope of this paper, I make the following nominal substitutions. That is, I relabel extrapolative traders as those hedge funds without edge ($\hat{\alpha} \leq 0$ & / or $\hat{\beta} > 0$) and rational traders as those hedge funds with edge ($\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$) , where edge is defined as a hedge fund whose track record has an estimated $\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$. In addition, I refer to the market portfolio as the Short VIX strategy benchmark.

All together, this leads me to the following re-interpretation of their model. Hedge funds without edge extrapolate the performance of the Short VIX strategy and build positions according to their level of sentiment. Hedge funds with edge know the true data generating process and are able to exploit significant price dislocations that are exacerbated by the extrapolators' mistakes. Specifically, as the Short VIX strategy experiences better performance, hedge funds without edge load more positively on the Short VIX strategy. When this dynamic leads to prices deviating especially far from fundamentals, hedge funds with edge take the opposite bet by loading more negatively on the Short VIX strategy. Inevitably, once dividend growth is sufficiently smaller than what is priced in the benchmark portfolio, the Short VIX strategy suffers a drawdown. Importantly, the drawdown occurs exactly at the moment when hedge funds without edge have their largest positive positions (i.e. maximum leverage). These hedge funds start selling in anticipation of future negative performance of the Short VIX strategy. This dynamic ends up going too far in the opposite direction. Hence, hedge funds with edge are opportunistic in this environment as well.

I follow Barberis et al. (2015) closely by replicating their results in Section 5 where they evaluate ratio-based quantities. As in their paper, I run 10,000 simulations based on their main specification which has the fraction of rational traders set at $\mu = 0.25$ and the discount factor, β, equal to 0.5. Table 15 presents the simulation evidence conditioned at the trader-level. The simulation evidence is entirely consistent with the new empirical findings of this paper. Hedge funds without edge have *lower* SRs (-0.08) and *negative* skewness (-0.30) compared to hedge funds with edge that have *higher* SRs (0.16) and *positive* skewness (0.34). It is important to note that the magnitudes are significantly different which is a direct result of the assumptions made regarding the price changes of the market portfolio following a Gaussian distribution (i.e. perfectly symmetric with no skewness). Given the assumptions made by Barberis et al. (2015), the market portfolio also has a relatively low SR in comparison to the highly profitable Short VIX strategy. This lends more credibility to the empirical finding in this paper given that the simulation results produces the same separation with respect to both SR and skewness in a significantly different setting based on the assumptions made.

In sum, this section explains the main empirical finding of the paper by re-examining the influential work of Barberis et al. (2015) X-CAPM model at the trader-level. It turns out that hedge funds without edge can be viewed as traders that have extrapolative expecations of recent price changes of the benchmark portfolio.

8 Conclusion

I document a novel empirical finding regarding hedge fund returns: The consensus view that hedge fund returns can largely be explained by offering investors concentrated exposure to market crashes is incomplete and too coarse a representation of this important market participant. This study presents evidence that shows hedge funds can be divided into two groups, ex-ante: one group, with edge, that adds value to investors by offering relatively high SRs and positive skewness and another, without edge, with relatively low SRs and negative skewness. Investors allocating to hedge funds in the latter group would be able to get similar exposure that hedge funds provide by shorting VIX futures contracts on a monthly basis. Moreover, these investors would be better off since they would no longer have to pay the relatively high fees associated with hedge funds while at the same time earn a higher SR. Investors that have been conditioned to expect high SRs at the expense of negative skewness should instead expect a hedge fund that adds value to their portfolio to offer high SRs and positive skewness.

The classification approach that allows us to predict OOS hedge funds with both higher SRs and positive skewness forces us to revisit the leading explanation regarding hedge fund returns and exposure to crash risk. How is it possible that hedge funds can offer both higher SRs and benefit from market dislocations (i.e. positive skewness)? This study highlights an understudied area in the hedge fund literature as it relates to hedge funds that offer high SRs and positive skewness. In particular, future work needs to address why hedge fund investors are willing to allocate to hedge funds with negative skewness when they can instead invest in hedge funds that offer both higher SRs and convex payoffs. Tackling this line of inquiry will likely lead to a deeper understanding of both hedge funds and investor behavior.

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Table 1: Hedge Fund Counts
The table presents the unique number of hedge funds over the sample period from May 2004 to December 2022 from the cleaned Lipper Database. The data is reported by primary category for all, survived and dead hedge funds.

Hedge Fund Category	All (#)	All (%)	Survived (#)	Survived (%)	Dead (#)	Dead (%)
Convertible Arbitrage	72	1.77	6	0.74	66	2.02
Dedicated Short Bias	10	0.25	0	0.00	10	0.31
Emerging Markets	257	6.30	47	5.80	210	6.43
Equity Market Neutral	180	4.41	25	3.08	155	4.74
Event Driven	247	6.06	55	6.78	192	5.88
Fixed Income Arb	109	2.67	17	2.10	92	2.82
Fund of Funds	1,500	36.78	236	29.10	1,264	38.69
Global Macro	186	4.56	38	4.69	148	4.53
L/S Equity Hedge	1,013	24.84	247	30.46	766	23.45
Managed Futures	10	0.25	6	0.74	4	0.12
Multi Strat.	468	11.48	130	16.03	338	10.35
Options Strategy	26	0.64	4	0.49	22	0.67
All Hedge Funds	4,078	100.00	811	100.00	3,267	100.00

Table 2: Spanning Test of Short VIX versus the S&P 500 and OTM Put-Writing Strategy
Panel A reports univariate regression results of Short VIX monthly returns on the S&P 500 monthly returns and OTM Put-Writing Strategy monthly returns, respectively, from May 2004 to December 2022. The alphas from these regressions as well as the coefficient on the main predictor of returns are reported along with their Newey and West (1987) t-statistics (in parentheses) and the R^2 from the regression. Panel B reports the reverse univariate regression of the returns to the S&P 500 and OTM Put-Writing Strategy on Short VIX returns.

Panel A: Regressing Short VIX Futures Returns on Related Measures

	S&P 500	OTM Put-Writing Strategy
Alpha	0.028	0.013
	(3.88)	(1.82)
Coefficient	2.675	2.514
	(11.66)	(6.84)
R^2	0.61	0.56

Panel B: Regressing Related Measures on Short VIX Futures Returns

	S&P 500	OTM Put-Writing Strategy
Alpha	-0.005	0.002
	(-1.81)	(0.79)
Coefficient	0.227	0.221
	(11.96)	(6.31)

Table 3: Summary Statistics of Hedge Fund Returns and Hedge Fund Substitutes
The table presents the summary statistics for the HFRI 500 Index, TASS equal-weighted portfolio, Short Fung and Hsieh (2001) Stock Index Lookback Straddle (PTFSSTK), FH8 portfolio returns (scaled to have same volatility as Short VIX strategy), OTM Put-Writing Strategy and Short VIX strategy. All summary statistics (expressed in decimal form) are annualized from a monthly frequency and calculated over the sample period from January 2005 to December 2022.

	HFRI 500	TASS	PTFSSTK	FH8	Short Put	Short VIX
Average	0.04	0.02	0.47	0.02	0.13	0.48
Volatility	0.06	0.11	0.57	0.52	0.16	0.52
Sharpe Ratio	0.61	0.21	0.82	0.03	0.85	0.91
Skewness	-1.18	-0.81	-2.44	-1.96	-2.26	-1.26
Correlation	1.00	0.97	0.40	0.53	0.74	0.72

Table 4: Asset Pricing Factor Model Alphas of Hedge Fund Returns and Hedge Fund Substitutes

The table presents the alphas with their Newey and West (1987) t-statistics (in parentheses) from monthly time series regressions of hedge fund returns and their substitutes (HFRI 500 Index, TASS equal-weighted portfolio, PTFSSTK, FH8, , OTM Put-Writing Strategy and Short VIX) on four models: (i) the CAPM (market factor from Fama and French (1992)), (ii) FF3 (Fama and French, 1992), (iii) FF5 (Fama and French, 2015), and (iv) FF5 (Fama and French, 2015) + MOM (Carhart, 1997). The alphas are expressed in decimal form. The sample period is from January 2005 to December 2022.

	HFRI 500	TASS	PTFSSTK	FH8	Short Put	Short VIX
CAPM	0.001	-0.002	0.029	-0.012	0.003	0.021
	(1.08)	(-1.76)	(2.24)	(-1.11)	(2.07)	(2.80)
FF3	0.001	-0.002	0.030	-0.011	0.003	0.022
	(1.07)	(-1.74)	(2.38)	(-1.08)	(2.16)	(3.24)
FF5	0.001	-0.002	0.028	-0.009	0.003	0.023
	(1.50)	(-1.48)	(2.06)	(-0.84)	(1.90)	(3.31)
FF5 + MOM	0.001	-0.002	0.026	-0.008	0.003	0.022
	(1.40)	(-1.51)	(1.87)	(-0.78)	(1.88)	(3.22)

Table 5: Spanning tests of Short VIX relative to other predictors that replicate hedge fund returns

Panel A reports univariate regression results, at a monthly frequency, of Short VIX returns on the HFRI 500 Index, TASS equal-weighted portfolio, Short Stock Index Lookback Straddle (PTFSSTK), FH8 model (scaled to have same volatility as Short VIX strategy). The alphas from these regressions as well as the coefficient on the predictor are reported along with their Newey and West (1987) t-statistics (in parentheses) and the R^2 from the regression. Panel B reports the reverse univariate regression of the returns to the predictor on Short VIX returns. The coefficients and alphas are expressed in decimal form. The sample period is January 2005 to December 2022.

Panel A: Regressing Short VIX Futures Returns on Hedge Fund Substitutes

	HFRI 500	TASS	PTFSSTK	FH8
Alpha	0.020	0.033	0.018	0.039
	(2.47)	(3.76)	(1.98)	(4.65)
Coefficient	6.310	3.331	0.563	0.601
	(12.34)	(13.82)	(10.49)	(8.69)
R^2	0.52	0.53	0.37	0.36

Panel B: Regressing Hedge Fund Substitutes on Short VIX Futures Returns

	HFRI 500	TASS	PTFSSTK	FH8
Alpha	0.000	-0.004	-0.013	-0.022
	(-0.20)	(-2.23)	(-1.10)	(-1.92)
Coefficient	0.083	0.159	0.663	0.600
	(9.14)	(9.93)	(6.21)	(5.68)

Table 6: Panel Regressions (Full Sample)
The table reports the results from the panel regressions of the following Equation: $r_t^i = \alpha + a^i + b_t + \beta\text{Benchmark}_t + \varepsilon_t^i$, for each hedge fund strategy with hedge fund and year fixed effects, where a^i is a hedge fund-specific fixed effect, b_t are year fixed effects, α is unexplained return variation, Benchmark refers to the monthly returns from the ShortVIX$_t$ in Panel A and OTM Short Put$_t$ in Panel B, and β is the coefficient of interest that measures how well the benchmark explains returns. The sample period is May 2004 to December 2022 at a monthly frequency. Coefficient estimates (expressed in decimal form) of α and β along with their respective t-statistics and sample size are also reported. Standard errors are clustered at the hedge fund level. Asterisks denote the levels of statistical significance of the coefficient: 10% level (*), 5% level (**) and 1% level (***).

Panel A: Short VIX as the Hedge Fund Benchmark

Hedge Fund Strategy	Coefficient	t-stat	$\hat{\alpha}$	t-stat	R^2
Convertible Arbitrage***	0.180	6.99	-0.013	-4.16	0.21
Dedicated Short Bias***	-0.338	-4.48	0.006	0.87	0.35
Emerging Markets***	0.283	39.74	-0.003	-1.76	0.26
Equity Market Neutral***	0.080	10.01	0.002	1.25	0.12
Event Driven***	0.183	29.41	0.002	1.90	0.38
Fixed Income Arb***	0.084	17.10	0.003	2.35	0.21
Fund of Funds***	0.109	73.17	0.000	0.08	0.08
Global Macro***	0.044	4.83	0.006	2.77	0.04
L/S Equity Hedge***	0.225	59.83	-0.001	-1.80	0.33
Managed Futures	0.008	0.44	0.027	10.65	0.06
Multi Strat.***	0.108	29.73	0.001	0.29	0.17
Options Strategy***	0.050	2.67	0.002	0.58	0.12
All Strategies***	0.149	77.41	0.000	0.84	0.15

Panel B: OTM Short Put as the Hedge Fund Benchmark

Hedge Fund Strategy	Coefficient	t-stat	$\hat{\alpha}$	t-stat	R^2
Convertible Arbitrage***	0.685	7.58	-0.013	-4.37	0.27
Dedicated Short Bias***	-0.987	-8.29	0.002	0.48	0.39
Emerging Markets***	0.988	40.01	-0.001	-0.56	0.31
Equity Market Neutral***	0.189	7.14	0.004	2.43	0.09
Event Driven***	0.584	27.69	0.004	4.80	0.38
Fixed Income Arb***	0.290	15.16	0.004	2.81	0.24
Fund of Funds***	0.330	65.20	0.002	3.04	0.07
Global Macro***	0.161	6.11	0.007	2.91	0.05
L/S Equity Hedge***	0.710	52.65	0.002	2.78	0.33
Managed Futures	-0.025	-0.26	0.026	9.36	0.05
Multi Strat.***	0.380	24.28	0.001	0.59	0.18
Options Strategy***	0.199	2.76	0.001	0.31	0.10
All Strategies***	0.481	70.31	0.002	5.24	0.15

Table 7: Fama-MacBeth Regressions of Monthly Hedge Fund Returns

The table reports the results of monthly Fama-MacBeth regressions. Hedge Fund returns in year $t+1$ are regressed on loadings $\beta^{ShortVIX}$ as of year t. The loadings are estimated with rolling 5-year regressions of individual hedge fund returns on Short VIX returns. I removed any hedge funds that did not have at least 60 months of return data. The sample period is May 2010 to December 2022 to account for the initial estimation window. Coefficient estimates (in decimal form) of α and β along with their respective t-statistics, R^2 and sample size are also reported. Standard errors are clustered at the hedge fund level. Asterisks denote the levels of statistical significance of the coefficient: 10% level (*), 5% level (**) and 1% level (***).

	Coefficient	t-stat	$\hat{\alpha}$	t-stat	R^2	N
Convertible Arbitrage	-0.008	-0.32	0.013	2.11	0.02	1,890
Dedicated Short Bias	0.108	0.72	0.053	1.54	0.07	96
Emerging Markets	0.007	0.71	0.013	3.10	0.03	11,247
Equity Market Neutral	0.002	0.16	0.007	4.56	0.002	5,561
Event Driven**	0.025	2.03	0.008	2.36	0.03	9,573
Fixed Income Arbitrage	0.004	0.32	0.006	2.72	0.03	3,636
Fund of Funds	0.000	-0.07	0.006	6.68	0.01	56,091
Global Macro	-0.017	-1.28	0.019	7.94	0.02	6,679
Long/Short Equity Hedge*	0.007	1.76	0.014	10.58	0.04	42,787
Managed Futures	-0.010	-0.67	0.029	2.03	0.05	959
Multi-Strategy**	0.025	2.38	0.005	3.04	0.03	22,091
Options Strategy***	0.404	3.67	-0.041	-3.15	0.09	1,239
All Strategies*	0.005	1.76	0.010	14.07	0.02	161,849

Table 8: Classic Market Timing Models (Full Panel)
The table reports the results from market timing tests of Henriksson and Merton (1981) and Treynor and Mazuy (1966) with the Short VIX substituted for the market portfolio. In Panel A, I test the following panel regression with firm (γ_j) and year (b_t) fixed effects:
$r_{j,t+1} = \gamma_j + \lambda_j r_{\text{Short VIX},t+1} + a_j \text{Max}\left(r_{\text{Short VIX},t+1}, 0\right) + b_t + \varepsilon_{t+1}$,
where the coefficient a_j measures the hedge fund manager's market timing ability. In Panel B, I test the following panel regression with firm and year fixed effects:
$r_{j,t+1} = \gamma_j + \lambda_j r_{\text{Short VIX},t+1} + a_j r^2_{\text{Short VIX},t+1} + b_t + \varepsilon_{t+1}$,
where a_j measures the manager's market timing ability. The sample period is May 2004 to December 2022. I report the coefficient a_j and intercept (in decimal form) with its respective t-statistic and Overall R^2. Standard errors are clustered at the hedge fund level. Asterisks denote the levels of statistical significance of the coefficient: 10% level (*), 5% level (**) and 1% level (***).

Panel A: Henriksson and Merton (1981) Model

	a_j	t-stat	γ_j	t-stat	R^2
Convertible Arbitrage***	-0.144	-7.60	-0.006	-1.83	0.22
Dedicated Short Bias	0.015	0.12	0.005	0.42	0.35
Emerging Market***	-0.156	-18.49	0.005	2.66	0.27
Equity Market Neutral	-0.010	-1.31	0.003	1.56	0.12
Event Driven***	-0.115	-18.28	0.007	8.44	0.39
Fixed Income Arbitrage***	-0.088	-8.24	0.007	5.49	0.23
Fund of Funds***	-0.048	-18.44	0.002	4.11	0.08
Global Macro	0.008	0.80	0.006	2.57	0.04
Long/Short Equity Hedge***	-0.019	-4.34	0.000	-0.51	0.33
Managed Futures	-0.108	-1.47	0.033	5.32	0.06
Multi-Strategy***	-0.061	-8.98	0.004	1.67	0.18
Options Strategy***	-0.154	-4.14	0.009	2.70	0.13
All Strategies***	-0.053	-24.95	0.003	7.07	0.15

Panel B: Treynor and Mazuy (1966) Model

	a_j	t-stat	γ_j	t-stat	R^2
Convertible Arbitrage***	-0.213	-8.78	-0.009	-2.76	0.23
Dedicated Short Bias	-0.103	-0.62	0.009	0.81	0.36
Emerging Market***	-0.210	-18.07	0.001	0.78	0.27
Equity Market Neutral	-0.008	-0.67	0.002	1.39	0.12
Event Driven***	-0.136	-14.52	0.004	5.21	0.39
Fixed Income Arbitrage***	-0.117	-7.41	0.006	4.21	0.24
Fund of Funds***	-0.050	-16.44	0.001	2.06	0.08
Global Macro	0.014	0.98	0.006	2.62	0.04
Long/Short Equity Hedge***	-0.016	-2.63	-0.001	-1.35	0.33
Managed Futures	-0.047	-0.50	0.027	8.08	0.06
Multi-Strategy***	-0.064	-6.75	0.002	0.95	0.18
Options Strategy***	-0.191	-3.72	0.005	1.79	0.13
All Strategies***	-0.059	-20.02	0.002	3.91	0.15

Table 9: Alternative Approaches to Estimating an Unbiased Version of Jensen's Alpha

The table reports alternative methodologies, put forth by the most related and widely cited studies, to estimate Jensen's alpha that is unaffected by market timing bias present in fund performance data. These studies include Ferson and Schadt (1996); Henriksson and Merton (1981); Jensen (1972); Treynor and Mazuy (1966). As a means for comparison, the classification approach proposed in this study is displayed at the bottom of the table. In Ferson and Schadt (1996), r_{pt+1} refers to the return (in excess of the riskless rate) of a managed portfolio between time t and $t+1$. r_{mt} is the excess return of the market factor. $z_t = Z_t - \mathbb{E}[Z]$ is a vector of de-meaned instruments, Z_t based on time-t information. In Jensen (1972), R_M represents the excess returns on the market portfolio and $\pi_t = R_{Mt} - \mathbb{E}[R_M]$ is an unobservable market factor. Henriksson and Merton (1981); Treynor and Mazuy (1966) follow the same interpretation as in Table 8

	Regression Equation	Bias-Adjusted $\hat{\alpha}$
Treynor and Mazuy (1966)	$r_{j,t+1} = \gamma_j + \lambda_j r_{m,t+1} + a_j r_{m,t+1}^2 + \varepsilon_{t+1}$	$\hat{\gamma}_j > 0$
Jensen (1972)	$r_{jt} = \eta_0 + \eta_1 \pi_t + \eta_2 \pi_t^2 + v_{jt}$	$\hat{\alpha}_j = \hat{\eta}_0 - \left[\hat{\eta}_1 - \hat{\eta}_2 \bar{R}_M\right] \bar{R}_M > 0$
Henriksson and Merton (1981)	$r_{j,t+1} = \gamma_j + \lambda_j r_{m,t+1} + a_j \text{Max}\left(r_{m,t+1}, 0\right) + \varepsilon_{t+1}$	$\hat{\gamma}_j > 0$
Ferson and Schadt (1996)	$r_{pt+1} = \alpha_p + \delta_{1p} r_{mt+1} + \delta_{2p}' \left(z_t r_{mt+1}\right) + \epsilon_{pt+1}$	$\hat{\alpha}_p > 0$
Proposed Methodology	$r_{jt} = \alpha + \beta \text{ShortVIX}_t + \epsilon_{jt}$	$\hat{\alpha} > 0 \quad \& \quad \hat{\beta} \leq 0$

Table 10: Hedge Fund Portfolio Composition

The table presents the portfolio characteristics for the three equal-weighted portfolios from Figure 7: All Hedge Funds, Hedge Funds with $\hat{\alpha} > 0 \ \ \& \ \ \hat{\beta} \leq 0$ and Hedge Funds with $\hat{\alpha} \leq 0$ and / or $\hat{\beta} > 0$. I refer to those hedge funds that satisfy the investment rule as "Allocated" and those that fail to satisfy the investment rule as "Not Allocated." Panel A displays the primary hedge fund strategy (% of hedge fund months) by investment portfolio. Panel B displays the following investment portfolio characteristics by investment portfolio: Assets under Management ($ US mm), Fund Age (Years), Number of Funds (Mean), and the top three currency denominations (percentage of representation) in each portfolio. The sample period is May 2008 to December 2022.

Panel A: Primary Hedge Fund Strategy by Investment Portfolio

	All	Allocated	Not Allocated
Convertible Arbitrage	1.2	0.0	1.3
Dedicated Short Bias	0.1	3.3	0.0
Emerging Markets	7.1	1.2	7.2
Equity Market Neutral	3.6	7.6	3.5
Event Driven	5.8	0.8	5.9
Fixed Income Arbitrage	2.3	3.7	2.3
Fund of Funds	34.7	15.1	35.2
Global Macro	4.5	37.1	3.7
Long/Short Equity Hedge	26.5	11.2	26.8
Managed Futures	0.4	5.5	0.3
Multi-Strategy	13.0	10.5	13.1
Options Strategy	0.7	4.0	0.7

Panel B:Investment Portfolio Characteristics

	All	Allocated	Not Allocated
AUM (USD mm)	237	916	225
Fund Age (Years)	11	11	11
Number of Funds (Average)	1,187	29	1,158
Top Three Currency Denominations (% Representation)			
US Dollar	65	71	64
Euro	19	13	20
Swiss Franc	5	1	5

Table 11: Henriksson and Merton (1981) Market Timing Model Conditioned on Inv. Rules
The table reports the results from the market timing test of Henriksson and Merton (1981) conditioned on the proposed $\hat{\alpha} > 0$ & $\hat{\beta} \leq 0$ investment rule (Panel A) and Jensen (1968) $\hat{\alpha} > 0$ in Panel B. I test the following panel regression with hedge fund and year fixed effects: $r_{j,t+1} = \gamma_j + \lambda_j r_{\text{Short VIX},t+1} + a_j \text{Max}\left(r_{\text{Short VIX},t+1}, 0\right) + b_t + \varepsilon_{t+1}$,
where the coefficient a_j measures the manager's market timing ability and the hedge funds tested, r_j, are those that satisfy the investment rule. In Panel B the same panel regression is run except with hedge funds that satisfy a positive intercept from Jensen (1968) with the Short VIX taking the place of the market factor. The sample period is May 2004 to December 2022. I report the coefficient a_j and intercept (in decimal form) of the model with its respective t-statistic and overall R^2 for all hedge funds by primary strategy. Standard errors are clustered at the hedge fund level. Asterisks denote the levels of statistical significance of the coefficient: 10% level (*), 5% level (**) and 1% level (***).

Panel A: $\hat{\alpha} > 0$ & $\hat{\beta} \leq 0$ Hedge Funds

	a_j	t-stat	γ_j	t-stat	R^2
Convertible Arbitrage	n/a	n/a	n/a	n/a	n/a
Dedicated Short Bias	0.095	0.56	0.004	0.32	0.47
Emerging Market	0.180	0.52	-0.059	-5.86	0.22
Equity Market Neutral	0.051	1.07	-0.018	-5.38	0.04
Event Driven	0.580	1.46	-0.044	-1.64	0.12
Fixed Income Arbitrage***	0.162	2.91	-0.018	-6.36	0.63
Fund of Funds	0.216	0.66	0.041	1.84	0.00
Global Macro	0.028	0.58	0.000	0.15	0.04
Long/Short Equity Hedge	-0.024	-0.44	-0.017	-1.85	0.05
Managed Futures***	-0.493	-7.49	0.023	4.70	0.09
Multi-Strategy	-0.010	-0.13	0.010	1.63	0.06
Options Strategy	-0.029	-0.73	0.019	7.24	0.10
All Strategies	0.063	1.03	0.024	2.77	0.00

Panel B: Jensen (1968)'s $\hat{\alpha} > 0$ Hedge Funds

	a_j	t-stat	γ_j	t-stat	R^2
Convertible Arbitrage***	-0.088	-3.81	-0.012	-2.29	0.27
Dedicated Short Bias	0.095	0.56	0.004	0.32	0.47
Emerging Market***	-0.164	-6.55	-0.047	-6.29	0.33
Equity Market Neutral	0.023	0.93	-0.007	-1.88	0.05
Event Driven***	-0.112	-8.19	-0.012	-3.34	0.40
Fixed Income Arbitrage***	-0.122	-5.19	-0.010	-1.89	0.28
Fund of Funds	-0.022	-1.37	-0.009	-1.62	0.02
Global Macro	0.026	1.09	0.004	0.81	0.02
Long/Short Equity Hedge***	0.043	3.52	-0.012	-5.30	0.33
Managed Futures***	-0.307	-4.04	0.014	3.06	0.05
Multi-Strategy***	-0.066	-4.36	-0.003	-0.36	0.20
Options Strategy**	-0.146	-2.33	0.032	3.39	0.10
All Strategies***	-0.035	-5.14	-0.014	-6.78	0.07

Table 12: Manipulation-Proof Performance Measure Measure (MPPM) Results
The table reports the MPPM annualized results (in percent) for the following equal-weighted portfolios: all, $\hat{\alpha} > 0$ & $\hat{\beta} \leq 0$, and Jensen (1968) $\hat{\alpha} > 0$ hedge funds. In addition, to the hedge fund portfolios, the MPPM results for the Short VIX are provided since it has been shown to be the relevant hedge fund benchmark. The MPPM results are listed for risk aversion levels, ρ, equal to 1.18, 2, 3 and 4 (each indicated by a subscript). $\Delta MPPM_{\rho} =$ Hedge Fund Portfolio$_{\mathrm{MPPM}}$ $-$ Short VIX$_{\mathrm{MPPM}}$ The sample period is May 2008 to December 2022 to account for the initial estimation window of the 3 year rolling regressions.

	All	$\hat{\alpha} > 0$ & $\hat{\beta} \leq 0$	$\hat{\alpha} > 0$	Short VIX
$MPPM_{1.18}$	0.62	6.26	1.87	28.29
$MPPM_{2}$	0.01	5.48	1.36	4.35
$MPPM_{3}$	-0.76	4.60	0.73	-44.97
$MPPM_{4}$	-1.56	3.79	0.08	-135.84
$\Delta MPPM_{1.18}$	-27.67	-22.04	-26.42	n/a
$\Delta MPPM_{2}$	-4.34	1.13	-2.99	n/a
$\Delta MPPM_{3}$	44.21	49.57	45.70	n/a
$\Delta MPPM_{4}$	134.28	139.63	135.91	n/a
Equivalent Risk-Free Rate ($\rho = 3$)	-0.27	5.10	1.22	-43.67

Table 13: Goyal and Welch (2008) Predictive Regressions

The table reports the results from predictive regressions that use the Goyal and Welch (2008) methodology. The parameters are estimated via 3-year rolling regressions with Newey and West (1987) standard errors. The sample period is May 2008 to December 2022 to account for the initial estimation window.

Horizon	$\hat{\alpha}$	SE	$\hat{\beta}$	SE	R^2 (%)	R^2_{OOS} (%)
1 Mo	0.007	0.004	0.052	0.032	4.00	6.02
3 Mo	0.008	0.005	-0.044	0.042	2.62	2.72
6 Mo	0.008	0.005	0.004	0.048	1.51	1.71
1 yr	0.007	0.006	0.010	0.051	1.20	4.02
1.5 yr	0.002	0.010	0.098	0.097	6.43	3.00
2 yr	0.010	0.006	-0.106	0.088	6.21	5.22
3 yr	0.000	0.008	0.027	0.083	2.44	4.70

Table 14: Do Investment Rules Predict Top Quartile Performance?

The table reports the results from probit regressions by hedge funds' primary category. The indicator variable is with respect to whether a hedge funds' returns are in the top quartile within a given month is regressed on an indicator variable for whether the hedge fund satisfies the $\hat{\alpha} > 0$ & $\hat{\beta} \leq 0$ or Jensen (1968) $\hat{\alpha} > 0$ investment rule, lagged by one-year. The sample period is May 2008 to December 2022 to account for the initial estimation window based on three year rolling regressions. The average marginal effects (in decimal form) for each investment rule along with their respective t-statistics are reported. Standard errors are clustered at the hedge fund level. Asterisks denote the levels of statistical significance of the coefficient: 10% level (*), 5% level (**) and 1% level (***).

	$\hat{\alpha} > 0$ & $\hat{\beta} \leq 0$	t-stat	$\hat{\alpha} > 0$	t-stat
Convertible Arbitrage	n/a	n/a	-0.062	0.42
Dedicated Short Bias**	-0.283	-2.45	-0.283	-2.45
Emerging Markets	-0.041	-0.16	-0.031	-1.03
Equity Market Neutral	-0.009	-0.11	0.016	0.31
Event Driven***	0.323	6.96	-0.027	-0.61
Fixed Income Arbitrage***	-0.365	-4.58	0.073	1.00
Fund of Funds***	0.654	10.29	0.117	4.54
Global Macro	0.094	1.24	0.095	1.63
Long/Short Equity Hedge	0.051	0.74	-0.043	-2.22
Managed Futures***	-0.222	-3.94	-0.175	-4.20
Multi-Strategy***	0.321	3.34	0.407	9.44
Options Strategy**	0.239	2.16	0.483	7.77
All Strategies***	0.078	7.53	0.038	9.20

Table 15: Barberis et al. (2015) X-CAPM Simulation Evidence by Investor Type

The table reports the simulation results from the Barberis et al. (2015) X-CAPM conditioned at the investor level. I have re-labelled the investor types to the following correspondence for ease of interpretation: Hedge Funds without Edge refer to the Extrapolative Traders, Hedge Funds with Edge refer to the Rational Traders. In addition, I refer to the market portfolio as the Short VIX benchmark trading strategy. In this paper, edge is defined as a hedge fund whose track record has an estimated $\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$. The simulation evidence is based on the main specification from Barberis et al. (2015) whereby the fraction of rational traders, μ is 0.25 and the discount factor, β is 0.5. The average value is reported from 10,000 simulations.

	Sharpe Ratio	Skewness
HFs without Edge	-0.08	-0.30
HFs with Edge	0.16	0.34
Short VIX Strategy	0.35	0.00

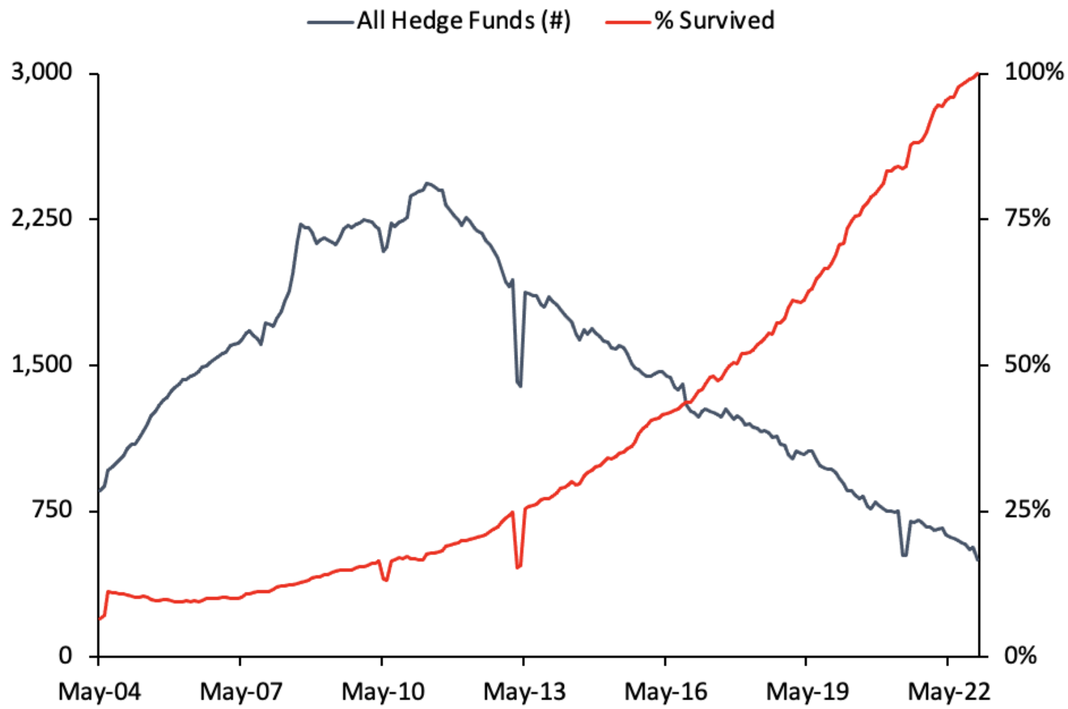


Figure 1: Hedge Fund Counts over Time: The figure displays the total number of hedge funds (blue line) reported in the cleaned Lipper Hedge Fund Database. In addition, the percent of survived hedge funds is also displayed (red line). The sample period is May 2004 to December 2022.

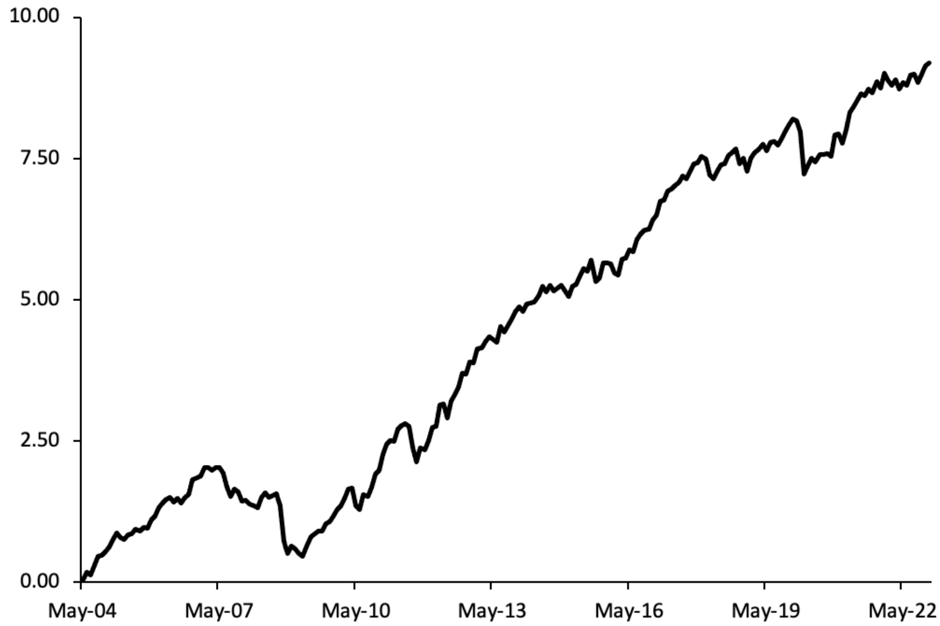
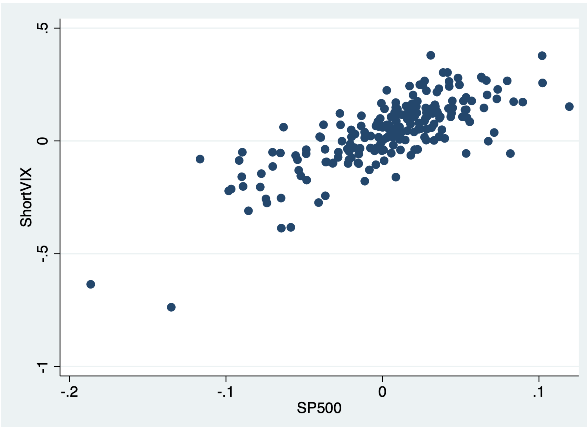
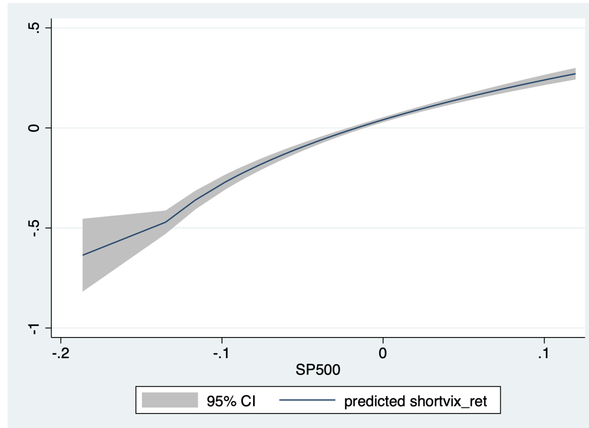


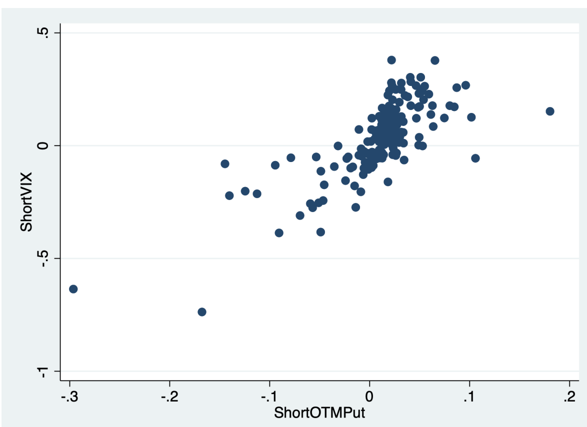
Figure 2: Short VIX Cumulative Returns: The figure displays the cumulative monthly returns of the Short VIX futures strategy. The sample period is from May 2004 until December 2022.



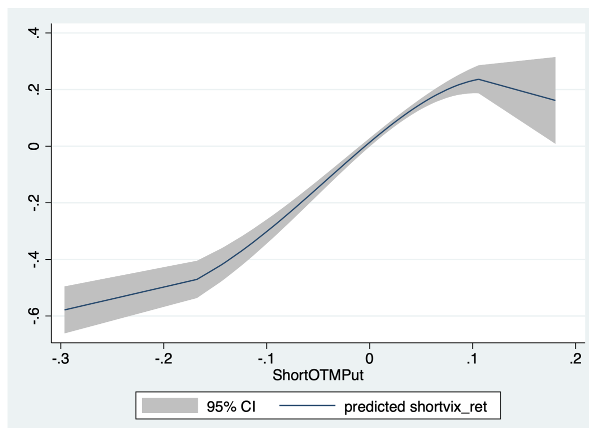
(a) Scatterplot of Short VIX vs. S&P 500



(b) Short VIX as a Fractional Polynomial of S&P 500



(c) Scatterplot of Short VIX vs. Short Put



(d) Short VIX as a Fractional Polynomial of Short Put

Figure 3: Short VIX vs. the S&P 500 and OTM Put-Writing Strategy: The figure displays the Short VIX Returns vs. S&P 500 and OTM Put-Writing Strategy returns at a monthly frequency from May 2004 to December 2022. Panels (a) and (c) correspond to scatterplots of the monthly returns between the Short VIX strategy and S&P 500 and OTM Put-Writing Strategy, respectively. Panels (b) and (d) correspond to predictions of Short VIX Returns as a Fractional Polynomial of the monthly returns from the S&P 500 and OTM Put-Writing Strategy, respectively. The 95% Confidence interval of the mean is the grey shaded region.

Figure 4: Rolling 36-Month Correlations: The figure displays the rolling 36-month correlations between the Short VIX futures strategy returns and the HFRI 500 Composite Index returns. The sample period is from December 2007 until December 2022.

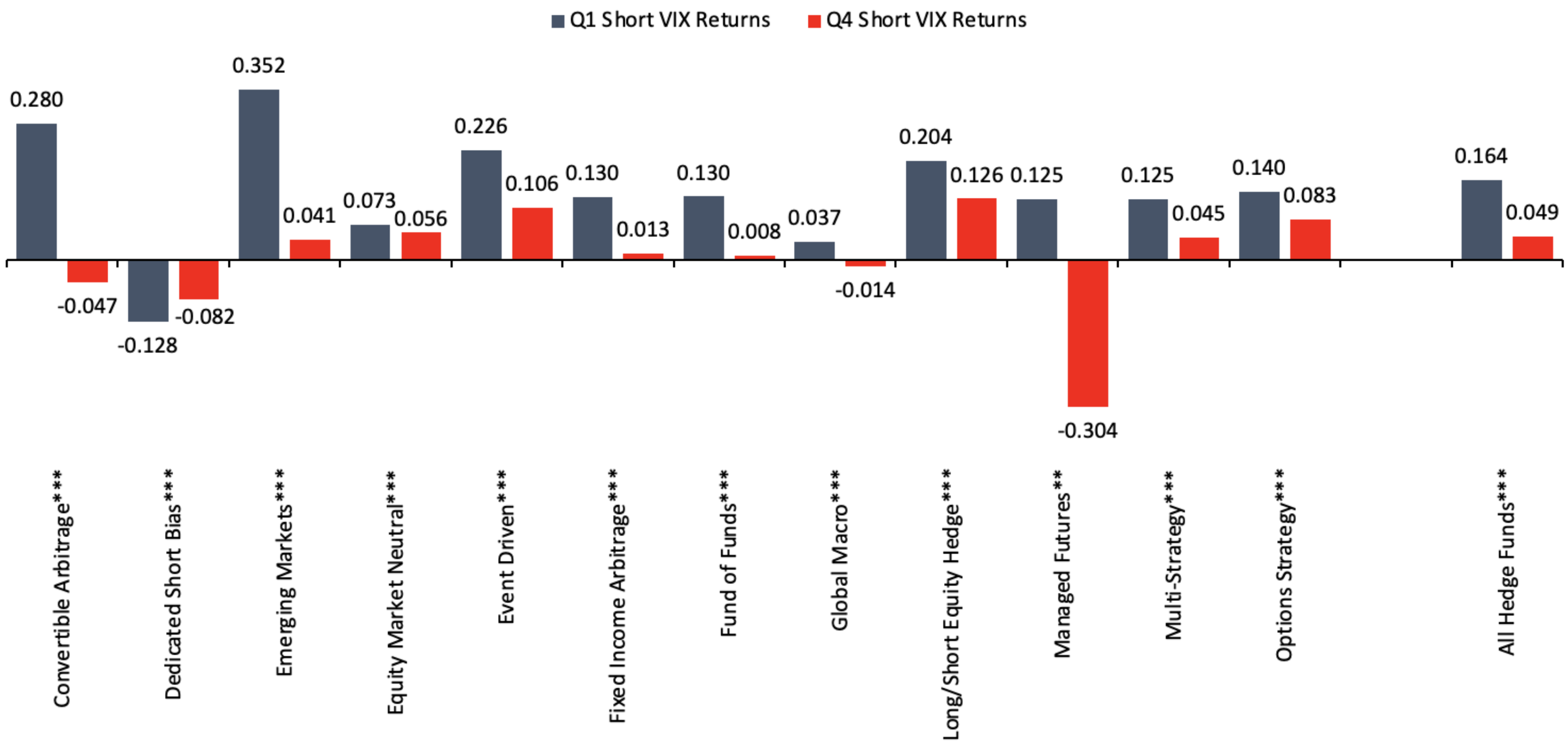
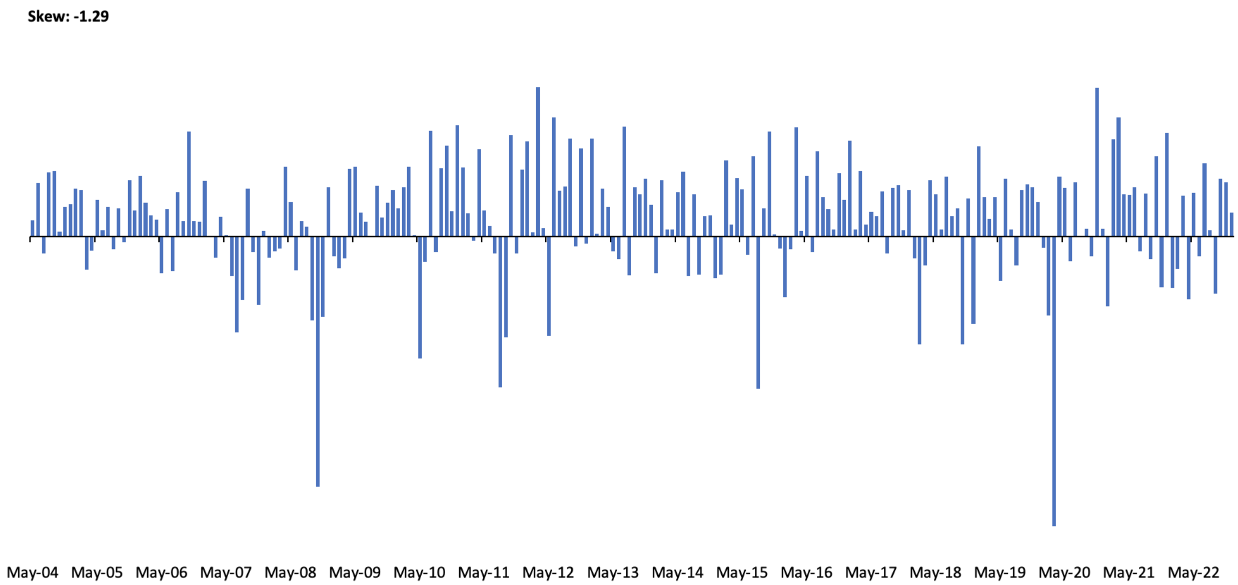
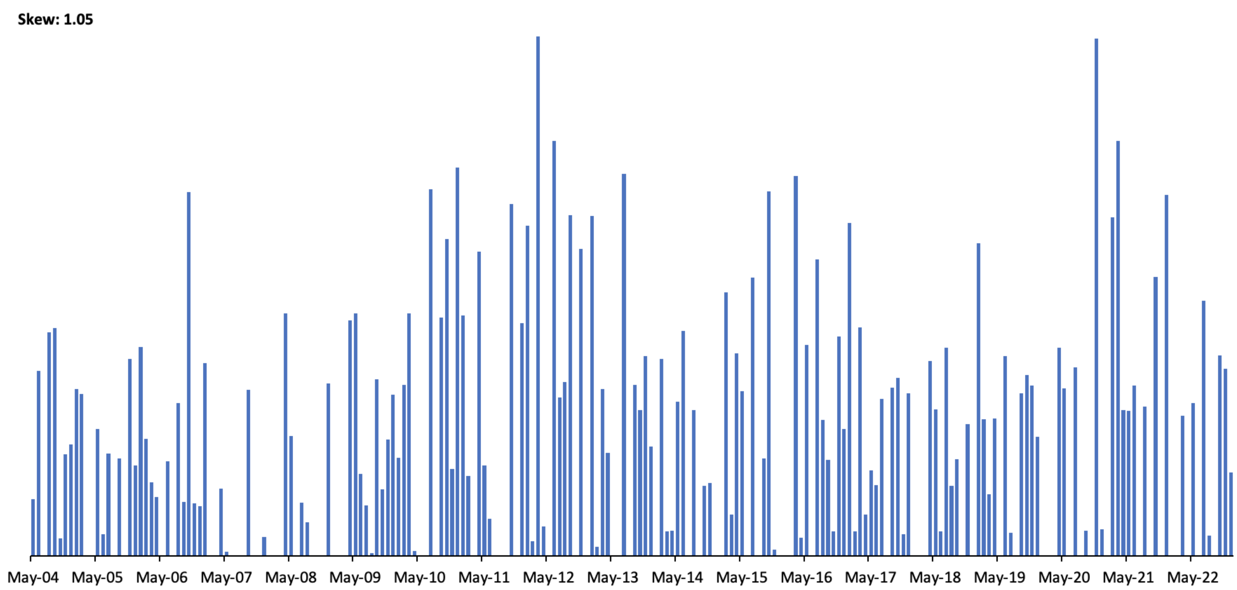


Figure 5: Hedge Fund Loadings During Market Dislocations vs. Market Calm: The figure displays the Short VIX return coefficient estimates from two sets of panel regressions (with hedge fund and year fixed effects) by primary hedge fund category. The blue (red) bars correspond to regressions that are estimated over periods when the Short VIX returns are in the bottom (top) quartile. I refer to the bottom quartile as periods of market dislocations whereas the top quartile refers to periods of market calm. Standard errors are clustered at the hedge fund level. The sample period is from May 2004 to December 2022. Asterisks denote the levels of statistical significance: 10% level (*), 5% level (**) and 1% level (***).

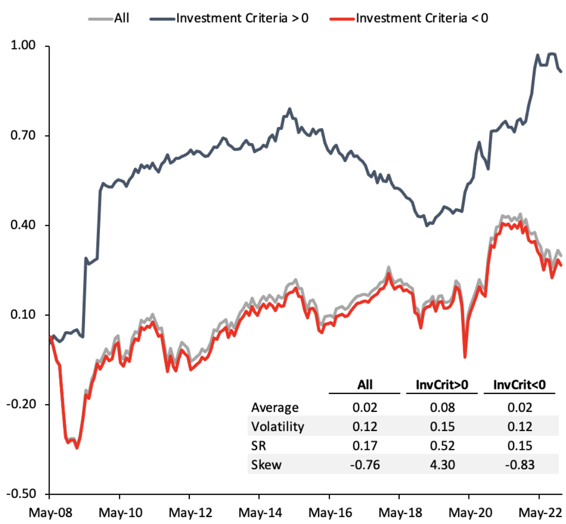


(a) Monthly Short VIX Returns (%)

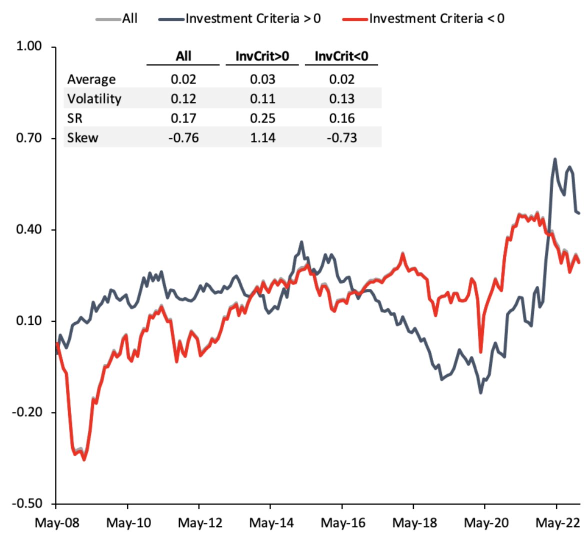


(b) Monthly Short VIX Returns (%) based on Max($0,r_t$)

Figure 6: Monthly Short VIX Returns (%) and Skewness: The figure displays the monthly returns and skewness of the Short VIX strategy from May 2004 to December 2022. Panel (a) displays the returns to shorting one second-dated VIX futures contract, whereas Panel (b) displays the same return series whereby I've replaced a negative return with a zero (i.e. the payoff profile of a call option where the underlying is the Short VIX strategy). The skewness of each return series is shown in the top left hand corner of each respective subfigure.

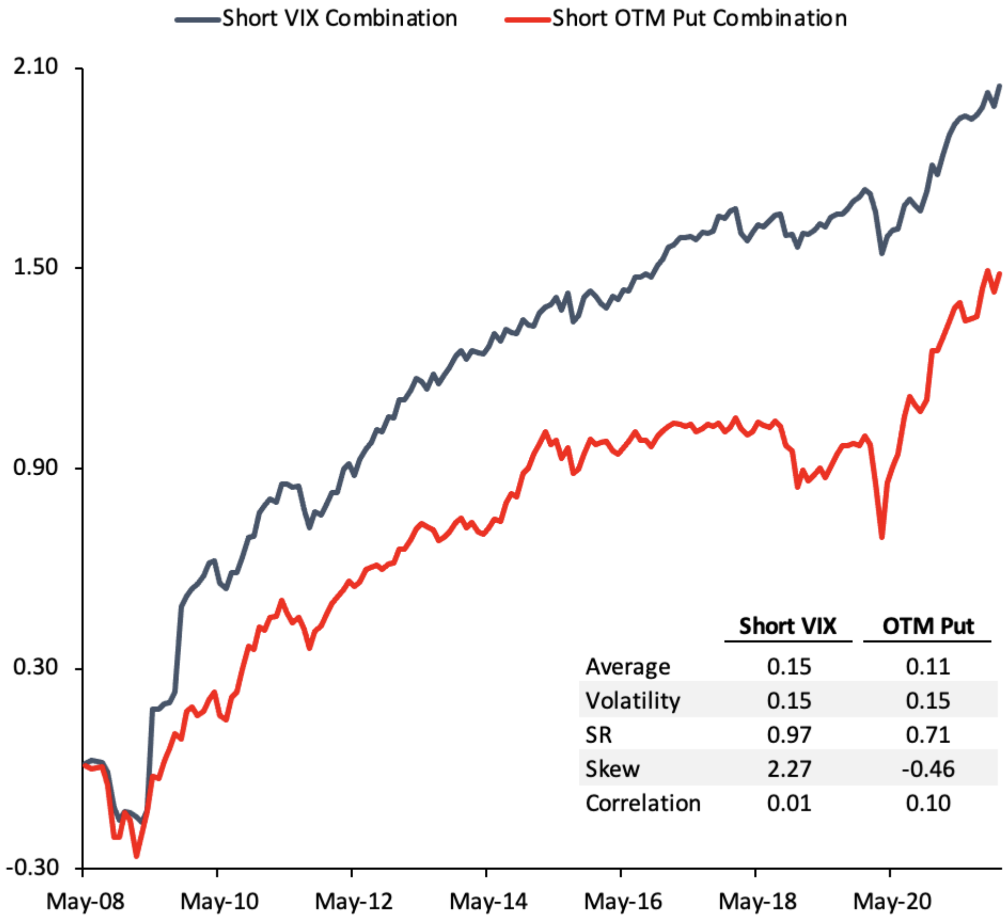


(a) Short VIX Strategy



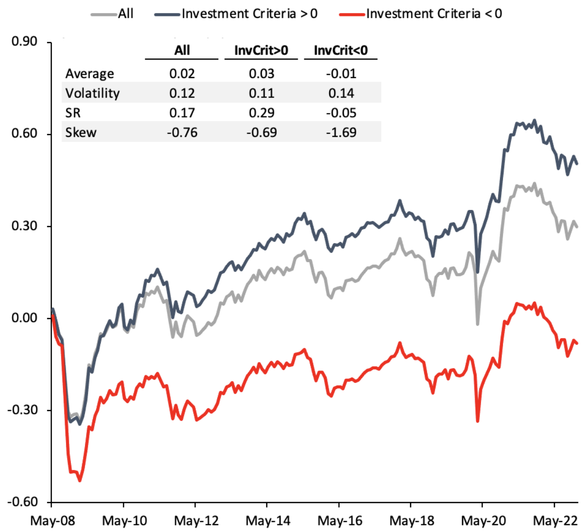
(b) OTM S&P 500 Put Option Strategy

Figure 7: Cumulative Returns of Investment Rule (OOS): The figure displays the cumulative returns to equal-weighted portfolios of hedge funds. The grey line is comprised of all hedge funds in the Lipper Database. The blue line is a portfolio of hedge funds that satisfy the proposed investment rule. The red line is a portfolio of hedge funds that do not meet the investment rule. The parameters that are the basis for the investment rule are estimated by 3-year rolling regressions. The investment rule is based on an annual rebalancing that takes place each December. The sample is from May 2008 until December 2022 to account for the initial estimation window. Panel (a) is based on parameters estimated via the Short VIX returns in contrast to Panel (b) which is estimated using the OTM Short Put returns.

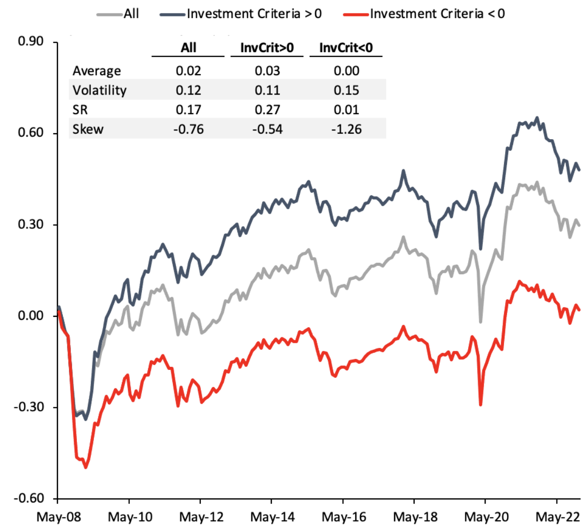


	Short VIX	OTM Put
Average	0.15	0.11
Volatility	0.15	0.15
SR	0.97	0.71
Skew	2.27	-0.46
Correlation	0.01	0.10

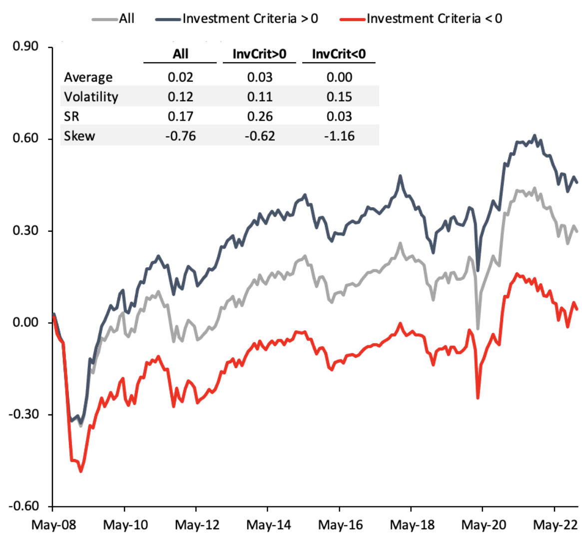
Figure 8: OOS Combination Portfolio Cumulative Returns: The figure displays the cumulative returns to two portfolios with the same investment rule that differ on the benchmark being either the Short VIX or the OTM Put. The two different strategies each have an equal risk-weighting between the hedge fund portfolio and the underlying benchmark. The blue line corresponds to an equal risk-weighting between the Short VIX strategy and the hedge fund portfolio that satisfies the investment rule estimated using the Short VIX. The red line corresponds to an equal risk-weighting between the Short OTM Put strategy and the hedge fund portfolio that satisfies the investment rule estimated using the Short OTM Put. The investment rule is based on an annual rebalancing that takes place each December. The sample is from May 2008 until December 2021 to account for the initial estimation window and the limitation of the OptionMetrics data ending December 2021.



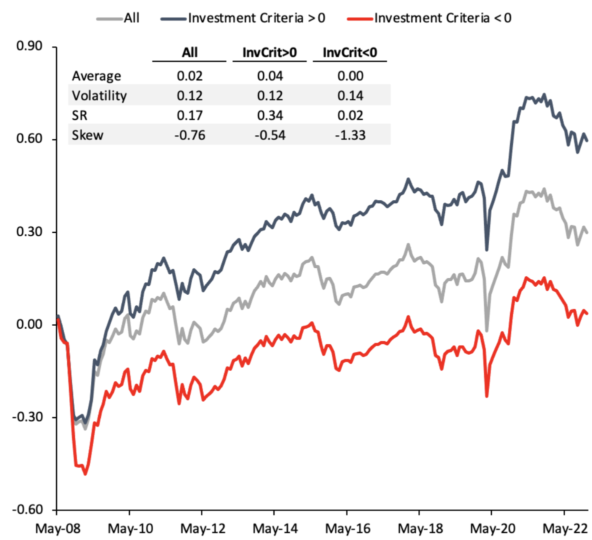
(a) Jensen (1968)



(b) Treynor and Mazuy (1966)



(c) Henriksson and Merton (1981)



(d) Ferson and Schadt (1996)

Figure 9: Cumulative Returns of Alternative Investment Rules (OOS):: This figure displays the cumulative returns to equal-weighted portfolios of hedge funds as in Figure 7. In contrast to the previous figure, each panel corresponds to a different investment rule. Panel (a) corresponds to the original Jensen's alpha from Jensen (1968). Panel (b) refers to Treynor and Mazuy (1966), Panel (c) refers to Henriksson and Merton (1981) and Panel (d) refers to Ferson and Schadt (1996). Each regression that is estimated in Panels (b), (c) and (d) is based on the corresponding regression equations displayed in Table 9. I have substituted the Short VIX for the market factor.

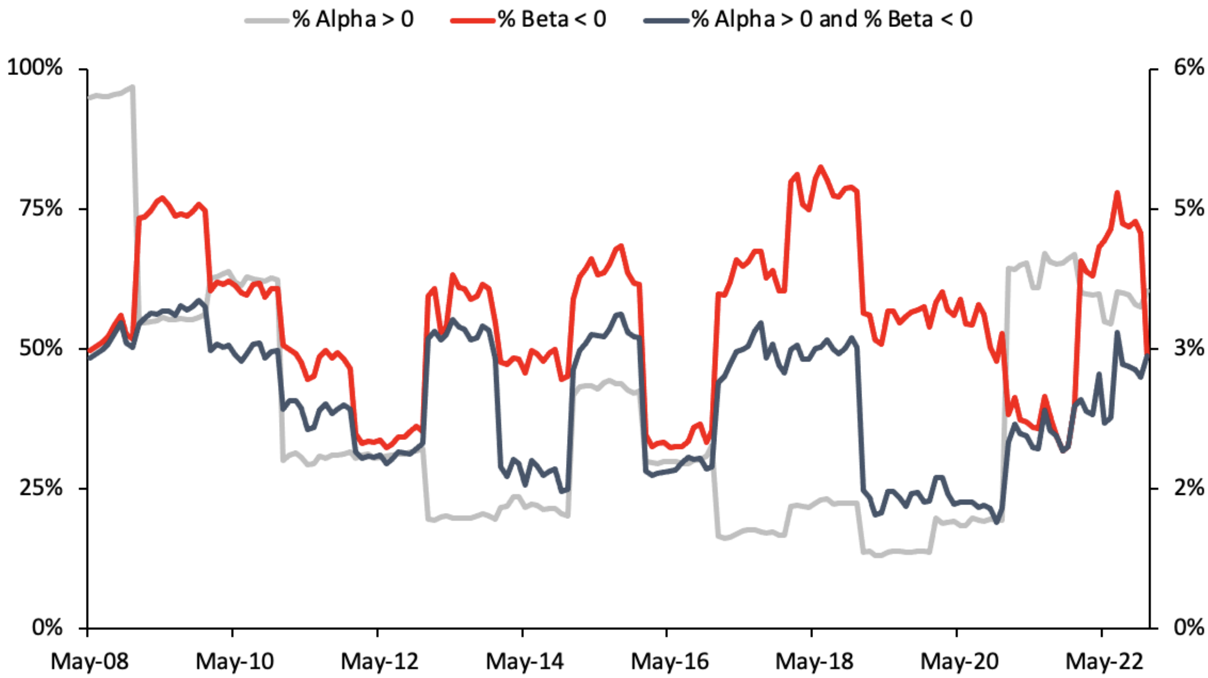


Figure 10: Investment Rule Parameters: The figure displays the percentage of hedge funds that satisfy the investment rule and its component parts. The investment rule parameters are estimated via rolling 3-year regressions. The grey line corresponds to the LHS vertical axis whereas the red and blue lines correspond to the RHS vertical axis. The sample is from May 2008 until December 2022 to account for the initial estimation window.

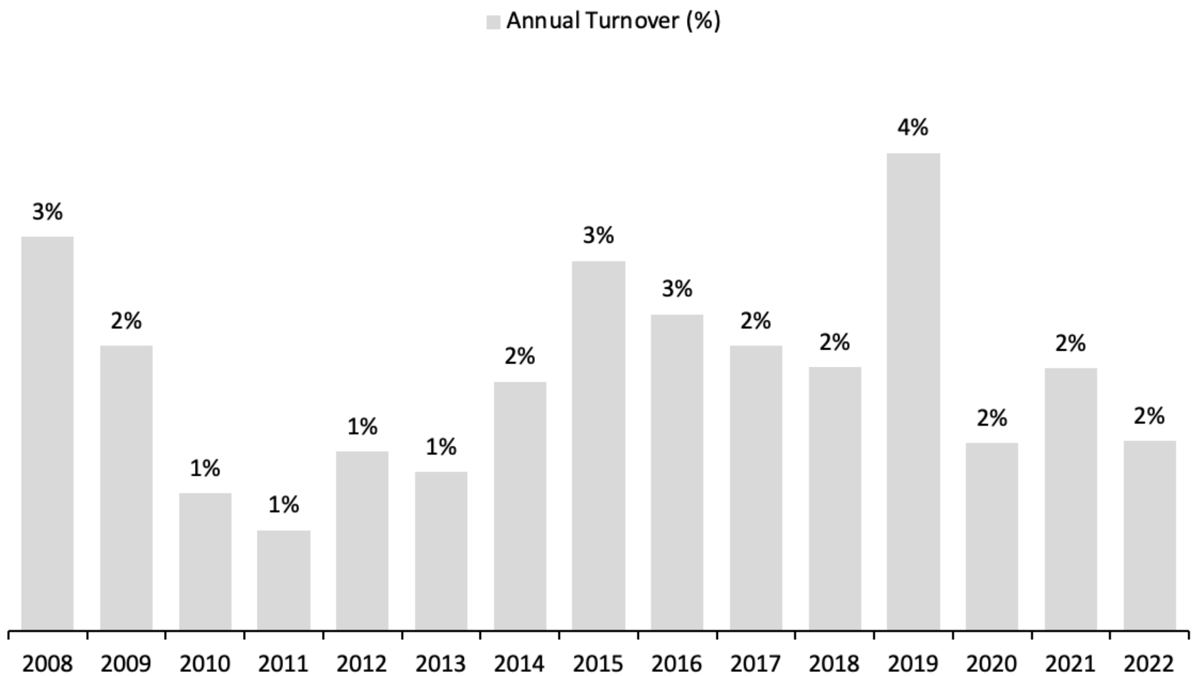
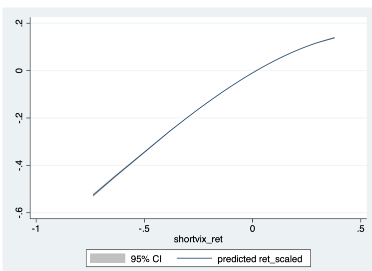
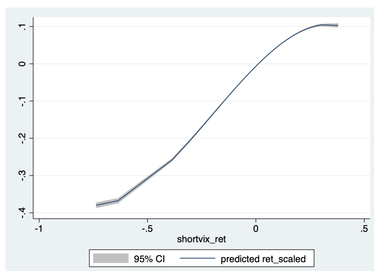


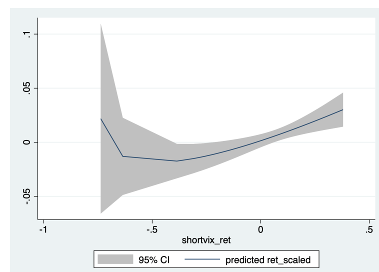
Figure 11: Annual Portfolio Turnover (%): The figure displays the percentage of hedge funds that are invested and/or redeemed each year based on satisfying the proposed investment rule. The sample is from May 2008 until December 2022 to account for the initial estimation window.



(a) All HFs



(b) $\hat{\alpha} > 0$ HFs



(c) $\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$ HFs

Figure 12: Fractional Polynomial Fit of HFs Conditional on Investment Rule: The left column is based on all hedge funds, the center column is based on those hedge funds with a positive intercept ($\hat{\alpha} > 0$) and the right most column is based on hedge funds that satisfy the investment rule ($\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$). The sample period is from May 2008 to December 2022 to account for the initial estimation window.

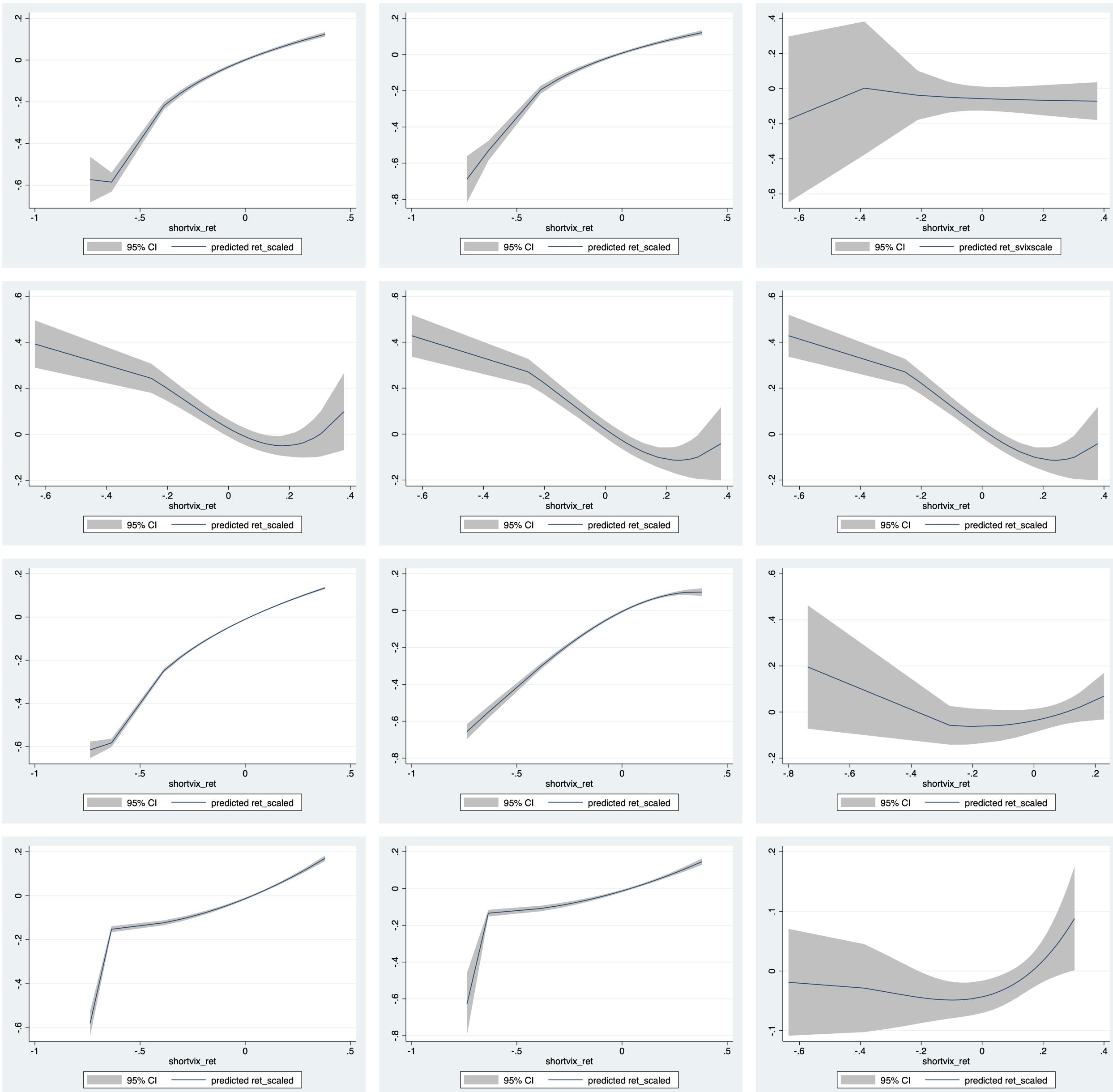


Figure 13: Fractional Polynomial Fit of HFs Conditional on Investment Rule (By Strategy): From top to bottom, the subfigures correspond to the following primary strategies: Convertible Arbitrage, Short Bias, Emerging Markets, Equity Market Neutral. The left column is based on all hedge funds, the center column is based on those hedge funds with a positive intercept ($\hat{\alpha} > 0$) and the right most column is based on hedge funds that satisfy the investment rule ($\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$). The sample period is from May 2008 to December 2022 to account for the initial estimation window.

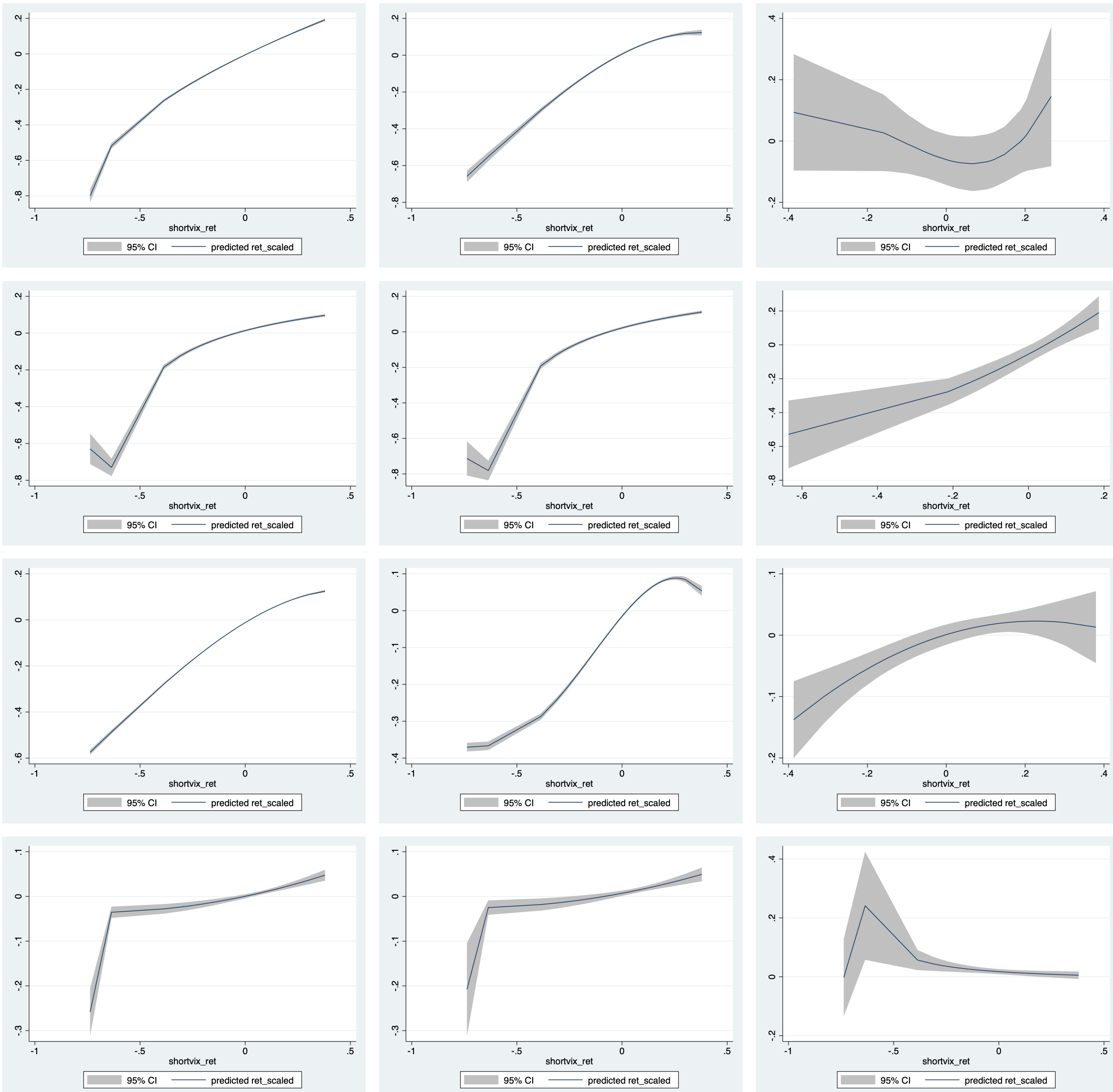


Figure 14: Fractional Polynomial Fit of HFs Conditional on Investment Rule (By Strategy): From top to bottom, the subfigures correspond to the following primary strategies: Event Driven, Fixed-Income Arbitrage, Fund of Funds, Global Macro. The left column is based on all hedge funds, the center column is based on those hedge funds with a positive intercept ($\hat{\alpha} > 0$) and the right most column is based on hedge funds that satisfy the investment rule ($\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$). The sample period is from May 2008 to December 2022 to account for the initial estimation window.

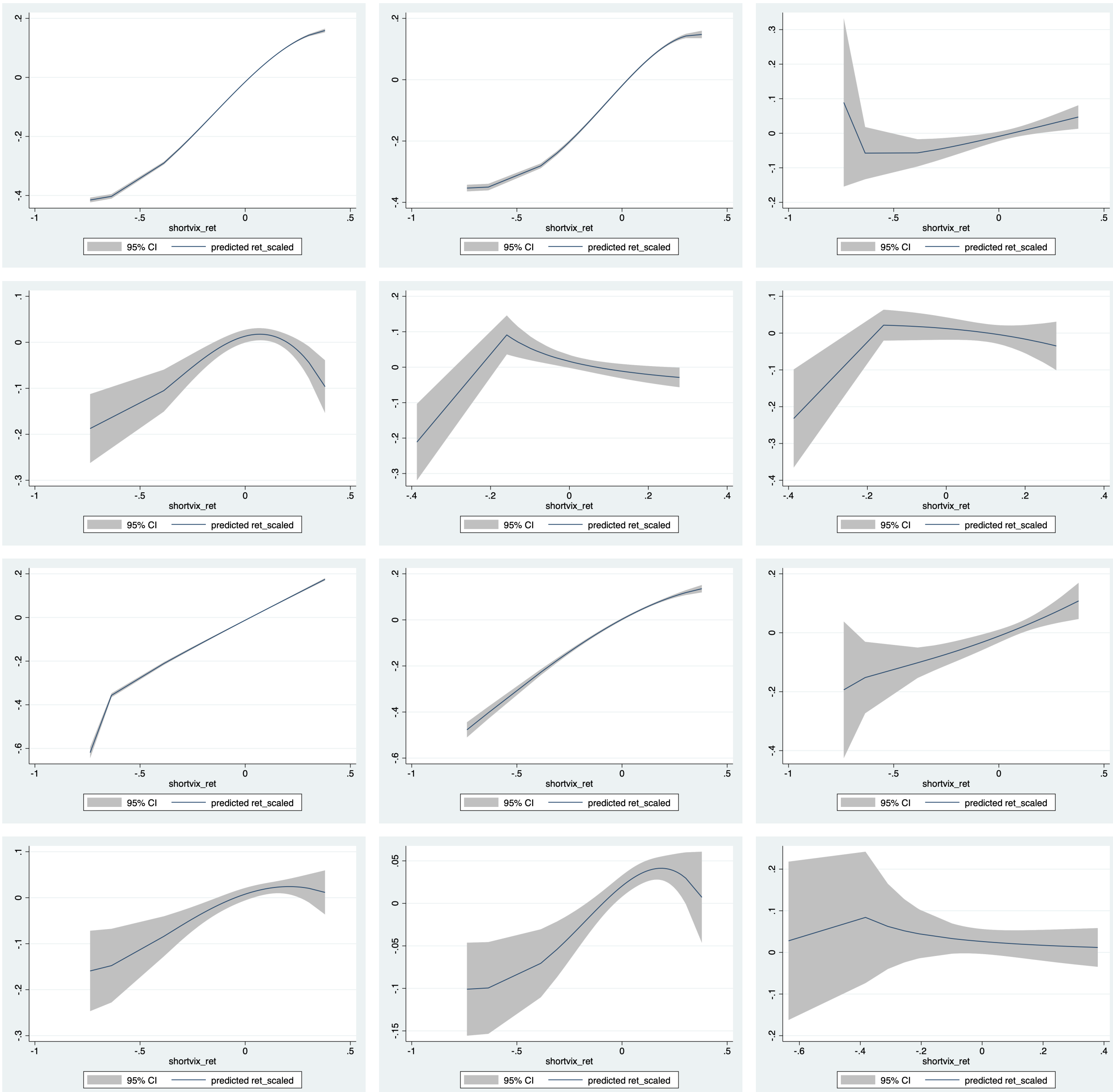


Figure 15: Fractional Polynomial Fit of HFs Conditional on Investment Rule (By Strategy): From top to bottom, the subfigures correspond to the following primary strategies: L/S Equity Hedge, Managed Futures, Multi-Strategy, Options Strategy. The left column is based on all hedge funds, the center column is based on those hedge funds with a positive intercept ($\hat{\alpha} > 0$) and the right most column is based on hedge funds that satisfy the investment rule ($\hat{\alpha} > 0$ and $\hat{\beta} \leq 0$). The sample period is from May 2008 to December 2022 to account for the initial estimation window.