DISCUSSION PAPER SERIES

No. 10236

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FINANCIAL ECONOMICS

Centre for Economic Policy Research

ISSN 0265-8003

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Discussion Paper No. 10236
November 2014
Submitted 31 October 2014

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Abstract

This paper presents an innovative approach to extracting factors which are shown to predict the VIX, the S&P 500 Realized Volatility and the Variance Risk Premium. The approach is innovative along two different dimensions, namely: (1) we extract factors from panels of filtered volatilities - in particular large panels of univariate financial asset ARCH-type models and (2) we price equity volatility risk using factors which go beyond the equity class. These are volatility factors extracted from panels of volatilities of short-term funding and long-run corporate spreads as well as volatilities of energy and metals commodities returns and sport/future spreads.

JEL Classification: C2, C5 and G1
Keywords: arch filters and factor asset pricing models

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† The first author acknowledges support of the European Research Council under the European Community FP7/2008-2013 ERC grant 209116 and would like to thank Sophia Kyriakou for research assistance. The second author benefited from funding from a Marie Curie FP7-PEOPLE-2010-IIF grant. We thank Torben Andersen, Tim Bollerslev, Christian Brownlees, Peter Carr, Ron Gallant, Lars Hansen, Jonathan Hill, Andrew Karolyi, Adam McCloskey, Serena Ng and Eric Renault for some helpful comments as well as Peter Christoffersen for providing us his Realized Skewness series, Giang Nguyen for providing the CDS factor data and Viktor Todorov for providing us his daily VIX, VRP and FEAR index data. We also thank seminar participants at Bocconi University, Brown University, the Federal Reserve Bank of Chicago, the Norges Bank, Northwestern University, the University of Chicago, the 2013 Barcelona GSE Summer Forum and the 2014 ESSEC conference on Modelling and Forecasting Risk Premia.

1 Introduction

This paper presents an innovative approach to extract volatility factors which are shown to predict the VIX, the Realized Volatility (RV) of the S&P 500 and the Variance Risk Premium (henceforth VRP).[1] The approach is innovative along two different dimensions, namely: (1) we extract factors from panels of filtered volatilities - in particular large panels of univariate financial asset ARCH-type models and (2) we price equity volatility risk using factors which go beyond the equity class. More specifically we find the most successful models feature volatility factors extracted from panels of volatilities of short-term funding and long-run corporate spreads as well as volatilities of energy and metals commodities returns and spot/futures spreads. Besides statistical evidence, we also document the economic significance of our volatility factors in predicting the VIX^2 using a simple trading strategy for pricing VIX^2 futures contracts.

Our analysis is largely data-driven, namely, simple ARCH-type models function as filters (the ARCH-type parameter estimates are not of any direct interest), and principal component analysis is applied to time series of cross-sections of financial assets volatilities. Note that even though ARCH-type models are potentially misspecified, they can still be viewed as *filters* and deliver reliable estimates of volatility (see e.g. Nelson (1990), Nelson and Foster (1994), Nelson (1996)). A number of papers have considered extracting factors from panels of option-based implied volatilities - see e.g. Carr and Wu (2009), Egloff, Leippold, and Wu (2010), Zhou (2010), Bakshi, Panayotov, and Skoulakis (2011), or from a cross-section of Realized Volatility measures, see e.g. Anderson and Vahid-Araghi (2007) as well as Luciani and Veredas (2011). Our approach is related, but different from the existing literature. Because we use simple ARCH-type models our analysis is (1) not confined to asset classes with traded options - since we do not use implied volatilities - and (2) is not confined to assets with reliable intra-daily high-frequency data - since we do not use realized volatilities based on intra-daily data.

The extraction of risk factors is typically confined to a particular asset class. Fama-French factors are extracted from cross-sections of stock returns and are meant to price equity risk (but not say bond or commodities returns). Level, slope and curvature factors are extracted from fixed income securities and meant to price the term structure. A number of attempts have been made to extract factors jointly from stocks and bonds using the class of affine asset pricing models, see Bakshi and Chen (1997), Bekaert and Grenadier (1999), Bakshi and Chen (2005), Bekaert, Engstrom, and Xing (2009), Bekaert, Engstrom, and Grenadier (2010), Koijen, Lustig, and Van Nieuwerburgh (2010), Lettau and Wachter (2011), among others. Our approach also crosses asset classes and can be cast in an underlying affine asset pricing model. In particular, to predict equity volatility we do not exclusively rely on factors driven by stock returns. We form homogeneous panels stratified by asset class and compute the first principal component of the ARCH-type model filtered volatilities. Therefore, our volatility factors will have labels, e.g. the first principal component of short-term funding market instruments volatilities will be called accordingly. We take a rather

[1] Whenever we refer to the VIX in the paper we use the VIX^2 which is the component directly related to VRP.

agnostic approach and consider various asset classes, ranging from short term funding risk, corporate debt instruments, commodities, etc.

Using our novel volatility factor approach we revisit the prediction of VIX^2, RV of the S&P 500 and the VRP at different investment horizons. We find empirically that volatility factors associated with (i) long-run corporate spreads, (ii) short-run funding spreads and (iii) energy and metals commodities returns and spreads, are important in predicting future VIX^2, RV and the VRP. We refer to what are essentially a new set of empirical volatility factors as respectively the long-run corporate spreads volatility factor, the short-run funding spreads volatility factor and the energy and metals commodities volatility factor. More specifically, we find that two volatility factors appear to be key in predicting the VRP, VIX^2 and S&P 500 RV. The short-run funding spreads volatility factor is strongly significant at all forecasting horizons from six months up to a year for forecasting the VIX^2. The volatility factor related to energy and metal returns and spreads is also significant mostly for short investment horizons of six months for predicting the VIX^2. The significant role of our factors also holds for pricing VIX^2 futures contracts. We test the economic significance of the VIX^2 predictability results using a simple trading strategy for the VIX^2 futures prices. Our two volatility factors are also significant for forecasting the RV of the S&P 500. In the RV predictive regressions, our short-run funding risk factor appears to be the relatively most significant factor for all forecasting horizons vis-à-vis the other factors, whereas the energy and metals volatility factor, appears to be significant for relatively shorter horizons of 5 months and insignificant for longer horizons of one year. Interestingly, the lagged RV is only significant for six months whereas the short-run volatility factor is significant for all horizons considered from 6 to 12 months for forecasting the S&P 500 RV. Furthermore we find that the VRP is driven by the volatility of the volatility of consumption empirical proxy for longer horizons of a year, which is consistent with the long-run risk models. However, for shorter horizons of 6 to 9 months, this consumption risk factor becomes insignificant and we find that our short-run funding volatility becomes the driving factor of VRP. Furthermore, we show using a comprehensive and robust empirical evidence that our proposed factors have additional predictive ability for the VIX^2, RV and VRP over the single factor model that focuses on consumption risk as well as a number of other factors/indicators in the literature. The above results are valid for the period from 1999-2010, with or without the period associated with Lehman Brothers bankruptcy and its aftermath. Finally, our volatility factors can also predict the excess equity returns. It is important to note that all our empirical analysis controls for lagged VIX and/or lagged S&P 500 RV and therefore controls for information embedded in equity market risk measures.

The implications of our findings are intriguing in several regards. The prior literature has put considerable emphasis on a single factor model for the VRP. The single factor argument has been used extensively in a number of recent papers, including Zhou (2010), Mueller, Vedolin, and Zhou (2011) and Wang, Zhou, and Zhou (2013), among others, to argue that the VRP predicts risk premia across equity, bond, currency, and credit markets. These findings are inspired by e.g. the Bansal and Yaron (2004) and Drechsler and Yaron (2011) general equilibrium model that explains the VRP via consumption growth volatility uncertainty combined with recursive utility preferences of a representative agent. There is reason to believe, however,

based on empirical evidence in Carr and Wu (2009), Egloff, Leippold, and Wu (2010), Bakshi, Panayotov, and Skoulakis (2011), Corradi, Distaso, and Mele (2013), among others, that a single factor model may not be adequate. Our analysis indeed finds that at least two factors are needed to model the VRP, VIX^2 and S&P 500 RV. The fact that volatility factors identified from asset classes other than equities drive the VIX^2 and VRP is also intriguing. Do our results suggest additional driving factors beyond the consumption-based long-run risk asset pricing model considered so far? The data-driven nature of our analysis can be used for prediction purposes. Although our analysis does not allow us to provide a direct link to specific existing asset pricing models, it can be used as a guide to extend the current long-run risk models. There are plenty of candidate models which suggest the types of links we uncover empirically. Adrian and Shin (2010) document that changes in dealer repos - the primary margin of adjustment for the aggregate balance sheets of intermediaries - forecast changes in financial market risk as measured by the innovations in the VIX. What they characterize as a liquidity and leverage link, relates to theoretical asset pricing models such as Gromb and Vayanos (2002), He and Krishnamurthy (2008), Brunnermeier and Pedersen (2009), among others. The link we find between equity volatility and commodity markets can also be related to the fact that commodity risk is priced in the cross-section of US stock returns, which is related to the findings of Boons, De Roon, and Szymanowska (2012).

One might wonder whether our factors are genuinely new. For example, one may think of the so called GZ factor, constructed by Gilchrist, Yankov, and Zakrajšek (2009) and Gilchrist and Zakrajšek (2012), or the St Louis Federal Reserve Bank Financial Stress Index (FSI) and the Chicago Federal Reserve Bank National Financial Index (NFCI) and their sub-indices which refer to series classified in three categories: Risk, Credit and Leverage. Our factors are common volatility factors extracted from panels of filtered volatilities whereas existing factors in the literature are mean/spreads factors. Moreover, in contrast to the existing literature we classify financial assets on the basis of their maturities and homogeneity and extract volatility factors from two classes, the long-run corporate assets and the short-run funding funding assets. Our factors show moderate correlations (between 0.60-0.75) with the aforementioned existing indices. In addition, our short-run funding risk volatility factor turns out to be the relatively most significant factor across different model specifications for predicting VRP, VIX^2 and S&P 500 RV at all horizons, among the aforementioned existing factors. One might also think of short term funding risk in the spirit of Adrian and Shin (2010) discussed earlier. Considering the principal component of CDS spreads for primary dealers, we find that this factor is insignificant in predicting the VIX^2, RV and VRP and adding it to predictive models does not affect the significance of our volatility factors. Similar findings hold for alternative liquidity factors and the CBOE skewness factor.

Following the recent literature on proxies of uncertainty and their relationship to measures of volatility in the financial markets and the real economy we investigate if the Economic Policy Uncertainty (EPU) index proposed by Bloom (2009) and the Macroeconomic Uncertainty (MU) indicator by Jurado, Ludvigson, and Ng (2013) are alternative driving factors of the VIX^2, RV and VRP and if they affect the significance of our proposed factors. Using either the EPU or the MU as single driving factors for the VIX^2 and VRP we

find both to be insignificant in our sample period. However, when our volatility factors are added to the predictive regressions then the EPU and the MU become weakly significant in some models of the VIX^2 and VRP.

The fact that stochastic volatility is important for the VIX and VRP has been emphasized by Drechsler and Yaron (2011) among others. In a continuous time setting, it has been argued that the jump component of volatility is the most important to explain variations in the VIX and VRP. Bollerslev and Todorov (2011) estimate the objective expectations of jump tail events and the market's pricing thereof. Key to their analysis is a FEAR index, a measure of disaster risk, or differences in the jump tails of the risk-neutral and objective distributions. Our analysis shares a virtue with Bollerslev and Todorov (2011), as both our and their approach rely on non-parametric procedures - although using different types of data. In our case, we rely on large panels of filtered volatilities using different types of assets, whereas Bollerslev and Todorov (2011) is based on intra-daily of S&P 500 return and options data. Their empirical results suggest that on average close to five percent of the equity premium may be attributed to the compensation for rare disaster events, which is characterized by a FEAR index, and that on average more than half of the historically observed VRP is directly attributable to disaster risk. When we estimate models to forecast the FEAR index we find that our short-run funding risk factor is a significant predictor above and beyond lagged FEAR index, VIX and a measure of consumption volatility. Hence, our short-run risk factor predicts disaster risk backed out of equity data. Finally, we also show that our short-run funding and corporate spreads and volatility factors can explain the equity risk premium in short horizons, since it has been argued that both the VRP ,Bollerslev, Tauchen, and Zhou (2009), and the FEAR index, Bollerslev and Todorov (2011), are significant predictors. Overall, we find that our two aforementioned factors go beyond the VRP and the FEAR index in explaining the equity risk premium in short horizons.

The paper is organized as follows: Section 2 discusses the factor models of panels of filtered volatilities. Section 3 discusses the factor estimation and details the alternative financial asset classes considered. Section 4 presents the empirical investigation on the driving forces of the VIX^2, the RV of the S&P 500 and the VRP and evaluates the role of our proposed factors. The section concludes assessing the economic significance of our forecasting results on the VIX^2 via a simple trading strategy using the VIX^2 futures. Section 5 presents a comprehensive robustness analysis of the results in Section 4. Section 6 provides a short illustration on whether our factors can predict in-sample the excess equity returns vis-à-vis a number of alternative classical and recent predictors of stock returns. The last section concludes the paper.

2 Factor Analysis with Panels of ARCH Filters

The consumption-based asset pricing literature has focused on factors driven by macroeconomic fundamentals, in particular consumption uncertainty in the context of long-run risk economies, with agents having preferences for early resolution of uncertainty and an aversion to increases in such uncertainty.

Starting with Bansal and Yaron (2004), various papers have formulated models based on Epstein and Zin (EZ) preferences in a framework in which exogenous state variables follow affine diffusion processes. We follow the particular convenient framework put forward by Eraker and Shaliastovich (2008) who start with the widely used class of continuous time affine diffusion (henceforth AD) asset pricing models. To fix notation, we follow the presentation of Duffie, Pan, and Singleton (2000) and consider a filtered probability space $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t\geq 0}, \mathbb{P})$ where $\mathbb{P}$ refers to the physical or historical probably measure.[2] Moreover, we suppose that the r-dimensional $\mathcal{F}$-adapted process $\mathcal{X}^f$ of state variables or factors is Markov in some state space $D \subset \mathbb{R}^r$, solving the stochastic differential equation:

$$d\mathcal{X}_t^f = \mu(\mathcal{X}_t^f)dt + \sigma(\mathcal{X}_t^f)dW_t$$

where W_t is an $\mathcal{F}_t$-adapted Brownian motion under $\mathbb{P}$ in $\mathbb{R}^r$, $\mu : D \to \mathbb{R}^r$, and $\sigma : D \to \mathbb{R}^{r\times r}$. Furthermore:

Assumption 2.1 (AD)**.** *The distribution of $\mathcal{X}^f$, given an initial known $\mathcal{X}_0^f$ at $t = 0$, is completely characterized by a pair (K, H) of parameters determining the affine functions:*

$$\begin{aligned} \mu(x) &= K_0 + K_1 x, & K \equiv (K_0, K_1) \in \mathbb{R}^r \times \mathbb{R}^{r\times r} \\ (\sigma(x)\sigma(x)')_{ij} &= (H_0)_{ij} + (H_1)'_{ij} x & H \equiv (H_0, H_1) \in \mathbb{R}^{r\times r} \times \mathbb{R}^{r\times r\times r} \end{aligned} \tag{2.1}$$

Given the state process, consumption and dividend growth are characterized as:

$$\begin{aligned} d\ln C_t &= \delta_c' d\mathcal{X}_t^f \\ d\ln D_t &= \delta_d' d\mathcal{X}_t^f \end{aligned} \tag{2.2}$$

The representative agent features EZ preference with parameters δ for time preference and $\theta = (1-\gamma)/(1-\frac{1}{\psi})$, where ψ is IES and γ is coefficient of risk aversion. Denoting the price - dividend ratio as:

$$v_t = \ln P_t - \ln D_t$$

To obtain explicit solutions in terms of the fundamental state variables, assume that the log price-consumption ratio v_t is affine in $\mathcal{X}_t^f$, it is assumed that:

$$v_t = A + B'\mathcal{X}_t^f$$

In equilibrium the evolution of the log pricing kernel can be written in terms of the economic fundamentals

[2]Technically speaking Eraker and Shaliastovich (2008) consider affine jump diffusions. As discussed later, if we rely on continuous record asymptotic - which we don't necessarily have to - then our analysis needs to exclude the presence of jumps.

as:

$$
\begin{aligned}
d\ln M_t &= (\theta \ln \delta - (\theta-1)\ln k_1 + (\theta-1)(k_1-1)B'(\mathcal{X}_t^f - E(\mathcal{X}_t^f)))dt + \lambda' d\mathcal{X}_t^f \qquad (2.3)\\
\lambda &= \gamma\delta_c + (1-\theta)k_1 B \\
k_1 &= \exp(E(v_t))/(1+\exp(E(v_t)))
\end{aligned}
$$

The above implies that the wedge between the historical ($\mathbb{P}$) and the risk-neutral ($\mathbb{Q}$) probability measures is driven by $\mathcal{X}_t^f$. As consumption growth is tied to the state process (e.g. equation (2.2)) it is not surprising that consumption uncertainty features prominently in the characterization of risk premia.

Measuring consumption risk empirically is arguably difficult given the quality of the data. We therefore take a different route - inspired by a more reduced form approach. Namely, in a generic affine diffusion no-arbitrage asset price setting, Duffie, Pan, and Singleton (2000) show that the bond, equity and variance premia at different investment horizons are linear functions of the same risk factors - say state variables $\mathcal{X}_t^f$. Following Britten-Jones and Neuberger (2000), Jiang and Tian (2005), and Carr and Wu (2009), we define the Variance Risk Premium (VRP) as the difference between expected variance between the time t expected equity return variance under $\mathbb{P}$ and $\mathbb{Q}$ probability measures. In an affine setting, over horizon τ this can be written as:

$$
\begin{aligned}
VRP(t,\tau) &= E_t^{\mathbb{P}}[V_{t,t+\tau}^r] - E_t^{\mathbb{Q}}[V_{t,t+\tau}^r] = \delta_{vrp}(\tau) + \gamma_{vrp}(\tau)\mathcal{X}_t^f \\
E_t^J[V_{t,t+\tau}^r] &= \mu_{rv}^J(\tau) + \gamma_{rv}^J(\tau)\mathcal{X}_t^f \qquad J = \mathbb{P}, \mathbb{Q} \qquad (2.4)
\end{aligned}
$$

where the parameters relate to the data generating processes for both $i = \mathbb{Q}$ and $\mathbb{P}$ measures (see for example Bollerslev, Tauchen, and Zhou (2009) and Todorov (2010), among others, for further details).

For some of the asset classes we consider we need to distinguish 'spread' factors from 'volatility' factors. Take for example a short-term credit spread. In such a case spread factors pertain to credit spreads, whereas the volatility factors pertain to their volatility. Hence, we denote by c_t a credit risk spread and V_t^c its spot volatility. In a linear affine setting these can be written as:

$$
c_t = \mu_c + \gamma_c \mathcal{X}_t^f, \qquad V_t^c = \mu_{cv} + \gamma_{cv}\mathcal{X}_t^f \qquad (2.5)
$$

Obviously, the loadings γ_c and γ_{cv} may contain zeros such that the subset of factors which affect (credit risk) spreads may be different from the subset driving (credit risk) volatility.

Given volatility is latent we need to think about filtering. Assume we consider $i = 1, \ldots, N$, i.e. a cross-section of asset volatilities (for the moment for any asset class). We can write spot volatility in a generic way, simplifying the notation, as:

$$
V_t^i = \mu_{iv} + \gamma_{iv}\mathcal{X}_t^f. \qquad (2.6)
$$

We use proxies, i.e. filtered volatilities, to replace the left hand side latent spot volatility in the above equation. Although the underlying affine asset pricing model is cast in a continuous time diffusion setting, we will rely on discrete time ARCH-type models. Even though such models are misspecified they can still be viewed as *filters* and deliver reliable estimates of spot volatility $\hat{V}_t^i$. Indeed, under suitable regularity conditions, discussed in detail by Nelson (1990), Nelson and Foster (1994), Nelson (1996), we know that ARCH filters yield consistent estimates of V_t^i.[3] Hence, we will apply univariate ARCH-type models/filters to produce an estimate of the conditional variances:

$$\hat{V}_t^i \equiv V_t^i + \hat{\varepsilon}_t^i = \mu_{iv} + \gamma_{iv}\mathcal{X}_t^f + \hat{\varepsilon}_t^i \tag{2.7}$$

where $\hat{\varepsilon}_t^i$ is a filtering error, i.e. the difference between the true spot volatility and the one obtained from the ARCH-filter.

We consider a cross-section of volatilities estimated separately for each financial asset return, namely i = $1, \ldots, N$ which are observed at dates t = $1, \ldots, T$. This setup is reminiscent of the large N and large T asymptotics for panel data models of Stock and Watson (2002), Bai and Ng (2002), Bai (2003), among others. In particular, we use principal component analysis (PCA) with panels of filtered volatilities to obtain estimates of $\mathcal{X}_t^f$. The PCA procedure is asymptotically valid as the errors $\hat{\varepsilon}_t^i$ in the panel are filtering errors which satisfy suitable regularity conditions which are standard in the panel data literature and yield desirable asymptotic properties of PCA (see Ghysels (2013) for a general discussion on the topic of PCA analysis with panels of volatility proxies). Although our estimation procedure is similar to Ludvigson and Ng (2007) our methods and factors are very different. Ludvigson and Ng (2007) also extract principal components from large panels of financial asset returns and spreads. However, they estimate the volatility of the factor by fitting a model (e.g. GARCH or RV) to their factor. Instead, we extract the common volatility factor directly from a panel of filtered ARCH-type volatilities. Hence they estimate the volatility of the (conditional mean) factor whereas we estimate factors common to panels of volatilities.

To proceed we need to introduce the commonly used notation for panel data, suitably modified to accommodate filtered volatilities data. To keep our analysis as close as possible to the standard large scale factor models in the literature, we will adopt the same notation with some modification and then discuss the mapping with the framework discussed so far. Namely, consider the vector form model representation:

$$X_t = \Lambda F_t + e_t \tag{2.8}$$

where $E(F_t) = 0$ and $E(F_t F_t')$ is a k-dimensional diagonal matrix (k = $\dim(\mathcal{X}_t^f)$) following the common normalization. The latter implies that the factors we will uncover are some affine transformation: F_t = $\mathcal{H}\bar{\mathcal{X}}_t^f$, with $\mathcal{H}$ a non-singular $k \times k$ matrix. Term structure applications of affine models in particular,

[3]The formal asymptotic analysis of extracting factors from panels is studied in Ghysels (2013). This analysis can also be generalized to integrated volatility. Here we focus on spot volatility due to the unavailability of high frequency data for some of the asset classes we consider in our empirical analysis.

involve anchoring factors to observable series - most notably the so called level, slope and curvature factors (see e.g. Dai and Singleton (2000) for a detailed discussion). In our analysis, there is no obvious way to calibrate the level and scale of F_t, and therefore we use a standard normalization. Moreover, we let (a) $X_t = v_t^i$ or X_t = $((\hat{V}_t^i - \bar{v}_T^i), i = 1, \ldots, N)'$, where $\bar{v}_T^i$ are the sample means for each volatility filter series in the cross-section - the demeaning absorbs the term μ_{iv} + $\gamma_{iv} E[\bar{\mathcal{X}}_t^f]$, in equation (2.7) since the factors and idiosyncratic errors are mean zero, (b) the factor loadings Λ = $(\lambda_1, \ldots, \lambda_N)'$ are non-random and, (c) e_t = $(\hat{\varepsilon}_t^i, i = 1, \ldots, N)'$. The matrix representation of the factor model is:

$$X = F\Lambda' + e \tag{2.9}$$

where X = $(X_1', \ldots, X_N')$ is a $T \times N$ matrix of observations or (demeaned) volatilities and e = $((e_1)', \ldots, (e_N)')$ a $T \times N$ matrix of idiosyncratic errors. Henceforth, to simplify notation we will denote the individual elements of X as x_{it}, and those of e as e_{it}.

The estimator we consider is standard, namely the method of asymptotic principal components, initially considered by Connor and Korajczyk (1986, 1988) and refined by Stock and Watson (2002), Bai and Ng (2002), Bai (2003), as an estimator of the factors in a large N and T setup. For any given r not necessarily equal to the true number of factors k, the principal components method constructs a $T \times r$ matrix of estimated factors and a corresponding $N \times r$ matrix of estimated loadings by solving the following optimization problem:

$$\min_{\Lambda, F} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \lambda_i' F_t)^2 \tag{2.10}$$

subject to the normalization that $(\Lambda_r' \Lambda_r)/N$ = I_r and $(F_r' F_r)$ being diagonal. The estimated factor matrix $\tilde{F}_t$ is $\sqrt{T}$ times the eigenvectors corresponding to the r largest eigenvalues of the $T \times T$ matrix XX'. Moreover, $\tilde{\Lambda}'$ = $(\tilde{F}'\tilde{F})^{-1}\tilde{F}'X$ are the corresponding factor loadings.

Finally, it is worth noting that we do not impose no-arbitrage conditions across pricing equations. Imposing such conditions is a much debated topic in the term structure of interest literature (see e.g. Duffee (2011)) and may be prone to mis-specification issues.

3 Extracting volatility factors from different asset classes

We extract factors from panels of asset volatilities beyond equity and show how these help price equity volatility risk, the RV of S&P 500 stock market returns, the VIX^2, the VRP as well as the FEAR index. More precisely we extract common factors from panels that are stratified by the following homogeneous asset classes: (1) long-run corporate bond spreads volatilities, (2) short-run funding spreads volatilities and

(3) energy and metals commodities returns and cash/futures spreads volatilities.[4] These three panels involve monthly filtered volatilities using an AR(1)-GARCH(1,1) model estimated for each univariate series during the period 1999m01 - 2010m12. An AR(1)-GARCH(1,1) model is estimated for each spread and returns series given that this simple volatility model is often considered as a benchmark in many financial asset volatility empirical studies to capture both conditional mean and variance dynamics. In the robustness section 5 we also examine the corresponding log volatility factors. In addition, we estimated AR(1)-EGARCH(1,1) models to account for asymmetries in volatilities and extracted the corresponding volatility factor. Given that our results were not affected by the type of ARCH filter we focus on the AR-GARCH filter.[5] We consider 1999 as the starting period due to the fact that the number of series in the cross-section, N increases significantly especially in the short-run funding spreads and long-run corporate spread panels as opposed to say having a starting period in 1990 where we have roughly half of the cross-section in the first two classes of assets. The data sources are the Haver Analytics and the Global Financial Database (GFD).

Note that in our empirical analysis, we control for volatility of the S&P 500 directly by including lagged VIX and/or RV, and therefore focus on volatilities beyond equities. While the analysis reported here focuses on long-run corporate bond spreads volatilities, short-run funding spreads and energy and metals commodities, it should be noted that we did examine other asset classes, including foreign exchange returns volatilities, but did not find much evidence of predictability. For the sake of conciseness we therefore limit our analysis on the three aforementioned asset classes.

We focus on the first principal component for each asset class and do not try to estimate the number of factors. It turns out that the first principal component goes a long way in explaining the variation in each panel, which justifies our approach (see details reported below). Moreover, the advantage of picking only the first principal component is that we have a label for each of the factors, referring to the panel being used to construct it. The acronyms and the names of our factors and other variables used in the paper are summarized in Table 1. The detailed descriptions of all series appear in Internet Appendix (see Andreou and Ghysels (2014)), Section A.1 as well as their correlation with our factors. The three panels of financial assets refer to the following series which are also summarized in Tables 2-4.

(1) The **long-run corporate risk** panel ($N = 74$) involves volatilities of relatively long-run Merrill Lynch bond corporate bond spreads (longer than one year) from different industries, indices, maturities, rating categories vis-à-vis the corresponding government bond maturity (e.g. 1,5,7,10 years). An AR-GARCH model is estimated for each long-run corporate spread. We then construct a panel of fitted volatilities from each corporate bond spread series. The first principal component estimated from this panel of filtered volatilities represents the common Long-Run Corporate spreads Volatility Factor, LRCOR_VF.

[4] All the series were transformed to ensure stationarity before estimating a volatility model for each financial asset series. Moreover, we have established that our results are robust to extracting volatilities factors from ARCH filters applied to either demeaned or demeaned and standardized returns and spreads data.

[5] Although our methods apply to Realized Volatility (RV) estimators we do not pursue this approach in the empirical analysis due to unavailability of intraday data for most of the financial series in our panels. Resorting to the daily frequency of our financial asset variables does not yield very precisely estimated RVs because of the small number of days aggregated within a month.

(2) The **short-run funding risk** panel ($N = 35$) comprises volatilities of short-run spreads indicators such as the TED as well as different short-run maturities (of 7 Days,1,3,6,12 months) of the LIBOR, Eurodollar, (Non) Commercial (Non) Financial papers spreads with respect to the Federal Funds (FF) rate, among others. The spreads and their volatilities considered here have a shorter horizon relative to those from the long-run corporate spreads panel above.[6] For each series an AR-GARCH model is estimated as a proxy of the filtered volatility of each spread. The first principal component represents the common volatility factor estimated from this panel of AR-GARCH fitted values, denoted as Short-run Funding spreads Volatility Factor, SRFUN_VF.

We also consider the enlarged cross-section of volatilities of both the long-run corporate spreads volatilities and the short-run funding spread volatilities with $N = 107$ series to extract the common (short-run and long-run) Corporate Volatility Factor, denoted by COR_VF.

(3) The **energy and metals commodities** risk block is based on a homogeneous panel of volatilities of energy and metal commodities ($N = 122$) of various spot and future returns and the corresponding spreads for each commodity. Examples of energy series include gas, oil, biofuel and of metals include gold, silver, aluminium e.t.c, as well as the corresponding energy and/or metals indices. For each commodity returns and cash/futures spreads we estimate an AR-GARCH model. The common volatility factor estimated from the panel of these volatilities is denoted by the Energy and Metals Volatility factor, or EM_VF.

In Figure 1 we plot three volatility factors, namely the short-run funding spreads volatility factor (SRFUN_VF), the long-run corporate spreads volatility factor (LRCOR_VF) and the (short- and long-run) corporate spreads volatility (COR_VF) during the monthly period 1999m01 - 2010m12. We note the distinctive spike during the global financial crisis - a spike which also appears in the VIX^2, RV and the VRP. The spike will prompt us to look at samples *without* the financial crisis as well, in order to examine if our results are sensitive to these extreme events which are triggered by the crisis. In Figure 1 we observe the relatively different behavior of SRFUN_VF from the other two volatility factors during the crisis. The short-run funding spreads volatility factor started increasing in September 2007 well before the rest of the other (long-run) corporate spreads volatility factors. In fact the first peak of the SRFUN_VF is much higher relative to the other two volatility factors in Figure 1. This first peak in SRFUN_VF is in February 2008 and is associated with diminished liquidity in the interbank funding rates and the announcement of the Federal Reserve Board to reduce its target for the federal funds rate as well as the primary credit rate. The second peak in SRFUN_VF is of the same size and coincides with the peak in the corporate volatility factors in September 2008 due to the bankruptcy of Lehman Brothers. Another interesting feature from Figure 1 is that SRFUN_VF reverted to its low historical mean level shortly after the Lehman crisis whereas the level of the (long-run) corporate volatility factors remained at a relatively higher level in the post-Lehman period and up to the end of 2010. We also notice that the long-run corporate spreads factor, LRCOR_VF, is highly correlated with COR_VF which is the factor extracted from both the long-run corporate spreads

[6] All series except the 1-year LIBOR spreads have horizon less than one year.

and short-run funding spreads volatilities. The correlation matrix of our factors as well as other related factors in the literature is presented in Table 5. We observe that the correlation between COR_VF and LRCOR_VF is around 0.9 whereas that of LRCOR_VF and SRFUN_VF is around 0.4 because they refer to different corporate risk assets. Interestingly the Chicago Fed National Conditions Index (NFCI) correlates highly with LRCOR_VF (with 0.9 correlation coefficient) and less so with SRFUN_VF (with 0.75 correlation coefficient).

Figure 2 displays the energy and metals returns spreads volatility factor (EM_VF) in the monthly period 1999m01 - 2010m12. Again, we note the effect of the recent crisis. The volatility factors displayed in both Figures 1 and 2 will play a prominent role in our empirical analysis.

We now turn to examine the percentage of the variation that the first volatility factor explains in each panel and the correlation of each volatility factor with some individual volatility series. In the corporate risk panel the common factor extracted from the AR-GARCH univariate filters of long-run corporate spreads, LRCOR_VF, explains 75% of the cross-sectional variation of the series in the panel. The LRCOR_VF factor loads heavily on the following types of volatility spreads vis-à-vis the corresponding maturity government bond: the Merrill Lynch (ML) Treasury Master Effective Yield, the ML Treasury Master Yield To Worst, the ML Corporate Industrials Bonds 1 to 3 Years Effective Yield and the ML Corporate Utilities Bonds 1 to 3 Years Effective Yield. These individual volatilities have an R^2 of around 0.7 with the LRCOR_VF. Other spreads volatilities that correlate highly with LRCOR_VF relate to corporate AA-type bond or bonds of Industrial, Utilities, Automobiles and Financials corporations. In contrast, the Moody's corporate bond spreads Baa-Aaa volatility yields an R^2 of 0.2 with LRCOR_VF whereas the Baa minus the 10 Year government bond volatility has a corresponding R^2 of 0.5 with LRCOR_VF. These results are found in the Internet Appendix, Section A.1 (see Andreou and Ghysels (2014)).

The short-run funding risk factor, SRFUN_VF, explains 65% of the variation of the panel. This factor loads heavily on (financial and nonfinancial) commercial paper spreads and the short-run LIBOR spreads. In particular the R^2 of the SRFUN_VF ranges from 0.7 to 0.4 with the following spreads: the 15Day A2/P2/F2 Nonfinancial Commercial Paper minus the 15Day Aa Financial Commercial Paper, the 15Day A2/P2/F2 Nonfinancial Commercial Paper minus the 15Day Aa Nonfinancial Commercial Paper and the 7Day London Interbank Offered Rate minus the Fed Funds rate. Again these results are found in the Internet Appendix, Section A.1.

The last panel refers to the energy and metals commodities returns and spreads volatilities. The first principal component yields a common volatility factor, EM_VF, which explains 95% of the variation of this panel of asset volatilities and correlates highly with the volatilities of the following series: the S&P GSCI Heating Oil Total Returns Index and Futures and the S&P GSCI Energy Commodities Total Return Index. The R^2 of the individual series of this panel with EM_VF (found in the Internet Appendix, Section A.1) show that the fitted volatility of many oil type series (returns, excess returns, futures), the Gas and Oil index as well as Energy and Metals commodities index volatilities correlates 0.5-0.6 with the EM_VF factor. Other metals

like gold, aluminium, have an R^2 of around 0.25-0.4 with EM_VF.

Further to extracting volatility factors from the above three cross-sections of filtered AR-GARCH series we can also extract factors from the spreads of the series (as opposed to the volatility of the spreads). This is relatively standard in the literature. For completeness and comparison purposes we also pursue this approach and relate our factors extracted from the spreads or returns to other factors in the literature. Examples of these are the Gilchrist and Zakrajšek (2012) spread, GZ_SPR, the Chicago Federal Reserve Bank Financial Index (NFCI) and the St Louis Financial Stress Index (FSI). The corresponding factors from our four panels are the Long-Run Corporate Spreads, LRCOR_SF, the Short-Run Funding Spreads, SRFUN_SF, the Corporate Spreads (both short-run and long-run), COR_SF, as well as the Energy and Metals Returns and cash/futures Spreads, EM_RF.[7] Figure 3 shows the time series behavior of our corporate spreads factor (COR_SF) with the aforementioned factors, GZ_SPR, FSI and NFCI. It is evident how correlated these factors are. This is also shown by the correlation matrix of our factors and others related in this literature in Table 5. It is worth mentioning at the outset that our volatility factors are relatively better empirically than the corresponding spreads factors in explaining the VIX^2, the RV and the VRP. Hence we focus our discussion on the volatility factors, but also provide some results for comparison purposes with the corresponding spreads factors in the robustness section 5.

4 What drives the VIX^2, RV, VRP and the FEAR index?

The first objective is to examine the ability of our three volatility factors, SRFUN_VF, LRCOR_VF and EM_VF, to predict the VIX^2, the Realized Volatility (RV) of the S&P 500, the VRP and the FEAR index at different horizons. Our monthly RV for the S&P 500 is the summation of the 78 within day five-minute squared returns covering the normal trading hours from 9:30am to 4:00pm plus the close-to-open overnight squared return. For a typical month with 22 trading days, this leaves us with a total of $T = 22 \times 78 = 1716$ five-minute returns augmented with 22 overnight squared returns. The Variance Risk Premium, VRP, is not directly observable and therefore an empirical proxy can be constructed. We follow Bollerslev, Tauchen, and Zhou (2009) we assume that $E_t(RV_{t+1}) = RV_t$, i.e. RV_t follows a random walk, such that the $VRP_t = VIX_t^2 - RV_t$ becomes directly observable at time t. An alternative approach, pursued by Drechsler and Yaron (2011), is to assume that the estimate $E_t(RV_{t+1})$ follows a twelve month lag moving average which does not involve parameter estimation. Different methods and models can also be adopted to approximate the conditional expectation of RV_t such as, for instance, the conditional expectation is replaced by the forecasts of different reduced-form model specifications for RV. Bekaert and Hoerova (2014) emphasize this point and show that alternative RV forecasts not only affect the VRP but also have implications on the role of the latter variable in predicting stock returns, economic activity and financial instability. For this reason, we also

[7] Following the standard practice, before extracting factors we transform all individual series in the panels to ensure stationarity and then we demean and standardize them. For the commodity prices we take first log differences whereas for all the spreads we consider their levels.

consider an alternative approach using a jump-diffusion model to specify the VRP following e.g. Todorov (2010). The VRP and additional results related to this alternative are reported in the robustness section 5 and in the Internet Appendix, Section A.2. The FEAR index data are obtained from Bollerslev and Todorov (2011).

We estimate predictive regressions for the VIX^2, S&P 500 RV and the VRP over various horizons, H, using our volatility factors as well as other variables as predictors.[8] We focus the discussion on the results related to the short-run funding spreads volatility factor, SRFUN_VF, and the energy and metals volatility factor, EM_VF, as these factors turn out to be key to our empirical findings.[9]

4.1 Empirical Results

Table 6 presents the estimated linear predictive regression models for the VIX^2 during the period 1999m01 - 2010m12 for forecasting horizons of H = 6, 9 and 12 months. For each model, the least squares parameter estimates and the Newey West HAC standard errors with fixed bandwidth are reported along with the adjusted R^2. The following models are specified: In model 1 the VIX^2 depends on its own lag, VIX$^2(-H)$. In model 2 the VIX^2 is driven by the volatility of consumption following Drechsler and Yaron (2011) and by VIX$^2(-H)$. We proxy the volatility of consumption using the AR-GARCH fitted values of the monthly per capita consumption on non-durables and services which is denoted by DLC_V. This approach is also used in Drechsler and Yaron (2011) and Bansal and Shaliastovich (2013). Drechsler and Yaron (2011) use a GARCH model while Bollerslev, Tauchen, and Zhou (2009) use an AR-GARCH model to estimate the volatility of different consumption measures. We also address alternative measures of consumption volatility in the robustness section 5. The corresponding single factor model specification for the VIX^2 which is closer to the consumption-based asset pricing theory of, e.g. Bansal and Yaron (2004), Drechsler and Yaron (2011), is given by model 7 and includes only the volatility of consumption, DLC_V($-H$), i.e. without the lagged VIX^2. The remaining models considered in Table 6 incorporate our new volatility factors, the Energy and Metals returns and spreads volatility factor, EM_VF($-H$) and the short-run funding spreads volatility factor, SRFUN_VF($-H$) or just one of these factors at a time, with and without VIX$^2(-H)$ in models 3-6 and models 8-9, respectively.

Three broad conclusions can be inferred from the results in Table 6: (i) The general specification of the three factor models which include the volatility of consumption, DLC_V($-H$), the energy and metals

[8] Bai and Ng (2006) show that the assumption in the factor model that $N, T \to \infty$ with $\sqrt{T}/N \to 0$ implies that the least squares estimates of our predictive models are $\sqrt{T}$ consistent and asymptotically normal and the pre-estimation of factors in the first-step does not affect the asymptotic variance of our estimates in the predictive regressions of the second-step and therefore inference is standard.

[9] The third factor extracted from the Long-run Corporate Bonds spreads, LRCOR_SF, and volatilities, LRCOR_VF, is less significant in explaining future VIX^2, RV and VRP for $H > 6$ and therefore we do not report results for this factor in this section. Yet, these two corporate factors turn out to be significant in predicting the monthly excess returns which we turn to these in section 6. A comprehensive comparison of performance of all our factors as well as other related factors in the literature is addressed in the robustness section 5.

volatility factor, EM_VF($-H$), and the short-run funding spreads volatility factor, SRFUN_VF($-H$), shows that the last two factors are statistically significant in explaining the VIX^2. This result holds for horizons $H = 6, 9, 12$ months. In general the volatility of consumption DLC_V($-H$) turns out to be statistically insignificant in explaining the VIX^2. (ii) The short-run funding risk volatility factor, SRFUN_VF($-H$), in particular, is statistically significant (at the 1% level) in almost all forecast horizons, H = 6, 9 and 12 and alternative model specifications in Table 6. Most importantly the SRFUN_VF($-H$) factor provides significant gains in terms of adjusted R^2 for all H horizons vis-à-vis models 1, 7 and 2, which use either the VIX^2($-H$), the DLC_V($-H$) or both of these predictors, respectively. (iii) The adjusted R^2 gains in models with our two factors, SRFUN_VF and/or EM_VF, are higher for the shorter horizons of 6 and 9 months compared to those of one year. For example, for H = 6 months models 1 and 2 yield adjusted R^2 of 6% whereas incorporating the SRFUN_VF($-H$) factor can improve the adjusted R^2 by on average 35% for explaining the VIX^2 during this period.

Table 7 turns to the role of our volatility factors in forecasting S&P 500 RV at different horizons H. We examine whether our two factors, SRFUN_VF and EM_VF, can predict the RV for the same sample period 1999m01 - 2010m12. Table 7 has a similar structure to that of Table 6. The difference in Table 7 is that models 1-6 control for the lags of both the RV and the VIX^2. Two general results follow from Table 7: (i) The SRFUN_VF($-H$) and EM_VF($-H$) factors are both statistically significant at H = 6 and 9 months whereas the SRFUN_VF is significant at all three horizons including a year. Overall the SRFUN_VF appears to be the relatively most significant factor for all H vis-à-vis the other factors. In contrast, the energy and metals volatility factor, EM_VF, appears to be significant for relatively shorter horizons of 6 months and insignificant for longer horizons of one year. Interestingly, the lagged RV($-H$) is only significant for H = 6 whereas the SRFUN_VF is significant for all horizons considered from 6 to 12 months. (ii) The adjusted R^2 gains in models with our two factors are higher for the shorter horizons of 6 and 9 months. For example, using just the RV($-H$) yields a low adjusted R^2 of 1% whereas incorporating the SRFUN_VF factor can improve the adjusted R^2 by on average 30% and 20% for H = 6 and H = 9 months, respectively.[10]

Table 8 turns to the corresponding predictive regression models for the VRP for the sample period 1999m01 - 2010m12, again for forecasting horizons H = 6, 9 and 12 months. We compare the performance of our factors with models 1, 2 and 7. Model 1 uses the VIX^2($-H$) predictor. Model 7 is driven by the single factor of the volatility of the volatility of consumption, approximated by DLC_V($-H$). Model 7 is directly related to the long-run risk model of e.g. Bansal and Yaron (2004) and Drechsler and Yaron (2011). Model 2 can also be considered as another benchmark model which includes both VIX^2($-H$) and DLC_V($-H$). The reported results in Table 8 yield the following interesting conclusions: (i) In accordance with the theory the VRP can be explained by the single factor model namely the volatility of the volatility of consumption which is approximated by the DLC_V which turns out to be significant in longer horizons of 12 months. In

[10]The empirical literature on predictive models for the Realized Volatility (RV) also considers the logRV transformation. The results in Table 7 are robust to the log transformation of all the variables. In addition the logRV transformation yields further improvements in the adjusted R^2 compared to these reported in Table 7 for the RV.

particular, in the last panel of Table 8 the DLC_V(-12) is significant even in the presence of our two factors as well as the lagged VIX^2. However, in shorter horizons of H = 6 this consumption risk factor becomes insignificant or weakly significant in some models for H = 9. These empirical results are not inconsistent with the theory. Overall the empirical findings for the VRP and DLC_V are consistent with Drechsler and Yaron (2011), namely that the volatility of volatility of consumption is a long-run risk factor driving the VRP such as a 12-months horizon in our analysis. (ii) Interestingly the energy and metals volatility factor, EM_VF$(-H)$ has an opposite and complementary role in driving the VRP compared to the DLC_V. The EM_VF is significant for shorter horizons of H = 6 months only and turns out to be insignificant for longer horizons of H = 12 months. (iii) The factor that remains strongly significant in all forecast horizons and all predictive model specifications is SRFUN_VF. This short-run funding volatility factor appears to be driving the VRP and it is the factor which also improves the adjusted R^2 for all H and especially H = 6. Hence our two new volatility factors provide a significant and complementary role to that of consumption volatility in explaining the VRP.

The results in Tables 6-8 refer to the sample period that ends in 2010m12 which includes the bankruptcy of Lehman Brother and its aftermath during September and October 2008. We therefore re-examine our results, excluding the unusual nature of the global financial crisis. In Tables 9-11 we estimate the same models as those in Tables 6-8 but exclude the months of the Lehman brothers collapse using a dummy variable equal to one during the two aformentioned months. We also consider the alternative approach in dealing with the Lehman Brothers period by trimming the sample, where we obtain similar results to those reported in Tables 9-11.[11] Table 9 shows the predictive regression models results for the VIX^2 excluding the two months related to the Lehman Brothers collapse. Comparing the results in Tables 6 and 9 with and without the observations of 2008m09 and m10, respectively, we find that overall the results described in Table 6 are qualitatively the same as those with Table 9. Namely, for the VIX^2 predictive regressions the SRFUN_VF$(-H)$ is still the most strongly significant predictor for all horizons H = 6, 9 and 12. The EM_VF$(-H)$ is significant only at shorter horizons H = 6 and 9, whereas the DLC_V$(-H)$ still turns out to be insignificant in all models and horizons except in explaining the VRP at H = 12 months. The notable difference between the results in Tables 6 and 9 is the fact that excluding the Lehman Brothers collapse improves significantly the adjusted R^2's of the models 1, 2 and 7, for all H, which use either the lagged dependent term, or DLC_V$(-H)$ or both. Yet, including our factors and especially SRFUN_VF$(-H)$ for H = 6 and 9 months still improves the adjusted R^2. In some cases our factors can double the adjusted R^2 vis-à-vis those of models 1, 7 and 2 for the VIX^2. Similarly in Tables 10 and 11 we find that excluding the effect of the Lehman bankruptcy improves the adjusted R^2's of the simple models 1 and 2, respectively. Consequently, the corresponding improvements from adding our factors in the predictive models for the RV and VRP turn out to be relatively lower when the crisis months are not in the sample. Still in the RV predictive regressions in Table 10 our

[11] Using a trimming of 2% and 2.5% removes many of the outliers including the Lehman Brother bankruptcy period. In particular 2008m10, 2008m11 and 2009m02 are excluded using a trimming of 2% and the corresponding 2008m09, 2008m10, 2008m11 and 2009m02 are the excluded dates using a trimming of 2.5%. We find that in trimming the sample the results remain robust to those reported in Tables 9-11.

two proposed factors, SRFUN_VF and EM_VF, are the two significant factors (especially for $H = 6$ and 9) and improve the adjusted R^2's. These results are consistent with the corresponding ones in Table 8 which does not exclude the two months associated with the Lehman Brothers crisis. A notable difference in the results of the VRP predictive regressions in Table 11 from the rest of the results is that there are no gains in the adjusted R^2 from including our factors vis-à-vis models 1 and 2, that incorporate VIX$^2(-H)$ and/or DLC_V(-1). Yet, our SRFUN_VF factor remains significant at H = 12. Concluding, the overall results in Tables 6-11 show the significance of our factors and especially SRFUN_VF across all horizons $H = 6, 9, 12$ and all predictive models of the VRP and especially the VIX^2 and RV, which is robust to incorporating or excluding the period of the Lehman Brother bankruptcy and its aftermath.

Last but not least, we examine whether our two volatility factors can also be used as predictors for the monthly FEAR index proposed by Bollerslev and Todorov (2011). Hence we estimate the models 1-9 as specified in Table 12 for the FEAR index allowing also for FEAR(-H) as a predictor. For the monthly sample from 1999m01-2010m12 we find that our SRFUN_VF is a significant predictor of the FEAR index in all horizons from H = 6, 9, 12 months and yields relatively higher improvements in terms of adjusted R^2 over the benchmark models with the FEAR(-H), the VIX^2(-H) and the lagged consumption volatility, especially for H = 9 and 12 months horizons. Excluding the period of the Lehman Brother bankruptcy from our sample we find that the SRFUN_VF is still a significant predictor for the monthly FEAR index, yet the gains from the adjusted R^2 are smaller, as reported in Table 13.

4.2 Illustrating the economic significance of our volatility factors for the VIX^2

In this section we illustrate the economic significance of our results using a simple trading strategy. We exploit the forecasts of our models and proposed factors for the VIX^2 in order to evaluate the profits from buying or selling VIX^2 futures. To appraise the success of the strategy, we use the VIX^2 futures price index available from the CBOE Futures Exchange website. Due to data availability we focus on the period 2007m11-2010m12 and consider the shorter horizons H from 1 to 6 months ahead given the relative short span of the VIX^2 futures series. The VIX^2 futures price series was constructed such that for each date the closing price of the last day of the month which is H months ahead is recorded.

The strategies considered were as follows. We consider a six-month contract quoted on the last day of a particular month.[12] A decision is made to buy or sell VIX futures based on the quantity $\left(\text{VIX}^2/12 - \text{Discounted Forecast}\right)/|\text{VIX}^2/12 - \text{Discounted Forecast}|$, using our model predictions with H = 6, such that for values equal to -1 an investor would sell and for $+1$ an investor would buy. The long or short position in the six-month contract is held three (i.e. sell or buy a H = 3 contract). Upon unwinding the position a profit or loss was recorded.

The descriptive statistics for the returns generated by the aforementioned trading strategies based on the

[12]The results for horizons H = 5 and below were similar and hence are not reported here for conciseness purposes.

alternative models of the VIX^2 futures during the period 2007m11-2010m12, as well as the period after the collapse of Lehman Brothers, 2008m11-2010m12, are presented in Table 14. The table contains the mean, median return as well as standard deviation of the profits/losses for models 1-9. Based on the reported results in Table 14 we find that the best forecasting models 3, 4, 5 and 8 in terms of H = 6 (reported at bottom in table) give identical results for both sample periods. They yield a 10 % return for the three month holding period. All these models use our proposed volatility factors (SRFUN_VF or/and EM_VF) as predictors. It should also be noted, however, that the trading strategy has also high standard deviations, and thus considerable risk.

We complement the above VIX^2 futures price analysis by performing an additional out-of-sample forecasting exercise in order to evaluate how the alternative VIX^2 model specifications of models 1-9 can predict the realized VIX^2 for a forecasting horizon of H = 6 months ahead. The forecast evaluation is also reported at the end of Table 14. The Mean Square Error (MSE) of each model is used as the forecasting evaluation criterion. The squared errors of the predictions of each model were calculated by squaring the difference between the discounted realized VIX^2 (VIX^2/risk-free rate$^{0.5}$) and the discounted forecasts of each model (VIX$^2(t+H)$/risk-free rate$^{0.5}$).[13] The last panel of Table 14 reports the ratio of the MSEs (RatMSE) obtained as the MSE of model i, $i = 2, \ldots, 9$, divided by the MSE of model 1, which includes the lagged dependent term only. We find that model 3 which is driven by the lagged VIX^2 and SRFUN_VF can improve the forecasting performance in terms of MSE by almost 40 percent compared to model 1 for the VIX^2. This improvement is evident in both sample periods - prior and post the Lehman Brothers bankruptcy, 2007m11-2010m12 and 2008m11-2010m12, respectively. Interestingly the models which incorporate our two volatility factors, the EM_VF and especially the SRFUN_VF as predictors, always yield ratios of MSEs below one which suggests that in terms of MSE our models provide forecasting gains for H = 6 months ahead.

5 Robustness checks

In this section we summarize the findings of an extensive robustness analysis of the results reported in Section 4 focusing on the predictive models for the VIX^2, RV and VRP. The details are reported in an Internet Appendix, Section A.2. To save space, we only highlight the main findings as the analysis is quite lengthy and detailed. We report a small selection of results in the main body of the paper. The default, however, is that all the details appear in tables reported in the Internet Appendix, Section A.2. Hence, we mainly summarize many robustness results in this section, skipping all the specific details.

(i) Comparing the spreads and volatility factors in predictive models for VIX^2, RV and VRP

In the previous section we focused exclusively on discussing the effects of volatility factors. As mentioned

[13] The risk free rate is equal to 1 plus the annualized rate (%).

in section 3 our empirical analysis does not deal exclusively with panels of spot volatility filters, it also extracts factors from various panels of return and spread series. Recall that we focused on three panels of financial assets: (1) the long-run corporate risk panel, (2) the short-run funding risk panel and (3) the energy and metals commodities. In each of the three cases we augment our analysis with principal components extracted from the spread series (for (1) and (2)) and commodity returns or cash/futures spread series (for (3)). Hence, we have the first principal component estimated from each of these panels namely the Long-run Corporate Spreads factor, LRCOR_SF, the Short-run Funding Spreads factor, SRFUN_SF, and finally, the Energy and Metals Returns and cash/futures Spreads panel, EM_RF.

To appraise the difference between volatility factors and spread/return factors we provide a summary and a comparison of the adjusted R^2's and their significance obtained in the predictive models for the VIX^2, RV and VRP reported in Table 15 panels A, B and C, respectively. Our sample period remains the same, 1999m01-2010m12. The alternative corporate risk factors compared are: The three volatility factors SRFUN_VF, LRCOR_VF and COR_VF, as well as the corresponding three spreads factors SRFUN_SF, LRCOR_SF and COR_SF. In addition, we use the Gilchrist, Yankov, and Zakrajšek (2009) and Gilchrist and Zakrajšek (2012), so called GZ spread factor (GZ_SPR).[14] Note that the GZ_SPR correlates highly with our long-run corporate bonds spreads factor, LRCOR_SF, since some of the individual series in our panel are common to those of Gilchrist and Zakrajšek (2012). The correlation coefficient of the GZ_SPR with the LRCOR_SF is 0.9. Furthermore we consider the following factors: the St Louis Federal Reserve Bank Financial Stress Index (FSI) and the Chicago Federal Reserve Bank National Financial Index (NFCI) and sub-indices which refer to series classified in three categories: Risk, Credit and Leverage. Figure 3 presents the time series behavior and close relationship of our (short-run and long-run) Corporate Spreads factor, COR_SF with the FSI, the GZ_SPR and the NFCI.[15] The correlations of these factors are also reported in Table 5. The FSI and NFCI are highly correlated with the COR_SF, the LRCOR_SF and the GZ_SPR with correlation coefficient equal to 0.9. The FSI and NFCI are closely related to our spreads factors in the sense that we have a common set of series in the panels from which we estimate the first principal component of the observed spreads or rates of returns. Yet, our three volatility factors are different from the FSI and NFCI factors because they are extracted from the filtered volatilities of spreads and not from the mean of these series as is done for the FSI and NFCI. Both the FSI and NFCI are relatively less correlated with all our volatility factors in general with correlation being around 0.7. Interestingly, both the short-run funding spreads and volatility factors, SRFUN_SF or SRFUN_VF, show the relatively lowest correlation of 0.6-0.75 with any of the existing spreads factors in the literature (GZ_SPR, FSI, NFCI). Hence, the SRFUN_SF factor as well as all our volatility factors are different from existing factors in the literature. Last but not least, it is worth mentioning that both the FSI and NFCI incorporate equity market indices and most importantly the

[14]The main sources of data used the GZ spread are proprietary data on the corporate bond market purchased by the Federal Reserve Board. It contains information on all individual corporate bonds that comprised the Lehman Brothers Bond Indexes.

[15]Comparing the FSI which is constructed from 18 series and our SRFUN_SF we have 3 series in common namely the TED, the LOIS and the 3 month commercial paper minus the 3 month Treasury bill spread. The FSI and our COR_SF have 9 series in common which are related to all corporate and government bond spreads.

VIX^2, which is not the case for our factors.

Table 15 presents the summary results for the aforementioned alternative corporate factors by focusing on reporting the adjusted R^2 from the alternative predictive models which use these factors across different H to explain the VIX^2 (panel A), the RV (panel B) and the VRP (panel C). The first column in each panel reports the model specifications and the subsequent columns represent the factor used one at a time, denoted FACTOR_X, in the predictive regression model. The corresponding adjusted R^2's and significance levels of each factor are reported in each column. The overall result from Table 15 is that for H = 6 and 9 the SRFUN_VF provides the highest adjusted R^2 and strongest significance (at 1% level) relative to the other factors, in explaining the VIX^2 (panel A), the RV (panel B) and VRP (panel C). However, for H = 12 our SRFUN_VF factor, the FSI and NFCI have similar adjusted R^2 across all panels. Among the NFCI subindices those that refer to Risk and Credit are significant in predicting the VIX^2 and the VRP. In addition, the SRFUN_VF turns out to be the relatively most significant factor across different model specifications followed by NFCI, COR_SF and FSI and the GZ_SPR factors. It is worth noting that the adjusted R^2's are mildly higher when using the SRFUN_VF instead of the COR_SF (which includes both short- and long-run spreads) for explaining the VIX^2 (panel A). Interestingly the gains become more than double when using the SRFUN_VF instead of any of these factors (COR_SF or FSI or NFCI or GZ_SPR) to predict the RV for H = 6 and 9 (panel B). In addition the SRFUN_VF is strongly significant in predicting RV compared to NFCI or FSI. Similarly in panel C the adjusted R^2 from using SRFUN_VF for explaining the VRP at H = 6 are again almost double compared to those of FSI or NFCI or (LR)COR_SF or (LR)COR_VF. In the VRP predictive regressions for longer horizons (of $H = 9, 12$) all seven factors (namely SRFUN_VF, COR_SF, LRCOR_SF, GZ_SPR, FSI and NFCI) are significant albeit of their small adjusted R^2's. Overall, although the above factors are significant predictors of the VIX^2, the RV and the VRP, it is the SRFUN_VF that appears the relatively most significant and stronger predictor in terms of adjusted R^2 across all H and especially for the VIX^2 and the RV.

(ii) How many corporate risk factors affect the VIX^2, RV and VRP?

We examine how many corporate risk factors explain the VIX^2, RV and VRP for the period 1999m01 - 2010m12. Given that in Table 15 COR_SF and LRCOR_SF (the factors from the spreads of short-run funding and/or long-run corporate spreads which correlate highly with GZ spread) appear significant, we examine if there is an extra corporate risk factor in addition to SRFUN_VF by orthogonalizing say the COR_SF and SRFUN_VF factors. From the linear regression of COR_SF on SRFUN_VF we obtain the residuals which represent the new factor, denoted by CORSF_SRFUNVF, that is orthogonal to COR_SF and SRFUN_VF. We examine whether this latter factor is significant in addition to SRFUN_VF and EM_VF. The IV method is used to estimate these models and correct for the generated regressor, CORSF_SRFUNVF. The overall conclusion from this robustness exercise is that from the corporate risk panel considered the SRFUN_VF is the strongest factor leading the VIX^2, RV and VRP. The same results apply when we apply the approach to orthogonalizing the LRCOR_SF.

(iii) Reverse Causality analysis

We also examine the reverse causality namely whether the VIX^2 and RV can also help predict our volatility factors, SRFUN_VF, EM_VF, LRCOR_VF. Hence we test the null hypothesis of no reverse causality by estimating a VAR and testing the statistical significance of the coefficients of VIX$^2(-H)$ and RV$(-H)$ for various H using robust standard errors. The general result is that during 1999m01 - 2010m12 there is no empirical evidence that the VIX^2 and the RV Granger cause the SRFUN_VF or SRFUN_SF, the EM_VF or EM_RF for H = 6, 12 months.

(iv) Alternative consumption Volatility Proxies

The volatility of consumption is difficult to measure empirically. A number of papers (e.g. Bali and Zhou (2012), Bollerslev, Tauchen, and Zhou (2009), Zhou (2010), Mueller, Vedolin, and Zhou (2011), Wang, Zhou, and Zhou (2013)) approximate consumption volatility by monthly industrial production (IP) or the Chicago Fed National Activity Index (CFNAI) volatility instead of the per capita consumption on non-durables and services growth volatilities as done by Drechsler and Yaron (2011). Hence we replace the DLC_V in all models of Section 4 with the corresponding volatility of industrial production estimated by an AR-GARCH model for the growth rate of industrial production denoted by DLIP_V. Similarly we estimate an AR-GARCH for the CFNAI denoted as CFNAI_V. We examine the robustness of the consumption volatility factor using these alternative proxies. Overall we find that the volatility of the per capita consumption DLC_V used in Tables 6-11 is a relatively more significant factor compared to CFNAI_V and DLIP_V, especially in the predictive regressions of H = 9, 12 for the VRP. The latter result is useful given that the Drechsler and Yaron model refers to this being as a long-run risk factor which we find to be empirically stronger for the DLC_V proxy. As a last remark in this robustness exercise we note that the significance of our proposed factors SRFUN_VF and EM_VF is not affected by the type of consumption volatility series used in the empirical analysis.

(v) The impact of alternative Uncertainty Indices

Following the recent literature on proxies of uncertainty and their relationship to measures of volatility in the financial markets and the real economy we investigate if the Economic Policy Uncertainty (EPU) index proposed by Bloom (2009) and the Macroeconomic Uncertainty (MU) indicator by Jurado, Ludvigson, and Ng (2013) are alternative driving factors of the VIX^2, RV and VRP and if they affect the significance of our proposed factors. Therefore we re-estimate our models using the EPU or MU instead of DLC_V. Using either the EPU or the MU as single driving factors for the VIX^2 and VRP we find both to be insignificant in our sample period. However, when the SRFUN_VF and EM_VF factors are added to the predictive regressions then the EPU and the MU become weakly significant in some models of the VIX^2 and VRP.

(vi) The Ludvigson and Ng (2007) volatility factor approach

Ludvigson and Ng (2007) extract the common factors from a large panel of monthly financial assets returns

and spreads. Then they approximate the volatility of this factor by estimating a volatility model (e.g. a GARCH or a RV) for the factor extracted from the cross-section of the observed returns and spreads. Instead our analysis is based on extracting the common volatility factor directly from a panel of N filtered, ARCH-type, volatilities. Hence we differ in that they estimate the volatility of the factor whereas we extract a common volatility factor. We compare our results with those obtained following the Ludvigson and Ng (2007) approach. The common factors from the panel of the energy and metals returns and spot/futures spreads is EM_RF and the corresponding one from the short-run funding spreads is SRFUN_SF. Then we follow Ludvigson and Ng (2007) and estimate an AR-GARCH model for each of the SRFUN_SF and EM_RF. We denote the factors following the Ludvigson and Ng (2007) approach by SRFUNSF_V and EMSF_V. We then re-estimate the corresponding predictive regressions in Tables 6-11 using these new latter factors. We find that our volatility factors extracted directly from panels of volatilities yield relatively higher adjusted R^2 and more significant results in the VIX^2, the RV and the VRP predictive models compared to those obtained following Ludvigson and Ng (2007) over the sample period 1999m01-2010m12.

(vii) Factors of log volatilities

We evaluate the robustness of our results to the log volatility factors extracted from the panels of the log GARCH type filters as well as to the log specification of our predictive regressions. We find that the results in Tables 6-11 are robust in terms of statistical significance. A notable difference in the log volatility factor results is that the logVIX$^2(-H)$ is significant in the logVIX^2 and logVRP models with and without the Lehman Brothers bankruptcy crisis.

(viii) The skewness factor

We evaluate if the stock market skewness is an alternative factor driving the VIX^2, RV and VRP. We find that the CBOE skewness factor is generally insignificant and does not affect the significance of the other volatility factors. Similar results apply for a shorter time period ending in 2008M12 for the Chang, Christoffersen, and Jacobs (2013) Realized Skewness factor. Incorporating the dummy variable for the Lehman Brother effect does not alter these results.

(ix) Liquidity factors

We have also considered various alternative indicators of liquidity in order to establish whether these are also predictors of the VIX^2, RV and VRP and to what extend these are related to our SRFUN_VF factor. We used the three measures of liquidity proposed by Pastor and Stambaugh (2003) and found that these are insignificant predictors of the VIX^2, RV and VRP during our sample period. This result holds even if we augment all the models in Tables 6-11 with one of the three liquidity measures one at a time. The aggregate liquidity measure of Pastor and Stambaugh (2003) has a very low correlation coefficient of -0.194 with SRFUN_VF which is expected given that the former is a measure equity market illiquidity.

(x) Primary Dealers funding risk factors

One might also think of primary dealer short term funding risk in the spirit of Adrian and Shin (2010). Of all the primary dealers listed on New York Fed website between 2006 and 2011 we use the daily CDS price series based on the available data from Bloomberg. Only 6 primary dealers have complete data coverage from 2002 until now. These are Bank of America (BOFA), Citigroup (CINC), Goldman Sachs (GS), JP Morgan Chase (JPMCC), Merrill Lynch (MER), Morgan Stanley (MS). In fact, these are the parent banks of the primary dealers and not the primary dealers themselves. Given that there is no data available on the primary dealers we consider this to be the closest available data. The CDS price series are based on 5-year senior debt of these companies, quoted in USD. After demeaning and standardizing these 6 series, we extract the first principal component. Given that the data are highly persistent we also take the first differences of the the CDS series and after demeaning and standardising we also extract the corresponding first factor. We consider the CDS factor extracted from both levels and first differences. We find that the CDS factors are also insignificant in predicting the VIX^2, RV and VRP and adding them in the existing models of Tables 6-11 does not affect the significance of the rest of our volatility factors for the sample period since 2002 due to the CDS data availability.[16]

(xi) The effect of individual predictors

Some of the individual series in our three cross-sections of financial assets have been monitored as recent indicators of financial distress, as leading indicators of economic activity and as predictors of stock returns. Examples of these indicators are the TED spread, the Baa-Aaa spread as well as various energy and precious metals futures returns indicators. We examine whether these indicators as well as the volatility of these variables (again from a fitted AR-GARCH model) can predict the VIX^2, the RV and the VRP. In addition to the aforementioned indicators we also examine the predictive power of individual indicators and volatilities which are highly correlated with our factors. For instance, our short-run funding spread volatility factor, SRFUN_VF, correlates highly with the following individual series volatilities: the 7-Day AA Financial Commercial Paper minus the FedFunds rate with R^2 equal to 0.7, with the 1-Month AA Nonfinancial Commercial Paper spread with R^2 equal to 0.6 and less so with the TED which has R^2 equal to 0.2. Similarly our EM_VF correlates with the following individual series volatilities: the S&P GSCI Energy and Metals Total Excess Return Index with R^2 equal to 0.5, the S&P GSCI Precious Metals Total Excess Return Index with R^2 equal to 0.4, the Gas Oil Futures with R^2 equal to 0.5 and the Gold Futures with R^2 equal to 0.4.

We address the predictive ability of all the above individual spreads and their volatilities (one at time) and compare their adjusted R^2 and statistical significance vis-à-vis our volatility factors the SRFUN_VF and the EM_VF. Two interesting results can be extracted from the short-run funding and corporate spreads indicator. First we find that the volatility of the 7Day AA Financial Commercial Paper minus the FedFunds rate spread as well as the Moody's corporate spread Baa-Aaa yield the relatively highest adjusted R^2 and statistical

[16] Given that the above factors turn out to be insignificant we do not report them in the Internet Appendix, Andreou and Ghysels (2014).

significance among the rest of the predictors for explaining the VIX^2, the RV and the VRP. Second, their predictive ability holds across all H and compares favourably with SRFUN_VF except that for H = 12 when the Baa-Aaa spread fails to predict the VRP. Turning to the EM_VF we observe that it is the volatilities and not the returns or the spot/future spreads of the energy and metals individual series that can predict the VIX^2, the RV and the VRP. In fact the volatilities of the above two indices as well and the volatilities of the two futures series have relatively stronger predictive power for less than one year (i.e. for H = 6 and 9) for the VIX^2 and RV and for VRP (for just 6 months). We find similar results for our EM_VF.

(xii) Daily predictive models for the VIX^2 and RV

The daily analysis of the VIX^2 and RV models for the sample period from 11/01/1999-29/12/2010 matches that of the monthly period in the corresponding Tables 6-11. We use the CBOE daily VIX^2 and the daily RV of the S&P 500 from the University of Oxford, Oxford-Man Institute Realized library. We estimate daily AR-GARCH volatilities for all our individual series and extract the corresponding daily volatility factors, SRFUN_VF and EM_VF. Then we estimate the same predictive regressions as in Tables 6-11 but for forecast horizons $H = 20, 60$ and 80 days. We approximate the daily volatility of consumption by the fitted values of an AR-GARCH for the Aruoba, Diebold, and Scotti (2009) index (ADS) denoted as ADS_V. Overall we find that our daily SRFUN_VF extracted from the panel of daily AR-GARCH models is strongly significant for all H in the VIX^2 and RV models. In contrast our daily EM_VF is insignificant compared to the corresponding monthly factor. Moreover we find that although there are no gains in the adjusted R^2 for the daily model specifications which include the lagged dependent variables (models 1-6), there are substantial adjusted R^2 gains in models 7-9 which include only the volatility factors (and do not account for the lagged dependent term). Estimating these models and excluding the daily observations corresponding to the Lehman Brother collapse (02/09/2008-25/11/2008) we find that our daily SRFUN_VF factor is still relatively significant.

(xiii) Alternative monthly VIX^2, RV and VRP indicators

We also examine the monthly results for the alternative VIX^2 and VRP indicators proposed in Todorov (2010) and Bollerslev and Todorov (2011) for the shorter sample period from 1999m01-2008m12 due to data availability. Overall the results are robust for the SRFUN_VF which turns out to be significant in the same predictive models in Tables 6-8 but for these alternative measures of VIX^2 at $H = 9, 12$, of RV at $H = 6, 9$ and of VRP at $H = 6, 9$ with corresponding gains in the adjusted R^2. These results are also robust to excluding the Lehman Brother crisis period.

6 Equity Return Predictability Results

So far we focused on pricing volatility risk with volatility factors. An affine asset pricing model, as noted in section 3, implies that risk pricing for each asset class is linear in $\mathcal{X}^f$, including expected excess log returns

(on the market portfolio). In particular, the equity risk premium - in analogy with the variance risk premium in equation (2.4), can be written as:

$$E_t^{\mathbb{P}}[r_{t,t+\tau}] - E_t^{\mathbb{Q}}[r_{t,t+\tau}] = \gamma_{er}(\tau)\mathcal{X}_t^f. \tag{6.1}$$

The empirical evidence in the previous section suggests that some of our factors, especially the corporate risk type factors, can predict the VRP. We therefore examine whether our factors can also predict the equity returns by improving the in-sample fit of classical and new predictors in the literature.[17] Hence we revisit the traditional equity predictability results and study whether our factors have any additional predictive ability beyond that of the VRP as well as some of the most popular predictors of returns, such as the log Price-Dividend ratio, log(P/D), the Moody's bonds default spread Baa-Aaa, the log Price-Earnings ratio, log(P/E), the term spread TMSP, defined as the difference between the ten-year and three-month Treasury yields and the stochastically detrended risk-free rate RREL defined as the one-month bill rate minus its trailing twelve-month moving averages. Given the relatively short 12 year span of our sample period we focus on the short-run equity return predictability evidence for one month ahead.

Table 16 presents the monthly S&P 500 excess returns predictive regression least squares estimation results and robust standard errors based on the Newey West HAC estimator with fixed bandwidth. The VRP is taken as the benchmark predictor in model 1 as well as the rest of the models in Table 16 given the results in Bollerslev, Tauchen, and Zhou (2009).[18] Hence, all models in the top panel in Table 16 control for the VRP and include the following factors one at a time in order to address the relative role of each corporate factor as a predictor: our short-run funding risk factors based on spreads (SRFUN_SF) and factor based on their volatilities (SRFUN_VF) as well as corporate risk factors based on spreads (COR_SF) and based on their volatilities (COR_VF). We also consider the GZ credit spread (GZ_SPR). In the predictive models 2-6 all these factors are included in addition to VRP, one at a time, in order to compare their relative predictive ability. The results in the top panel of Table 16 show that VRP is significant in all models which is consistent with the evidence in Bollerslev, Tauchen, and Zhou (2009). Interestingly our risk factors and in particular the short-run funding volatility factor (SRFUN_VF), the short-run funding spreads factor (SRFUN_SF) and the short- and long-run corporate spreads factor (COR_SF) are always statistically significant even in the presence of VRP. The same applies to the GZ spread (GZ_SPR) factor. In addition these alternative factors provide higher adjusted R^2 compared to the corresponding models which include only the VRP as predictor (model 1) or the VRP and Baa-Aaa (model 7). Additionally, in the models which include both the VRP and the Baa-Aaa default spread as well as our factors (models 8-12) reported in the second panel of Table 16, we find that our factors are significant and the default spread is insignificant.

In the third panel in Table 16 we perform the same analysis as above but control for both the VRP and

[17] Note that the empirical results in this section focus on the corporate risk type factors and not the Energy and Metals factor because the latter was found to be an insignificant in-sample predictor for stock market returns.

[18] In the robustness section we provide results which control for both the VRP and the FEAR index (Bollerslev and Todorov (2011)).

log(P/D) predictors in model 13 and examine if our factors have any additional predictive ability (models 14-18) vis-à-vis the new benchmark model 13. In the next three panels of Table 16 we consider the corresponding predictive models controlling for the VRP and either the log earnings-price ratio, log(P/E) (models 19-24), the term spread , TMSP (models 25-30), and the detrended risk-free rate RREL (models 31-36). In all these models we observe that including the short-run funding risk factors i.e. the SRFUN_VF and SRFUN_SF as well as the corporate spreads factors, COR_SF and the GZ_SPR, can improve the adjusted R^2 of the corresponding benchmark models with the log(P/E), TMSP, RREL in models 19, 25, 31, respectively. Similarly in models 37-42 we also control for both the VRP and the Baltic Dry Index (BDI) growth rate predictor proposed by Bakshi, Panayotov, and Skoulakis (2011) which is related to commodity prices and we find that our factors provide additional information in predicting excess returns.

Summarizing, in all the models presented in Table 16 we obtain similar results. Namely the SRFUN_VF, the SRFUN_SF and the COR_SF are always statistically significant vis-à-vis the corresponding benchmark models which include most of the traditional predictors discussed above. Overall the SRFUN_SF yields the relatively highest improvement in the adjusted R^2 and including this predictor along with the classical benchmark predictors above can in some cases double the adjusted R^2 vis-à-vis the models with the traditional predictors as benchmarks.

Last but not least, we perform two additional empirical investigations. The first is a robustness check which re-estimates the models in Table 16 controlling in addition for the monthly FEAR index of Bollerslev and Todorov (2011). These results are available in the Internet Appendix, Section A.2. We find that our factors namely the SRFUN_SF, SRFUN_VF and the COR_SF remain significant when controlling for both the VRP and FEAR indices in the excess S&P500 market returns predictive regressions. Interestingly though the VRP loses its significance in the presence of the FEAR index. In addition, the adjusted R^2 of all models become much smaller when the FEAR index enters the predictive models while our factors, and especially SRFUN_SF and COR_SF, are still relatively significant. In fact the SRFUN_SF provides significant gains in terms of adjusted R^2 for the S&P500 excess market predictive regressions over other benchmark models which include the VRP, FEAR as well as classical predictors such as the corporate bond spread Baa-Aaa, the log price-dividend ratio, the log price-earning ratio, the term spread term, among others.

The second exercise is an illustrative out-of-sample forecasting exercise for the S&P500 excess returns. These results are also reported in the Internet Appendix. We study the out-of-sample predictability results of the S&P500 excess returns for one month ahead during the period 2007M01-2010M12. The models in Table 16 were estimated for the period 1999M01-2006M12 and the Root Mean Squared Forecast Error (RMSFE) is used to calculate the percentage RMSFE gains or losses vis-à-vis the constant mean model of returns. Overall we find that the SRFUN_SF factor yields the largest RMSFE gains relative to the rest of the predictors even if one compares or controls for the traditional predictors of excess returns. Indeed the parsimonious model with the VRP and SRFUN_SF predictors can improve the RMSFE by around 10% vis-à-vis the historical mean model of returns. This result is robust to the presence of the other predictors.

7 Conclusions

The procedure we propose is remarkably simple. One collects a large panel of asset returns, monthly in our case or possibly any other frequency such as daily returns considered in the robustness section. For each series in the panel one fits a standard ARCH-type volatility models and thus obtains a panel of filtered volatilities. One extracts principal components from the latter. The panels are stratified by asset class, and only the first principal component from each class is considered to facilitate interpretation of the sources of volatility risk.

While the procedure we propose is simple, the implications of our findings for equilibrium asset pricing are not that simple. So far, the emphasis has been almost exclusively on estimating parametric models for the S&P 500 involving both cash and options data (see e.g. Chernov and Ghysels (2000) and Pan (2002) and many subsequent papers) or some type of non-parametric procedure combining high frequency cash market data and options on the market index (see Bollerslev, Tauchen, and Zhou (2009) and many subsequent papers). The literature has mostly found that either volatility risk or more specifically a disaster fear affecting consumption and the overall economy are the driving forces of the VIX and the VRP.

Our analysis goes beyond the confines of the market index. The empirical analysis takes as given that volatility risk is pervasive and interconnected across a wide range of assets. There are at least two interpretations of our empirical findings. First, it is fair to say that the panel data setting allows us to estimate volatility risk more precisely. There is in fact a theoretical justification for this argument, although it is not explicitly exploited in the current paper. In particular, Ghysels (2013) shows that the interaction of high frequency data used to compute the realized or filtered volatilities and the usual panel data asymptotics yields better (in terms of faster convergence rates) estimate of volatility risk factors. Hence, we can take for granted that the panel based approach yields better estimates of volatility factors. Are these improved estimates telling us indirectly something about consumption volatility risk - which is hard to pin down using either conventional aggregate consumption or activity related series? Is this fundamental volatility risk better measured via our (i) long-run corporate spreads volatilities, (ii) short-run funding spreads volatilities and (iii) volatilities of energy and metals commodities returns and spreads? Perhaps this is the case. However, what makes this line of thought a bit more difficult is the fact that the literature has recently put more emphasis on the jump component of volatility in the context of the underlying general equilibrium affine asset pricing model. In particular, the fact that our factors also help to predict, what is identified as jumps, raises some doubts about a possible interpretation of our procedure as uncovering better estimates of consumption volatility risk.

A second interpretation of our results is that we uncover drivers of the VIX and VRP that relate to a different asset pricing model, not necessarily driven by consumption volatility risk. Should we think of production-based asset pricing models? A credit risk interpretation of our short-run funding risk factor would surely not rule this out. Note that here too the argument of more efficient estimation of volatility risk factors through

panel data methods, as advocated in this paper, equally applies. Hence, alternative measures, such as factors based on for example the GZ spread may not be as informative. Should we think of our results as given more credence to models which rely on financial intermediation risk channels? It surely may, and perhaps we are also better at capturing this risk channel with our novel approach, compared to say looking at the aggregate balance sheets of intermediaries or the CDS spreads of their parent companies. Our robustness analysis suggests that in terms of capturing the dynamics of the VIX and VRP we do better than the direct measures of financial intermediaries balance sheet constraints. Hence, our empirical findings provide a lot of challenges and food for thought for future research.

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Figure 1: The short-run funding spreads volatility factor (SRFUN_VF), the long-run corporate spreads volatility factor (LRCOR_VF) and the (short- and long-run) corporate spreads volatility factor (COR_VF) in the monthly period 1999m01 - 2010m12.

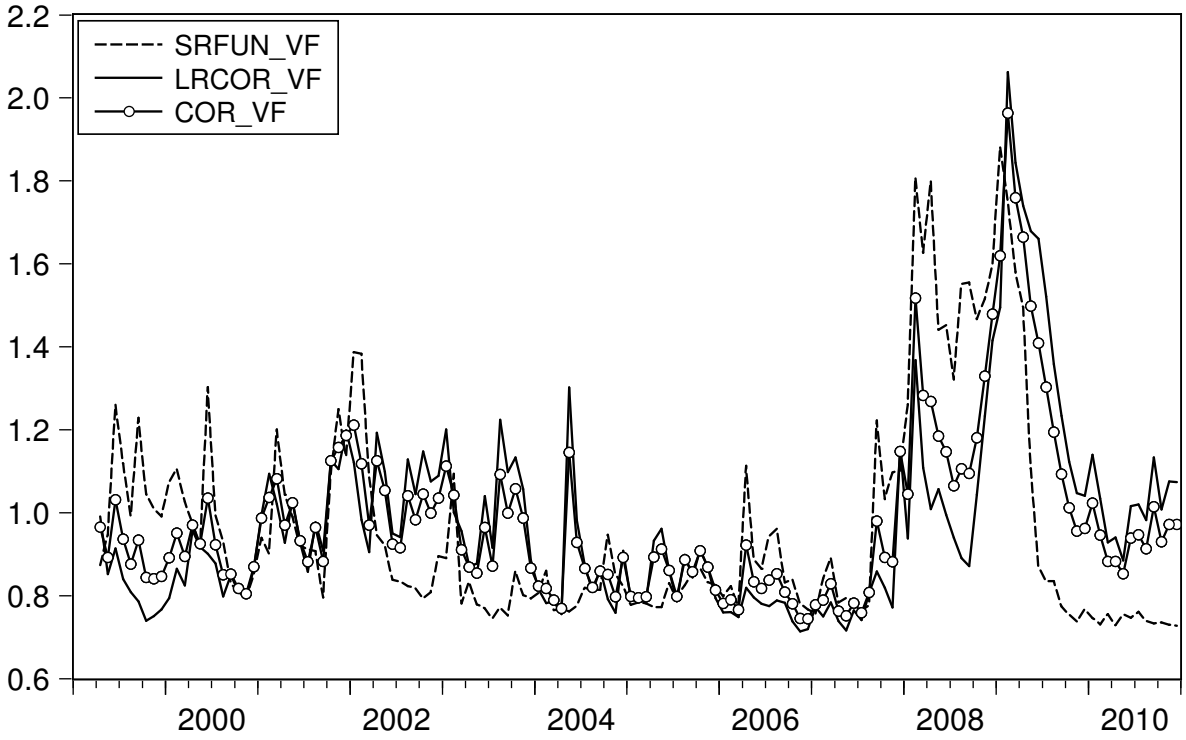

Figure 2: The energy and metals returns and spreads volatility factor (EM_VF) in the monthly period 1999m01 - 2010m12.

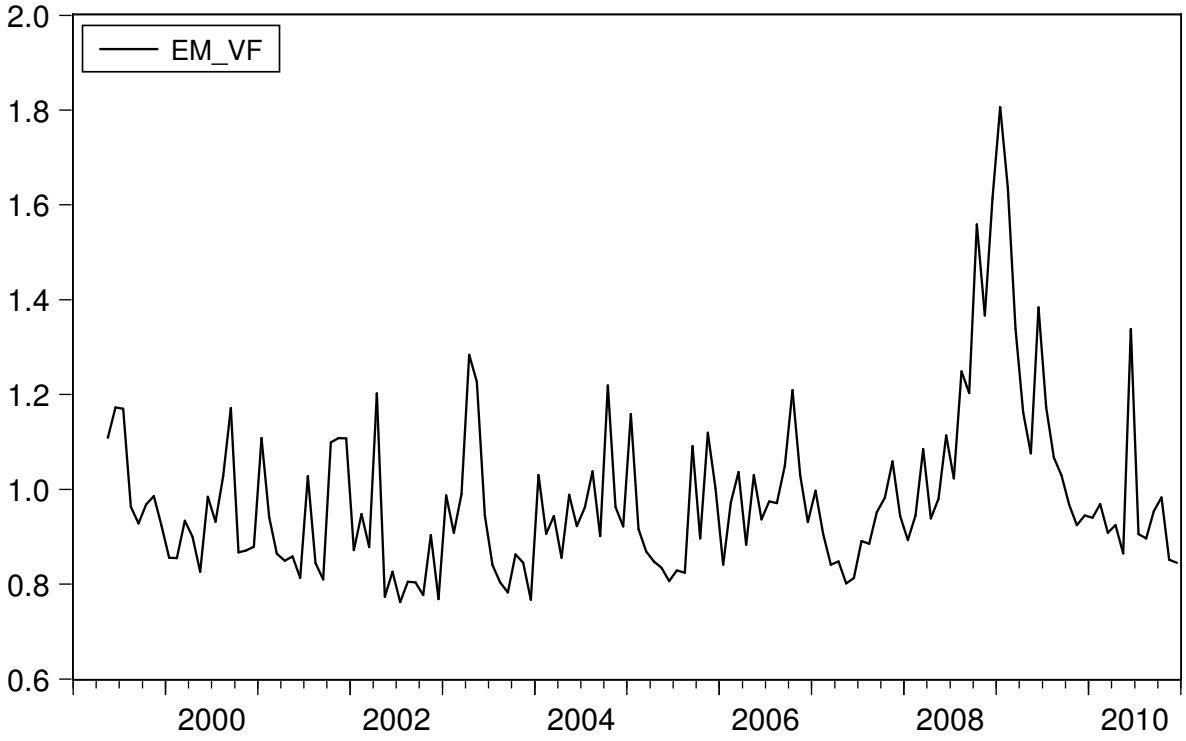

Figure 3: The (short- and long-run) corporate spreads factor (COR_SF), the Gildchrist and Zakrajšek spread factor (GZ_SPR), the Chicago Fed National Financial Index (NFCI) and the St Louis Fed Financial Stress Index (FSI) in the monthly period 1999m01 - 2010m12.

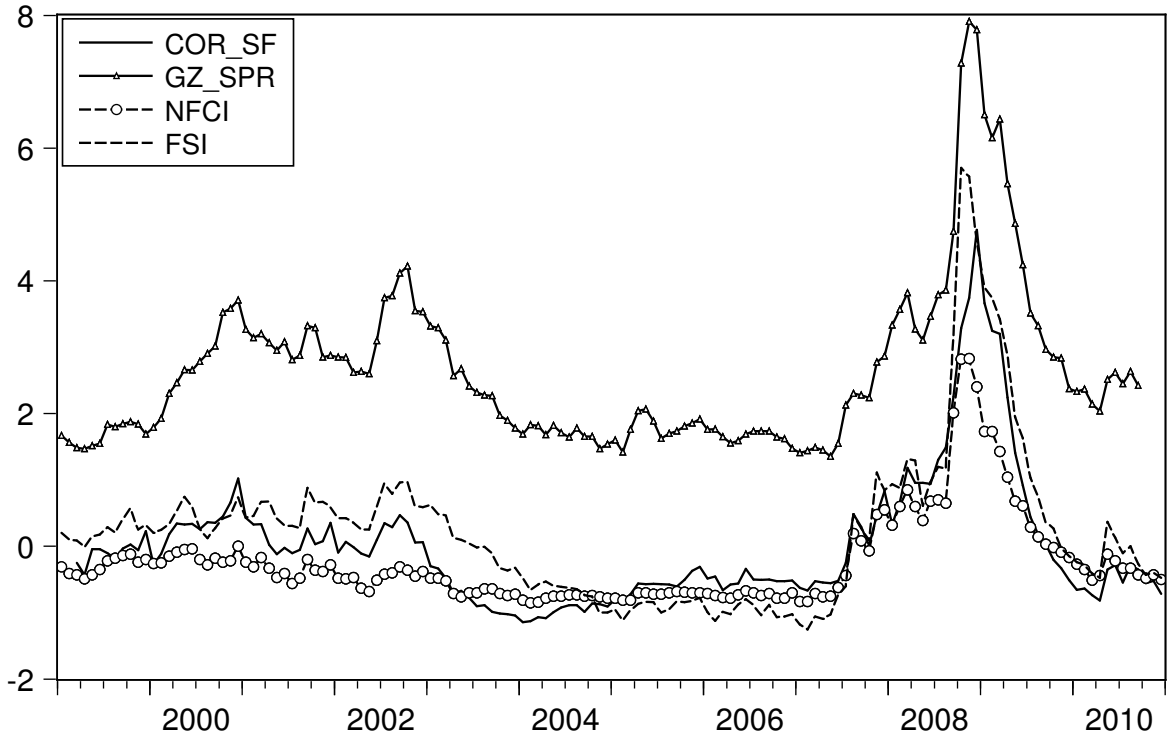

Table 1: Acronyms and Names of Variables and Factors

Acronym	Long Name
ADS_V	Fitted volatility from an AR-GARCH of Aruoba, Diebold, and Scotti (2009) index
Baa-Aaa	Moody's Baa- and Aaa-rated long-run industrial corporate bonds spread
BDI	Baltic Dry Index growth rate (Bakshi, Panayotov and Skoulakis, 2011)
CFNAI_V	Fitted volatility from an AR-GARCH of Chicago Fed National Activity Index
COR_SF	Corporate bonds spreads and Short-run funding spreads Factor
CORSF_SRFUNVF	Residuals from the linear regression of COR_SF on SRFUN_VF
COR_VF	Corporate bonds spreads and Short-run funding spreads Volatility Factor
DLC_V	Fitted volatility from an AR-GARCH of consumption (Services and Non-durables) growth rate
DLIP_V	Fitted volatility from an AR-GARCH of industrial production growth rate
EMI	S&P GSCI Energy and Metals Total Excess Return Index
EM_RF	Energy and Metals commodities spot/futures spreads and Returns Factor
EMRF_V	Energy and Metals Spreads factor volatility following the Ludvigson and Ng (2007) approach
EM_VF	Energy and Metals commodities spot/futures spreads and returns Volatility Factor
EPU	Bloom (2009) Economic Policy Uncertainty index
FEAR	FEAR Index (Bollerslev and Todorov, 2011)
FSI	St Louis Fed Financial Stress Index
GasOilFut	Gas Oil Futures Price: 1st Expiring Contract Settlement
GoldFut	Gold Futures Price: 6-Month Contract Settlement
GZ_SPR	Gilchrist and Zakrajšek (2012) Spreads factor
log(P/D)	log Price-Dividend ratio
log(P/E)	log Price-Earnings ratio
LRCOR_SF	Long-run Corporate bonds spreads Factor
LRCOR_VF	Long-run Corporate bond spreads Volatility Factor
MU	Jurado, Ludvigson, and Ng (2013) Macroeconomic Uncertainty indicator
NFCI	Chicago Fed National Financial Conditions Index
NFCI_Credit	NFCI subindex which refers to the Credit series
NFCI_Leverage	NFCI subindex which refers to the Leverage series
NFCI_Risk	NFCI subindex which refers to the Risk series
PreciousMet	S&P GSCI Precious Metals Total Excess Return Index
RREL	Detrended risk-free rate
SKEW	CBOE S&P 500 Realized Skewness factor
SRFUN_SF	Short-run Funding Spreads Factor
SRFUNSF_V	Short-run Funding Spreads factor volatility following the Ludvigson and Ng (2007) approach
SRFUN_VF	Short-run Funding spreads Volatility Factor
TED	3-Month London Interbank Offered Rate minus the 3-Month Treasury Bill
TMSP	Term spread
7D-AAFCP-FF	7-Day AA Financial Commercial Paper-FedFunds rate (FF)
1M-NonFCP-FF	1-Month AA Nonfinancial Commercial Paper-FedFunds rate (FF)

Table 2: Data description summary of the long-run corporate (LRCOR) spreads series categories

Moody's Corporate Bond Yield (AAA, BBB) - Govt bond corresponding maturity
Moody's Corporate Baa-Aaa spread
Merrill Lynch Corporate Bonds: (A, AA, AAA, BBB, 1-3Y, 3-5Y, 5-7Y): Effective Yield - Govt bond corresp. maturity
Merrill Lynch Corporate Bonds:Industrials: (A, AA, AAA, BBB, 1-3Y, 3-5Y, 5-7Y, 7-10Y): Eff. Yield - Govt bond corresp. maturity
Merrill Lynch Corporate Bonds:Financials: (A, AA, AAA, BBB, 1-3Y, 3-5Y, 5-7Y, 7-10Y): Eff. Yield - Govt bond corresp. maturity
Merrill Lynch Corporate Bonds:Utilities: (A, AA, AAA, BBB, 1-3Y, 3-5Y, 5-7Y, 7-10Y): Eff. Yield - Govt bond corresp. maturity
Merrill Lynch (Treasury, Domestic) Master: (Eff. Yield, Yield to Worst, Yield to Maturity) -Govt bond corresp. maturity
Merrill Lynch (Agency, Corporate & Govt) Master: (Eff. Yield, Yield to Worst, Yield to Maturity) -Govt bond corresp. maturity
Merrill Lynch Treasuries Current 10 Year Master: (Effective Yield, Yield to Worst, Yield to Maturity) -Govt bond corresp. maturity
Merrill Lynch Treasury/Agency: AAA Master: (Effective Yield, Yield to Worst, Yield to Maturity) -Govt bond corresp. maturity
Merrill Lynch (Treasury, Domestic, Agency, Corporate & Government) Master: Yield to Maturity
Merrill Lynch (Treasuries Current 10 Yr, Treasury/Agency:AAA) Master: Yield to Maturity
Merrill Lynch Broad Market: (Eff, YTW, YTM) -Govt bond corresp. maturity
Merrill Lynch (Mortgage, Corporate) Master: Eff - Govt bond corresp. maturity
Merrill Lynch High Yield Corporates: (Ii, B, BB, CCC & Lower) : Effective Yield - Govt bond corresp. maturity
Merrill Lynch High Yield Corporates: Cash Pay: (B, BB, CCC & Lower) : Effective Yield - Govt bond corresp. maturity
Merrill Lynch Asset-Backeds: (Automobiles, Home Equity): Fixed Rate: Effective Yield - Govt bond corresp. maturity

Table 3: Data description summary of the short-run funding (SRFUN) spreads series categories

TED = 3 Month London Interbank Offered Rate - 3 Month Tbill
(7D, 1M, 3M, 6M, 1Y) LIBOR-FedFunds rate
(1M, 3M, 6M) Eurodollar Deposits-FedFunds rate
1M (Financial, Nonfinancial) Commercial Paper-FedFunds rate
(1D, 7D, 15D, 1M) AAFCP-FedFunds rate
(1D, 7D, 15D, 1M) AA Nonfinancial Commercial Paper-FedFunds rate
(1M, 3M, 6M) Certificates of Deposit-FedFunds rate
(1D, 7D, 15D, 1M) A2/P2/F2 Nonfinancial Commercial Paper-AA (Nonfinancial,Financial) Commercial Paper
(1D, 7D, 15D, 1M) A2/P2/F2 Nonfinancial Commercial Paper-FedFunds rate

Table 4: Data description summary of the energy and metal (EM) commodities series categories

S&P GSCI (Lead, Zinc, Silver, Gold, Precious Metals, Industrial Metals) Index, Total Return and Total Excess Return Index
S&P GSCI (Nickel, Copper, Aluminium, Brent Crude) Index, Total Return and Total Excess Return Index
S&P GSCI (Energy Commodities, Crude, Heating and Gas Oil) Index, Total Return and Total Excess Return Index
S&P GSCI (Four Energy Commodities, Unleaded Gasoline, Natural Gas) Index, Total Return and Total Excess Return Index
S&P GSCI (Light Energy CPW 4, Ultra-Light Energy CPW 8) Index, Total Return and Total Excess Return Index
S&P GSCI (Energy & Metals, All Crude, Biofuel) Index, Total Return and Total Excess Return Index
Commodity Prices (Zinc, Benzene, Hides, Burlap, Aluminum, Copper & Steel Scrap)
Commodity Prices (Tallow, Random Lengths' Structural Panel Composite)
Domestic Spot Market Price (West Texas Intermediate, Crude West Texas Sour, Crude Louisiana Sweet, Alaskan North Slope Oil)
(Light Sweet Crude, No 2 Heating, Gas, Natural Gas) Oil Futures Price: 1st Expiring Contract Settlement
(Cushing OK Crude, NY Harbor 2 Heating, Natural Gas) Oil Futures Price: 2-Month Contract Settlement
(Light Sweet Crude, No 2 Heating) Oil Futures Price: 3-Month Contract Settlement
Gold Futures Price: 6-Month Contract Settlement
Lme (Zinc, Tin, Nickel, Copper Grade A, Aluminum, Aluminum Alloy, London Gold Bullion): Closing Cash Price
Lme (Lead, Tin, Nickel, Copper Grade A, Aluminum, Aluminum Alloy): Closing 3-Month Forward Price
Unleaded Gas Price, (Regular, Premium), Non-Oxygenated
Oil Price: Fuel Oil No 2, Propane Price: Mont Belvieu and Commodity Prices: Crude Oil, West Texas Intermediate
FIBER Industrial Materials Price Index: Metals, Crude Oil and Benzene
European Free Market Price: Brent Crude Oil and Random Length's Framing Lumber Composite
(Cushing OK WTI, Europe Brent, US Gulf Coast Conventional Gasoline Regular, Crb Metals) Spot Price FOB
(Kerosene-Type Jet Fuel and No 2 Diesel Low Sulfur, New York Harbor Conventional Gasoline Regular) Spot Price FOB
(No 2 Diesel Low Sulfur and Heating Oil, Los Angeles CA No 2 Diesel, Mont Belvieu TX Propane) Spot Price FOB
Philadelphia (Semiconductor, Exchange Gold & Silver) Index

Table 5: Correlation matrix of financial factors for the period 1999M01-2010M12

The definition of the variables in this table are found in Table 1.

	COR_SF	CORSF_ SRFUNVF	COR_VF	EM_RF	EMRF_V	EM_VF	FSI	GZ_SPR	LRCOR_SF	LRCOR_VF	NFCI	NFCI_ Credit	NFCI_ Leverage	NFCI_ Risk	SRFUN_SF	SRFUNSF_V	SRFUN_VF
COR_SF	1.00	-0.65	0.74	-0.34	0.50	0.64	0.92	0.91	0.99	0.58	0.94	0.93	0.67	0.94	0.77	0.62	0.76
CORSF_SRFUNVF	-0.65	1.00	-0.29	0.40	-0.39	-0.38	-0.60	-0.68	-0.65	-0.38	-0.57	-0.62	-0.27	-0.56	-0.45	-0.03	0.00
COR_VF	0.74	-0.29	1.00	-0.03	0.25	0.55	0.76	0.78	0.72	0.93	0.72	0.81	0.45	0.76	0.56	0.58	0.73
EM_RF	-0.34	0.40	-0.03	1.00	-0.33	-0.26	-0.37	-0.35	-0.32	0.02	-0.36	-0.29	-0.17	-0.31	-0.33	-0.04	-0.10
EMRF_V	0.50	-0.39	0.25	-0.33	1.00	0.55	0.54	0.52	0.48	0.16	0.53	0.52	0.44	0.55	0.46	0.34	0.33
EM_VF	0.64	-0.38	0.55	-0.26	0.55	1.00	0.60	0.57	0.61	0.45	0.64	0.66	0.55	0.66	0.57	0.54	0.52
FSI	0.92	-0.60	0.76	-0.37	0.54	0.60	1.00	0.95	0.91	0.64	0.94	0.91	0.60	0.93	0.71	0.56	0.71
GZ_SPR	0.91	-0.68	0.78	-0.35	0.52	0.57	0.95	1.00	0.91	0.69	0.88	0.92	0.47	0.88	0.66	0.50	0.62
LRCOR_SF	0.99	-0.65	0.72	-0.32	0.48	0.61	0.91	0.91	1.00	0.56	0.91	0.90	0.62	0.91	0.65	0.58	0.74
LRCOR_VF	0.58	-0.38	0.93	0.02	0.16	0.45	0.64	0.69	0.56	1.00	0.56	0.70	0.26	0.61	0.41	0.36	0.43
NFCI	0.94	-0.57	0.72	-0.36	0.53	0.64	0.94	0.88	0.91	0.56	1.00	0.93	0.77	0.98	0.78	0.59	0.75
NFCI_Credit	0.93	-0.62	0.81	-0.29	0.52	0.66	0.91	0.92	0.90	0.70	0.93	1.00	0.61	0.95	0.71	0.57	0.69
NFCI_Leverage	0.67	-0.27	0.45	-0.17	0.44	0.55	0.60	0.47	0.62	0.26	0.77	0.61	1.00	0.78	0.65	0.58	0.64
NFCI_Risk	0.94	-0.56	0.76	-0.31	0.55	0.66	0.93	0.88	0.91	0.61	0.98	0.95	0.78	1.00	0.76	0.61	0.75
SRFUN_SF	0.77	-0.45	0.56	-0.33	0.46	0.57	0.71	0.66	0.65	0.41	0.78	0.71	0.65	0.76	1.00	0.56	0.63
SRFUNSF_V	0.62	-0.03	0.58	-0.04	0.34	0.54	0.56	0.50	0.58	0.36	0.59	0.57	0.58	0.61	0.56	1.00	0.78
SRFUN_VF	0.76	0.00	0.73	-0.10	0.33	0.52	0.71	0.62	0.74	0.43	0.75	0.69	0.64	0.75	0.63	0.78	1.00

Table 6: Predictive regression models for the VIX^2 for the period 1999m01 - 2010m12 using the short-run funding spreads volatility factor, SRFUN_VF, and the Energy and Metals returns and spreads volatility factor, EM_VF.

The OLS estimation results are reported and (***), (**), (*) refer to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) found in the parentheses refer to the NW HAC estimator with 12 lags. The variables are defined in Table 1.

Horizon	Model	Predictors				Adj. R^2
		VIX^2(-H)	**DLC_V(-H)**	**SRFUN_VF(-H)**	**EM_VF(-H)**	
$H = 6$	1	0.26	-	-	-	0.06
		(0.09)***	-	-	-	
	2	0.28	-1.81	-	-	0.06
		(0.09)***	(4.55)	-	-	
	3	-0.04	-	8.25	-	0.34
		(0.17)	-	(3.07)***	-	
	4	-0.03	-3.68	8.29	-	0.34
		(0.16)	(5.60)	(3.10)***	-	
	5	0.05	-1.41	9.31	4.67	0.37
		(0.13)	(4.77)	(3.14)***	(1.65)***	
	6	0.04	-	9.32	4.76	0.37
		(0.13)	-	(3.15)***	(1.79)***	
	7	-	3.58	-	-	0.01
		-	(4.12)	-	-	
	8	-	-0.99	9.51	4.35	0.37
		-	(5.36)	(2.70)***	(2.01)**	
	9	-	-	9.50	4.44	0.38
		-	-	(2.66)***	(2.29)*	
$H = 9$	1	0.17	-	-	-	0.02
		(0.10)	-	-	-	
	2	0.19	-0.82	-	-	0.02
		(0.12)	(4.42)	-	-	
	3	-0.17	-	9.01	-	0.34
		(0.16)	-	(3.11)***	-	
	4	-0.16	-2.25	9.03	-	0.34
		(0.14)	(4.34)	(3.12)***	-	
	5	-0.08	0.53	10.32	5.46	0.38
		(0.09)	(2.72)	(3.37)***	(2.92)	
	6	-0.08	-	10.32	5.42	0.38
		(0.09)	-	(3.36)***	(3.01)*	
	7	-	2.98	-	-	0.01
		-	(4.17)	-	-	
	8	-	-0.23	9.96	5.96	0.38
		-	(3.00)	(3.29)***	(3.47)*	
	9	-	-	9.96	5.98	0.38
		-	-	(3.26)***	(3.65)	
$H = 12$	1	0.13	-	-	-	0.01
		(0.10)	-	-	-	
	2	0.16	-4.17	-	-	0.01
		(0.11)	(3.65)	-	-	
	3	-0.09	-	5.97	-	0.14
		(0.13)	-	(2.68)**	-	
	4	-0.07	-5.27	6.02	-	0.14
		(0.12)	(3.23)	(2.64)**	-	
	5	-0.03	-3.60	6.77	3.10	0.15
		(0.11)	(2.85)	(2.63)**	(1.86)	
	6	-0.04	-	6.80	3.34	0.15
		(0.11)	-	(2.66)**	(1.93)*	
	7	-	-0.93	-	-	0.01
		-	(3.65)	-	-	
	8	-	-3.84	6.65	3.26	0.16
		-	(3.46)	(2.46)***	(2.00)	
	9	-	-	6.62	3.60	0.16
		-	-	(2.47)***	(2.18)	

Table 7: Predictive regression models for the RV for the period 1999m01 - 2010m12 using the short-run funding spreads volatility factor, SRFUN_VF, and the Energy and Metals returns and spreads volatility factor, EM_VF.

The OLS estimation results are reported and (***), (**), (*) refer to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) found in the parentheses refer to the NW HAC estimator with 12 lags. The variables are defined in Table 1.

Horizon	Model	Predictors					Adj. R^2
		RV(-H)	**VIX^2(-H)**	**DLC_V(-H)**	**SRFUN_VF(-H)**	**EM_VF(-H)**	
$H = 6$	1	0.13	-0.02	-	-	-	0.01
		(0.06)**	(0.13)	-	-	-	
	2	0.11	0.02	-4.21	-	-	0.01
		(0.08)	(0.15)	(4.36)	-	-	
	3	0.17	-0.44	-	9.86	-	0.29
		(0.17)	(0.36)	-	(4.07)**	-	
	4	0.17	-0.41	-6.59	9.93	-	0.29
		(0.18)	(0.35)	(4.77)	(4.07)**	-	
	5	0.16	-0.31	-4.02	11.08	5.24	0.32
		(0.16)	(0.28)	(3.47)	(4.30)**	(2.35)**	
	6	0.16	-0.32	-	11.10	5.49	0.32
		(0.16)	(0.28)	-	(4.32)**	(2.56)**	
	7	-	-	-1.66	-	-	0.01
		-	-	(4.14)	-	-	
	8	-	-	-5.29	10.42	6.29	0.31
		-	-	(4.32)	(3.92)***	(3.53)	
	9	-	-	-	10.36	6.73	0.31
		-	-	-	(3.94)***	(3.87)*	
$H = 9$	1	0.10	-0.02	-	-	-	0.01
		(0.18)	(0.18)	-	-	-	
	2	0.07	0.02	-1.30	-	-	0.01
		(0.19)	(0.19)	(6.69)	-	-	
	3	0.17	-0.44	-	9.86	-	0.29
		(0.17)	(0.36)	-	(4.07)**	-	
	4	0.15	-0.37	-2.69	8.02	-	0.17
		(0.20)	(0.33)	(6.71)	(3.17)**	-	
	5	0.15	-0.27	0.63	9.58	6.59	0.21
		(0.19)	(0.24)	(5.38)	(3.50)***	(3.61)*	
	6	0.15	-0.27	-	9.57	6.55	0.21
		(0.19)	(0.25)	-	(3.49)***	(3.71)*	
	7	-	-	0.54	-	-	0.01
		-	-	(6.46)	-	-	
	8	-	-	-0.52	8.94	7.29	0.21
		-	-	(5.05)	(3.50)**	(3.98)*	
	9	-	-	-	8.94	7.34	0.22
		-	-	-	(3.49)**	(4.18)*	
$H = 12$	1	0.05	-0.06	-	-	-	0.01
		(0.10)	(0.16)	-	-	-	
	2	0.03	-0.03	-0.21	-	-	0.01
		(0.11)	(0.18)	(0.37)	-	-	
	3	0.08	-0.26	-	4.37	-	0.03
		(0.12)	(0.25)	-	(2.17)**	-	
	4	0.08	-0.24	-0.29	4.40	-	0.02
		(0.12)	(0.24)	(0.39)	(2.15)**	-	
	5	0.08	-0.23	-0.18	4.86	1.67	0.02
		(0.12)	(0.23)	(0.37)	(2.07)**	(1.13)	
	6	0.08	-0.24	-	4.88	1.79	0.03
		(0.12)	(0.24)	-	(2.08)**	(1.21)	
	7	-	-	-0.20	-	-	0.01
		-	-	(0.42)	-	-	
	8	-	-	-0.31	4.14	2.56	0.03
		-	-	(0.40)	(1.80)**	(1.67)	
	9	-	-	-	4.11	2.84	0.03
		-	-	-	(1.80)**	(1.92)	

Table 8: Predictive regression models for the VRP for the period 1999m01 - 2010m12 using the short-run funding spreads volatility factor, SRFUN_VF, and the Energy and Metals returns and spreads volatility factor, EM_VF.

The OLS estimation results are reported and (***), (**), (*) refer to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) found in the parentheses refer to the NW HAC estimator with 12 lags. The variables are defined in Table 1.

Horizon	Model	Predictors				Adj. R^2
		VIX^2(-H)	**DLC_V(-H)**	**SRFUN_VF(-H)**	**EM_VF(-H)**	
$H = 6$	1	0.08	-	-	-	0.01
		(0.05)	-	-	-	
	2	0.08	0.55	-	-	0.01
		(0.05)	(2.03)	-	-	
	3	-0.05	-	3.43	-	0.14
		(0.09)	-	(1.31)***	-	
	4	-0.05	-0.11	3.43	-	0.13
		(0.09)	(2.62)	(1.33)**	-	
	5	-0.01	1.10	3.98	2.50	0.16
		(0.07)	(2.09)	(1.38)***	(0.89)***	
	6	-0.01	-	3.98	2.43	0.16
		(0.07)	-	(1.37)***	(0.92)***	
	7	-	2.04	-	-	0.01
		-	(2.29)	-	-	
	8	-	1.00	3.93	2.57	0.16
		-	(2.42)	(1.18)***	(1.15)**	
	9	-	-	3.94	2.49	0.17
		-	-	(1.15)***	(1.25)**	
$H = 9$	1	0.07	-	-	-	0.01
		(0.04)*	-	-	-	
	2	0.07	1.71	-	-	0.01
		(0.04)*	(1.54)	-	-	
	3	0.02	-	1.61	-	0.03
		(0.05)	-	(0.60)***	-	
	4	0.01	1.50	1.60	-	0.03
		(0.05)	(1.54)	(0.62)**	-	
	5	0.02	2.05	1.84	0.97	0.02
		(0.04)	(1.20)*	(0.77)**	(1.18)	
	6	0.03	-	1.83	0.84	0.03
		(0.04)	-	(0.76)**	(1.18)	
	7	-	3.19	-	-	0.01
		-	(1.59)**	-	-	
	8	-	2.29	1.96	0.82	0.03
		-	(1.36)*	(0.74)***	(1.11)	
	9	-	-	1.97	0.62	0.03
		-	-	(0.73)***	(1.11)	
$H = 12$	1	0.07	-	-	-	0.01
		(0.04)*	-	-	-	
	2	0.09	-0.28	-	-	0.01
		(0.04)**	(0.13)**	-	-	
	3	-0.01	-	2.02	-	0.04
		(0.05)	-	(1.02)**	-	
	4	0.01	-0.32	2.05	-	0.04
		(0.05)	(0.11)***	(0.99)**	-	
	5	0.03	-0.26	2.35	1.19	0.04
		(0.05)	(0.11)**	(1.03)**	(0.90)	
	6	0.02	-	2.36	1.36	0.05
		(0.05)	-	(1.04)**	(0.91)	
	7	-	-0.11	-	-	0.01
		-	(0.13)	-	-	
	8	-	-0.23	2.46	1.03	0.05
		-	(0.11)**	(0.91)***	(0.89)	
	9	-	-	4.11	2.84	0.03
		-	-	(1.80)**	(1.92)	

Table 9: Predictive regression models for the VIX^2 with a Dummy for the effect of the Lehman Brothers bankruptcy using the short-run funding spreads volatility factor, SRFUN_VF, and the Energy and Metals returns and spreads volatility factor, EM_VF during 1999m01 - 2010m12.

The OLS estimation results are reported and (***), (**), (*) refer to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) found in the parentheses refer to the NW HAC estimator with 12 lags. The dummy variable excludes the following observations: 2008m09 and 2008m10. The variables are defined in Table 1.

Horizon	Model	Predictors				Adj. R^2
		VIX^2(-H)	**DLC_V(-H)**	**SRFUN_VF(-H)**	**EM_VF(-H)**	
$H = 6$	1	0.26	-	-	-	0.29
		(0.08)***	-	-	-	
	2	0.28	-0.68	-	-	0.29
		(0.08)***	(4.03)	-	-	
	3	0.03	-	6.23	-	0.42
		(0.15)	-	(2.58)**	-	
	4	0.04	-2.44	6.27	-	0.42
		(0.14)	(5.27)	(2.65)**	-	
	5	0.10	-0.66	7.24	3.82	0.44
		(0.12)	(4.70)	(2.76)***	(1.38)***	
	6	0.10	-	7.23	3.86	0.44
		(0.12)	-	(2.75)***	(1.48)**	
	7	-	4.68	-	-	0.22
		-	(3.55)	-	-	
	8	-	0.18	7.75	3.19	0.44
		-	(5.33)	(2.31)***	(1.54)**	
	9	-	-	7.75	3.18	0.44
		-	-	(2.24)***	(1.76)*	
$H = 9$	1	0.17	-	-	-	0.25
		(0.09)*	-	-	-	
	2	0.18	-0.38	-	-	0.25
		(0.11)*	(4.13)	-	-	
	3	-0.15	-	8.29	-	0.52
		(0.15)	-	(2.88)***	-	
	4	-0.14	-1.72	8.30	-	0.51
		(0.14)	(4.12)	(2.89)***	-	
	5	-0.08	0.50	9.37	4.34	0.54
		(0.09)	(2.85)	(3.07)***	(2.18)**	
	6	-0.07	-	9.37	4.31	0.54
		(0.10)	-	(3.07)***	(2.29)*	
	7	-	3.31	-	-	0.22
		-	(3.93)	-	-	
	8	-	0.21	9.03	4.81	0.54
		-	(3.24)	(2.93)***	(2.82)*	
	9	-	-	9.03	4.83	0.54
		-	-	(2.91)***	(3.03)	
$H = 12$	1	0.16	-	-	-	0.24
		(0.09)*	-	-	-	
	2	0.19	-3.57	-	-	0.24
		(0.11)*	(3.32)	-	-	
	3	-0.03	-	5.13	-	0.34
		(0.11)	-	(2.40)**	-	
	4	-0.02	-4.54	5.17	-	0.34
		(0.10)	(3.02)	(2.36)**	-	
	5	0.03	-2.98	5.88	2.87	0.35
		(0.09)	(2.60)	(2.41)**	(1.92)	
	6	0.02	-	5.90	3.07	0.35
		(0.09)	-	(2.44)**	(1.98)	
	7	-	0.14	-	-	0.22
		-	(3.08)	-	-	
	8	-	-2.75	6.00	2.71	0.35
		-	(2.97)	(2.31)**	(1.88)	
	9	-	-	5.98	2.95	0.36
		-	-	(2.31)***	(2.01)	

Table 10: Predictive regression models for the RV with a Dummy for the effect of the Lehman Brothers bankruptcy using the short-run funding spreads volatility factor, SRFUN_VF, and the Energy and Metals returns and spreads volatility factor, EM_VF during 1999m01 - 2010m12.

The OLS estimation results are reported and (***), (**), (*) refer to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) found in the parentheses refer to the NW HAC estimator with 12 lags. The dummy variable excludes the following observations: 2008m09 and 2008m10. The variables are defined in Table 1.

Horizon	Model	Predictors					Adj. R^2
		RV(-H)	**VIX^2(-H)**	**DLC_V(-H)**	**SRFUN_VF(-H)**	**EM_VF(-H)**	
$H = 6$	1	0.08	0.03	-	-	-	0.46
		(0.05)	(0.10)	-	-	-	
	2	0.07	0.06	-2.36	-	-	0.45
		(0.07)	(0.12)	(3.02)	-	-	
	3	0.11	-0.22	-	5.84	-	0.54
		(0.13)	(0.24)	-	(2.31)**	-	
	4	0.11	-0.20	-4.16	5.91	-	0.54
		(0.13)	(0.23)	(3.68)	(2.35)**	-	
	5	0.10	-0.14	-2.50	6.81	3.52	0.55
		(0.12)	(0.20)	(3.06)	(2.54)***	(1.28)***	
	6	0.10	-0.15	-	6.80	3.68	0.55
		(0.12)	(0.20)	-	(2.54)***	(1.41)**	
	7	-	-	0.14	-	-	0.45
		-	-	(2.73)	-	-	
	8	-	-	-2.75	6.59	3.76	0.55
		-	-	(3.46)	(2.15)***	(1.74)**	
	9	-	-	-	6.54	3.98	0.56
		-	-	-	(2.12)***	(1.95)**	
$H = 9$	1	0.00	0.07	-	-	-	0.45
		(0.09)	(0.13)	-	-	-	
	2	-0.03	0.12	-0.61	-	-	0.45
		(0.11)	(0.14)	(6.29)	-	-	
	3	0.04	-0.22	-	6.66	-	0.57
		(0.15)	(0.26)	-	(2.56)**	-	
	4	0.04	-0.21	-1.81	6.67	-	0.57
		(0.15)	(0.24)	(6.32)	(2.57)**	-	
	5	0.04	-0.15	0.52	7.80	4.62	0.59
		(0.14)	(0.19)	(5.49)	(2.70)***	(2.16)**	
	6	0.04	-0.15	-	7.80	4.58	0.60
		(0.12)	(0.20)	-	(2.54)***	(1.41)**	
	7	-	-	1.08	-	-	0.45
		-	-	(6.19)	-	-	
	8	-	-	-0.50	7.29	5.26	0.59
		-	-	(5.49)	(2.67)***	(2.64)**	
	9	-	-	-	7.28	5.31	0.60
		-	-	-	(2.65)***	(2.89)*	
$H = 12$	1	0.03	0.01	-	-	-	0.45
		(0.89)	(0.11)	-	-	-	
	2	0.00	0.04	-1.14	-	-	0.44
		(0.10)	(0.14)	(3.49)	-	-	
	3	0.04	-0.11	-	2.92	-	0.47
		(0.10)	(0.18)	-	(1.50)*	-	
	4	0.04	-0.11	1.61	2.93	-	0.46
		(0.10)	(0.17)	(3.65)	(1.49)*	-	
	5	0.05	-0.10	-0.74	3.31	1.27	0.46
		(0.10)	(0.16)	(3.55)	(1.49)**	(1.20)	
	6	0.05	-0.11	-	3.32	1.32	0.47
		(0.10)	(0.16)	-	(1.50)**	(1.25)	
	7	-	-	-0.26	-	-	0.45
		-	-	(3.80)	-	-	
	8	-	-	-1.25	3.01	1.61	0.47
		-	-	(3.60)	(1.44)**	(1.41)	
	9	-	-	-	3.00	1.72	0.47
		-	-	-	(1.44)**	(1.56)	

Table 11: Predictive regression models for the VRP with a Dummy for the effect of the Lehman Brothers bankruptcy using the short-run funding spreads volatility factor, SRFUN_VF, and the Energy and Metals returns and spreads volatility factor, EM_VF during 1999m01 - 2010m12.

The OLS estimation results are reported and (***), (**), (*) refer to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) found in the parentheses refer to the NW HAC estimator with 12 lags. The dummy variable excludes the following observations: 2008m09 and 2008m10. The variables are defined in Table 1.

Horizon	Model	Predictors				Adj. R^2
		VIX^2(-H)	**DLC_V(-H)**	**SRFUN_VF(-H)**	**EM_VF(-H)**	
$H = 6$	1	0.08	-	-	-	0.45
		(0.04)*	-	-	-	
	2	0.08	1.49	-	-	0.45
		(0.04)*	(1.80)	-	-	
	3	0.04	-	1.11	-	0.47
		(0.06)	-	(0.78)	-	
	4	0.03	1.33	1.09	-	0.46
		(0.06)	(2.11)	(0.78)	-	
	5	0.06	2.00	1.45	1.47	0.47
		(0.06)	(1.99)	(0.89)	(0.65)**	
	6	0.06	-	1.45	1.34	0.47
		(0.06)	-	(0.90)	(0.64)**	
	7	-	2.95	-	-	0.44
		-	(1.99)	-	-	
	8	-	2.46	1.73	1.12	0.47
		-	(2.44)	(0.78)**	(0.68)	
	9	-	-	1.77	0.93	0.47
		-	-	(0.79)**	(0.70)	
$H = 9$	1	0.07	-	-	-	0.45
		(0.03)**	-	-	-	
	2	0.07	2.08	-	-	0.46
		(0.03)**	(1.39)	-	-	
	3	0.04	-	0.94	-	0.46
		(0.04)	-	(0.62)	-	
	4	0.03	2.00	0.93	-	0.46
		(0.04)	(1.41)	(0.62)	-	
	5	0.03	2.02	0.92	0.10	0.46
		(0.04)	(1.33)	(0.70)	(0.66)	
	6	0.04	-	0.91	0.24	0.46
		(0.04)	-	(0.70)	(0.68)	
	7	-	3.46	-	-	0.45
		-	(1.44)**	-	-	
	8	-	2.30	1.06	0.28	0.46
		-	(1.54)	(0.64)	(0.64)	
	9	-	-	1.07	0.49	0.46
		-	-	(0.64)*	(0.68)	
$H = 12$	1	0.10	-	-	-	0.46
		(0.03)***	-	-	-	
	2	0.11	-2.35	-	-	0.47
		(0.04)***	(1.14)**	-	-	
	3	0.05	-	1.29	-	0.46
		(0.03)	-	(0.72)*	-	
	4	0.06	-2.57	1.32	-	0.48
		(0.03)*	(1.07)**	(0.71)*	-	
	5	0.07	-2.02	1.57	0.99	0.48
		(0.04)*	(0.97)**	(0.78)**	(0.93)	
	6	0.06	-	1.58	1.12	0.48
		(0.03)*	-	(0.79)**	(0.94)	
	7	-	-0.19	-	-	0.44
		-	(0.91)	-	-	
	8	-	-1.38	1.90	0.55	0.48
		-	(0.88)	(0.74)**	(0.80)	
	9	-	-	1.89	0.68	0.48
		-	-	(0.75)**	(0.78)	

Table 12: Predictive regression models for the FEAR for the period 1999m01 - 2010m12 using the short-run funding spreads volatility factor, SRFUN_VF, and the Energy and Metals returns and spreads volatility factor, EM_VF.

The OLS estimation results are reported and (***), (**), (*) refer to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) found in the parentheses refer to the NW HAC estimator with 12 lags. The variables are defined in Table 1.

Horizon	Model	Predictors					Adj. R^2
		FEAR(-H)	**VIX^2(-H)**	**DLC_V(-H)**	**SRFUN_VF(-H)**	**EM_VF(-H)**	
$H = 6$	1	-0.77	0.19	-	-	-	0.05
		(0.51)	(0.10)*	-	-	-	
	2	-0.83	0.20	-0.04	-	-	0.04
		(0.61)	(0.12)	(0.12)	-	-	
	3	0.03	-0.03	-	1.66	-	0.31
		(0.34)	(0.09)	-	(0.63)**	-	
	4	0.01	-0.02	-0.05	1.66	-	0.31
		(0.35)	(0.08)	(0.13)	(0.63)***	-	
	5	0.07	-0.02	-0.01	1.84	-0.77	0.32
		(0.33)	(0.08)	(0.11)	(0.66)***	(0.37)**	
	6	0.07	-0.02	-	1.84	-0.77	0.33
		(0.32)	(0.08)	-	(0.66)***	(0.40)*	
	7	-	-	0.07	-	-	0.01
		-	-	(0.09)	-	-	
	8	-	-	-0.02	1.79	-0.83	0.33
		-	-	(0.12)	(0.57)***	(0.49)*	
	9	-	-	-	1.78	-0.85	0.34
		-	-	-	(0.56)***	(0.54)	
$H = 9$	1	-1.44	0.31	-	-	-	0.08
		(0.66)**	(0.13)**	-	-	-	
	2	-1.58	0.34	-0.07	-	-	0.08
		(0.76)**	(0.15)**	(0.13)	-	-	
	3	-0.76	0.11	-	1.67	-	0.34
		(0.30)**	(0.07)*	-	(0.56)***	-	
	4	-0.80	0.12	-0.07	1.67	-	0.34
		(0.32)**	(0.06)*	(0.10)	(0.55)***	-	
	5	-0.73	0.12	-0.03	1.86	-0.78	0.36
		(0.29)*	(0.06)*	(0.08)	(0.64)***	(0.58)	
	6	-0.71	0.11	-	1.87	-0.80	0.36
		(0.28)**	(0.06)*	-	(0.64)***	(0.61)	
	7	-	-	0.04	-	-	0.01
		-	-	(0.08)	-	-	
	8	-	-	-0.03	1.86	-1.01	0.34
		-	-	(0.06)	(0.66)***	(0.72)	
	9	-	-	-	1.86	-1.03	0.35
		-	-	-	(0.66)***	(0.76)	
$H = 12$	1	-0.83	0.19	-	-	-	0.03
		(0.62)	(0.12)	-	-	-	
	2	-0.89	0.21	-0.09	-	-	0.03
		(0.71)	(0.14)	(0.10)	-	-	
	3	-0.38	0.06	-	1.02	-	0.12
		(0.37)	(0.07)	-	(0.49)**	-	
	4	-0.44	0.08	-0.10	1.02	-	0.12
		(0.41)	(0.08)	(0.08)	(0.49)**	-	
	5	-0.39	0.08	-0.07	1.14	-0.46	0.12
		(0.39)	(0.08)	(0.07)	(0.49)**	(0.34)	
	6	-0.35	0.07	-	1.15	-0.51	0.12
		(0.36)	(0.07)	-	(0.49)**	(0.36)	
	7	-	-	0.01	-	-	0.01
		-	-	(0.07)	-	-	
	8	-	-	-0.06	1.19	-0.50	0.13
		-	-	(0.07)	(0.47)**	(0.36)	
	9	-	-	-	1.19	-0.55	0.13
		-	-	-	(0.47)**	(0.40)	

Table 13: Predictive regression models for the FEAR with a Dummy for the effect of the Lehman Brothers bankruptcy for the period 1999m01 - 2010m12 using the short-run funding spreads volatility factor, SRFUN_VF, and the Energy and Metals returns and spreads volatility factor, EM_VF.

The OLS estimation results are reported and (***), (**), (*) refer to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) found in the parentheses refer to the NW HAC estimator with 12 lags. The variables are defined in Table 1. Note that the following observations were excluded from this sample as representing the Lehman Brothers bankruptcy dummy: 2008m09-2008m11.

Horizon	Model	Predictors					Adj. R^2
		FEAR(-H)	**VIX^2(-H)**	**DLC_V(-H)**	**SRFUN_VF(-H)**	**EM_VF(-H)**	
$H = 6$	1	-0.30	0.10	-	-	-	0.51
		(0.24)	(0.05)*	-	-	-	
	2	-0.29	0.10	0.01	-	-	0.50
		(0.29)	(0.06)	(0.09)	-	-	
	3	0.06	-0.01	-	0.89	-	0.57
		(0.30)	(0.07)	-	(0.38)**	-	
	4	0.06	-0.01	0.01	0.89	-	0.56
		(0.31)	(0.07)	(0.11)	(0.39)**	-	
	5	0.10	-0.01	0.02	1.01	-0.44	0.57
		(0.29)	(0.07)	(0.10)	(0.42)**	(0.27)	
	6	0.09	-0.01	-	1.01	-0.43	0.57
		(0.29)	(0.07)	-	(0.42)**	(0.28)	
	7	-	-	0.11	-	-	0.47
		-	-	(0.47)	-	-	
	8	-	-	0.03	1.07	-0.35	0.57
		-	-	(0.11)	(0.35)***	(0.29)	
	9	-	-	-	1.08	-0.32	0.57
		-	-	-	(0.34)***	(0.32)	
$H = 9$	1	-0.98	0.21	-	-	-	0.51
		(0.36)***	(0.07)***	-	-	-	
	2	-1.06	0.23	-0.02	-	-	0.51
		(0.42)**	(0.08)***	(0.09)	-	-	
	3	-0.53	0.08	-	1.23	-	0.64
		(0.29)*	(0.07)	-	(0.40)***	-	
	4	-0.55	0.09	-0.03	1.23	-	0.64
		(0.29)*	(0.07)	(0.08)	(0.40)***	-	
	5	-0.53	0.08	-0.01	1.31	-0.30	0.64
		(0.29)*	(0.06)	(0.07)	(0.46)***	(0.27)	
	6	-0.52	0.08	-	1.31	-0.31	0.64
		(0.28)*	(0.06)	-	(0.46)***	(0.30)	
	7	-	-	0.07	-	-	0.46
		-	-	(0.07)	-	-	
	8	-	-	-0.01	1.30	-0.46	0.63
		-	-	(0.06)	(0.42)***	(0.41)	
	9	-	-	-	1.30	-0.47	0.63
		-	-	-	(0.42)***	(0.45)	
$H = 12$	1	-0.70	0.17	-	-	-	0.50
		(0.49)	(0.10)*	-	-	-	
	2	-0.72	0.18	-0.05	-	-	0.51
		(0.55)	(0.11)	(0.07)	-	-	
	3	-0.35	0.07	-	0.76	-	0.56
		(0.30)	(0.06)	-	(0.40)*	-	
	4	-0.38	0.08	-0.05	0.76	-	0.56
		(0.32)	(0.06)	(0.06)	(0.40)*	-	
	5	-0.34	0.08	-0.03	0.89	-0.49	0.56
		(0.31)	(0.06)	(0.05)	(0.43)**	(0.41)	
	6	-0.32	0.08	-	0.90	-0.51	0.57
		(0.29)	(0.06)	-	(0.43)**	(0.42)	
	7	-	-	0.05	-	-	0.46
		-	-	(0.04)	-	-	
	8	-	-	-0.01	1.01	-0.43	0.56
		-	-	(0.05)	(0.42)**	(0.39)	
	9	-	-	-	1.01	-0.43	0.57
		-	-	-	(0.42)**	(0.38)	

Table 14: Descriptive Statistics for the trading strategies based on the alternative models of the VIX^2 futures during the periods 2007m11-2010m12 and 2008m11-2010m12 using the VIX^2 predictive models.

Descriptive Statistics (Mean, Median, Standard Deviation and the ratio of the Mean Square Error for the VIX^2 forecasts given the realized VIX^2 for the periods 2007m11 - 2010m12 and 2008m11-2010m12. The ratio of the Mean Square Error is defined as MSE of model i / MSE of model 1, $i = 2, \ldots, 9$. The predictors of the models are as follows: Model 1: VIX^2(-H), Model 2: VIX^2(-H), DLC_V(-H), Model 3: VIX^2(-H), SRFUN_VF(-H), Model 4: VIX^2(-H), DLC_V(-H), SRFUN_VF(-H), Model 5: VIX^2(-H), DLC_V(-H), SRFUN_VF(-H), EM_VF(-H), Model 6: VIX^2(-H), SRFUN_VF(-H), EM_VF(-H), Model 7: DLC_V(-H), Model 8: DLC_V(-H), SRFUN_VF(-H), EM_VF(-H) and Model 9: SRFUN_VF(-H), EM_VF(-H). The variables are defined in Table 1. The strategies considered were as follows. A decision is made to buy or sell VIX futures based on the quantity $\left(\text{VIX}^2/12 - \text{Discounted Forecast}\right) / |\text{VIX}^2/12 - \text{Discounted Forecast}|$, using model predictions with H = 6, such that for values equal to -1 an investor would sell and for $+1$ an investor would buy. The long or short position in the six-month contract is held three (i.e. sell or buy a H = 3 contract). Upon unwinding the position a profit or loss was recorded. Entries are mean, median or standard deviations of realized profits/losses. The last entry in the table also reports the MSE ratios with respect to model 1 (lagged VIX only) for H = 6.

		2007m11 - 2010m12									2008m11 - 2010m12								
		1	2	3	4	5	6	7	8	9	1	2	3	4	5	6	7	8	9
	Mean	0.07	0.08	0.10	0.10	0.10	0.10	0.04	0.10	0.10	0.06	0.07	0.11	0.10	0.10	0.11	0.04	0.10	0.11
	Median	0.06	0.09	0.11	0.11	0.11	0.11	0.04	0.11	0.11	0.06	0.08	0.11	0.11	0.11	0.11	0.04	0.11	0.11
	Std. Dev.	0.18	0.18	0.17	0.17	0.17	0.17	0.19	0.17	0.17	0.21	0.20	0.18	0.19	0.19	0.19	0.21	0.19	0.19
	Ratio of the MSEs for the VIX^2 forecasts based on models 1-9. MSE of model 1 is the benchmark model																		
H = 6	RatMSE	-	1.06	0.65	0.70	0.76	0.73	1.37	0.75	0.79	-	1.06	0.59	0.64	0.70	0.67	1.38	0.68	0.71

Table 15: Summarizing results for alternative corporate factors "FACTOR_X", 1999m01 - 2010m12

The Adjusted R^2 are reported and (***), (**), (*) refer to rejecting the null hypothesis of insignificant "FACTOR_X" predictor at 1%, 5% and 10% respectively, using the NW HAC estimator with 12 lags. The variables are defined in Table 1. The notation "FACTOR_X" refers to the predictor used in each column one at a time, namely our volatility factors, SRFUN_VF, COR_VF, LRCOR_VF, our spreads factors, SRFUN_SF, COR_SF, LRCOR_SF, and other factors such as the Gildchrist and Zakrajšek spread, GZ_SPR, the St Louis Financial Stress Index (FSI), the Chicago National Financial Conditions Index (NFCI) and the NFCI subindices which refer to the Risk, Credit and Leverage series.

Panel A: Monthly VIX^2 Predictive Regressions for alternative corporate factors "FACTOR_X", 1999m01 - 2010m12, for alternative H: Adjusted R^2 and significance of factors

	Volatility Factors			Spreads Factors				Financial Stress and Conditions Indices				
	SRFUN_VF	COR_VF	LRCOR_VF	SRFUN_SF	COR_SF	LRCOR_SF	GZ_SPR	FSI	NFCI	NFCI_Risk	NFCI_Credit	NFCI_Leverage
Predictive Regressions	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2
H = 6												
VIX^2(-H)	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
VIX^2(-H), DLC_V(-H)	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
VIX^2(-H), FACTOR_X(-H)	0.34***	0.12	0.06	0.16	0.24**	0.22**	0.14	0.29**	0.29**	0.23*	0.24*	0.09
VIX^2(-H), DLC_V(-H), FACTOR_X(-H)	0.34***	0.12	0.05	0.16	0.25**	0.22*	0.17	0.30**	0.30**	0.25*	0.27*	0.09
VIX^2(-H), DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.37***	0.12	0.05	0.34*	0.28**	0.24**	0.19*	0.32**	0.34**	0.29**	0.31**	0.09
VIX^2(-H), FACTOR_X(-H), EM_X(-H)	0.37***	0.13	0.05	0.22*	0.32**	0.23**	0.16*	0.31**	0.34**	0.28**	0.29**	0.09
DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.37***	0.12**	0.01	0.34***	0.38***	0.22***	0.16***	0.22***	0.29***	0.26***	0.29***	0.07
FACTOR_X(-H), EM_X(-H)	0.38***	0.13**	0.02	0.35***	0.21**	0.22***	0.16***	0.21***	0.29***	0.25***	0.26***	0.07
H = 9												
VIX^2(-H)	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
VIX^2(-H), DLC_V(-H)	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
VIX^2(-H), FACTOR_X(-H)	0.34***	0.16	0.05	0.06*	0.16**	0.15**	0.07	0.18**	0.22**	0.20*	0.19*	0.07
VIX^2(-H), DLC_V(-H), FACTOR_X(-H)	0.34***	0.16	0.04	0.05*	0.16**	0.15**	0.10	0.19**	0.22**	0.21*	0.20**	0.06
VIX^2(-H), DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.38***	0.17	0.03	0.05*	0.32***	0.16**	0.19*	0.20**	0.26**	0.25**	0.25**	0.07
VIX^2(-H), FACTOR_X(-H), EM_X(-H)	0.38***	0.17	0.04	0.05**	0.31	0.16**	0.18*	0.20**	0.26**	0.24**	0.23***	0.07
DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.38***	0.17*	0.03	0.06**	0.31	0.13**	0.08*	0.11**	0.20**	0.20**	0.20**	0.07
FACTOR_X(-H), EM_X(-H)	0.38***	0.18*	0.04	0.07**	0.14*	0.14**	0.09*	0.12**	0.20**	0.19**	0.19**	0.07
H = 12												
VIX^2(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
VIX^2(-H), DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
VIX^2(-H), FACTOR_X(-H)	0.14**	0.03	0.01	0.03	0.10*	0.09**	0.03	0.14**	0.18**	0.15*	0.09*	0.08
VIX^2(-H), DLC_V(-H), FACTOR_X(-H)	0.14**	0.03	0.01	0.03	0.11**	0.10**	0.04*	0.16**	0.20**	0.17**	0.12**	0.08
VIX^2(-H), DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.15**	0.02	0.01	0.03	0.11**	0.11**	0.04*	0.17**	0.23**	0.20**	0.13**	0.08
VIX^2(-H), FACTOR_X(-H), EM_X(-H)	0.15**	0.02	0.01	0.03	0.09*	0.09*	0.04*	0.16**	0.22**	0.18**	0.11**	0.08
DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.16***	0.03	0.01	0.03*	0.09*	0.08*	0.04*	0.08**	0.16**	0.15**	0.11**	0.08
FACTOR_X(-H), EM_X(-H)	0.16***	0.03	0.01	0.03*	0.08	0.08*	0.03*	0.08**	0.15**	0.14**	0.10**	0.09

Panel B: Monthly RV Predictive Regressions for alternative corporate factors "FACTOR_X", 1999m01 - 2010m12, for alternative H: Adjusted R^2 and significance of factors

	Volatility Factors			Spreads Factors				Financial Stress and Conditions Indices				
	SRFUN_VF	COR_VF	LRCOR_VF	SRFUN_SF	COR_SF	LRCOR_SF	GZ_SPR	FSI	NFCI	NFCI_Risk	NFCI_Credit	NFCI_Leverage
Predictive Regressions	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2
					H = 6							
RV(-H), VIX^2(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
RV(-H), VIX^2(-H) ,DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
RV(-H), VIX^2(-H), FACTOR_X(-H)	0.29**	0.07	0.01	0.07	0.12*	0.10*	0.05	0.16*	0.18**	0.16*	0.14	0.04
RV(-H), VIX^2(-H), DLC_V(-H), FACTOR_X(-H)	0.29**	0.08	0.01	0.08	0.14*	0.11*	0.07	0.17*	0.20**	0.18*	0.17	0.04
RV(-H), VIX^2(-H), DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.32**	0.08	0.01	0.08*	0.15*	0.11*	0.07	0.18*	0.22**	0.21*	0.20*	0.04
RV(-H), VIX^2(-H), FACTOR_X(-H), EM_X(-H)	0.32**	0.09	0.01	0.08*	0.14*	0.09*	0.06	0.17*	0.21**	0.19*	0.17	0.05
DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.31***	0.06	0.01	0.09*	0.12**	0.07*	0.04**	0.08**	0.15**	0.15**	0.14*	0.06
FACTOR_X(-H), EM_X(-H)	0.31***	0.06	0.01	0.09**	0.10**	0.06	0.04**	0.07**	0.14**	0.13**	0.12*	0.06
					H = 9							
RV(-H), VIX^2(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
RV(-H), VIX^2(-H), DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
RV(-H), VIX^2(-H), FACTOR_X(-H)	0.29**	0.06	0.01	0.01	0.03	0.03	0.01	0.05*	0.08*	0.08	0.05	0.03
RV(-H), VIX^2(-H), DLC_V(-H), FACTOR_X(-H)	0.17**	0.06	0.01	0.01	0.02	0.03	0.01	0.04	0.08*	0.08	0.05	0.03
RV(-H), VIX^2(-H), DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.21***	0.07	0.01	0.01	0.04*	0.03	0.12**	0.06*	0.12**	0.12*	0.08	0.04
RV(-H), VIX^2(-H), FACTOR_X(-H), EM_X(-H)	0.21***	0.08	0.01	0.01	0.04*	0.03	0.12**	0.06*	0.12**	0.12*	0.08	0.05
DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.21**	0.06	0.01	0.01	0.04	0.02	0.01	0.03	0.08	0.09	0.06	0.06
FACTOR_X(-H), EM_X(-H)	0.22**	0.07	0.01	0.01	0.04	0.03	0.01	0.03	0.09*	0.09	0.06	0.07
					H = 12							
RV(-H), VIX^2(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
RV(-H), VIX^2(-H), DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
RV(-H), VIX^2(-H), FACTOR_X(-H)	0.03**	0.01	0.01	0.01	0.02	0.01*	0.01	0.04	0.06	0.06	0.02	0.05
RV(-H), VIX^2(-H), DLC_V(-H), FACTOR_X(-H)	0.02**	0.01	0.01	0.01	0.01	0.01*	0.01	0.04*	0.06	0.06	0.02	0.04
RV(-H), VIX^2(-H), DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.02**	0.01	0.01	0.01	0.01	0.01	0.01	0.04*	0.07*	0.07*	0.02*	0.04
RV(-H), VIX^2(-H), FACTOR_X(-H), EM_X(-H)	0.03**	0.01	0.01	0.01	0.02	0.01*	0.01	0.04*	0.08*	0.07*	0.02*	0.05
DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.03**	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.03	0.01*	0.05
FACTOR_X(-H), EM_X(-H)	0.03**	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.03	0.03	0.01	0.05

Panel C: Monthly VRP Predictive Regressions for alternative corporate factors "FACTOR_X", 1999m01 - 2010m12, for alternative H: Adjusted R^2 and significance of factors

	Volatility Factors			Spreads Factors				Financial Stress and Conditions Indices				
	SRFUN_VF	COR_VF	LRCOR_VF	SRFUN_SF	COR_SF	LRCOR_SF	GZ_SPR	FSI	NFCI	NFCI_Risk	NFCI_Credit	NFCI_Leverage
Predictive Regressions	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2
					H = 6							
VIX^2(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
VIX^2(-H), DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
VIX^2(-H), FACTOR_X(-H)	0.14***	0.05*	0.01*	0.02	0.07**	0.07**	0.03	0.08**	0.10**	0.06*	0.09*	0.01
VIX^2(-H), DLC_V(-H), FACTOR_X(-H)	0.13**	0.04*	0.01*	0.01	0.06**	0.06**	0.04	0.08**	0.10**	0.06	0.09*	0.01
VIX^2(-H), DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.16***	0.05**	0.01*	0.01	0.08**	0.06**	0.05*	0.09**	0.11**	0.08**	0.12**	0.01
VIX^2(-H), FACTOR_X(-H), EM_X(-H)	0.16***	0.05**	0.01**	0.02	0.08**	0.06**	0.05**	0.10***	0.12**	0.08**	0.12**	0.01
DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.16***	0.05***	0.01**	0.02	0.04***	0.05**	0.04**	0.07***	0.06***	0.07***	0.10***	0.01
FACTOR_X(-H), EM_X(-H)	0.17***	0.06***	0.01**	0.02*	0.05***	0.05**	0.05***	0.08***	0.07***	0.08***	0.10***	0.01
					H = 9							
VIX^2(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
VIX^2(-H), DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
VIX^2(-H), FACTOR_X(-H)	0.03***	0.02*	0.01	0.02**	0.04**	0.04**	0.03	0.05**	0.06***	0.08**	0.07**	0.02
VIX^2(-H), DLC_V(-H), FACTOR_X(-H)	0.03**	0.01*	0.01	0.01*	0.04**	0.03	0.03	0.04**	0.06**	0.07*	0.07**	0.01
VIX^2(-H), DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.02**	0.01*	0.01	0.01*	0.04**	0.03	0.01	0.04**	0.06**	0.08*	0.08*	0.01
VIX^2(-H), FACTOR_X(-H), EM_X(-H)	0.03**	0.01*	0.01	0.02**	0.05**	0.04	0.02**	0.05**	0.06**	0.09*	0.09**	0.01
DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.03***	0.01**	0.01*	0.01**	0.04**	0.03**	0.02	0.04*	0.03**	0.07*	0.07**	0.01
FACTOR_X(-H), EM_X(-H)	0.03***	0.02**	0.01*	0.02***	0.05**	0.04***	0.02**	0.05**	0.04**	0.08*	0.08**	0.01
					H = 12							
VIX^2(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
VIX^2(-H), DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
VIX^2(-H), FACTOR_X(-H)	0.04**	0.01	0.01	0.01	0.02	0.03**	0.01	0.03**	0.04**	0.04*	0.04*	0.01
VIX^2(-H), DLC_V(-H), FACTOR_X(-H)	0.04**	0.01	0.01	0.01	0.03**	0.03***	0.02**	0.03***	0.04**	0.05**	0.05**	0.01
VIX^2(-H), DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.04**	0.01	0.01	0.01	0.03**	0.03**	0.02***	0.03***	0.04***	0.05**	0.06**	0.01
VIX^2(-H), FACTOR_X(-H), EM_X(-H)	0.05**	0.01	0.01	0.01	0.02**	0.03**	0.01**	0.03***	0.04***	0.05**	0.04**	0.01
DLC_V(-H)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DLC_V(-H), FACTOR_X(-H), EM_X(-H)	0.05***	0.01	0.01	0.01**	0.03**	0.04***	0.02***	0.02***	0.04***	0.05***	0.06***	0.01
FACTOR_X(-H), EM_X(-H)	0.03**	0.01	0.01	0.01*	0.03***	0.04**	0.02**	0.02***	0.04***	0.05***	0.05***	0.01

Table 16: Equity Return Predictability, 1999m01 - 2010m12

The OLS estimation results are reported and (***), (**), (*) refer to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) found in the parentheses refer to the NW HAC estimator with 12 lags. The variables are defined in Table 1.

Predictive models for $H = 1$ monthly S&P 500 excess returns:

Predictors	1	2	3	4	5	6
VRP(-H)	0.56	0.56	0.58	0.50	0.55	0.56
	(0.11)***	(0.12)***	(0.09)***	(0.15)***	(0.15)***	(0.14)***
SRFUN_VF(-H)	-	-3.15	-	-	-	-
	-	(1.49)**	-	-	-	-
COR_VF(-H)	-	-	-1.26	-	-	-
	-	-	(2.16)	-	-	-
SRFUN_SF(-H)	-	-	-	-1.22	-	-
	-	-	-	(0.41)***	-	-
COR_SF(-H)	-	-	-	-	0.95	-
	-	-	-	-	(0.38)**	-
GZ_SPR(-H)	-	-	-	-	-	-0.60
	-	-	-	-	-	(0.28)**
Adj. R^2	0.046	0.068	0.040	0.105	0.079	0.065

	7	8	9	10	11	12
VRP(-H)	0.55	0.56	0.52	0.47	0.55	0.57
	(0.13)***	(0.12)***	(0.15)***	(0.11)***	(0.12)***	(0.13)***
Baa-Aaa(-H)	-0.76	0.42	-1.02	1.86	2.78	2.28
	(0.79)	(0.98)	(1.43)	(1.47)	(1.68)	(1.24)*
SRFUN_VF(-H)	-	-3.66	-	-	-	-
	-	(2.16)*	-	-	-	-
COR_VF(-H)	-	-	0.94	-	-	-
	-	-	(4.21)	-	-	-
SRFUN_SF(-H)	-	-	-	-1.90	-	-
	-	-	-	(0.96)**	-	-
COR_SF(-H)	-	-	-	-	2.16	-
	-	-	-	-	(0.87)**	-
GZ_SPR(-H)	-	-	-	-	-	-1.43
	-	-	-	-	-	(0.45)***
Adj. R^2	0.046	0.063	0.037	0.120	0.099	0.072

	13	14	15	16	17	18
VRP(-H)	0.56	0.55	0.63	0.45	0.53	0.56
	(0.10)***	(0.10)***	(0.08)***	(0.11)***	(0.12)***	(0.12)***
log(P/D)(-H)	-1.01	-2.63	-2.83	-5.35	-4.06	-4.14
	(2.12)	(1.51)*	(2.11)	(1.93)***	(1.83)**	(1.46)***
SRFUN_VF(-H)	-	-3.99	-	-	-	-
	-	(1.87)**	-	-	-	-
COR_VF(-H)	-	-	-3.39	-	-	-
	-	-	(1.99)*	-	-	-
SRFUN_SF(-H)	-	-	-	-1.94	-	-
	-	-	-	(0.61)***	-	-
COR_SF(-H)	-	-	-	-	1.46	-
	-	-	-	-	(0.40)***	-
GZ_SPR(-H)	-	-	-	-	-	-1.08
	-	-	-	-	-	(0.19)***
Adj. R^2	0.042	0.079	0.047	0.156	0.106	0.090

	19	20	21	22	23	24
VRP(-H)	0.55	0.54	0.61	0.45	0.53	0.55
	(0.10)***	(0.10)***	(0.08)***	(0.12)***	(0.12)***	(0.13)***
log(P/E)(-H)	1.05	1.98	2.63	4.07	2.88	3.61
	(1.50)	(1.50)	(1.57)*	(2.06)**	(1.81)	(1.53)**
SRFUN_VF(-H)	-	-3.48	-	-	-	-
	-	(1.79)*	-	-	-	-
COR_VF(-H)	-	-	-3.11	-	-	-
	-	-	(1.97)	-	-	-
SRFUN_SF(-H)	-	-	-	-1.69	-	-
	-	-	-	(0.55)***	-	-
COR_SF(-H)	-	-	-	-	1.22	-
	-	-	-	-	(0.38)***	-
GZ_SPR(-H)	-	-	-	-	-	-1.02
	-	-	-	-	-	(0.23)***
Adj. R^2	0.043	0.073	0.048	0.141	0.095	0.089

Table 16 - Continued

	25	26	27	28	29	30
VRP(-H)	0.56	0.56	0.58	0.48	0.56	0.55
	(0.11)***	(0.12)***	(0.09)***	(0.15)***	(0.15)***	(0.14)***
TMSP(-H)	-0.14	-0.09	-0.06	0.14	-0.11	0.05
	(0.33)	(0.31)	(0.34)	(0.34)	(0.29)	(0.30)
SRFUN_VF(-H)	-	-3.12	-	-	-	-
	-	(1.48)**	-	-	-	-
COR_VF(-H)	-	-	-1.10	-	-	-
	-	-	(2.22)	-	-	-
SRFUN_SF(-H)	-	-	-	-1.27	-	-
	-	-	-	(0.44)***	-	-
COR_SF(-H)	-	-	-	-	0.94	-
	-	-	-	-	(0.38)**	-
GZ_SPR(-H)	-	-	-	-	-	-0.60
	-	-	-	-	-	(0.29)**
Adj. R^2	0.039	0.062	0.033	0.100	0.072	0.056

	31	32	33	34	35	36
VRP(-H)	0.56	0.55	0.58	0.45	0.54	0.54
	(0.11)***	(0.12)***	(0.09)***	(0.13)***	(0.14)***	(0.13)***
RREL(-H)	0.81	-1.11	-2.10	-7.76	-1.80	-4.77
	(5.95)	(5.21)	(5.79)	(6.02)	(4.78)	(4.42)
SRFUN_VF(-H)	-	-3.18	-	-	-	-
	-	(1.50)**	-	-	-	-
COR_VF(-H)	-	-	-1.59	-	-	-
	-	-	(2.29)	-	-	-
SRFUN_SF(-H)	-	-	-	-1.41	-	-
	-	-	-	(0.46)***	-	-
COR_SF(-H)	-	-	-	-	0.96	-
	-	-	-	-	(0.37)***	-
GZ_SPR(-H)	-	-	-	-	-	-0.70
	-	-	-	-	-	(0.27)**
Adj. R^2	0.040	0.062	0.034	0.109	0.072	0.062

	37	38	39	40	41	42
VRP(-H)	0.43	0.44	0.45	0.40	0.44	0.45
	(0.13)***	(0.12)***	(0.12)***	(0.14)***	(0.14)***	(0.14)***
BDI(-H)	4.39	3.76	4.19	3.33	3.55	3.74
	(0.32)***	(1.51)**	(1.36)***	(1.87)*	(1.70)**	(1.64)**
SRFUN_VF(-H)	-	-2.71	-	-	-	-
	-	(1.44)*	-	-	-	-
COR_VF(-H)	-	-	-0.87	-	-	-
	-	-	(1.83)	-	-	-
SRFUN_SF(-H)	-	-	-	-1.09	-	-
	-	-	-	(0.41)***	-	-
COR_SF(-H)	-	-	-	-	0.79	-
	-	-	-	-	(0.37)**	-
GZ_SPR(-H)	-	-	-	-	-	-0.45
	-	-	-	-	-	(0.27)*
Adj. R^2	0.077	0.088	0.067	0.120	0.095	0.084