ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS

MASTER THESIS

The Volatility Risk Premium Everywhere

an investigation across asset classes and countries

A thesis submitted in partial fulfillment of the requirements for the degree of
MASTER IN ECONOMETRICS AND MANAGEMENT SCIENCE

Authors:
Wouter TILGENKAMP
student ID: 294543

University Supervisor:
Michel VAN DER WEL
University Co-reader:
Erik KOLE
Company Supervisor:
Martin MARTENS

April 24, 2017

Abstract

We study the volatility risk premium, where the implied volatility exceeds the realized volatility, in multiple asset classes and countries simultaneously. Extracting the volatility risk premium by means of shorting delta hedged straddles produces economically significant average returns in bonds, credits, commodities, currencies and equity indices. Combining the asset class portfolios in a diversified global volatility risk premium factor results in a Sharpe ratio of 1.45. By studying the returns in the cross section we gain deeper insights about the consistency, commonality and patterns in the characteristics and risks of the volatility risk premium compared to individual asset studies. The volatility risk premium is not explained by common explanations offered in literature, downside risk, volatility risk or factor exposures only partially explain the excess returns. We do find a strong common risk component that the asset class portfolios tend to suffer drawdowns during recessions when volatility rises across all asset classes. We explore the robustness of the strategy and find that the premium can be further enhanced by considering alternative hedging and weighting schemes.

Keywords: volatility risk premium, options, asset pricing, credits, government bonds, equity indices, commodities, currencies, delta hedging

Acknowledgements

My special thanks goes out towards Michel van der Wel for his encouragement and insights over the course of my thesis. I would like to thank co-reader Erik Kole for providing me with valuable feedback for my thesis. I thank Martin Martens and Casper Zomerdijk and more generally the Quant Research Department for bringing me on board Robeco after Financial Case Studies which ultimately led to this thesis and my employment at the Trading Desk. The quant internship and the contact with my fellow interns was very enjoyable.

I wish to thank my parents and brother for motivating me through life and inspiring me to go my own way. I thank Jessica Paardekooper for her endless support. I hope to never stop learning, in the words of David Hilbert *"wir müssen wissen, wir werden wissen"*.

Contents

1 Introduction

The difference between the realized and implied volatility, often referred to as the volatility risk premium, is the focus of this study[1]. Eraker (2008) notes that on average the implied volatility exceeds the realized volatility in the S&P 500 by roughly 3%. An investor trying to benefit from this volatility risk premium would sell volatility as it yields a positive average pay off if the implied volatility structurally exceeds the realized volatility.

Selling volatility can be done through selling straddles[2]. A short straddle position has a positive payoff if the underlying is less volatile than was priced in the options. On the other end the position loses money if the underlying moves to a greater extend than was priced in the option. A common risk-based explanation for the existence of a negative volatility risk premium is that investors are willing to pay a premium to protect themselves against losses due to sudden increases in volatility ("bad-states of the world"). The payoff of a straddle is not symmetrical as the maximum the seller can gain is the option premium where he loses a multitude of the premium if the underlying would move abruptly in one direction before expiring. Most studies regarding the volatility risk premium are individual asset studies and find a negative volatility risk premium, a situation in which the implied volatility on average exceeds the realized volatility of the underlying. This study aims to bridge the gap between the individual asset studies and study the returns in the various asset classes simultaneously.

We conduct a comprehensive study on the volatility risk premium simultaneously applied to multiple asset classes using a total of sixty assets. Our research adds to a growing literature that studies the returns of factor investing in the cross section. This is the same approach as Moskowitz et al. (2012) for time-series momentum, Asness et al. (2013) for value and cross-sectional momentum, Frazzini and Pedersen (2014) for betting-against-beta, and very recently Koijen et al. (2015) for carry. By studying the returns in the cross section we gain deeper insights about the consistency, commonality and patterns in the characteristics and risks of the volatility risk premium compared to individual asset studies. To benefit from a negative volatility risk premium we write delta hedged straddles on the assets using option data from the OptionMetrics IvyDB US database.

We make several contributions to the literature. Firstly, we are the first to study the volatility risk premium in the cross section and find that statistically and economically

[1]Practitioners also use the term volatility risk premium for the excess returns that can be earned by selling options. In this study we use the term volatility risk premium in both contexts.

[2]A straddle is a combined option package consisting of an at-the-money call and put option.

significant excess returns can be earned by capturing the volatility risk premium across credits, government bonds, commodities, currencies and equity indices. The asset class portfolios all have negative skewness associated with the tail risk of shorting volatility. This negative skewness is hardly reduced when we create a diversified global volatility risk premium portfolio over the asset classes. This points at a strong common risk component between the asset classes as large losses tend to coincide with global turmoil where the volatility rises across all asset classes. During normal times the asset class portfolios do provide diversification. Several explanations offered in the literature for the excess returns are considered. Volatility, liquidity and downside risk among others all partly explain the excess returns but fall short of explaining the returns in its entirety. Additionally, we are the first to uncover the volatility risk premium in credits and find that the volatility risk premium produces strong returns and a Sharpe ratio of 1.55.

Secondly, the performance of the global volatility risk premium portfolio is further improved by altering the equal weighting scheme by deviating the weight based on the difference between the historical realized volatility and the implied volatility. Applying the weighting scheme to indices across several asset classes adds to the original research done by Goyal and Saretto (2007) who applied the weighting scheme on single stocks.

Thirdly, we study unhedged option returns across asset classes for both call and put options and by doing so we revisit the "overpriced puts puzzle" posed by Bondarenko (2014). We conclude that puts have remained overpriced in a sample period that includes the financial crisis of 2008 that was not included in Bondarenko (2014) and gives evidence that the Peso-problem can not explain these returns. The term structure of the average returns for S&P 500 has kept the same shape in which further out of the money put options are more overpriced compared to in the money put options.

Fourthly, we examine the term structure of the average returns across different assets for different maturities and moneyness and observe persistent patterns. We propose a new linear regression model to explain the term structure of the average returns and perform an portfolio management exercise based on the regression model and a simulated covariance matrix.

Several studies investigate the profits of selling volatility by means of writing (delta hedged) options or shorting variance swaps[3]. However most authors study the returns over a short sample or a single asset class. An overview of the research conducted on the

[3]A variance swap is an over-the-counter derivative that pays the difference between the realized volatility and the implied volatility.

volatility risk premium is provided in Table 1. The majority of research pertains to the volatility risk premium in equity (index) options. Bakshi and Kapadia (2003) show that the returns of delta hedged option portfolios are related to the sign and magnitude of the volatility risk premium. Their sample for the S&P 500 spans between January 1988 and December 1995 and the results are supportive of a negative market volatility risk premium. The sample considered in this study for the S&P 500 starts where Bakshi and Kapadia (2003) finishes and can be therefore regarded as an out-of-sample study in which we again find evidence of a negative volatility risk premium. Eraker (2008) finds that the VIX index[4] averages around 19% between 1990 and 2007 while the unconditional annualized standard deviation is only 15.7%. This suggests that there is a substantial premium for the investor who writes atm options on the S&P 500. Driessen and Maenhout (2006) write options on S&P 500, FTSE 100 and Nikkei 225 indexes over the period April 1992 until the end of June 2001. They find crash neutral[5] straddles produce positive excess returns in all three markets. Coval and Shumway (2001) evaluate the weekly returns of European call and put options on the S&P 500 index from January 1990 to October 1995 and find an annualized Sharpe ratio around 1.02 for crash neutral straddles.

Individual naked (unhedged) call and put option returns have also been investigated. Bondarenko (2014) studies the overpriced puts puzzle, he argues that because puts are negatively correlated with the market and contain leverage the magnitude of the risk premium could be large. He addresses the Peso problem, a situation in which a catastrophic event could have taken place but did not happen in the sample. He finds an annualized Sharpe of 1.21 for at-the-money puts over the period August 1987 till December 2000. Broadie et al. (2007) show that without taking the volatility risk premium into consideration that writing 6% out-the-money puts earns an average monthly return of 22.6% under the Black Scholes Model where CAPM holds and the annual Sharpe ratio of the stock market is 0.4 under the assumption that the market has a 6% average excess return and a 15% annual standard deviation. This large return comes solely from the leverage contained in the out-the-money option and its directional stock price exposure.

For currencies, Guo (1998) examines currency option returns for the Deutsche mark, Japanese yen, British pound sterling, Swiss franc, Australian dollar, Canadian dollar over the period January 1987 till December 1992. He concludes that the market price of variance

[4] The VIX has become the industry standard that gives a model free option implied estimate of the volatility of the S&P 500.

[5] Crash neutral straddles control for crash risk by hedging the far downside exposure through an out-the-money (otm) put

Table 1: Overview Research volatility risk premium

Overview of previous research conducted on the volatility risk premium in different asset classes.

Research	Credits	Government Bonds	Commodities	Currencies	Equities	Time Period
Coval and Shumway (2001)					✓	1990–1995
Bakshi and Kapadia (2003)					✓	1988–1995
Driessen et al. (2009)					✓	1996–2003
Guo (1998)				✓		1987–1992
Low and Zhang (2005)				✓		1996–2002
Neely (2003)			✓			1987–1998
Trolle and Schwartz (2008)			✓			1996–2006
Goodman and Ho (1997)		✓				1991–1996
Duarte et al. (2007)		✓				1988–2004
This study	✓	✓	✓	✓	✓	1996–2015

is non zero in currency options. Low and Zhang (2005) find significant negative risk premia in the British Pound, the Euro, the Japanese Yen and the Swiss Franc with a term structure that is decreasing in maturity.

In the case of commodity options, Neely (2003) find a significant negative risk premium in gold future options over the period January 1987 till December 1998. The (implied) volatility tends to increase for equities (indexes) when the underlying moves down, empirical evidence shows that the same holds true for gold[6]. Trolle and Schwartz (2008) find a significant negative risk premium in energy options over the period January 1996 till November 2006, and the risk premium is time-varying. The variance for natural gas exhibits strong seasonality and peaks during the cold months of the year. They show the risk premium is also higher during this period. Doran and Ronn (2008) demonstrate numerically that a negative market price of volatility risk is the key risk premium in explaining the difference between risk-neutral and statistical volatility in both equity and commodity-energy markets. Whereas prices and volatilities are negatively correlated in the equity markets, they display a positive correlation in the energy markets.

[6]https://www.cmegroup.com/education/files/gold-storm-on-the-horizon.pdf

Recent literature on the volatility risk premium in the fixed income asset class, such as Goodman and Ho (1997) and Duarte et al. (2007), examine the existence and sign of the volatility risk premium by means of a delta hedged option portfolio. Duyvesteyn and de Zwart (2015) conduct empirical analysis of the term structure of the volatility risk premium by creating portfolios of long-short portfolios of atm straddles in the four major swaption markets (USD, JPY, EUR, GBP). They report a concave upward sloping maturity structure, with the largest negative premium for the shortest maturity. Trolle and Schwartz (2009) derive, under simplifying assumptions, that the volatility risk premium in US Treasury market based on variance swaps should be negative. To the best of our knowledge, there is no literature regarding the volatility premium in the corporate bond market.

Apart from the literature written about a negative risk premium in single assets and asset classes, advances in recent years have also been made in exploring the difference in implied volatility and realized volatility between assets by means of long-short portfolios. Goyal and Saretto (2007) explore the difference between the historical variance and the implied volatility for individual equity options. By going long the undervalued options (low implied versus realized volatility) and short the overvalued options (high implied versus realized volatility) they find strong excess returns. It is important to note that this research does not relate directly to the volatility risk premium as the portfolios are long-short and do not carry a short volatility exposure as such. In our research we first consider the volatility risk premium by shorting volatility but later incorporate the findings of Goyal and Saretto (2007). Driessen et al. (2009) explore the difference in returns between equity options and equity index options. The volatility risk premium is found to be negative in both equities and equity indices, but far more negative for indices than for the individual equities. To benefit from the difference Driessen et al. (2009) consider a correlation strategy of selling index straddles and buying individual stock straddles and realize a Sharpe ratio of 0.73. This strategy is short correlation as the index volatility increases when correlation increases and therefore they conclude that the correlation premium is negative.

Eraker (2008) points out that the payoffs for selling volatility through options are non-Gaussian such that an investor requires significant premiums for the tail-risks. Furthermore the returns for selling an out-the-money option has a big chance of a small positive return and a small chance of a high negative return. The strategy can look to be deceptively low risk when the sample does not contain a market crash.

2 Methodology

This section describes the methodology we use to calculate returns, construct portfolios and shows the mathematical connection between delta hedged straddles returns and the volatility risk premium. In Section 2.1 we discuss the pricing of an option under the Black–Scholes model and its terminal value. In Section 2.2 we show the mathematical connection between delta hedged portfolio returns and the size of the volatility risk premium. In Section 2.3 we explain the portfolio construction. Section 2.4 shows the return calculation of the portfolios. Lastly we explain the realized volatility measure that we use in Section 2.5.

2.1 Payoff Options

In this study we are concerned with both call and put options. A call option gives the holder the right but not the obligation to buy the underlying stock for strike price K at maturity T. A put option gives the holder the right but not the obligation to sell the underlying stock for strike price K at maturity T. Some options are cash settled in which the terminal value of the options is paid, others require delivery of the underlying when the option gets exercised. Regular options are American or European style, European options can only be exercised at maturity T where American options can be exercised anywhere between the current time t and the maturity date T. When dividends are not existent it is never optimal to exercise an American call option early. For very deep in-the-money put options it can be optimal to exercise early theoretically. For European options closed form formulas exist under certain assumptions, the most popular one is the Black Scholes model. The Black-Scholes model prices a call option at time t with maturity T and strike price K for an underlying with price S as

$$P_{call} = SN(d_1) - Ke^{-r(T-t)}N(d_2) \tag{1}$$

σ denotes the annualized implied volatility and r the interest rate over the period $T - t$. The value of a put option under the Black-Scholes model is defined as

$$P_{put} = Ke^{-r(T-t)}N(-d_2) - SN(-d_1) \tag{2}$$

$$d_1 = \frac{ln(\frac{S}{K}) + (r + \frac{\sigma^2}{2})(T-t)}{\sigma(T-t)}$$
$$d_2 = d_1 - \sigma(T-t)$$

In the case of a dividend bearing equity with dividend D at time t_1, S gets replaced by S^* in (1) and (2), with S^* defined as,

$$S^* = S - De^{-r(t_1 - t)} \tag{3}$$

An option priced under the Black–Scholes model has a sensitivity to all the input parameters, these sensitivities are usually referred to as "the Greeks" and can be found in Appendix G. The most important one for this study is delta (Δ), which is the sensitivity of the price of an option to the price of the underlying. When we hedge this sensitivity by taking an offsetting position in the underlying we are left with first order sensitivities to the risk free rate and the implied volatility (vega) of the option. The sensitivity to the risk free rate for short term options is negligible compared to the sensitivity to changes in the implied volatility. This is precisely why we study delta hedged straddles, as the remaining exposure of the option is dominated by the sensitivity to the implied volatility and the exposure to the second derivative of the option to the underlying (gamma). Excess returns of short delta hedged straddles should then be related to the volatility risk premium as we will further explore in Section 2.2.

The Black–Scholes model is useful when the option still has time to maturity left. When the option matures the option achieves its terminal value. For a put option the terminal value is zero when the underlying price is above the strike price, given that the investor would rather opt for selling the underlying in the market for a higher price. In case that the underlying price is below the strike price the holder should exercise its option and sell the underlying for K after which he can instantly buy it back in the market for S, the value is therefore equal to $K - S$. For a call option the terminal value is derived through the same logic, the option expires valueless when the underlying is below the strike price and equal to $S - K$ when it finishes above the strike price because now you can buy the underlying for K at expiry and instantaneously sell it back for S in the market. More formally the terminal value of a call option is equal to,

$$V_{term} = max(S - K, 0) \tag{4}$$

For put options the terminal value is determined as,

$$V_{term} = max(K - S, 0) \tag{5}$$

2.2 Delta Hedged Straddles and the Volatility Risk Premium

Here we describe the mathematical connection between the volatility risk premium and the returns of delta hedged straddle portfolios following the notation of Bakshi and Kapadia (2003). Often times mathematical derivations are done under the assumption that you can continuously hedge the exposure of the option towards the underlying, something that is not practically feasible and the considered daily data does not permit. Furthermore volatility is often times assumed to be static instead of stochastic. To validate our research approach, we explore the connection between discrete delta hedged returns under stochastic volatility and the volatility risk premium. In Section 2.2.1 we define the returns of a delta hedged option under discrete hedging. In Section 2.2.2 we explore the connection between delta hedged returns under stochastic volatility and the sign of the volatility risk premium.

2.2.1 Delta Hedged Returns with Discrete Hedging

Let $C_{t+\tau}$ represent the price of a European call maturing in τ periods from time t, with strike price K. Denote the corresponding delta by $\Delta = \frac{\delta C}{\delta S}$. The continuously delta hedged return, $\pi_{t,t+\tau}$, for a long delta hedged call position, where the net investment earns the risk-free rate is

$$\pi_{t,t+\tau} \equiv C_{t+\tau} - C_t - \int_t^{t+\tau} \Delta_u dS_u - \int_t^{t+\tau} r(C_u - \Delta_u S_u)du \tag{6}$$

The expected $\pi_{t,t+\tau}$ can be interpreted as the excess rate of return on the delta hedged call portfolio[7]. When the hedge is rebalanced discretely the expected $\pi_{t,t+\tau}$ will not necessarily be zero. Fortunately, Bertsimas et al. (2000) show that the delta hedged gains for a discretely hedged portfolio has an asymptotic distribution that is symmetric with zero mean if volatility risk is not priced. If we now translate equation (6) to its discrete version in which we hedge N times we find,

[7] The excess rate of return of a long delta hedged put portfolio (long put, long stock) with $\Delta = \frac{\delta P}{\delta S}$ is defined in the same way with $\pi_{t,t+\tau} \equiv P_{t+\tau} - P_t - \int_t^{t+\tau} \Delta_u dS_u - \int_t^{t+\tau} r(P_u - \Delta_u S_u)du$.

$$\pi_{t,t+\tau} \equiv \underbrace{C_{t+\tau} - C_t} - \underbrace{\sum_{n=0}^{N-1} \Delta_{t_n}(S_{t_{n+1}} - S_{t_n})} - \underbrace{\sum_{n=0}^{N-1} r(C_t - \Delta_{t_n} S_{t_n})\frac{\tau}{N}} \tag{7}$$

From equation (7) we can see that the delta hedged gains $\pi_{t,t+\tau}$ consists of three parts, $C_{t+\tau} - C_t$ denotes the option return over the holding period. $\sum_{n=0}^{N-1} \Delta_{t_n}(S_{t_{n+1}} - S_{t_n})$ denotes the return of the stock position that is kept as a hedge for the option. Finally $\sum_{n=0}^{N-1} r(C_t - \Delta_{t_n} S_{t_n})\frac{\tau}{N}$ refers to the interest that is earned (paid) over the cash position of the portfolio over the holding period.

2.2.2 Delta Hedged Returns under Stochastic Volatility

Assume a stock process and stochastic volatility process,

$$\frac{dS_t}{S_t} = \mu_t[S_t, \sigma_t]dt + \sigma_t dW_t^1 \tag{8}$$

$$d\sigma_t = \theta_t[\sigma_t]dt + \eta[d\sigma_t]dW_t^2 \tag{9}$$

with correlation ρ between the two Wiener process W_t^1 and W_t^2. θ_t denote the drift coefficient, and $\eta[d\sigma_t]$ the diffusion coefficient. By Ito's lemma,

$$C_{t+\tau} = C_t + \int_t^{t+\tau} \frac{\delta C_u}{\delta S_u} dS_u + \int_t^{t+\tau} \frac{\delta C_u}{\delta \sigma_u} d\sigma_u + \int_t^{t+\tau} (r(C_u - S_u \frac{\delta C_u}{\delta S_u} - (\theta_u[\sigma_u] - \lambda_u[\sigma_u])\frac{\delta C_u}{\delta \sigma_u})du \tag{10}$$

Where $\lambda_t[\sigma_t]$ represents the price of volatility risk. The volatility risk premium will be related to risk aversion. This can be rewritten to,

$$C_{t+\tau} = C_t + \int_t^{t+\tau} \frac{\delta C_u}{\delta S_u} dS_u + \int_t^{t+\tau} r(C_u - \frac{\delta C_u}{\delta S_u} S_u)du + \int_t^{t+\tau} \lambda_u \frac{\delta C_u}{\delta \sigma_u} du + \int_t^{t+\tau} \eta \frac{\delta C_u}{\delta \sigma_u} dW_u^2 \tag{11}$$

Bakshi and Kapadia (2003) then proof in their first proposition that the expected delta hedged return is equal to,

$$E_t(\pi_{t,t+\tau}) = \int_t^{t+\tau} E_t(\lambda_u[\sigma_u]\frac{\delta C_u}{\delta \sigma_u})du \tag{12}$$

We conclude that if volatility risk is priced the expected return of the delta hedged portfolio is determined by the vega ($\frac{\delta C_u}{\delta \sigma_u}$) and the volatility risk premium as can be seen from equation (12). When delta hedged discretely the average $\pi_{t,t+\tau}$ can deviate from zero but Bakshi and Kapadia (2003) show that this deviation gets smaller as the delta hedge frequency increases. The outlined framework allows us to test whether the sign of the volatility risk premium is positive or negative by looking at the average delta hedged gains over the sample period. Positive average delta hedged return for a long straddle portfolio implies a positive risk premium and vice versa.

2.3 Portfolio Construction

Within each asset we construct straddle portfolios on a monthly basis. At the last trading day of each month we select the most atm strike and open short straddle position with 40-60 days till expiry. We delta hedge in all assets at the end of each day over the holding period of one month. This ensures that at the end of the day we have no exposure to the underlying under the Black–Scholes model. At the last trading day of the following month we close our short straddle positions and open a new one at the most atm strike with again 40-60 days till expiry. We repeat this process over the sample period of 1996-2015. There does not always exist a strike that is exactly at-the-money. In that case we pick the strike that is closest to atm with the restriction that the absolute delta of the call and put for the atm strike can not deviate more then 0.1 from 0.5 (call) or -0.5 (put). This means that the residual delta exposure of the straddle is between -0.2 and +0.2. If there is no qualifying strike that merits these requirements we skip the month and record no return.

In order to delta hedge we use the delta provided by OptionMetrics where possible. If the OptionMetrics data does not provide Greeks for a given option we approximate the delta in the following way, we first look for the call (put) with the same strike price and calculate the approximated delta by solving $1 = -\Delta_{put} + \Delta_{call}$. If that Δ is also missing we look for all the puts (calls) that are available at that time with the same maturity and linearly interpolate the missing delta, with the restriction that a call (put) delta should be strictly positive (negative) and smaller (greater) than 1 (-1). Very occasionally OptionMetrics does not hold data for an option for one day during the holding period, in this case we keep the delta hedge equal to the preceding day and adjust the following day when the option reappears in the OptionMetrics database.

2.4 Portfolio Returns

For each asset we create atm straddle portfolios. We choose to relate the monetary return of the portfolio to the initial cost of the straddle at the beginning of the holding period in line with Bakshi and Kapadia (2003)[8]. The monetary return of the delta hedged straddle portfolio consists of four parts, the call return, the put return, the return for delta hedging the straddle and the interest rate received/paid for the varying cash position to remain delta hedged over the holding period. Using equation (7) we find,

$$r = \frac{-\pi^{put}_{t,t+\tau} - \pi^{call}_{t,t+\tau}}{P^{put}_t + P^{call}_t} \tag{13}$$

where π denotes the portfolio gains. The negative sign for π relates to our strategy of shorting straddles as we want to benefit from a negative volatility risk premium.

Theoretically the returns of the delta hedged put and delta hedged call should be very close (see Figure 1). So alternatively to delta hedging the straddle we could delta hedge the put following the approach of Bakshi and Kapadia (2003). However by combining the put and call option into a straddle we have the benefit that we can average out possible erroneous prices in the OptionMetrics database. Secondly when measuring the return for the delta hedged atm put it can be that the initial price of the atm put is fairly small due to the most atm put being slightly out of the money. This makes measuring the percentage return noisy as the denominator (initial price put) is small. When we combine the put and call the denominator (initial price straddle) is greater and more stable, mitigating the chance of dividing by quantities close to zero.

2.5 Realized versus Implied Volatility

Implied volatility is forward looking in the sense that it is the markets estimate of the future volatility of the underlying. Realized volatility is backward looking and is calculated as the volatility that has been realized. We follow the definition of Goyal and Saretto (2007) for the annualized realized volatility over a n day period.

$$RV_t = \sqrt{\frac{252}{n} \sum_{i=1}^{n} \ln\left(\frac{P_{t-i}}{P_{t-i-1}}\right)^2} \tag{14}$$

Based on the relationship we found between the volatility risk premium and the returns of the delta hedged straddles we expect a long position in a delta hedged atm straddle to suffer a loss when the implied volatility exceeds the realized volatility.

Financial returns are often found to display volatility clustering. Mandelbrot (1963)

[8]Alternatively you can relate the monetary return of the portfolio to the price of the underlying, which relates to the return of a covered call strategy. Our results are robust under both measures.

reports evidence that large changes are often followed by large changes and small changes by small changes. The squared returns display positively slowly decaying auto correlations which led to the frequent use of GARCH models to forecast volatility as volatility shocks today influence the expectation of volatility far into the future. Volatility is also found to be mean reverting which is generally interpreted as their being a normal level of volatility to which volatility will eventually return.

Goyal and Saretto (2007) indeed found that historical volatility has predictive power for the future volatility. Sorting on the difference between the historical realized volatility (RV) and the forward looking implied volatility (IV) they construct buckets that produce excess returns when they go long the decile with assets where the IV is relatively low compared to the RV and go short the decile with assets where the IV is relatively high compared to the RV. Their look back period to calculate the historical volatility was one year so that their model was primarily motivated by the mean-reverting property of realized volatility. Picking a much shorter look back period would be more related to the volatility clustering property of volatility.

To formalize, the RV is calculated using equation (14). We then sort on the log difference between the RV and the IV,

$$R_t = \ln RV_t - \ln IV_t \tag{15}$$

Based on the sorting Goyal and Saretto (2007) go long the top decile (high RV compared to IV) and short the bottom decile. We deviate from their weighting scheme as our study is considered with 60 assets with an average of 12 assets per asset class, making buckets would lead to very small number of assets per bucket. Therefore we opt for a weighting scheme in which all assets are assigned a weight but differ in magnitude. We use two different weighting schemes. In Section 4.4 we use a weighting scheme where the weights sum to -1 to stay consistent with being short volatility for the k assets at time t. Equation (16) shows the weighting formula.

$$weight_t^i = -\frac{ranking_t^i}{\sum_{i=1}^{k} ranking_t^i} \tag{16}$$

In Appendix J a weighting scheme is used to created a long-short portfolio for the k assets at time t that aims to benefit from the relative volatility mispricing between assets without being short volatility at a portfolio level. Equation (17) contains the weighting formula.

$$weight_t^i = -z_t(rank_t^i - \frac{k+1}{2}) \tag{17}$$

z_t is a scalar that ensures that the long and short positions equal 1 and -1. We apply this long short weighting scheme to all the assets within an asset class. The weighting scheme in equation (17) is identical to the weighting scheme in Koijen et al. (2015) where they create long-short carry portfolios.

3 Data

The data for this study comes from the IvyDB US database of OptionMetrics and covers the time period January 1996 to August 2015. The database is a frequently used standard for academic studies, the database contains historical price and implied volatility data of the US markets for 4409 optionable securities. Most of these securities are common stocks, ADR's and mutual funds. After removing these securities we are left with 632 ETFs and 34 indices. Per asset class we try to include as many individual securities as possible under the condition that they have sufficient trading volume and for ETFs that they have sizable Assets Under Management (AUM). We also avoid including the exact same asset twice, but do include assets related to the same sector (oil for example) that have different constituents. If we have two identical securities which have available options every month we take the security with the longest available data. For example we have option data on both the SPX index and the SPY ETF. We included the SPX index as the data goes back to 1996 where SPY data starts in 2005. In total we select 40 ETFs and 20 indices across the different asset classes, see Table 2. The data set is very size-able with the raw option data over 16.1 gigabytes in size. The SPX index alone has over 7 million daily observations for all the different options combined. The total for all 60 assets combined is well over a hundred million daily observations. This made it important to structure and filter the data to make backtesting the delta hedged strategies feasible.

For credits we cover 3 ETFs with the earliest starting in 2003. The first ETF covers investment grade corporate bonds while the two other ETFs cover high yield corporate bonds. For government bonds we include 4 indices and 4 ETFs. These are all US treasury related but cover different maturities from 13 weeks till 30 year bonds[9]. For currencies our data starts in 2007 and covers 12 securities including the U.S. Dollar, Great British Pound, Japanese Yen, Canadian Dollar, Swiss Franc, Chinese Reminbi and the Euro. Within the commodity asset class we include Gold, Silver, Oil gas and agriculture securities for a total

[9]We also collected swaption data from an anonymous broker covering Germany, Japan and the U.K. and found similar results.

of 9 securities. Lastly we include 10 indices and 18 ETFs of different global equity markets, covering Germany, Sweden, U.S., Canada, China, Australia, Japan, Italy, Hong Kong and emerging markets. The descriptions of all the different securities, including AUM for ETFs, can be found in Appendix A. Appendix B provides an overview of the total volume over the sample period in the various securities.

Table 2: Overview Data

General overview of the different assets grouped per asset class included in this study. In brackets you can find the Bloomberg codes. This table contains a subset of all considered assets.

Equity Index	**Currency**	**Bonds**
US (SPX, DJX)	Australia (XDA, FXA)	US 13 weeks (IRX)
China (FXI, GXC)	Canada (XDC, FXC)	US 1-3 year (SHY)
Europe (VGK, EZU)	Yen (FXY, XDN)	US 3-7 year (IEI)
World (VEU, ACWI)	Swiss Franc (XDS, FXF)	US 7-10 year (IEF)
Germany (EWG)	British Pound (FXB)	US 10-20 year (TNX)
South Korea (EWY)	US Dollar (UUP)	US 20+ year (TLT)
Japan (EWJ)	Reminbi (CYB)	US 30 year (TYX)
Italy (EWI)	Euro (FXE)	
Hong Kong (EWH)		
	Commodities	**Credits**
	Gold (GLD, IAU)	Investment Grade (LQD)
	Silver (SLV, XAU)	High Yield (HYG, JNK)
	Oil (OIL, USO, OSX)	
	Gas (UNG)	
	Agriculture (DBA)	

The IvyDB US database also contains risk free rate series and the historical (closing) prices of the associated underlying instruments and option sensitivities for all the different options (delta/gamma/vega etc). This makes it possible to backtest option trading strategies, including hedging strategies for different greeks. We delta hedge our straddle positions and use the delta provided by the database where possible. IvyDB US calculates the greeks for European options using the Black & Scholes formula based on the midpoint price. For American options the greeks are calculated using a proprietary algorithm based on Cox, Ross and Rubinstein binomial tree model (Cox et al. (1979)). Sometimes the deltas are missing for an individual option. In that case we use the data available at that specific point of time and extrapolate or interpolate to find the missing deltas. Battalio and Schultz (2006) note that option prices and underlying prices are frequently recorded at a different time in IvyDB US. This is due to the different times the options and the underlying cease trading for the day.

Duplicate Assets

We study the volatility premium by using options. For a European call the vega and gamma is equal to the vega and gamma of the European put (see Appendix G). This means that after we delta hedge both options, the assets are identical in terms of delta, gamma and vega exposure [10]. In this sense our study of delta hedged straddles is the same as the approach Bakshi and Kapadia (2003) in which they delta hedge puts instead of straddles. With our approach of delta hedging a straddle we attempt to average out measurement errors in the calculated returns of our option portfolio which are caused by our inability to measure the exact fair value as we take the midpoint of the bid-ask spread. In Figure 1 you find the put and call returns for the SPX index and see that returns are indeed very similar with a correlation of 0.89, but not exactly the same.

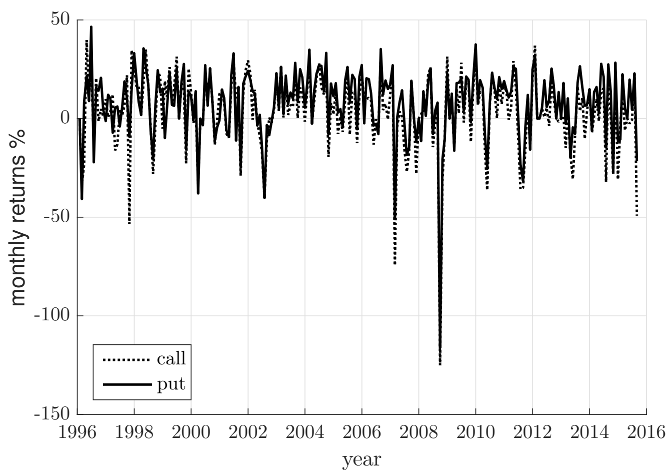


Figure 1: Monthly returns delta hedged SPX calls and versus puts

This figure shows the returns of the monthly atm delta-hedging strategy for the atm call options and the atm put options over the sample February 1996 till August 2015 for the SPX Index. The return is related to the price of the option at the beginning of the holding period and includes the interest that is earned (paid) by selling (buying) the stock.

In a similar way we show the relation between ETF and Index options on the same underlying. The SPX Index and SPY ETF are both assets that are based on the S&P

[10] We ignore here the difference between American and European options.

500. This means that the two assets should trade within arbitrage bounds of each other as when the SPY ETF becomes overvalued compared to the underlying S&P 500 basket you can redeem your ETF shares and substitute them for shares of the underlying basket. Arbitragers step in every time these arbitrage bounds are violated and make a risk free profit. Apart from the similarities between the SPY and the SPX there are the following differences, the SPY ETF started trading later than Index options on the SPX and the SPY trades at one tenth of the value of the SPX. This makes the SPY ETF more accessible to smaller investors having to put down a smaller amount of money to gain exposure. Trading in the SPY ETF is more liquid than the SPX options in the sample period where both are available from February 2005 till August 2015[11]. We established the arbitrage bounds for the Index versus the ETF, the same holds for the options. Since the options on the SPY and SPX are based on essentially the same underlying, arbitrage bounds keep the prices in line. To show this we compare the returns of the SPX and the SPY atm delta hedged options. Figure 12 in Appendix E clearly shows that the monthly returns for the delta hedged strategy from Section 2.3 are almost identical.

Option trading volumes

In Appendix D you can find the cumulative interest in the different asset classes in terms of contracts traded for the put and call options. In every asset class we see the same general pattern for both put and call options, volumes increase as we move from in the money to out of the money and peaks slightly out of the money. The relative interest between put and call options differs between asset classes. For commodities and currency we see cumulatively more call options trade, where for equity indices and (corporate) bonds the put options are relatively more popular. Gold (GLD) options for example have a call put ratio of 1.35 meaning that there is 35% higher volume in the call options than the put options, on the opposite side of the spectrum the call put ratio for the SPX options is 0.60. The put call ratios are highly persistent through time.

[11]By liquidity we here mean quantity volume, in terms of notional the index is still larger.

4 The Global Volatility Risk Premium

In this section we analyze the summary statistics of the volatility risk premium portfolios in the different asset classes. First we analyze them by asset class in Section 4.1. Secondly we analyze the global volatility risk premium by combining the asset class portfolios risk equally weighted in Section 4.2. Thirdly we analyze the global volatility risk premium portfolio where we do not delta hedge in Section 4.3. Lastly we alter the equal weighting scheme in an asset class based on the difference between the historical realized volatility and the implied volatility in Section 4.4.

4.1 The Volatility Risk Premium per Asset Class

For each asset within each asset class we write delta hedged at-the-money straddles and calculate the returns using equation (13). Table 3 reports the annualized mean, standard deviation, skewness, kurtosis, best and worst monthly return and Sharpe ratio of the Volatility Risk Premium (VRP) for each asset class. We are the first to examine the VRP for credits made possible by the existence of three large ETFs - one with AUM in excess of 32 billion for investment grade and two in excess of 10 billion for high yield. We find an impressive Sharpe ratio of 1.55 for credits. All other asset classes have been investigated before, but in most cases by studying the period 1996 to 2015 we are looking to a large extent at an out-of-sample period including the 2008 market crash. The results for government bonds, commodities and equity indices are all highly significant with a Sharpe ratio above one. Only for currencies (which has the shortest sample from 2007-2015) we see a modest VRP with a Sharpe of 0.27.

Out of the 60 considered assets 50 have a positive Sharpe showing that the result is robust for many different assets and not determined by a few positive outliers. The Sharpe ratios range from -1.31 to 3.55 over all the assets. The robust results indicate that the volatility risk premium is a strong factor across asset classes. And this result is achieved by using a single uniform strategy in all asset classes: writing delta hedged at-the-money straddles. Appendix C shows the results per individual asset, including the sample period over which each individual asset is available.

It is worth noting that in each of the five asset classes the skewness is negative, ranging from -0.8 for commodities to -4.2 for currencies. The currency portfolio also has a very high kurtosis of 28.43, this is mostly due to the event where the Swiss currency appreciated more than 20% relatively to the euro on 15 January 2015 as the central bank abandoned

Table 3: The Returns of the Volatility Risk Premium per Asset Class

This table reports for each asset class the mean annualized excess return, the annualized standard deviation of return, the skewness of monthly returns, kurtosis of monthly returns, the worst and best monthly return, and the annualized Sharpe ratio of the Volatility Risk Premium (VRP). This strategy at the start of each month writes delta hedged at-the-money straddles on all individual assets within each asset class. The final column shows the results when combining the returns of the VRP in the individual asset classes by scaling each portfolio return to a 10 percent standard deviation based on the full-sample standard deviation and then equally weighting the scaled return series. The resulting portfolio is called the Global Volatility Risk Premium (GVRP).

	Credits	Government Bonds	Commodities	Currencies	Equity Indices	GVRP
Mean %	112.61	73.43	50.78	24.08	63.64	10.95
St. Dev. %	72.72	62.42	48.09	89.11	54.26	7.57
Skewness	−1.05	−1.04	−0.81	−4.23	−1.48	−1.28
Kurtosis	4.54	4.69	3.66	28.43	7.73	6.42
Min %	−64.52	−62.55	−45.62	−180.19	−86.58	−10.30
Max %	54.22	43.99	32.45	30.21	30.47	6.30
Sharpe	1.55	1.18	1.06	0.27	1.17	1.45

the cap. The asymmetrical payoff is to be expected as the payout is closely related to the difference between the implied volatility and the realized volatility. Both realized volatility (RV) and implied volatility (IV) can suddenly spike with specific events, which will cause large losses for the strategy, and then gradually returns to normal levels resulting in steady gains. Also the excess kurtosis is high indicating fat-tailed positive and negative returns.

In the Appendix in Figure 13 you can find the cumulative log excess returns of the VRP returns per asset class. In general the performance is strong over time for each asset class. We also see substantial drawdowns which can coincide, for example in Q4 2008, and sometimes are specific to that asset class alone. Credits do not suffer a drawdown in 2008 but this is caused by the assets having no atm straddles available leading to us recording no returns. If there would have been options available it is likely we would have suffered a loss.

4.2 The Global Volatility Risk Premium

The final column in Table 3 reports the performance of the portfolio that invests in the VRP in all asset classes. For this purpose we construct a risk equally weighted portfolio that each VRP contributes equally to the total volatility of the Global Volatility Risk Premium (GVRP). To make all the assets contribute equally, we scale all the asset classes to 10% annual standard deviation before combining them. This procedure is the same as in Moskowitz et al. (2012), Asness et al. (2013), and Koijen et al. (2015).

The GVRP has a Sharpe ratio of 1.45 making it one of the strongest factors in the academic literature. The Sharpe ratios for the five asset classes average 1.05, hence there are diversification benefits of applying the VRP across asset classes. On the other hand if the VRP returns per asset class would have zero correlation with each other we would have expected the Sharpe ratio to increase by a factor $\sqrt{5}$ whereas the actual increase is roughly 40 percent. This suggests that there is quite some correlation between the VRP returns of the different asset classes. The interdependence is also visible from the negative skewness of -1.28, suggesting that large losses in each asset class tend to coincide.

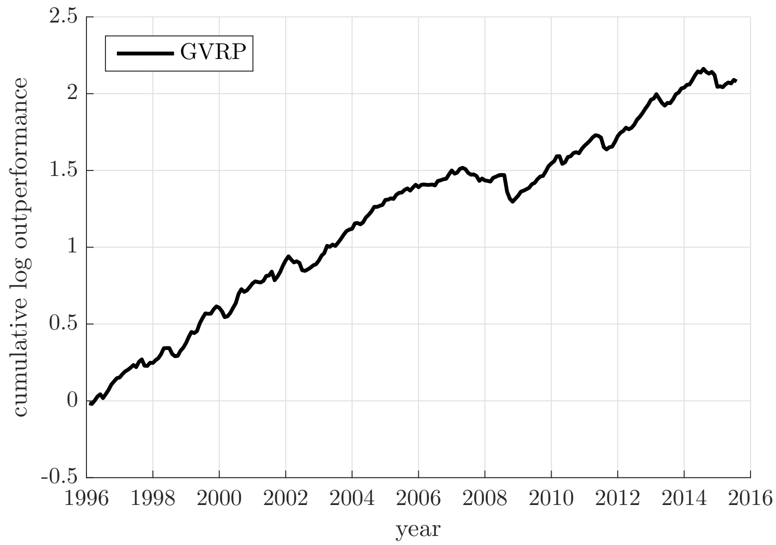


Figure 2: Cumulative Performance of the GVRP

This figure shows the cumulative sum of the log excess returns of the Global Volatility Risk Premium portfolio (GVRP). The GVRP returns are calculated as the equally weighted average of the returns of the VRP per asset class after scaling these returns to 10% annualized volatility. The sample period is from February 1996 till August 2015.

Figure 2 contains the log cumulative performance of the GVRP. The returns for the GVRP are impressive throughout the sample, but it also exhibits a large drawdown in the fourth quarter of 2008 when both the RV and the IV spiked in all asset classes leading to losses in all VRPs. In Section 5 we will further investigate the dependence between the VRP's as well as study possible explanations of the strong results for the GVRP.

4.3 The Global Volatility Risk Premium Naked

Delta-hedging the straddle positions generates more transaction costs as the frequency of delta-hedging N over the holding period increases. Therefore less frequent delta-hedging can be seen as beneficial for practitioners who do not want to keep track of the delta position on a daily basis or want to avoid the transactions costs involved.

A special case is when we choose N to equal zero so we do not delta hedge over the holding period. This has considerable consequences for the returns of the strategy. First in Section 3 we showed how the returns of a delta hedged atm put and a delta hedged atm call on the same underlying are empirically highly positively correlated. For the unhedged option returns the delta of the atm call (0.5) is the opposite of the atm put (-0.5). This means that an upward move in the underlying results in a profit for the long call position while the long put position suffers a loss of the same magnitude. The returns of the naked long call and put position are now negatively correlated instead of positively correlated if we were to delta-hedge.

Due to the second derivative (gamma) of the option to the underlying the delta of the long atm call position becomes more positive as the underlying drift upwards, while the delta of the put decreases and becomes less negative. As a result a further upward drift in the underlying leads to a bigger positive gain for the long call position then the loss for long atm call position. Hence as we move further away from the atm strike the negative correlation between the call and the put decreases. Since the correlation fluctuates the average realized return for the put and the call as well as the realized volatility can differ.

Not delta-hedging has as a consequence that the return of the straddle portfolio becomes more path dependent. Consider a daily delta hedged long straddle portfolio. Two consecutive daily returns in the underlying of -1% and again -1% produces roughly the same portfolio return as two daily returns in the underlying of -1% and 1%[12]. This is due to the fact that we delta hedge the exposure to the underlying every end of day so that the return of the delta hedged straddle is mostly driven by gamma and changes in the implied volatility.

An unhedged straddle portfolio has an equal return to the delta hedged straddle portfolio after the first day of the holding period as the straddle portfolio initial has a zero delta. However the unhedged straddle portfolio has a negative delta position at the end of day one, compared to the zero delta exposure of the delta hedged straddle. If the underlying experiences a negative return of -1% again the unhedged portfolio becomes more valuable

[12] We ignore the reduction in gamma as we move further away from the strike.

both because of the gamma - and the negative delta position. If the underlying moves up 1% we end up where we started, the unhedged straddle is now worth less than two days earlier as the option now has less time to maturity left.

The methodology for the unhedged straddle portfolios simplifies to selling the straddle at the beginning of the holding period and buying it back at the end of the holding period. The monetary return for a short straddle portfolio over holding period t till $t+\tau$ then simplifies to $P_t - P_{t+\tau} + C_t - C_{t+\tau}$.

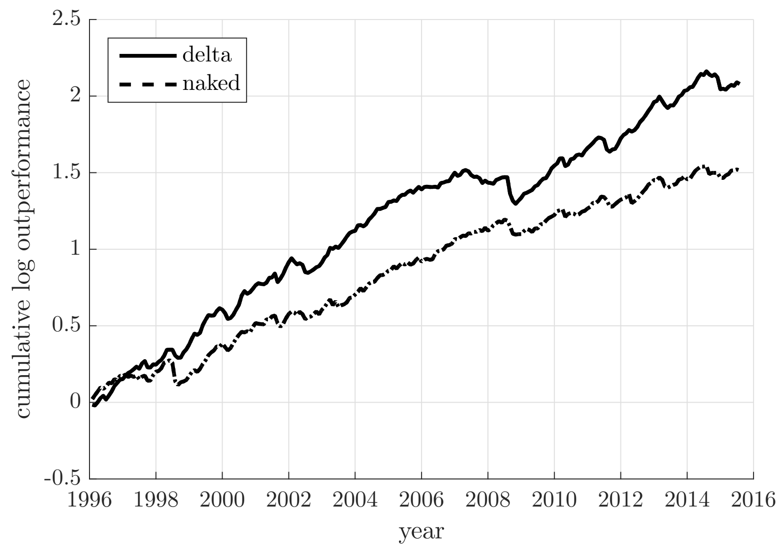


Figure 3: Naked versus delta hedged

This Figure shows the cumulative log outperformance of the delta hedged global volatility risk premium portfolio and the naked portfolio. For both portfolios the asset class portfolios are scaled to have 10% annual standard deviation before combining them equally weighted. The sample period is from February 1996 till August 2015.

We again construct the GVRP portfolio with the condition that we keep all the straddles naked for our 60 assets within the 5 asset classes. We scaled the resulting asset class portfolio to have 10% annual standard deviation for easy comparison with the delta hedged GVRP. In Figure 3 you can see the log cumulative outperformance of the naked and as a benchmark the delta hedged portfolio. The Sharpe ratio is 1.15 with average excess yearly returns of 8.0% and standard deviation of 7.0%. The returns of the delta hedged and unhedged straddle portfolio follow a similar pattern. However the unhedged strategy earns less per unit risk and therefore the cumulative performance of the naked portfolio lacks behind the delta hedged portfolio.

The returns of the two constituents of the unhedged straddle can be vastly different.

Hence the return of the total straddle can be dominated by the return of the put or the call option. For the S&P 500 the annualized average return of the short naked put is 266.2%, compared to 34.6% for the naked short call. The average returns differ almost 8 fold in size. We observe the same pattern for bonds (TLT) with -122% average annual return for short call and 201.7% average annual return for the put. In both cases the option that pays off in bad states of the world carries the largest premium. We will study the unhedged returns of the call and put in more detail in Section 6.

4.4 The Global Volatility Risk Premium Enhanced

In section 4.2 we constructed the Global Volatility Risk Premium (GVRP) portfolio by combining the asset class returns risk equally weighted. Each asset class portfolio is constructed by combining all the constituents equally weighted. However recent research by Goyal and Saretto (2007) showed that outperformance can be achieved in US equities by taking into account the difference between implied volatility (IV) and the realized volatility (RV) in order to identify over- and underpriced options. Goyal and Saretto (2007) sort stock options based on the difference between the historical realized volatility and at-the-money implied volatilities and construct straddle portfolios. They find economically significant returns for a zero-cost trading strategy that goes long in assets with a large positive difference between the historical and implied volatility and short where we have a large negative difference. We apply the same measure between the realized and the implied volatility for our GVRP portfolio in order to see if we can more efficiently go short volatility by shorting the most where the opportunity is the largest. Our hypothesis is that an underlying where the implied volatility is relatively large compared to its historical volatility relative to the other underlyings this underlying offers a bigger opportunity relatively to the others.

We evaluate both the last month RV, and the yearly RV for sorting, Figure 4 shows the results. For the 1 year RV we find an average annual return of 11.62% with a standard deviation of 7.51% for a Sharpe ratio of 1.55. For the 1 month RV we find an average annual return of 11.49% with a standard deviation of 7.45% for a Sharpe ratio of 1.54. This is compared to the average return of 10.95% with standard deviaton of 7.57% with a Sharpe ratio of 1.45 for the original GVRP portfolio. In both cases the Sharpe ratio improves over the original GVRP portfolio. We perform the Jobson and Korkie (1981) Sharpe ratio test with the correction from Memmel (2003) to test if the Sharpe ratios significantly increase over the original GVRP portfolio. We find a significant p-value of 0.001 for the 1 month

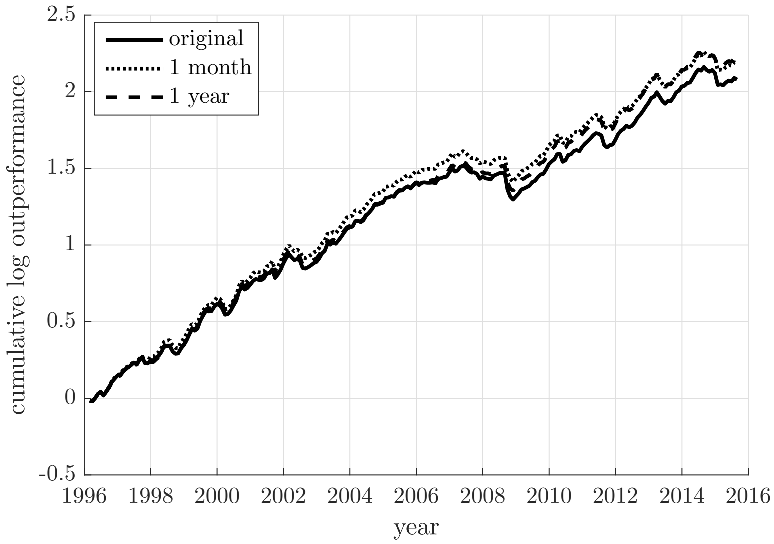


Figure 4: Comparison GVRP Enhanced

This Figure shows the cumulative log outperformance of the portfolios sorted on the 1 month realized volatility, the 1 year realized volatility and for comparison the original GVRP portfolio. For all three portfolios the asset class portfolios are scaled to have 10% annual standard deviation before combining them equally weighted. The sample period is from February 1996 till August 2015.

RV portfolio and 0.003 for the 1 year RV portfolio. Hence we conclude that sorting on the difference between the RV and the IV can improve the performance of the GVRP portfolio significantly further[13].

5 Potential Explanations for the VRP

We find a highly statistical and economical significant global volatility risk premium, we now investigate possible explanations for this result. What is driving the global volatility risk premium? We first look for common variation in the volatility risk premium across asset classes in Section 5.1 to check whether a common risk factor could explain the premium. Secondly, we study the relation between the global volatility risk premium and various candidates for the common risk factor: volatility risk, crash risk, liquidity risk, macroeconomic risk and the relation with other global factors.

[13]In Appendix J we also consider long short portfolios instead of short only and find positive excess returns.

5.1 Common Risks

Table 4 reports the monthly correlations of VRP returns across the five asset classes. All the correlations are positive, but the average correlation is a modest 38 percent. These moderate correlations suggest that substantial diversification benefits can be achieved by combining the five VRP's into the GVRP. However, correlations will be downward biased due to the noise in monthly returns and are not saying anything about co-movements in returns in for example bad times.

Table 4: Correlations between VRP Returns of Different Asset Classes

This table shows the monthly return correlations between the VRP returns of the five asset classes.

	Credits	Government Bonds	Commodities	Currencies	Equity Indices
Credits	1	0.44	0.22	0.28	0.39
Government Bonds		1	0.23	0.39	0.43
Commodities			1	0.48	0.48
Currencies				1	0.5
Equity Indices					1

Following the methodology of Koijen et al. (2015) we investigate the commonality for the VRP across asset classes by looking at correlations during GVRP expansions (positive performance) and drawdowns (negative performance). The results in Table 5 show the correlations during drawdowns (left bottom triangle) and expansions (upper right triangle). In general most correlations between the VRP returns across asset classes are higher during drawdowns. Also the correlation of each VRP with the GVRP is larger during GVRP drawdowns.

Another way to look at commonality in the VRP returns for the different asset classes is to regress each individual asset class VRP returns on the GVRP, see Table 6. For each asset class the VRP loads significantly on the GVRP, also when excluding the VRP of that asset class from the GVRP. Hence there is a significant commonality in the VRP returns. For credits, commodities, and equities this even leads to a no longer significant alpha. This indicates to a strong common component in the VRP returns of the different asset classes.

5.2 Risk-Adjusted Performance and Exposure to Other Factors

The first attempt to explain the common variation in the VRP returns reported in the previous section is to see to what extent the VRP returns can be explained by the underly-

Table 5: correlation Drawdown-Expansion

This table provides the correlations between the asset class portfolios and the gvrp portfolio in drawdons and expansions of the gvrp portfolio. The left bottom triangle contains the correlation between the asset classes under the condition that GVRP has a negative return. Vica versa the top right triangle contains the correlations between the asset classes when the GVRP portfolio has a positive return.

	Credits	Government Bonds	Commodities	Currencies	Equity Indices
Credits	1	0.15	−0.07	−0.11	0.02
Government Bonds	0.56	1	−0.09	0.01	0.13
Commodities	−0.02	−0.15	1	0.38	0.14
Currency	−0.03	0.01	0.19	1	0.29
Equity Indices	0.21	0.25	0.17	0.25	1

Table 6: Individual VRP exposure to GVRP

This table provides the results from regressing the VRP of each asset class on the GVRP including the VRP of that asset class (columns labelled 'incl') or the GVRP excluding the VRP of that asset class (columns labelled 'excl'). We report the intercept or α and the beta ('GVRP') along with the t-statistics, and the R^2 from the regression.

	Credits		Government Bonds		Commodities		Currencies		Equity Indices	
	incl	excl	incl	excl	incl	excl	incl	excl	incl	excl
mean	1.29	1.29	0.98	0.98	0.88	0.88	0.23	0.23	0.98	0.98
t-stat	(4.60)	(4.60)	(4.79)	(4.79)	(4.66)	(4.66)	(0.76)	(0.76)	(5.19)	(5.19)
α	0.14	0.61	0.08	0.52	0.00	0.41	−0.39	−0.27	0.00	0.36
t-stat	(0.41)	(1.48)	(0.4)	(2.03)	(−0.01)	(1.72)	(−1.16)	(−0.78)	(0.02)	(1.59)
GVRP	1.08	0.67	0.99	0.53	0.96	0.5	0.88	0.59	1.07	0.69
t-stat	(10.77)	(4.46)	(14.43)	(5.08)	(12.7)	(6.28)	(4.07)	(5.68)	(12.00)	(5.89)
R^2	46.78	19.04	49.03	16.46	52.66	17.4	54.99	25.99	65.24	31.02

ing market (equally weighted return of the assets underlying the options) and factors that also generate strong returns: value, cross-sectional momentum and time-series momentum. The results in Table 7 show that the alpha, i.e. the risk-adjusted performance, for each VRP is positive and significant for all five asset classes. In fact for government bonds and currencies the alpha is even higher than the unadjusted performance (the mean is shown in row one of Table 6). The market and factors explain most for currencies and equity indices. For equity indices we see a strong loading on the equity market indicating that the VRP returns are more positive when equity markets are rallying and more negative in equity bear markets. This makes sense as equity bear markets are often accompanied by rising equity volatility which is detrimental for the VRP returns. Interestingly the VRP for government bonds loads negatively on the bond market. One example from 2008 is that the implied volatility for the bond options reached an all-time high leading to a large loss for the VRP, whilst government bond returns were very positive.

Table 7: VRP Exposures to Other Factors

This table provides the results from regressing the VRP of each asset class on the underlying market (equally weighted return of all the assets underlying the options), value, cross-sectional momentum (mom) and time-series momentum (tsmom). We report the risk-adjusted performance (α), the beta coefficients of the market and the factors, t-statistics, and the R^2.

Panel A: Regression Per Asset Class All Factors										
	Credits		Gov. Bonds		Commodities		Currencies		Equity Indices	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
α	0.79	(2.0)	1.23	(5.5)	0.83	(3.4)	0.71	(2.8)	0.83	(4.1)
passive	0.22	(1.1)	−0.24	(−3.7)	0.06	(1.6)	0.15	(1.4)	0.20	(3.9)
value	−0.37	(−0.6)	−0.60	(−1.9)	0.06	(1.3)	−0.27	(−3.2)	0.38	(3.2)
mom	−0.43	(−0.9)	0.44	(1.2)	0.13	(3.2)	0.11	(1.0)	0.23	(2.3)
tsmom	−0.01	(−0.2)	−0.04	(−1.5)	−0.05	(−0.9)	−0.01	(−0.3)	0.00	(0.1)
R^2	4.0		11.6		6.0		30.8		23.3	

Panel B: Regression Per Asset Passive Long										
	Credits		Gov. Bonds		Commodities		Currencies		Equity Indices	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
α	1.20	(3.2)	0.99	(4.6)	0.87	(4.0)	0.18	(0.6)	0.86	(4.5)
passive	0.27	(1.3)	−0.14	(−2.3)	0.07	(1.8)	0.29	(2.5)	0.21	(4.0)
R^2	3.4		3.1		3.8		5.2		15.5	

5.3 Crashes and Downside Risk Exposure

A popular hypothesis for strong factor returns is whether the returns compensate investors for crash risk or negative returns during "bad times". One way to test this is to look at whether VRP returns are poor when the underlying assets have negative returns. For this Henriksson and Merton (1981) propose the following regression,

$$r_t = \alpha + \beta_{mkt} r_{mkt} + \beta_{down} \max(0, -r_{mkt}) + \epsilon_t \tag{18}$$

where the market return for an asset class is the equally weighted return of all the underlyings for the options in an asset class. The results in Table 8 Panel A indeed show a strong significant loading on β_{down} for all asset classes. The R squared is now also more than 20 percent for credits, commodities and equity indices indicating that a substantial part in variation of the VRP returns can be explained by downside risk. However, the alphas for credits, government bonds, commodities and equity indices are still highly significant. Hence crash risk can only partly explain the VRP returns.

An alternative version of equation (18) is to only consider negative market returns when they exceed minus one standard deviation instead of looking at all negative market returns, following Lettau et al. (2014). Panel B in Table 8 shows the results. We see similar results as in Panel A. There is a significant loading on downside risk[14], with the exception of credits where we have only a small number of observations with market returns more negative than one standard deviation. In general the alphas in Panel B are lower than in Panel A. But they are still highly significant for credits, government bonds, commodities and equity indices.

5.4 Global Liquidity and Volatility Risk

Several studies have looked at liquidity risks and volatility risk to explain excess returns. We measure market liquidity by looking at the TED spread, the difference between interest rates on interbank loans and on short-term U.S. government debt. Our TED measure is the average taken over the G10 countries rather than only the U.S. We measure volatility risk by changes in the VIX, the implied volatility index for S&P 500 index options. Table 9 shows the results from regressing the VRP returns on liquidity risk and volatility changes.

In general both liquidity risk and volatility changes are important. For the latter this is as expected. A rise in equity implied volatilities is obviously detrimental for the VRP applied to equity indices as the payoff of the delta hedged straddle is directly related to the difference between the implied volatility at the start of writing the straddle and the realized volatility in the subsequent month. A rise in VIX during that month will imply a rise in the realized volatility which in turn will lower or even turn negative the difference between the implied volatility at the start of the month and the realized volatility. Hence

[14]Bollerslev et al. (2015) use high frequency data to accurately measure realized volatility for the S&P 500 returns to get a daily measure of the VRP for the S&P 500. This allows to identify two types of risks that can explain the existence of the VRP. One attributable to market fears and a special compensation for jump tail risk. It appears we have traction with the downside risk in terms of fear for market losses, but get nothing extra out of looking at more extreme negative market returns.

Table 8: Exposure to Downside Risk

In this Table we report the results from regressing the VRP returns on the market (the equally average return of all the assets underlying the options) on downside risk measures. Panel A reports the regression results from the Henriksson and Merton (1981) model, where downside beta is estimated on the market beta and the maximum of zero and minus the market. The results include the α (risk-adjusted performance), market beta and downside beta along with their t-statistics. The final column shows the R^2. In Panel B we report the Lettau et al. (2014) downside risk measure where we estimate the market beta and the conditional beta where the excess market return is one standard deviation below zero.

Panel A: Regression Henrikkson and Merton (1981)

	α	t-stat	β_{mkt}	t-stat	β_{down}	t-stat	R^2
Credits	2.51	(4.8)	−0.52	(−2.0)	−1.88	(−2.9)	22.6
Government Bonds	1.80	(6.5)	−0.44	(−5.3)	−0.68	(−3.9)	11.5
Commodities	2.40	(10.5)	−0.18	(−5.0)	−0.49	(−9.5)	24.6
Currency	0.84	(1.5)	−0.02	(−0.2)	−0.81	(−1.9)	9.2
Equity Indices	1.94	(6.8)	−0.05	(−0.9)	−0.51	(−4.4)	24.3

Panel B: Regression Lettau, Maggiori and Weber (2014)

	α	t-stat	β_{mkt}	t-stat	β_{down}	t-stat	R^2
Credits	1.34	(3.4)	0.13	(0.6)	−0.61	(−1.0)	6.0
Government Bonds	1.36	(5.9)	−0.33	(−4.5)	−0.49	(−3.5)	9.5
Commodities	2.20	(10.1)	−0.16	(−4.5)	−0.46	(−9.3)	25.8
Currency	0.43	(1.2)	0.10	(1.3)	−0.87	(−3.3)	12.0
Equity Indices	1.56	(6.5)	0.02	(0.4)	−0.39	(−3.9)	22.9

no surprise to see for the VRP for equity indices the highly significant negative loading on changes in VIX with a t-statistic of -10.8. The fact that changes in VIX also have significant explanatory power for VRP returns in the other asset classes simply illustrate again a strong commonality in volatility changes across asset classes. VIX increases are likely to coincide with increases in implied and realized volatilities for credits, government bonds, commodities and currencies as illustrated by the significant negative loadings on VIX changes for these asset classes. Nevertheless the alphas are still highly significant for all asset classes except for currencies.

5.5 Drawdowns

We analyze the drawdown periods of the GVRP portfolio in terms of length, severity and check if these periods coincide with a global crises. First we present summary statistics about the five biggest drawdowns the GVRP portfolio suffers which can be found in Table

Table 9: Global Liquidity and Volatility Risk

This table shows the results from the regression of volatility risk premium (VRP) returns of each asset class on the changes in VIX, the implied volatlity index for the S&P 500 index options, and the TED spread as a proxy for liquidity risk. The TED spread is the difference between the interest rates on interbank loans and on short-term U.S. government debt. Our measure is an average taken over the G10 countries rather than using only the U.S. TED spread. The table shows the alpha, the betas for liquidity (TED spread), the change in VIX (ΔVIX) and the R^2.

	Credits		Gov. Bonds		Commodities		Currencies		Equity Indices	
	beta	*t*-stat	beta	*t*-stat	beta	*t*-stat	beta	*t*-stat	beta	*t*-stat
α	2.89	(7.6)	1.38	(4.1)	1.40	(5.4)	0.63	(1.1)	1.79	(7.5)
TED spread	–0.03	(–6.9)	–0.01	(–1.7)	–0.01	(–3.5)	–0.01	(–1.4)	–0.01	(–4.0)
ΔVIX	–0.17	(–2.6)	–0.16	(–3.3)	–0.23	(–6.6)	–0.18	(–4.5)	–0.36	(–10.8)
R^2	28.2		9.7		18.3		16.3		42.7	

10.

Table 10: Drawdowns

This table contains summary statistics for the 5 worst drawdowns of the GVRP portfolio over the period 1996 till 2015. The column named months contains the amount of months it takes between the start of the drawdown and the start of the recovery.

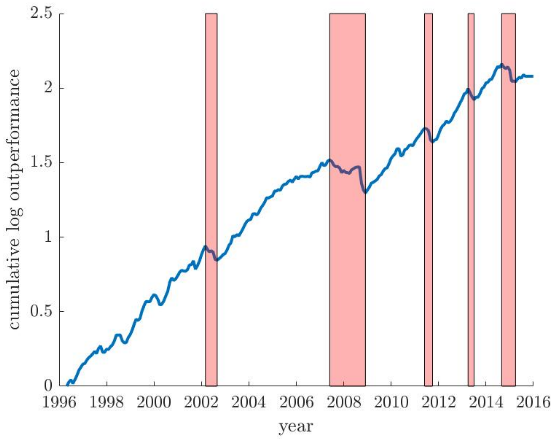
start drawdown	start recovery	end recovery	months	peak-through (%)
05–2007	11–2008	12–2009	18	–22.0
08–2014	03–2015	12–2015	7	–12.0
03–2002	08–2002	03–2003	6	–9.5
05–2011	09–2011	03–2012	4	–9.3
03–2013	06–2013	11–2013	3	–7.5

We see that the worst drawdown in 2007/2008 coincides with the biggest global crisis in recent years which put the US in a recession. In 2011 the GVRP portfolio experiences a drawdown together with the European Debt crisis. The drawdown in August 2014 is caused by turmoil in commodities and currencies.

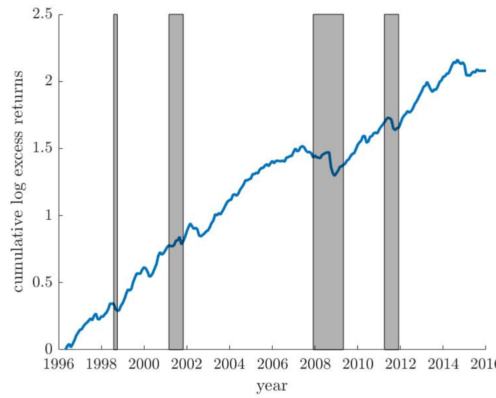
We use the recession indicator of the National Bureau of Economic Research which is based on the US business cycle[15]. In recent years this indicator records two recessions: March 2001 till November 2001 (8 months) and December 2007 till June 2009 (18 months). In Figure 5a you can find the cumulative log returns of the GVRP portfolio and shaded in

[15] http://www.nber.org/cycles.html

red are the periods where the portfolio suffered a drawdown. We see that both recessions overlap with a period in which the global VRP portfolio suffers a drawdown.



(a) Drawdowns GVRP



(b) Recessions

Figure 5: Cumulative return GVRP with recessions / drawdowns

Figure 5a contains the cumulative log returns of the GVRP portfolio. Shaded are the periods in which the portfolio experience one of its 5 worst drawdowns. In Figure 5b the cumulative log returns are again plotted but now shaded are the recession indicator of the NBER and seperately shaded are the Ruble crisis and the Greece debt crisis.

6 The Term Structure of the Volatility Premium

The average return of the naked call and the naked put on the same strike for the same underlying can differ significantly as the options have opposite sensitivity towards the underlying. This leads to the question if allocating evenly to the atm put and call is optimal if the returns of the call and put differ or if we can optimize the weighting in order to get better results. To optimize we will need a deeper understanding of the option returns and the correlations between call and put options of different maturity and moneyness. Therefore we first study the returns of the naked put and call options on the S&P 500 separately to gain insight in what a potential model for these returns should be able to explain. Then we evaluate if the found insights carry over to bonds and gold which belong to different asset classes. Lastly we propose a regression model to explain and forecast the average returns alongside the covariance matrix and evaluate the performance.

6.1 S&P 500 Naked Returns

The returns of the individual call and put options of the S&P 500 have been studied by Bondarenko (2014). They found that the naked put options on the S&P 500 were grossly overpriced over the period 1987 till 2000. The average excess return per month is -39% for atm and -95% for far out of the money naked puts. Over our sample (which is entirely out-of-sample compared to Bondarenko (2014)) from 1996 till 2015, which includes the global financial crisis of 2008, puts have remained overpriced with an average excess return per month of -41.4% for atm and -95.7% for far otm naked put options. Bondarenko (2014) noted that naked put options correlate negatively with the market which carries a positive risk premium so we can expect a negative put premium. Furthermore options carry leverage which could magnify this effect. Put options pay off in bad states of the world for which investors are willing to pay a premium depending on how risk averse they are.

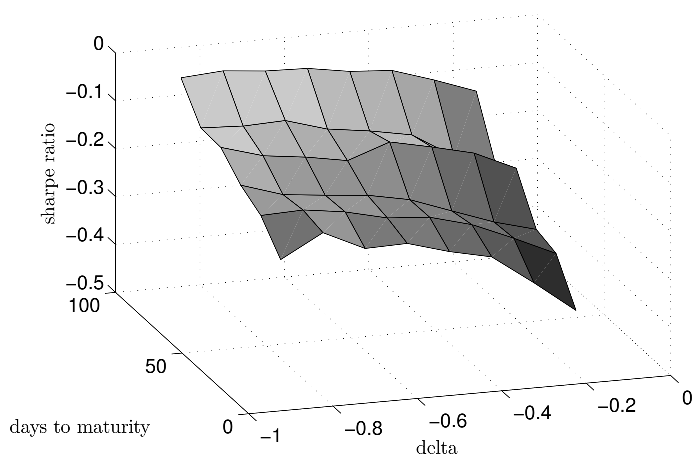


Figure 6: Term Structure Sharpe Ratio SPX Put options

This Figure shows the term structure of the Sharpe ratio for put options on the SPX Index based on delta and time to maturity over the period February 1996 till August 2015. The surface is created by making buckets based on the delta with a width of 0.1 and based on the time to maturity with a width of 10 days. The width is chosen as a too small width would lead to a very noisy surface with few observation belonging to each bucket.

In Figure 7 we see the term structure of the monthly average excess returns for put options on the S&P500. The returns are rescaled to a 30 day holding period in line with Bondarenko (2014) to make the returns between different maturities comparable. It can be clearly seen that the returns are decreasing as we go further out of the money and as the time to maturity decreases. Based on these expected returns we could argue that selling an atm put is sub optimal to selling an otm put. In Figure 6 you can see the Sharpe ratio as a function of delta and the time to maturity. Again based on the Sharpe ratio shorting out of the money options on the S&P 500 would be the best choice.

In Figure 7 you can find the term structure of the average monthly returns of the SPX Index put options over the period January 1996 till August 2015. The surface is created by making buckets based on the delta with width 0.1 and based on the time to maturity with a width of 10 days. The returns are rescaled to a 30 day holding period to make the returns for different maturities comparable (in line with Bondarenko (2014). We picked these stepsizes because picking the buckets with a too small window of expiry or delta leads to a very noisy surface that is very difficult to fit when minimizing quadratic errors. We see that in line with Bondarenko (2014) that as we have less days to maturity the average return becomes more negative, furthermore we see that as we move further out of the money the returns become more negative. Bondarenko (2014) found that atm put options with one month to maturity had on average -39% return and far out the money -95% return. We find very similar results over our sample period, which includes the crash of 2008, with -41.3% average return for atm options and -95.7% for very far out of the money options.

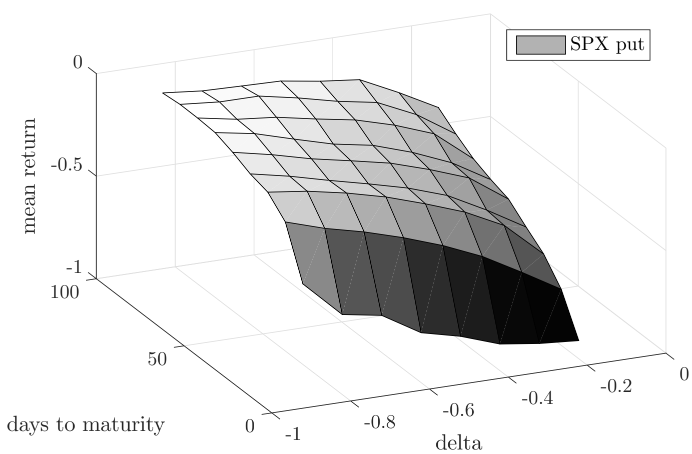


Figure 7: Term Structure SPX Put options

This Figure shows the term structure of the average returns for put options on the SPX Index based on delta and time to maturity over the period February 1996 till August 2015. The surface is created by making buckets based on the delta with a width of 0.1 and based on the time to maturity with a width of 10 days. The width is chosen as a too small width would lead to a very noisy surface with few observation belonging to each bucket.

6.2 Gold and Bonds Naked Options

Here we investigate if the term structure that we found for S&P 500 (SPX) put options is consistent across other assets. We focus on the gold (GLD) options and the government bond (TLT) options as they are liquid and belong to different asset classes than equity indices. In Appendix I you can find the term structures for the call and put options on gold, bonds and the S&P 500 over the full sample period. Gold is an interesting candidate as the ratio between the call and put volumes is higher than one at 1.35 over the full sample, meaning that there is more interest in calls relatively to puts. For bonds and equity index options it is the opposite as the call put ratio is lower than one, with 0.89 for bonds and 0.60 for the the S&P 500.

It is important to note that we find the same shape for the term structure for S&P 500 put options, bond put options and gold call options. The average returns for these options are strictly negative and downwards sloping as we get closer to expiry and further out of the money. This coincides with the call put volume ratio being above or below one, so where most trading takes place the average returns are negative. For the S&P 500 and the bond index the average investor is naturally long and would consider a very negative return as undesirable. In that sense there is a natural hedge demand for put options in both these assets. For gold options, one could argue that very positive returns for gold would coincide with a bad-state of the world, therefore we expect the same shape of the term structure not for the put options but for the call options. However, you could argue that negative average returns for puts (calls) are just caused by a positive (negative) returns of the underlying over the sample period (directional exposure). This argument does not hold as the average return for gold has been positive over the sample period but the average return for naked call options still are consistently negative. We conclude that the term structure seems to be consistent across asset classes based on where the bad state is for the average investor[16].

6.3 Model

In the previous sections we described the term structure found in the different assets. Any potential model should be able to capture the characteristics of the term structure of the

[16] As a proxy for where the natural hedging interest is one could look at the call put ratio. So for equities and bonds on the put side, and for gold on the call side.

average excess returns. We propose the following model for the term structure,

$$R_t = \alpha + \beta_{maturity} \frac{1}{T-t} + \beta_{delta} \frac{1}{|\Delta|} + \epsilon_t \tag{19}$$

We use the inverse of the absolute delta as a measure of the leverage of the option in order to capture the difference in average returns as we vary the moneyness of the option. Secondly we use the inverse of the time to maturity $T - t$ as a measure for the time to expiry. For example if there are still 90 days left till expiry the passing of 1 day is not very important as you still have 89 days left, where with 2 days to expiry 1 day represents 50% of the time that your option has to finish in-the-money. For near to expiry options the volatility of volatility is also higher compared to long term options which could be a reason for a higher premium.

We evaluate all the available options from the OptionMetrics database for which the delta is available. This should make it moderately easy to replicate the stated results as one does not need to fill in the missing deltas or delta hedge. We evaluate the options on every day and keep it naked till the option expires. For any option series that has N business days till expiry we will also get N option returns with different time to maturity but identical strike but varying moneyness (delta) as the stock (implied volatility) increases or decreases.

In Figure 8 you can find the visual fit of our regression model to the realized average return. The stepsize is 10 for the amount of days, and stepsize 0.1 for the delta region. We leave out all options with less than 20 days to expiry and options that are very far out of the money. For very far otm options the absolute spread becomes large compared to the value of the options and therefore using midpoint valuation to determine the return becomes problematic.

We see that overall the fit is decent and the residuals are centered around zero. The adjusted R-squared is equal to 0.80. In order to test if this model is promising we will perform a portfolio exercise that uses this model in Section 6.5.

6.4 Covariance Put and Call option

Our objective is to get a portfolio with the best return risk ratio. To adequately determine the riskiness of our portfolio we need a robust estimation of the covariance matrix between the put and call options for different maturities. Luckily we optimize per asset which means that all the options we use are on the same underlying. Therefore we are able

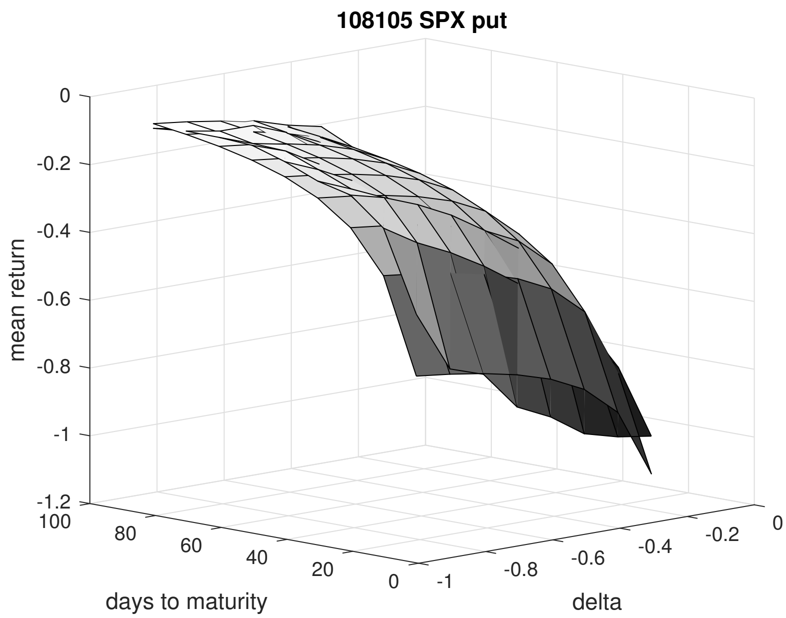


Figure 8: Term Structure Put options SPX

This figure shows the fit between the realized returns of SPX put options and the fit from our model.

to estimate the covariance matrix based on the assumption that the Black-Scholes model holds. Where the correlation between assets can differ over time, and is very difficult to estimate, this is not the case for options. When the underlying moves up all call options will become more valuable while all put options will become less valuable ceterus paribus. In order to simulate the covariance matrix of the put and call options we will simulate the returns of the underlying and calculate the returns and covariance matrix where we keep the implied volatility constant for all options. Since we select options based on delta and not moneyness the volatility of the underlying stock is not very important as the delta scales with (implied) volatility. We simulate a stock with 16% annual volatility, over a 30 day period with 3000 time steps. The stock is simulated as a discrete process from equation (20).

$$S_{t+1} = S_t e^{\left(r-\frac{\sigma^2}{2}\right)\Delta t+\sqrt{\Delta t}\sigma W_t} \tag{20}$$

Afterwards we calculate the returns under the Black–Scholes model for a fine grid of strike prices around S_t and 30-60 days to maturity. We simulate the stock return 100.000 times and calculate the 3000 by 3000 theoretical co-variance matrix under the Black–Scholes model.

6.5 Portfolio Optimization

Based on the simulated covariance matrix from Section 6.4 and the regression model from Section 6.3 for the expected returns we try to improve the performance of the GVRP portfolio. We try two different directions per asset, to improve the performance in terms of return per unit risk.

On an asset level we first relax the restriction that the portfolio needs to consist of one naked put and one naked call. Coval and Shumway (2001) show that if the stochastic discount factor is negatively correlated with the price of the underlying, any call option on that security will have a positive expected return that is increasing in the strike price. Likewise the expected return for the put option on that security will have a negative expected return that is increasing in strike price. We apply this insight by relaxing the weights of the put and call, but we do force the weights to be strictly negative as we want to stay consistent with shorting volatility. Secondly we broaden the investment universe in any period by including an otm put and an otm call into the optimization. Again the weights are strictly negative. The optimization allocates towards the otm put and otm call if this results in a higher expected return per unit risk.

6.5.1 Vary Allocation Straddle

First we optimize the allocation between atm put and call option with the restriction that the weights needs to be negative, to stay consistent with a negative volatility risk premium. At time t we pick the option expiry that has the most options available between 40 and 60 days till expiry. Within this set of options we pick the most atm put and call option. Based on the regression model and the simulated covariance matrix we pick the portfolio weights that maximizes the return per unit risk. The out of sample period starts 10 year after the first data become available. We do this for all assets after which we risk equally combine the return per asset class. In Figure 9 you can find the result. The average excess return is equal to 7.54% with an annualized standard deviation of 7.60% for a Sharpe ratio of 0.99. Compared to the GVRP portfolio over the same sample period with an average excess return of 6.43% with annual standard deviation of 6.26% for a Sharpe ratio of 1.09. We conclude that although our optimization produced a better average return the overall Sharpe ratio decreases compared to the GVRP portfolio due to an increase in standard deviation.

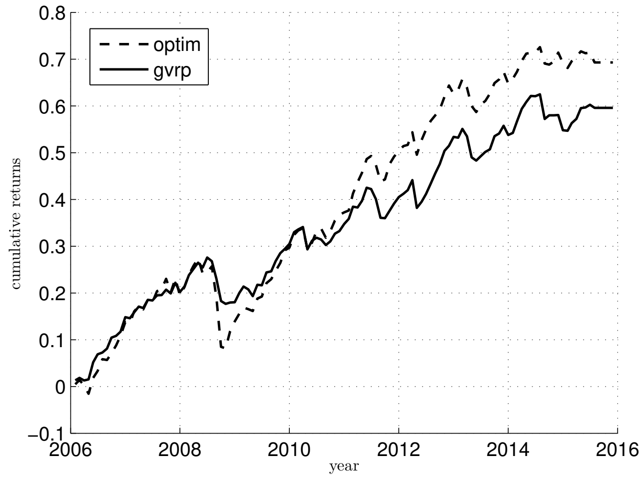


Figure 9: Cumulative Performance Portfolio Optimzation

This Figure contains the cumulative performance of the GVRP portfolio and the optimization for the atm call and put options. Every month the most atm put and call are selected and based on the regression model and the simulated covariance matrix the optimal point on the efficient frontier is determined. The sample period is February 2006 till July 2015

6.5.2 Vary Allocation Strangle-Straddle

Secondly we expand the investment universe by apart from the atm put and call also including an otm put and call. Formally at time t we pick the option expiry that has the most options available between 40 and 60 days till expiry. Within these options we pick the four options that are closest to delta 0.5, 0.25, -0.25 and -0.5 as there is more liquidity in out-the-money than in-the-money options[17]. The selected options are an atm call and put and an otm call and put. Secondly we select the four by four covariance matrix by selecting the options in the simulated covariance matrix that most closely match the four selected options in terms of delta and times to maturity. we estimate the expected return based on our regression model fitted to the growing sample of expired options. The weights of the considered options are restricted to be negative to stay consistent with a negative volatility premium. The out of sample period starts 10 years after first available data to have a robust estimate of the average returns.

The results can be found in Figure 10. The average excess return is equal to 9.09% with an annualized standard deviation of 7.57% for a Sharpe ratio of 1.20. This Sharpe

[17] including all options which are highly correlated into the optimization results in a near singular inverse covariance matrix which leads to numerical instability.

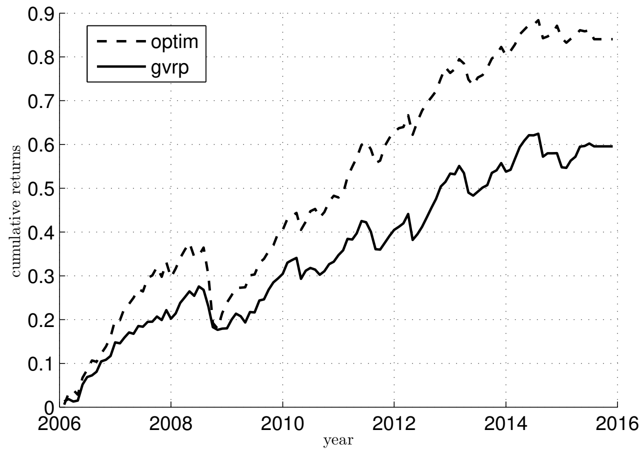


Figure 10: Cumulative Performance Portfolio Optimzation

This Figure contains the cumulative performance of the GVRP portfolio and the optimization for the atm/otm call and put options. Every month the most atm put and call are selected together with a delta 0.25 call and -0.25 put and based on the regression model and the simulated covariance matrix the optimal point on the efficient frontier is determined.

ratio is better than both the GVRP portfolio and the optimisation for the atm put and call options.

7 Conclusion

The volatility premium, extracted by shorting delta hedged atm straddles, produces economically meaningful and statistical significant average returns over a sample spanning nearly two decades across bonds, credits, currencies, commodities and equity indices. The volatility risk premium is not explained by common explanations offered in literature, downside risk, volatility risk or factor exposures only partially explain the excess returns. The closest we come to a risk-based explanation for the global volatility risk premium is the negative returns in bad states of the world. We do find a strong common risk component that the asset class portfolios tend to suffer drawdowns during recessions when volatility rises across all asset classes. All asset class portfolios contain sizable tail risk which does not disappear when you create a diversified global volatility risk premium portfolio by combining the asset class portfolios risk equally weighted. During normal times the assets do provide diversification benefits which leads to a Sharpe ratio of 1.45 for the GVRP. We explore the robustness of the strategy and find that the premium can be further enhanced by considering alternative weighting schemes taking into account the relative difference between the historical and the implied volatility among the different assets.

Put options on the S&P 500 remained overpriced over the period 1996-2015 with more negative returns for further out-the-money options in line with previous studies. We find a similar pattern in the average returns for gold call and bond put options. We introduce a new regression model for the term structure of the average returns. Using the model and a simulated covariance matrix we perform a portfolio optimization and significantly improve the performance over the GVRP portfolio when we include out of the money options into the optimization.

A Description Data

Description underlying securities I

Panel A: Commodities			
Asset	Market cap	Class	Description
XAU	173.62bln	Index	XAU PHLX Gold-Silver Index, Index of 30 miners.
OSX	197.68bln	Index	The PHLX oil service index (OSX) is a price weighted index composed of companies involved in the oil services sector
GLD US	41.2bln	ETF	SPDR Gold Trust, tracks gold bullion, physically backed
IAU US	9.61bln	ETF	iShares Gold Trust, tracks Gold Bullion, physically backed
USO US	3.55bln	ETF	tracks light sweet crude oil, futures based NYME
OIL US	0.8bln	ETF	tracks S&P GSCI crude oil total return index, through futures on WTI
UNG US	0.48bln	ETF	tracks natural gas futures through futures
SLV US	6.98bln	ETF	tracks Silver Bullion, physically backed
DBA US	0.81bln	ETF	Agriculture, tracks DBIQ diversified agriculture index excess return

Panel B: Government Bonds			
Asset	Market cap	Class	Description
TNX		Index	CBOE 10year Treasury Note, cash settled, option on 10 times the yield
IRX		Index	CBOE annualized discount rate on the most recently auctioned 13 week treasury bill, option on 10x yield
FVX		Index	CBOE 5 year treasury note Index, option on 10x yield
TLT	8.06bln	ETF	20+ year treasury bond, tracks Barclays Capital US 20+ year Treasury bond index
IEF	9.24bln	ETF	7-10 year treasury bond, tracks Barclays Capital US 7-10 year Treasury bond Index
SHY	10.24bln	ETF	1-3 year treasury bond, track Barclays Capital US 1-3 year Treasury bond index
IEI	6.41bln	ETF	3-7 year treasury bond etf, Barclays Capital US 3-7 year treasury bond index
TYX		Index	CBOE 30 year treasury yield index, option on 10 times the annualized yield

Panel C: Equity Indices I			
Asset	Market cap	Class	Description
RUI	22.37T	Index	Russell 1000 index
XMI	3.74T	Index	NYSE Arca Major Market Index, american price weighted stock market index made up of 20 blue chip industrial stocks US corporations
MID	-	Index	S&P400 Mid caps US
RUT	2.02T	Index	Russell 2000 Index
SML	-	Index	S&P600 small cap US
DJX	-	Index	Dow Jones Industrial Average
NDX	5.57T	Index	Nasdaq 100
SPX	-	Index	S&P 500
OEX	-	Index	S&P100 American Style
XEO	12.31T	Index	S&P100 European Style
FEZ	2.82bln	ETF	SPDR Euro Stoxx 50 ETF, tracks EURO STOXX 50 Index
EFA	60.76bln	ETF	iShares MSCI EAFE ETF, tracks MSCI EAFE Index, measures performance of equity markets in European, Australasian and Far Eastern
FXI	3.88bln	ETF	iShares China Large Cap ETF, tracks FTSE China 25 Index, measures performance largest companies in the China Equity Market
VGK	11.87bln	ETF	Vanguard FTSE Europe ETF, tracks FTSE Developed Europe Index, index comprises of large and midcap stocks
VEU	14.08bln	ETF	Vanguard FTSE All world ex US ETF, tracks FTSE All world ex US Index, includes approx 2200 stocks from 46 countries, both developed and emerging
ACWI	5.63bln	ETF	iShares MSCI ACWI ETF, MSCI All country World Index, measure performance global equity markets
VT	6.13bln	ETF	Vanguard Total Stock Market ETF, tracks CRSP US TOTAL Market Index, 4000 constituents representing nearly 100% of the US investable equity market
GXC	0.77bln	ETF	SPDR S&P China ETF, tracks S&P China BMI Index, investable universe of publicly traded companies domiciled in China, but legally available to foreign investors

Panel C: Equity Indices II			
Asset	Market cap	Class	Description
EEM	21.8bln	ETF	iShares MSCI Emerging Markets ETF, tracks MSCI Emerging Markets Index, index consists of 21 emerging markets
EWH	1.6bln	ETF	iShares MSCI Hong Kong ETF, tracks MSCI Hong Kong Index, tracks performance Hong Kong Equity market
EWI	0.7bln	ETF	iShares MSCI Italy Capped ETF, tracks MSCI Italy Index, tracks italian equity market
EWJ	14.8bln	ETF	iShares MSCI Japan ETF, tracks MSCI Japan Index, track Japan equity market
EWY	3.1bln	ETF	iShares MSCI South Korea Capped ETF, tracks MSCI Korea Index
EWD	0.3bln	ETF	iShares MSCI Sweden ETF, tracks Swedish Equity market
EWL	1.1bln	ETF	iShares MSCI Switzerland Capped ETF, tracks MSCI Switzerland Index
EWC	2.8bln	ETF	iShares MSCI Canada ETF, tracks MSCI Canada Index
EZU	10bln	ETF	iShares MSCI EMU ETF, tracks MSCI EMU INDEX, tracks performance of equity market of European Union members that have adopted the Euro
EWG	3.9bln	ETF	iShares MSCI Germany ETF, tracks MSCI Germany Index, index measures performance German Equity market

Panel D: Credits			
Asset	Market cap	Class	Description
LQD	32.55bln	ETF	tracks Iboxx $ Liquid Investment Grade Index, the index tracks the performance of 600 highly liquid investment grade corporate bonds
HYG	16.64bln	ETF	tracks Iboxx $ Liquid High Yield Index, junk bonds, high yield corporate bonds for sale in the US, there is no limit to the number of issues in the index
JNK	12.28bln	ETF	SPDR Barclays Capital High Yield Bond ETF, tracks Barclays Capital High Yield Very Liquid Index, non investment grade.

Panel E: Currencies			
Asset	Market cap	Class	Description
XDA	-	Index	PHLX Australian dollar
XDC	-	Index	PHLX Canadian dollar
XDN	-	Index	PHLX Yen
XDS	-	Index	PHLX Swiss Franc
FXB	55mln	ETF	Guggenheim CurrencyShares British Pound Sterling Trust
FXA	0.17bln	ETF	Guggenheim CurrencyShares Australian Dollar Trust ETF
FXF	0.16bln	ETF	Guggenheim CurrencyShares Swiss Franc Trust ETF
FXC	0.2bln	ETF	Guggenheim CurrencyShares Canadian Dollar Trust ETF
FXY	0.15bln	ETF	Guggenheim CurrencyShares Japanese Yen Trust ETF, tracks JPY
UUP	0.8bln	ETF	PowerShares DB US Dollar Index Bullish Fund, basket of currencies versus US dollar.
CYB	50mln	ETF	WisdomTree China ex State Owned Enterprises Fund, Reminbi
FXE	0.3bln	ETF	Guggenheim CurrencyShares Euro Trust ETF, offers exposure to EURDOL. Increases when EURO strenghtens.

B Option Volumes per Asset

Government Bond Options Summary Statistics

This Table contains the Bonds summary statistics. The first column contains the asset name by Bloomberg Ticker, in the second, third and fourth column the total options traded.

Asset	Total volume	Calls	Puts
IEI	62,422	52,365	10,057
IRX	21,069	10,028	11,041
SHY	416,054	110,595	305,459
FVX	26,720	14,658	12,062
TNX	218,121	131,173	86,948
TYX	425,696	227,482	198,214
IEF	3,182,246	1,403,263	1,778,983
TLT	90,526,048	42,581,008	47,945,040

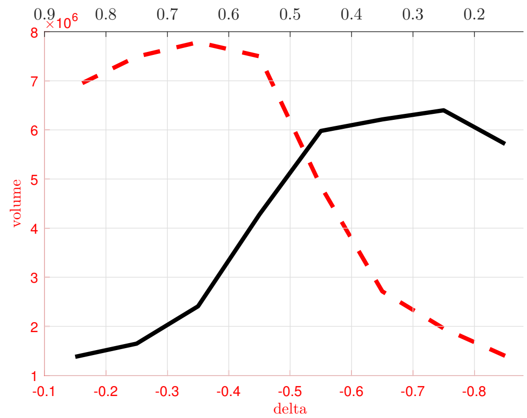
Currency Option Summary Statistics

This Table contains the Currency summary statistics. The first column contains the asset name by Bloomberg Ticker, in the second, third and fourth column the total options traded.

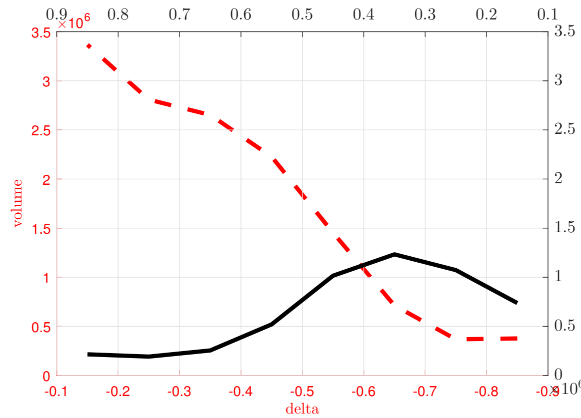
Asset	Total volume	Calls	Puts
CYB	361,519	227,444	134,075
UUP	31,036,782	24,762,546	6,274,236
FXF	642,903	333,298	309,605
FXC	1,487,628	742,076	745,552
FXA	2,240,397	840,256	1,400,141
FXB	1,132 390	368,131	764,259
XDA	1,203,479	922,998	280,481
XDC	719,349	423,709	295,640
XDS	650,730	456,903	193,827
XDN	1,419,841	815,308	604,533
FXY	7,626,572	2,334,677	5,291,895
FXE	23,981,193	6,871,866	17,109,327

C Summary Statistics Option Portfolios

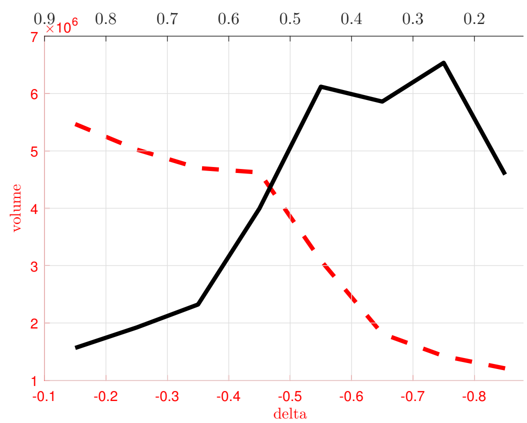
D Option Volumes



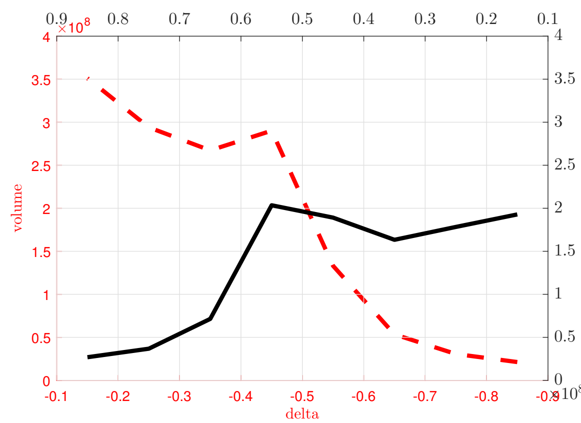
(a) Bond



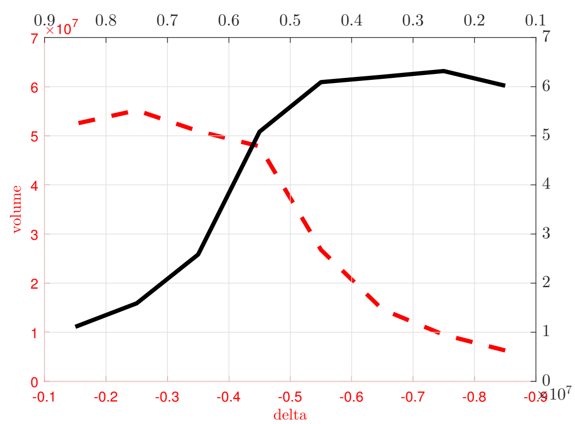
(b) Credits



(c) Currency



(d) Equity index



(e) Commodities

Figure 11: This Figure shows the option volumes (contracts traded) aggregated for the different asset classes. The dotted red line denotes the volume traded in the puts per delta group. The solid black line denotes the traded volume for the calls per delta group.

Equity Index Options Summary Statistics

This Table contains the Equity Index summary statistics. The first column contains the asset name by Bloomberg Ticker, in the second, third and fourth column the total options traded.

Asset	Total volume	Calls	Puts
EWL	16,597	8,257	8,340
VT	49,371	36,729	12,642
EZU	148,586	79,017	69,569
ACWI	55,721	29,358	26,363
EWI	702,647	308,158	394,489
EWD	17,308	7,604	9,704
FEZ	1,622,484	569,983	1,052,501
VEU	128,934	96,199	32,735
GXC	53,139	31,647	21,492
EWJ	43,300,682	27,309,031	15,991,651
EWH	7,333,278	3,506,402	3,826,876
EWC	2,101,928	878,999	1,222,929
EWG	4,512,607	2,297,990	2,214,617
VGK	1,158,062	616,611	541,451
SML	452,992	228,057	224,935
RUI	285,267	108,638	176,629
XMI	3,143,556	1,596,039	1,547,517
EWY	7,995,947	3,413,468	4,582,479
MID	1,583,413	714,844	868,569
EFA	105,853,002	45,774,265	60,078,737
FXI	164,097,789	79,457,796	84,639,993
XEO	24,487,482	10,986,789	13,500,693
OEX	287,049,256	132,584,790	154,464,466
DJX	93,989,306	40,729,916	53,259,390
MNX	73,368,544	32,956,928	40,411,616
RUT	207,670,174	90,373,512	117,296,662
NDX	134,816,341	57,545,122	77,271,219
SPX	2,052,121,912	769,549,278	1,282,572,634

Commodity Option Summary Statistics

This Table contains the Commodity summary statistics. The first column contains the asset name by Bloomberg Ticker, in the second, third and fourth column the total options traded.

Asset	Total volume	Calls	Puts
IAU	1,751,250	1,403,922	347,328
OIL	2,053,789	968,770	1,085,019
DBA	7,617,573	5,638,275	1,979,298
UNG	86,027,853	51,058,742	34,969,111
SLV	195,814,566	119,527,404	76,287,162
USO	159,903,825	77,243,210	82,660,615
XAU	17,079,323	9,170,456	7,908,867
OSX	18,519,087	8,413,139	10,105,948
GLD	313,191,996	179,729,550	133,462,446

Credits Summary Statistics

This Table contains the Credits summary statistics. The first column contains the asset name by Bloomberg Ticker, in the second, third and fourth column the total options traded.

Asset	Total volume	Calls	Puts
JNK	2,948,540	808,800	2,139,740
LQD	1,251,963	459,788	792,175
HYG	18,127,234	5,384,683	12,742,551

Equity Indices

This Table displays the summary statistics for the delta hedged atm straddles in Equity Indices. The mean and standard deviation (Std.) is reported as $1\% = 0.01$.

Asset	Mean	Std.	Sharpe	t-stat	Begin	End	Skewness	Kurtosis
EWL	−0.75	1.57	−0.48	−0.36	2012	2015	−1.97	5.00
VT	0.70	0.67	1.05	1.00	2012	2015	−0.29	1.88
EZU	−1.34	1.02	−1.31	−1.56	2009	2015	−1.07	3.35
ACWI	0.36	0.87	0.41	0.31	2013	2015	−0.51	1.91
EWI	−0.02	0.56	−0.03	−0.05	2010	2015	−0.30	3.18
EWD	1.02	0.92	1.11	1.11	2007	2015	−1.15	3.59
FEZ	0.01	0.70	0.01	0.02	2007	2015	−0.78	3.16
VEU	0.05	0.77	0.07	0.12	2008	2015	−0.57	3.62
GXC	−0.90	0.84	−1.06	−1.19	2008	2015	−0.60	3.93
EWJ	1.01	0.66	1.52	3.17	2005	2015	−1.41	7.01
EWH	0.59	0.84	0.71	1.65	2006	2015	−0.97	4.52
EWC	0.45	0.68	0.67	1.58	2006	2015	−0.90	3.58
EWG	0.13	0.74	0.17	0.40	2007	2015	−1.36	6.02
VGK	−0.06	0.92	−0.07	−0.15	2006	2015	−2.12	8.73
SML	1.21	0.59	2.04	3.27	1997	2011	0.14	2.76
RUI	1.18	0.47	2.53	2.19	2005	2010	−1.45	3.88
XMI	0.85	0.57	1.49	3.07	1996	2007	−0.65	3.59
EWY	0.67	0.80	0.85	2.21	2007	2015	−4.17	28.97
MID	1.34	0.54	2.49	4.97	1996	2011	−1.01	3.41
EFA	0.21	0.76	0.27	0.86	2003	2015	−1.03	4.22
FXI	−0.16	1.19	−0.13	−0.41	2005	2015	−5.32	44.26
XEO	0.57	0.70	0.81	2.55	2001	2015	−2.66	17.31
OEX	0.56	0.90	0.62	2.66	1996	2015	−6.16	62.73
DJX	0.89	0.64	1.38	5.82	1997	2015	−2.02	12.44
MNX	0.47	0.56	0.84	3.06	2000	2015	−0.79	3.45
RUT	0.99	0.60	1.65	6.65	1996	2015	−1.33	8.03
NDX	0.41	0.54	0.77	3.13	1996	2015	−0.76	3.33
SPX	0.72	0.63	1.14	4.95	1996	2015	−2.07	12.94

Currency

This Table displays the summary statistics for the delta hedged atm straddles in Currency. The mean and standard deviation (Std.) is reported as 1% = 0.01.

Asset	Mean	Std.	Sharpe	t-stat	Begin	End	Skewness	Kurtosis
CYB	0.60	0.79	0.76	0.49	2012	2015	−0.37	2.43
UUP	1.11	0.62	1.78	3.25	2008	2015	−0.61	3.24
FXF	−3.04	4.18	−0.73	−1.21	2008	2015	−5.05	27.93
FXC	0.59	0.63	0.94	1.99	2007	2015	−0.60	3.05
FXA	−0.07	0.80	−0.09	−0.22	2007	2015	−1.89	7.50
FXB	0.16	0.64	0.26	0.50	2007	2015	−1.66	6.37
XDA	−0.47	0.95	−0.49	−0.78	2007	2015	−1.41	4.41
XDC	0.09	0.73	0.13	0.22	2007	2015	−0.59	2.66
XDS	0.17	0.71	0.25	0.34	2007	2015	−0.84	4.96
XDN	−0.01	0.84	−0.02	−0.02	2007	2014	−1.04	3.39
FXY	0.65	0.82	0.80	1.90	2007	2015	−1.01	4.28
FXE	0.60	0.59	1.02	2.69	2007	2015	−1.09	4.98

Commodities

This Table displays the summary statistics for the delta hedged atm straddles in Commodities. The mean and standard deviation (Std.) is reported as 1% = 0.01.

Asset	Mean	Std.	Sharpe	t-stat	Begin	End	Skewness	Kurtosis
IAU	0.32	1.26	0.25	0.43	2009	2014	−3.55	17.87
OIL	0.68	0.71	0.97	1.83	2010	2015	−0.76	3.04
DBA	1.31	0.69	1.91	4.78	2007	2015	−0.74	3.71
UNG	0.54	0.58	0.94	2.47	2007	2015	−1.33	7.07
SLV	0.80	0.71	1.12	2.83	2009	2015	−1.68	8.64
USO	0.64	0.57	1.12	3.16	2007	2015	−0.51	3.01
OSX	0.38	0.59	0.64	2.32	1997	2014	−0.68	4.45
XAU	0.23	0.62	0.37	1.49	1996	2015	−1.17	5.55
GLD	0.72	0.86	0.84	2.19	2008	2015	−2.22	9.90

Credits

This Table displays the summary statistics for the delta hedged atm straddles in Credits. The mean and standard deviation (Std.) is reported as 1% = 0.01.

Asset	Mean	Std.	Sharpe	t-stat	Begin	End	Skewness	Kurtosis
LQD	0.45	0.79	0.57	1.47	2003	2015	−1.28	5.10
JNK	1.70	0.99	1.71	3.63	2009	2015	−3.34	17.46
HYG	1.56	0.92	1.70	3.90	2007	2015	−1.62	7.13

Government Bonds

This Table displays the summary statistics for the delta hedged atm straddles in Bonds. The mean and standard deviation (Std.) is reported as 1% = 0.01.

Asset	Mean	Std.	Sharpe	t-stat	Begin	End	Skewness	Kurtosis
IEI	1.96	0.66	2.97	2.84	2009	2015	0.70	3.07
IRX	3.36	0.95	3.55	2.71	1997	2007	−1.37	3.71
SHY	0.42	1.72	0.24	0.32	2004	2015	−1.47	3.95
FVX	1.41	0.74	1.91	1.56	1999	2006	0.23	1.50
TNX	1.00	0.61	1.64	2.93	1999	2008	−1.04	4.47
TYX	1.12	0.57	1.97	4.74	1996	2008	−0.14	2.79
IEF	0.90	0.56	1.62	4.42	2003	2015	−0.55	3.03
TLT	0.46	0.60	0.77	2.62	2003	2015	−1.32	5.93

E SPX versus SPY

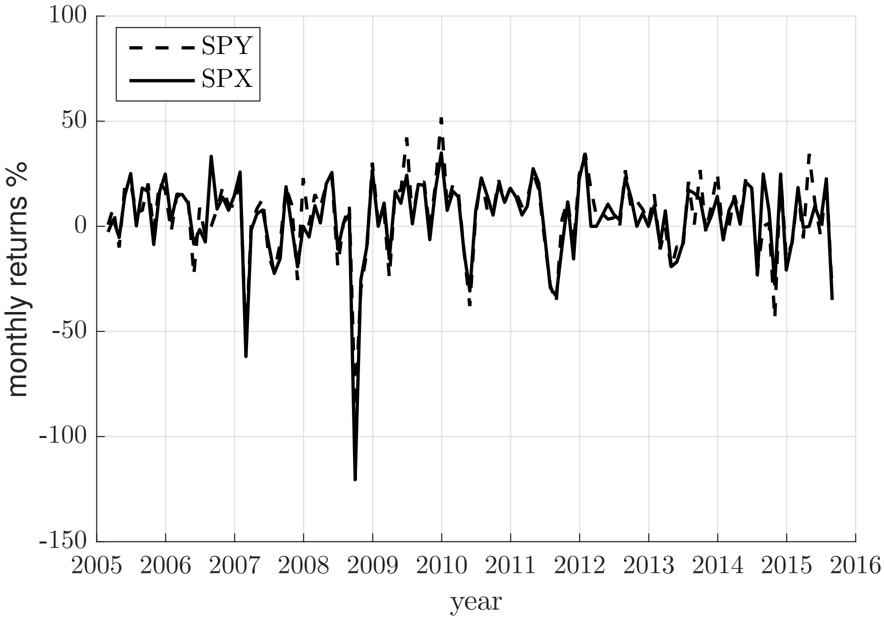


Figure 12: Monthly returns SPX versus SPY ETF options

This figure shows the returns of the monthly atm delta-hedging strategy for the SPX options and the SPY ETF options for the sample period February 2005 till August 2015 in which both assets trade. The SPY ETF trades at one tenth the value of the SPX Index and therefore the options should also trade at one tenth

F Spread Realized - Implied

Equity Indices

	IV	RV	spread	spread %	return
RUI	0.16	0.10	0.06	0.31	1.18
XMI	0.18	0.15	0.03	0.15	0.85
MID	0.20	0.17	0.04	0.19	1.34
RUT	0.23	0.21	0.03	0.13	0.99
SML	0.22	0.20	0.02	0.11	1.21
DJX	0.19	0.16	0.02	0.10	0.89
NDX	0.27	0.25	0.01	0.05	0.41
MNX	0.25	0.24	0.01	0.05	0.47
EWC	0.23	0.24	-0.01	-0.07	0.45
EZU	0.21	0.20	0.01	0.05	-1.34
EWL	0.19	0.13	0.06	0.31	-0.75
EWD	0.27	0.22	0.05	0.19	1.02
EWY	0.30	0.28	0.02	0.03	0.67
EWG	0.26	0.25	0.00	-0.02	0.13
EWJ	0.22	0.20	0.02	0.08	1.01
EWI	0.32	0.32	0.00	-0.01	-0.02
EWH	0.28	0.29	-0.01	-0.03	0.59
SPX	0.19	0.17	0.02	0.09	0.72
OEX	0.19	0.18	0.01	0.06	0.56
XEO	0.19	0.18	0.01	0.04	0.57
FEZ	0.21	0.20	0.02	0.05	0.01
EFA	0.20	0.23	-0.03	-0.28	0.21
FXI	0.31	0.35	-0.04	-0.11	-0.16
VGK	0.21	0.22	-0.01	-0.09	-0.06
VEU	0.21	0.21	0.00	-0.04	0.05
GXC	0.29	0.35	-0.05	-0.19	-0.90
ACWI	0.13	0.14	-0.01	-0.11	0.36
VT	0.16	0.12	0.04	0.22	0.70

Bonds

	IV	RV	spread	spread %	return
IRX	0.05	0.05	0.00	0.03	3.36
FVX	0.29	0.23	0.06	0.18	1.41
TNX	0.25	0.23	0.02	0.08	1.00
TYX	0.16	0.13	0.03	0.16	1.12
TLT	0.14	0.13	0.00	0.01	0.46
IEF	0.08	0.07	0.01	0.07	0.90
SHY	0.03	0.02	0.01	0.25	0.42
IEI	0.04	0.03	0.01	0.24	1.96

Credits

	IV	RV	spread	spread %	return
LQD	0.06	0.06	0.00	0.03	0.45
HYG	0.10	0.08	0.02	0.13	1.70
JNK	0.11	0.09	0.02	0.15	1.56

Commodities

	IV	RV	spread	spread %	return
XAU	0.40	0.38	0.02	0.04	0.23
OSX	0.38	0.38	0.01	0.01	0.38
GLD	0.21	0.19	0.02	0.07	0.72
IAU	0.21	0.21	0.00	0.00	0.32
USO	0.34	0.32	0.03	0.07	0.64
SLV	0.33	0.30	0.03	0.09	0.80
DBA	0.23	0.19	0.04	0.17	1.31
UNG	0.44	0.43	0.01	0.00	0.54
OIL	0.32	0.30	0.02	0.06	0.68

Currency

	IV	RV	spread	spread %	return
FXE	0.11	0.10	0.01	0.09	0.60
FXB	0.10	0.09	0.01	0.04	0.16
FXA	0.13	0.13	-0.01	-0.06	-0.07
FXF	0.12	0.12	0.00	-0.03	-3.04
FXC	0.10	0.08	0.01	0.11	0.59
FXY	0.11	0.10	0.01	0.08	0.65
UUP	0.12	0.10	0.02	0.13	1.11
XDS	0.13	0.13	0.00	-0.03	0.17
XDN	0.13	0.12	0.01	0.05	-0.01
XDA	0.13	0.14	-0.01	-0.13	-0.47
XDC	0.09	0.09	0.00	-0.01	0.09
CYB	0.09	0.02	0.07	0.75	0.60

G Greeks

Under the Black-Scholes model we can take derivatives to the different inputs of the Black-Scholes formula. In Table 11 you can find the derivatives that are essential for this study.

Table 11: Greeks

This Table displays the Greeks of the Black–Scholes Model for European options. V denotes the value of the option. S denotes the value of the stock, K the strike price and $T-t$ the time till maturity.

Name	Derivative	Call	Put
delta (Δ)	$\Delta = \frac{\delta V}{\delta S}$	$N(d_1)$	$-N(-d_1)$
gamma (Γ)	$\Delta = \frac{\delta^2 V}{\delta S^2}$	$\frac{N'(d_1)}{S\sigma\sqrt{T-t}}$	
vega (ν)	$\Delta = \frac{\delta V}{\delta \sigma}$	$SN'(d_1)\sqrt{T-t}$	

H Cumulative Performance VRP portfolios

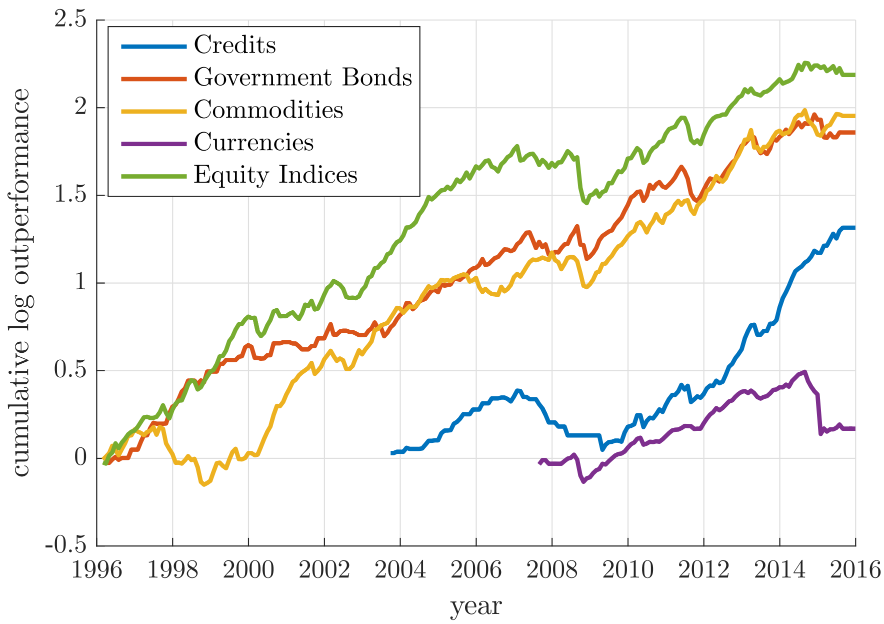
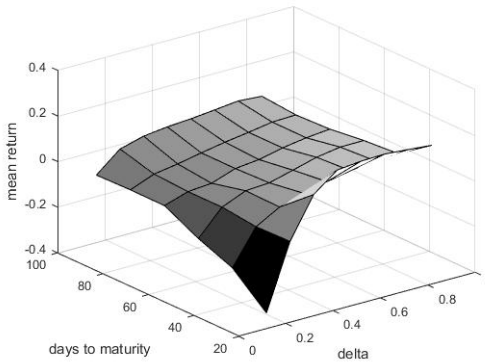


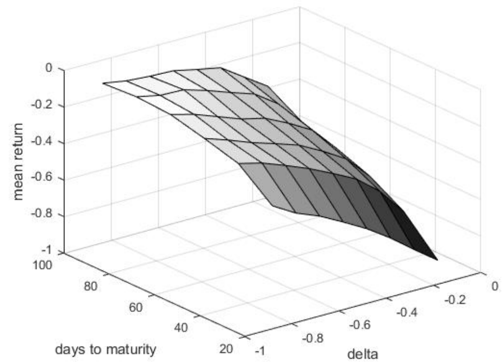
Figure 13: Cumulative Performance of the VRP per Asset Class

This figure shows the cumulative sum excess returns of the asset class returns. At the start of each month we write delta hedged at-the-money straddles on all individual assets within each asset class. The portfolio return for each asset class is the equally weighted return of all returns within that asset class. Afterwards the asset class portfolios are scaled to have 10% annualized volatility for easy comparison. The sample period is from February 1996 till August 2015.

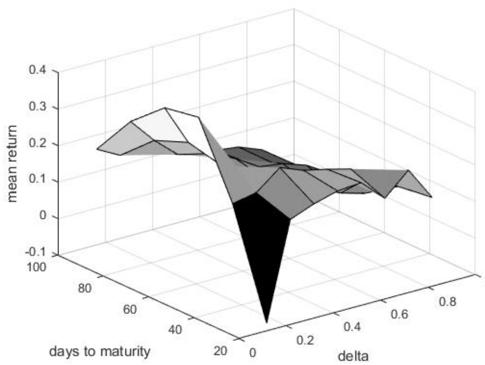
I Term structures



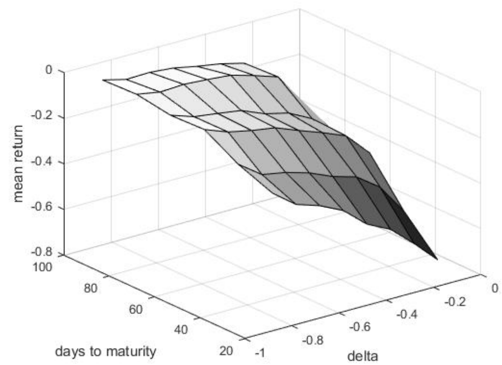
(a) SPX call



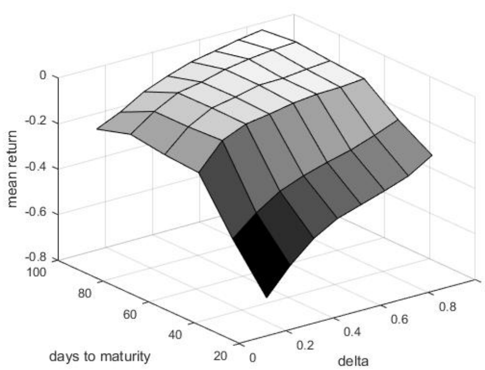
(b) SPX put



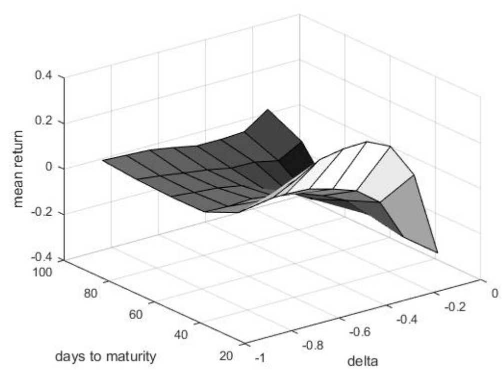
(c) TLT call



(d) TLT put



(e) Gold call



(f) Gold put

Figure 14: This Figure shows the term structure of the average returns of the unhedged call and put options over the sample period January 1996 till August 2015

J Straddles Long Short

In Section 4.4 we used the insight of Goyal and Saretto (2007) in order to be more short where the opportunity was the largest by means of the relative RV versus IV measure. In this Section we go long short instead of only short, staying closer to the methodology of Goyal and Saretto (2007). It is important to note that we now very temporary leave the volatility risk premium, as we no longer have a short volatility exposure, in order to gain additional insight. As an analogy consider the two major technology stocks Apple and Google. One can have a model which concludes that the entire technology sector is overvalued and as a result would short both Apple and Google. Alternatively one can have a model which concludes that Apple is overvalued compared to Google, as a result one would go short Apple and long Google in order to profit from the relative mispricing. This strategy is however no longer short the technology sector. The two strategies are therefore fundamentally different. As a results we expect a low correlation between the short volatility and the long short returns.

We again rank based on the log difference between RV and IV. The weights for the k assets available in the asset class at time t are determined as,

$$weight_t^i = -z_t(rank_t^i - \frac{k+1}{2}) \tag{21}$$

where z_t is a scalar that ensures that the long and short positions equal 1 and -1. We apply this long short weighting scheme to all the assets within an asset class.

For the 1 month look back realized volatility we find an average annual return of 8.67% with a standard deviation of 8.43% for a Sharpe ratio of 1.03. For the 1 year look back realized volatility we find an average annual return of 6.40% with a standard deviation of 7.45% for a Sharpe ratio of 0.86. In figure 15 you can find the cumulative log outperformance. Although the 1 month RV and 1 year RV portfolio do not nearly offer the same Sharpe ratio as the GVRP portfolio, it does offer a very uncorrelated performance driver. Interestingly enough the returns of the 1 month look back realized volatility are hardly correlated with the 1 year look back realized volatility. The correlation matrix is shown in Figure 12.

Table 12: Correlation long-short and GVRP

This Table contains the correlations between the GVRP portfolio and the 1 month 1 year long-short portfolios over the sample period March 1996 till August 2015.

	1 year	1 month	GVRP
1 year	1.00	-0.14	0.05
1 month	-0.14	1.00	-0.14
GVRP	0.05	-0.14	1.00

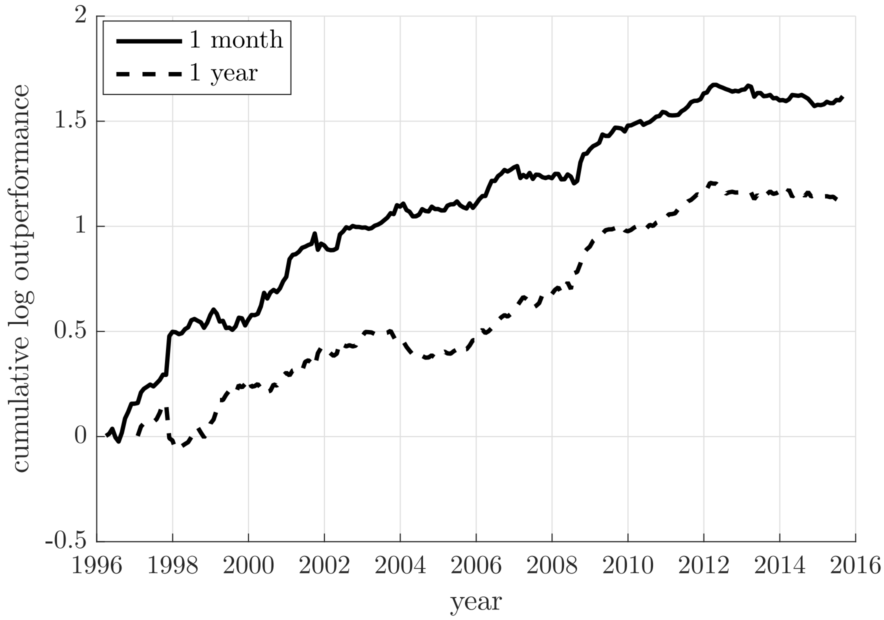


Figure 15: Long-short 1 year versus 1 month

This figure shows cumulative log outperformance for the long short portfolios based on the ranking of the IV versus the RV. For both portfolios we rescaled them to have 10% annual standard deviation. If the RV is not yet available, if the asset doesn't exist long enough, we record no return. The sample period is from February 1996 till August 2015.

References

Andersen, T. G., Bollerslev, T., Christoffersen, P., and Diebold, F. X. (2007). Practical volatility and correlation modeling for financial market risk management. In *The risks of financial institutions*, pages 513–548. University of Chicago Press.

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

Bakshi, G. and Kapadia, N. (2003). Delta-hedged gains and the negative market volatility risk premium. *Review of Financial Studies*, 16(2):527–566.

Battalio, R. and Schultz, P. (2006). Options and the bubble. *The Journal of Finance*, 61(5):2071–2102.

Bertsimas, D., Kogan, L., and Lo, A. W. (2000). When is time continuous? *Journal of Financial Economics*, 55(2):173–204.

Bollerslev, T., Tauchen, G., and Zhou, H. (2009). Expected stock returns and variance risk premia. *Review of Financial Studies*, 22(11):4463–4492.

Bollerslev, T., Todorov, V., and Xu, L. (2015). Tail risk premia and return predictability. *Journal of Financial Economics*, 118(1):113–134.

Bondarenko, O. (2014). Why are put options so expensive? *The Quarterly Journal of Finance*, 4(03):1450015.

Broadie, M., Chernov, M., and Johannes, M. (2007). Model specification and risk premia: Evidence from futures options. *The Journal of Finance*, 62(3):1453–1490.

Campbell, R., Koedijk, K., and Kofman, P. (2002). Increased correlation in bear markets. *Financial Analysts Journal*, 58(1):87–94.

Carr, P. and Wu, L. (2009). Variance risk premiums. *Review of Financial Studies*, 22(3):1311–1341.

Coval, J. D. and Shumway, T. (2001). Expected option returns. *The journal of Finance*, 56(3):983–1009.

Cox, J. C., Ross, S. A., and Rubinstein, M. (1979). Option pricing: A simplified approach. *Journal of financial Economics*, 7(3):229–263.

Doran, J. S. and Ronn, E. I. (2008). Computing the market price of volatility risk in the energy commodity markets. *Journal of Banking & Finance*, 32(12):2541–2552.

Driessen, J. and Maenhout, P. J. (2006). The world price of jump and volatility risk. In *AFA 2005 Philadelphia Meetings, Forthcoming*.

Driessen, J., Maenhout, P. J., and Vilkov, G. (2009). The price of correlation risk: Evidence from equity options. *The Journal of Finance*, 64(3):1377–1406.

Duarte, J., Longstaff, F. A., and Yu, F. (2007). Risk and return in fixed-income arbitrage: Nickels in front of a steamroller? *Review of Financial Studies*, 20(3):769–811.

Duyvesteyn, J. and de Zwart, G. (2015). Riding the swaption curve. *Journal of Banking & Finance*, 59:57–75.

Eraker, B. (2008). The volatility premium. *Manuscript*.

Fama, E. and French, K. (2014). A five-factor asset pricing model, fama-miller working paper.

Fama, E. F. and French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of financial economics*, 105(3):457–472.

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

Fung, W. and Hsieh, D. A. (1997). Empirical characteristics of dynamic trading strategies: The case of hedge funds. *Review of financial studies*, 10(2):275–302.

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

Goodman, L. S. and Ho, J. (1997). Are investors rewarded for shorting volatility? *The Journal of Fixed Income*, 7(1):38–42.

Goyal, A. and Saretto, A. (2007). Option returns and volatility mispricing. *Available at SSRN 889947*.

Green, T. C. and Figlewski, S. (1999). Market risk and model risk for a financial institution writing options. *The Journal of Finance*, 54(4):1465–1499.

Guo, D. (1998). The risk premium of volatility implicit in currency options. In *Computational Intelligence for Financial Engineering (CIFEr), 1998. Proceedings of the IEEE/IAFE/INFORMS 1998 Conference on*, pages 224–251. IEEE.

Henriksson, R. D. and Merton, R. C. (1981). On market timing and investment performance. ii. statistical procedures for evaluating forecasting skills. *Journal of business*, pages 513–533.

Jackwerth, J. C. and Rubinstein, M. (1996). Recovering probability distributions from option prices. *The Journal of Finance*, 51(5):1611–1631.

Jobson, J. D. and Korkie, B. M. (1981). Performance hypothesis testing with the sharpe and treynor measures. *The Journal of Finance*, 36(4):889–908.

Koijen, R., Moskowitz, T., Pedersen, L., and Vrugt, E. (2015). Carry.

Lettau, M., Maggiori, M., and Weber, M. (2014). Conditional risk premia in currency markets and other asset classes. *Journal of Financial Economics*, 114(2):197–225.

Low, B. S. and Zhang, S. (2005). The volatility risk premium embedded in currency options. *Journal of Financial and Quantitative Analysis*, 40(04):803–832.

Mandelbrot, B. (1963). The variation of certain speculative prices. *The Journal of Business*, 36(4):394–419.

Memmel, C. (2003). Performance hypothesis testing with the sharpe ratio. *Finance Letters*, 1(1).

Mittnik, S. (2014). Var-implied tail-correlation matrices. *Economics Letters*, 122(1):69–73.

Moskowitz, T. J., Ooi, Y. H., and Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, 104(2):228–250.

Neely, C. J. (2003). *Implied Volatility from Options on Gold Futures: Do Econometric Forecasts Add Value or Simply Paint the Lilly?* Federal Reserve Bank of St. Louis.

Newey, W. K. and West, K. D. (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*, pages 777–787.

Newey, W. K. and West, K. D. (1994). Automatic lag selection in covariance matrix estimation. *The Review of Economic Studies*, 61(4):631–653.

Pesaran, M. H. and Timmermann, A. (1992). A simple nonparametric test of predictive performance. *Journal of Business & Economic Statistics*, 10(4):461–465.

Stein, J. (1989). Overreactions in the options market. *The Journal of Finance*, 44(4):1011–1023.

Trolle, A. B. and Schwartz, E. S. (2008). Variance risk premia in energy commodities. *Available at SSRN 1160195*.

Trolle, A. B. and Schwartz, E. S. (2009). A general stochastic volatility model for the pricing of interest rate derivatives. *Review of Financial Studies*, 22(5):2007–2057.