WHAT DRIVES THE VIX AND THE VOLATILITY RISK PREMIUM?*

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First Draft: February 2012

This Draft: September 29, 2013

PRELIMINARY AND INCOMPLETE

Abstract

There is a long tradition in finance of characterizing compensation for risk as a linear function of factors. The most common examples are linear models for equity risk premia, such as the CAPM and APT pricing models. We develop an econometric methodology to infer factors from a large panels of (filtered) volatilities. The panels are not confined to equity volatilities, but cover a wide range of financial instruments. Motivated by affine jump diffusion no-arbitrage asset pricing models, we present a formal framework for factor estimation with panels consisting of various filtered volatilities, either ARCH-type or realized. The theoretical pricing formulas combined with the asymptotic properties of the filtering procedures allows us to invoke large factor model asymptotic theory to obtain factor estimates. Using a large panel of financial instruments related to corporate credit risk, default risk and commodities we extracted factors and show how they predict the VIX and determine the volatility risk premium.

*The second author benefited from funding from a Marie Curie FP7-PEOPLE-2010-IIF grant. We thank Ron Gallant, Lars Hansen, Jonathan Hill, Adam McCloskey, Serena Ng and Eric Renault for some helpful comments while writing the paper.

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1 Introduction

There is a long tradition in finance to characterize compensation for risk as determined by a linear function of factors. This is true for stock market valuation, where, for example, the widely used Fama-French three-factor model can be interpreted in the framework of the no-arbitrage theory of Ross (1976b), in yield curve and credit risk modeling, where models by Vasicek (1977), Duffie and Kan (1996), and Dai and Singleton (2000) are typical examples, as well as derivatives pricing (i.e., Heston (1993), Bates (1996), Duffie, Pan, and Singleton (2000)).

This paper is related to the extant literature in a number of ways. 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. Level, slope and curvature factors are extracted from fixed income securities and meant to price the term structure. Default risk is extracted from panels of corporate bonds and meant to assess such risk across a wide spectrum of credit quality, etc. A few attempts have been made to price across asset classes, 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, use the class of affine asset pricing models to extract factors jointly from stocks and bonds. Our paper proposes new ways to extract risk factors, and suggests how to use a broad class of assets ranging from equities, sovereign and corporate bonds, short term lending, commodities and foreign exchange, to do so.

While our primary focus is on volatility risk factors, in particular those related to the VIX, we find such factors are also useful in predicting future equity returns. Regarding the extraction of volatility risk factors, we propose a novel approach. In particular, we extract such factors from panels of filtered volatilities using ARCH-type models. We know for sure that ARCH models are the wrong models, yet as argued by Nelson (1990), Nelson and Foster (1994), Nelson (1996), among others, they can be viewed as *filters* and deliver reliable estimates of spot volatility despite their mis-specification. To obtain such results we need some continuous record asymptotic arguments about the samples used to estimate the volatilities. On top of this, we need both large cross-sections (of dimension N) of such volatilities and we need a reasonably long time series (of length T). This entails some challenges regarding the large sample analysis used to estimate the volatility risk factors. In a companion theory paper (Andreou and Ghysels (2013)) the authors show that, contrary to the root-N standard normal consistency, one finds N-consistency, also standard normal, due to the fact that the high frequency sampling scheme is tied to the size of the cross-section, boosting the rate of convergence. We apply this new estimation strategy to new panel data sets of filtered volatilities, to uncover the driving factor for the VIX and volatility risk premium.

A number of papers have considered extracting factors using a classical factor analysis using (finite dimensional) 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), among others. The advantage of our approach is that we use a much broader class of volatilities (and therefore large dimensional), as we are not limited to (liquid) option-based implied volatilities. Moreover, because of the richness of our panel in terms of coverage of different asset classes, including equities, commodities, corporate bonds and FX, we can identify factors by using only a specific asset class. More specifically, we can extract factors only from equities, or only from commodities, and use them to put labels on the sources of risk. Note also, that our analysis is largely data-driven, namely, simple GARCH models function as filters (the GARCH parameter estimates are not of any direct interest), and principal component analysis is applied to ever expanding cross-sections of time series using high frequency data to generate the panel data of estimated volatilities.

Obviously not all risk factors may be revealed by volatilities, despite the potentially large selection of cross-sectional observations. Therefore, we do not exclusively rely on panels of volatilities. Namely, we also consider panels of a broad class of assets, including commodity returns, credit risk spreads (as well as their volatilities), etc. Extracting risk factors from such data does not pose any new technical challenges - unlike the case of volatilities. Yet, the application goes beyond the traditional factor analysis.

As noted earlier, we use our analysis setup to extract fundamental asset pricing factors and revisit modeling the economic sources of the VIX and the volatility risk premium (VRP). Is it really the case that a single factor drives VRP, or are there multiple factors involved? 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 the Drechsler and Yaron (2011) general equilibrium model that incorporates consumption growth volatility uncertainty and recursive utility preferences of a representative agent. Empirically, the volatility of the volatility of consumption growth is hard to pin down, however, and therefore the model implied linear mapping between the so called vol of vol and VRP is exploited in empirical analysis. There is reason to believe, however, that a single factor model may not be an adequate. Indeed, several recent empirical studies suggest this is the case, including Carr and Wu (2009), Egloff, Leippold, and Wu (2010), Bakshi, Panayotov, and Skoulakis (2011), Christiansen, Schmeling, and Schrimpf (2012), Corradi, Distaso, and Mele (2013) and Engle, Ghysels, and Sohn (2013), among others. The empirical work in our paper is most closely related to recent work by Christiansen, Schmeling, and Schrimpf (2012), Corradi, Distaso, and Mele (2013) and Engle, Ghysels, and Sohn (2013). Corradi, Distaso, and Mele (2013) develop a no-arbitrage affine asset pricing model where stock market volatility is explicitly related to a number of macroeconomic and unobservable factors. The model is fully parameterized and involves two observable factors - inflation and industrial production growth - and an additional latent third orthogonal factor. While the theoretical framework is powerful and elegant with stock volatility linked to the factors by no-arbitrage restrictions, it is potentially prone to specification errors. For example, Corradi, Distaso, and Mele (2013) assume that inflation and industrial production (IP) growth are driven by two orthogonal factors described by univariate square root processes. In reality inflation and IP growth are not orthogonal, a specification error which affects the parameterization and implied arbitrage restrictions in the model. Moreover, Christiansen, Schmeling, and Schrimpf (2012) document that purely macroeconomic variables (as opposed to financial variables) hardly show up as important predictors of financial volatility. Along similar lines, Engle, Ghysels, and Sohn (2013) show that (the long term component) of volatility is not only driven by inflation and industrial production (IP) growth, but also by inflation and IP volatility. In addition, Christiansen, Schmeling, and Schrimpf (2012) find that default spreads stand out as useful predictors not only for equity market volatility but also for other asset classes, whereas measures of funding market (il)liquidity and heightened counter-party credit risk also matter for several asset classes.

INCOMPLETE

2 Affine Asset Pricing Models

We start with the widely used class of continuous time affine jump diffusion (henceforth AJD) 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 the filtration satisfies the usual conditions (see e.g. Protter (2004)) and $\mathbb{P}$ refers to the physical or historical probably measure. Moreover, we suppose that the k-dimensional $\mathcal{F}$-adapted process $\mathcal{X}^f$ of state variables or factors is Markov in some state space $D \subset \mathbb{R}^k$, solving the stochastic differential equation:

$$d\mathcal{X}_t^f = \mu^{\mathbb{P}}(\mathcal{X}_t^f)dt + \sigma(\mathcal{X}_t^f)dW_t^{\mathbb{P}} \tag{2.1}$$

where $W_t^{\mathbb{P}}$ is an $\mathcal{F}_t$-adapted Brownian motion under $\mathbb{P}$ in $\mathbb{R}^k$, $\mu^{\mathbb{P}} : D \to \mathbb{R}^k$, $\sigma : D \to \mathbb{R}^{k\times k}$. The empirical analysis in the paper involves asset classes which do not feature reliable intra-daily data, which precludes us from using realized variances using high frequency data. As a consequence, our analysis focuses on the estimation of ARCH-type models, which excludes the presence of jumps. In a richer data environment, we could easily extend the setting to one including affine jump diffusion processes, see Andreou and Ghysels (2013) for further details. Formally, the affine diffusions satisfy the following:

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

$$\begin{array}{rclll} \mu^{\mathbb{P}}(x) & = & K_0^{\mathbb{P}} + K_1^{\mathbb{P}} x, & & K^{\mathbb{P}} \equiv (K_0^{\mathbb{P}}, K_1^{\mathbb{P}}) \in \mathbb{R}^k \times \mathbb{R}^{k\times k} \\ (\sigma(x)\sigma(x)^{\boldsymbol{T}})_{ij} & = & (H_0)_{ij} + (H_1)_{ij}^{\boldsymbol{T}} x & & H \equiv (H_0, H_1) \in \mathbb{R}^{k\times k} \times \mathbb{R}^{k\times k\times k} \end{array} \tag{2.2}$$

Finally, we also assume absence of arbitrage, which implies the existence of $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t\geq 0}, \mathbb{Q})$ where $\mathbb{Q}$ is an equivalent martingale measure under the risk neutral world. Furthermore, we assume that $\mathcal{X}^f$ is also an affine diffusion under $\mathbb{Q}$, and therefore:

Assumption 2.2. *Under the risk-neutral equivalent martingale measure $\mathbb{Q}$ the process X is described by:*

$$d\mathcal{X}_t^f = \mu^{\mathbb{Q}}(\mathcal{X}_t^f)dt + \sigma(\mathcal{X}_t^f)dW_t^{\mathbb{Q}} \tag{2.3}$$

completely characterized by the pair $(K^{\mathbb{Q}}, H, l^{\mathbb{Q}})$ of parameters determining the affine functions:

$$\begin{aligned} \mu^{\mathbb{Q}}(x) &= K_0^{\mathbb{Q}} + K_1^{\mathbb{Q}}x, & K^{\mathbb{Q}} \equiv (K_0^{\mathbb{Q}}, K_1^{\mathbb{Q}}) \in \mathbb{R}^k \times \mathbb{R}^{k\times k} \\ (\sigma(x)\sigma(x)^{\boldsymbol{T}})_{ij} &= (H_0)_{ij} + (H_1)_{ij}^{\boldsymbol{T}}x & H \equiv (H_0, H_1) \in \mathbb{R}^{k\times k} \times \mathbb{R}^{k\times k\times k} \end{aligned} \tag{2.4}$$

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 - i.e. state variables $\mathcal{X}_t^f$. In the term structure literature it is common to rotate the factors such that they correspond to the commonly used level, slope and curvature factors. The equity premia literature has instead focused on factors driven by macroeconomic fundamentals, in particular consumption uncertainty in the context of long-run risk economies studied by Bansal and Yaron (2004), where agents have a preference for early resolution of uncertainty and therefore dislike increases in economic uncertainty.[1]

While we will consider a broad asset class, we start with equity returns. We start with a reduced form for expected excess log returns (on the market portfolio):

$$E_t^{\mathbb{P}}[r_{t,t+\tau}] = \gamma_{er}(\tau)\mathcal{X}_t^f, \tag{2.5}$$

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 under the risk-neutral measure and expected variance under the objective measure.

The VRP has been studied extensively as it relates to variance swap contracts for which there is an active market particularly pertaining to the S&P 500 stock market index. One leg of the swap will pay an amount based upon the realized variance of the price changes of the underlying. Conventionally, these price changes will be daily log returns. The other leg of the swap will pay a fixed amount, which is the strike, quoted at the deal's inception. Thus the net payoff to the counter-parties will be the difference between these two and will be settled in cash at the expiration. Hence, at maturity, the payoff to the long side of the swap is equal to the difference between the realized variance over the life of the contract and a constant called the variance swap rate. No arbitrage dictates that the variance swap rate equals the risk-neutral expected value of the realized variance, i.e. $E_t^{\mathbb{Q}}[V_{t,t+\tau}^r]$, $V_{t,t+\tau}^r$ is the equity return forward integrated variance over the time interval t to t + τ. The VRP is the difference between the time t expected equity returns variance under the historical ($\mathbb{P}$) and the risk-neutral ($\mathbb{Q}$) probability measures, over horizon τ can be written as:

$$VRP(t,\tau) = E_t^{\mathbb{Q}}[V_{t,t+\tau}^r] - E_t^{\mathbb{P}}[V_{t,t+\tau}^r] \tag{2.6}$$

[1] See in particular Eraker and Shaliastovich (2008) for the linear pricing characterization of long-run risk equilibrium models.

With the linear affine risk premia setting, one obtains respectively:

$$VRP(t,\tau) = \delta_{vrp}(\tau) + \gamma_{vrp}(\tau)\mathcal{X}_t^f, \tag{2.7}$$

where δ_{vrp} and γ_{vrp} relate to the data generating process, i.e. relate to α^i and β^i for i = $\mathbb{Q}$ and $\mathbb{P}$ (see for example Todorov (2010), among others, for further details). Similarly, the pricing of future integrated volatility can be written as:

$$E_t^{\mathbb{Q}}[V_{t,t+\tau}^r] = \mu_{rv}^{\mathbb{Q}}(\tau) + \gamma_{rv}^{\mathbb{Q}}(\tau)\mathcal{X}_t^f, \qquad E_t^{\mathbb{P}}[V_{t,t+\tau}^r] = \mu_{rv}^{\mathbb{P}}(\tau) + \gamma_{rv}^{\mathbb{P}}(\tau)\mathcal{X}_t^f \tag{2.8}$$

The above linear pricing schemes have been used extensively, although with assumed factor representations - and their interpretation - that are different. See notably Carr and Wu (2009), Egloff, Leippold, and Wu (2010), Zhou (2010), Bakshi, Panayotov, and Skoulakis (2011), Mueller, Vedolin, and Zhou (2011), Wang, Zhou, and Zhou (2013) and Corradi, Distaso, and Mele (2013), among others. In the next section, we present a novel approach of estimating $\mathcal{X}_t^f$.

By analogy with the term structure of interest rates, one can estimate the principal components for a panel of variance risk premia with different maturities. Bühler (2006), Amengual (2009), Egloff, Leippold, and Wu (2010) and Aït-Sahalia, Karaman, and Mancini (2012) apply principal component analysis (PCA) to panels of variance swap rates and find that two factors - which can be interpreted as level and slope - explain close to 100 % of the variation in variance swap rates for the S&P 500. The similarities with term structure of interest rates also brings us to the topic of stochastic singularity - since we have potentially large cross-sections of variance swap rates driven - according to equation (2.7 - by just a few state variables. Adding measurement errors to the variance swap rates is the standard solution. The analysis in the next section will not require us to add an ad hoc measurement error as filtered volatilities have a natural error distribution which we know how to characterize asymptotically.[2]

In the empirical section we use five homogeneous classes of assets. Risk pricing for each asset class is linearly affine in $\mathcal{X}^f$. Most importantly, however, the different asset classes will - via differences in exposure - give us different snapshots of factor space which spans risk in an unified affine asset pricing world. For convenience of presentation we conclude this section with a generic affine pricing formula indexed by an indicator defined for a set of asset classes ranging from equities (already discussed), sovereign and corporate bonds, short term lending, commodities and foreign exchange. We will also need to distinguish 'spread' factors from 'volatility' factors. The former pertain to respectively default, credit and maturity spreads, whereas the latter will pertain to their volatility, i.e. the volatility of default, credit and maturity spreads.

[2]Todorov (2010), Bollerslev and Todorov (2011), Aït-Sahalia, Karaman, and Mancini (2012) find that a large and time-varying jump risk component is embedded in variance swap rates. Regularity conditions underlying some of the factor filters discussed in the next section will exclude jump risk, the reason why we need the rely on the more restrictive Assumption 2.1.

The distinction is reminiscent of the excess equity returns and their volatility

$$\begin{aligned} E_t^{\mathbb{P}}[c_{t,t+\tau}] &= \mu_c^{\mathbb{P}}(\tau) + \gamma_c^{\mathbb{P}}(\tau)\mathcal{X}_t^f, \qquad E_t^{\mathbb{P}}[V_{t,t+\tau}^c] = \mu_{cv}^{\mathbb{P}}(\tau) + \gamma_{cv}^{\mathbb{P}}(\tau)\mathcal{X}_t^f \\ E_t^{\mathbb{Q}}[c_{t,t+\tau}] &= \mu_c^{\mathbb{Q}}(\tau) + \gamma_c^{\mathbb{Q}}(\tau)\mathcal{X}_t^f, \qquad E_t^{\mathbb{Q}}[V_{t,t+\tau}^c] = \mu_{cv}^{\mathbb{Q}}(\tau) + \gamma_{cv}^{\mathbb{Q}}(\tau)\mathcal{X}_t^f \end{aligned} \tag{2.9}$$

Before we do, it is worth noting that we do not impose no-arbitrage conditions across pricing equations - unlike for instance Corradi, Distaso, and Mele (2013). Imposing such conditions is a much debated topic in the term structure of interest literature (see e.g. Duffee (2011)) and as we noted in the Introduction may be prone to mis-specification issues. We therefore do not follow this route. Alternatively, and again similar to the term structure literature, one might think of backing out factors, using a sufficient number of financial assets - an approach pursued by Carr and Wu (2009), Zhou (2010), Bakshi, Panayotov, and Skoulakis (2011), among others. We will not pursue this approach either.

3 Factor Analysis with Panels of ARCH Filters

The idea to extract factors that determine risk premia has a long tradition both in the equity pricing (Merton (1973), Ross (1976a), Chamberlain and Rothschild (1983), among many others) and fixed income term structure (Fama and Bliss (1987), Campbell and Shiller (1991), Cochrane and Piazzesi (2005), among many others). The method we adopt relates to efforts by Ludvigson and Ng (2009) to find a direct relation between bond risk premia and the macro economy. However, we use their techniques in a novel way to extract common factors from a large panel of asset volatilities.

Technically speaking we will consider for any asset i with (log) price x_t^i which has exposure to (some of) the risk factors, i.e.:

$$x_t^i \equiv \delta_0^i + \delta^i \mathcal{X}_t^f \qquad \delta^i \neq 0 \tag{3.1}$$

such as for example the log price of an equity claim, log price of a zero-coupon bond, a risk spread, etc., and we are interested in two objects: (1) spot volatility and (2) integrated volatility. More precisely, we can write spot volatility, simplifying the notation, as:

$$V_t^i = \mu_{iv}^{\mathbb{P}}(0) + \gamma_{iv}^{\mathbb{P}}(0)\mathcal{X}_t^f \equiv \mu_{iv} + \gamma_{iv}\mathcal{X}_t^f \tag{3.2}$$

whereas the time t expectation of integrated volatility over horizon τ, namely $E_t^{\mathbb{P}}[V_{t,t+\tau}^i] = \mu_{iv}^{\mathbb{P}}(\tau) + \gamma_{iv}^{\mathbb{P}}(\tau)\mathcal{X}_t^f$, will be studied in the next section. We do not directly observe volatility, integrated or spot, (nor $\mathcal{X}_t^f$) but have at our disposable, for a large set of assets, some estimates for either type of volatility. We will start with the spot volatility case and consider integrated volatilities in the next section. We are working under the assumption that we can collect volatility data which span the space all the risk factors, formally defined later. Alternatively, we can think of estimating a sub-block of factors pertaining to volatility, which we still will denote by $\mathcal{X}_t^f$ to avoid further complicating notation.

Combining equation equations (2.1) and (3.3) implies that x_t^i satisfies the diffusion:

$$dx_t^i = \mu^i(\mathcal{X}_t^f)dt + \sigma^i(\mathcal{X}_t^f)dW_t^{\mathbb{P}} \tag{3.3}$$

where $\mathcal{X}_t^f$ satisfies Assumption 2.1, and therefore by Itô's lemma: $\mu^i(\mathcal{X}_t^f) \equiv \delta^i \mu^{\mathbb{P}}(\mathcal{X}_t^f)$ and $\sigma^i(\mathcal{X}_t^f) \equiv \sigma(\mathcal{X}_t^f)$.

When spot volatility is latent it is necessary to think about filtering. There are an abundant number of filtering schemes, many based on Markov Chain Monte Carlo simulation algorithms, inspired by the seminal work of Jacquier, Polson, and Rossi (2002). Such filtering schemes are analytically intractable and unattractive when we are dealing with potentially large cross-sections, like hundreds of individual asset volatilities. We therefore need to rely on computationally simple filters, convenient and analytically tractable. We therefore opt for ARCH-type models as *filters*, following the work of Nelson (1990), Nelson and Foster (1994), Nelson (1996), among others. Hence, we will rely on easy to estimate (univariate) ARCH-type models viewed as a filters through which one passes the data to produce an estimate of the conditional variance.

We lack continuous time observations x_t^i for asset i but have observations, denoted by $x[h]_{kh}^i$ with k integer, at arbitrary small time intervals equally spaced by h_i and such data can be collected at an ever increasing frequency, $h_i \downarrow 0 \; \forall \; i$. Suppose we denote the filtered volatility by $\hat{V}[h]_t^i$ and we define:

$$\hat{V}[h]_t^i \equiv V_t^i + \hat{\varepsilon}[h]_t^i = \mu_{iv} + \gamma_{iv}\bar{\mathcal{X}}_t^f + \hat{\varepsilon}[h]_t^i \tag{3.4}$$

where $\hat{\varepsilon}[h]_t^i$ is a filtering error, i.e. the difference between the true spot volatility and the one obtained from the ARCH-filter. Nelson and Foster (1994) use continuous record asymptotics, i.e. using asset log asset price data at arbitrary small time intervals, denoted by $x[h]_t^i$ for asset i in the cross-section, to characterize the distribution of the measurement error.

The data structure we have in mind involves three types of asymptotics. There is the cross-section of volatilities estimates at each point in time, namely $i = 1, \ldots, N$ 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 addition to the expanding N and T, we also have the sampling frequency h of data used to compute the volatility estimates using data collected at increasing frequency, $h \downarrow 0$, where $h \equiv \sup_{i=1,N} h_i$. The sampling scheme we therefore have in mind appears in the following diagram:

$$\begin{array}{ccccc} & & N \to \infty & & N \to \infty \\ & & \vdots & & \vdots \\ [x[h]^i_{t-Kh}, \ldots, x[h]^i_{t-h}, x[h]^i_t] & \rightsquigarrow & \hat{V}[h]^i_t & & \hat{V}[h]^i_{t+1} \quad \ldots \quad T \to \infty \\ \dashleftarrow \text{log price data } \{\mathbf{h} \downarrow \mathbf{0}\} \dashrightarrow & & \vdots & & \vdots \end{array}$$

$$\Delta\, t = 1 \text{ fixed}$$

Practically, we want to use principle component analysis (PCA) with panels of filtered volatilities to obtain estimates of $\mathcal{X}^f_t$. Since both N and T are allowed to grow and h to shrink, we need to prevent filtering errors to become a pervasive factor. The analysis in this section explains how to do this.

The time series of cross-sections is sampled at a fixed time interval, say $\Delta t = 1$. This means that we observe at best a discretization of $\mathcal{X}^f_t$, call it $\bar{\mathcal{X}}^f_t, \equiv \mathcal{X}^f_t$ for $t = k\Delta t$ $k \in \mathbb{N}$. This may leave the impression that the underlying affine diffusion setting is detached from the large panel framework, and therefore irrelevant, for the purpose of our analysis, since in general there is no straightforward mapping from the continuous time process to a finite time grid discretization, except in a few special cases. However, the continuous time process is relevant because it provides: (a) the foundations for the volatility filters and their relationship to $\bar{\mathcal{X}}^f_t$,, and (b) the stochastic properties of the idiosyncratic (i.e. measurement) errors in the panel data model, such that they satisfy the so called approximate (using the terminology of Chamberlain and Rothschild (1983)) panel structure.

The idea that we estimate, say GARCH(1,1) models for individual assets may raise the question that we may have to deal with near-unit root type of models, i.e. IGARCH, and that this may adversely affect the PCA we about to discuss next. It is important to note, however, that we only skip-sample $\hat{V}[h]^i_t$ at intervals Δt which are far apart in terms of the local time scale determined by h which is used to compute the filtered volatilities. Hence, as h shrinks, so does the serial dependence and among two subsequent panel data observations, i.e. $\hat{V}[h]^i_{t-1}$ and $\hat{V}[h]^i_t$ for any t. This issue will be further highlighted when we discuss the idiosyncratic error structure of the panel data models.

To proceed with need to introduce 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 commonly used notation with some modification and then discuss the mapping with the framework discussed so far. Namely, consider the vector form model representation:

$$X^{[h]}_t = \Lambda F_t + e^{[h]}_t \tag{3.5}$$

where the commonly used normalization $E(F_t) = 0$ and $E(F_t F'_t)$ is a k-dimensional diagonal matrix ($k = \dim(\bar{\mathcal{X}}^f_t)$) is assumed. The latter implies that the factors we will uncover are some affine transformation: $F_t = \mathcal{H}\bar{\mathcal{X}}^f_t$, with $\mathcal{H}$ a nonsingular $k \times k$ matrix. Term structure applications of affine models in particular, 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) $X_t^{[h]}$ = $((\hat{V}[h]_t^i - \bar{v}[h]_T^i), i = 1, \ldots, N)'$, where $\bar{v}[h]_T^i$ 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 (3.4) since the factors and idiosyncratic errors are mean zero, (b) the factor loadings Λ = $(\lambda_1, \ldots, \lambda_N)'$ are non-random and, (c) $e_t^{[h]}$ = $(\hat{\varepsilon}[h]_t^i, i = 1, \ldots, N)'$. The matrix representation of the factor model is:

$$X^{[h]} = F\Lambda' + e^{[h]} \tag{3.6}$$

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

The estimator we consider is standard, namely the method of asymptotic principal components, initiated by was first considered by Connor and Korajczyk ((1986) and (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 method of principal components (PC) 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 for a given h :

$$\min_{\Lambda, F} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it}^{[h]} - \lambda_i' F_t)^2 \tag{3.7}$$

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

Under suitable regularity conditions, Andreou and Ghysels (2013) show that if $\sqrt{N}/T \to 0$, then for each t :

$$(\sqrt{N}/h^{1/4})(\tilde{F}_t^{[h]} - \mathcal{H}\bar{\mathcal{X}}_t^f) \xrightarrow{d} N(0, V^{-1} Q \Lambda_t Q' V^{-1}),$$

We note from the above that the estimation of the factors has a rate of convergence $(\sqrt{N}/h^{1/4})$ instead of the standard $\sqrt{N}$ asymptotic results found in Bai and Ng (2002), Bai (2003), among others. The reason for the difference is the combination of the continuous record asymptotics of Nelson and Foster (1994) and the large panel data analysis. In the latter case, standard central limit theorems are *assumed* for the error process of the panel data model (see e.g. Assumption F of Bai (2003)). In our analysis, the dependence structure of the errors follow directly from the assumed sampling scheme for the ARCH filters. In fact, if we take as example h = N^{-2}, we simultaneously squeeze the ARCH filtering errors, and therefore the errors of the panel data. With h = N^{-2}, we actually obtain a rate of converge equal to N, instead of the usual $\sqrt{N}$. This actually implies that ARCH filter panel data models yield *super-consistent* estimators, borrowing a concept from the unit root literature (e.g. Dickey and Fuller (1981)), for the factor process $\bar{\mathcal{X}}_t^f$.

It should finally also be noted that the number of factors can be consistently estimated the number of factors k by analyzing the statistical properties of the minimand $V(\tilde{k})$ appearing in equation (3.7) as a function of $\tilde{k}$, where $\tilde{k}$ is not necessarily the true k. Bai and Ng (2002) showed that the number of factors can be estimated consistently by minimizing the following criterion:

$$IC(\tilde{k}) = \log\left(V(\tilde{k})\right) + \tilde{k}\left(\frac{N+T}{NT}\right)\log\left(\frac{NT}{N+T}\right)$$

In terms of practical implementation there is an important lesson which emerges from our analysis. Although we will study *monthly* panels, our GARCH models will be *daily* and we will pick the last day of the month in order to construct our panel data set. Such a strategy will enable us to exploit the idea of using higher frequency data to extract the monthly volatility risk factors.

4 Factors for the VIX and the Volatility Risk Premium

In the previous section we focused exclusively on extracting volatility risk factors. Our empirical analysis does not deal exclusively with panel of GARCH volatility filters, it also includes various risk spreads for example. Hence, we will drop the h index in this section, although in the background, we should keep in mind that higher frequency data is used to implement our empirical analysis. A consequence of the results discussed in the previous implies that we cannot pool panels of filtered volatilities with other standard panel data, since the convergence rates differ. We will therefore proceed with estimating factors by asset class and treat separately the return/spread and volatility panels. For each class we extract return/spread risk factors and return/spread volatility risk factors. In particular, we extract factors from a panel of homogeneous asset classes e.g. corporate risk, commodity price risk, which allow us to identify the specific sources of risk associated with these particular classes of financial assets. Second, we apply the ideas spelled out in the previous section, by extracting factors from daily GARCH models. Typically factors are extracted from a specific asset class (e.g. term structure) to price the same type of assets (e.g. fixed income derivatives). We extract factors of say, short term funding risk, long-run corporate spreads risk, commodity risk and show how it helps pricing equity volatility risk, the RV of S&P500 stock market returns, the VIX as well as VRP.

4.1 Factor Extraction

We extract common factors for panels that are stratified by asset class (e.g. commodities) and subclasses (e.g. energy and metals commodities). The panel of daily GARCH models sampled end of each month consist of (i) energy and metals commodity returns and spreads, (ii) long-run corporate bond spreads and

(iii) short-run funding spreads during 1999m01 - 2010m12, $T = 144$. More specifically:

(i) The **short-run funding risk** panel ($N = 35$) are volatilities of e.g. the LIBOR, Eurodollar, (Non) Commercial (Non) Financial paper short-run spreads and Tbills of different maturities (7 Days,1,3,6,12 months) with respect the Fed funds rate, summarized by category in Appendix Table A.1 and listed in detail in Appendix Table A.4. For each series an AR(1)-GARCH(1,1) model is estimated as a proxy of the volatility of each spread. The common volatility factor estimated from the volatility panel is denoted by SRFUN_VF. The corresponding factor estimated from the returns panel is SRFUN_SF.

(ii) The **long-run corporate risk** panel ($N = 74$) involves volatilities of corporate bond spreads from different industries, indices, maturities, rating categories vis-à-vis the corresponding government bond maturity (e.g. 1,5,7,10 years) summarized by category in Appendix Table A.2 and listed in detail in Appendix Table A.5. As above an AR(1)-GARCH(1,1) model is estimated for each spread series. The first principal component or factor estimated from this panel of volatilities is denoted by LRCOR_VF and the corresponding one from just the spreads LRCOR_SF.

(iii) 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 e.g. of gas, oil, biofuel and various metals e.g. gold, silver, aluminium e.t.c, as well as corresponding indices described by category in Appendix Table A.3, and the corresponding spreads between spot and futures prices of each commodity. The detailed list of the series can be found in Table A.6. For each series we estimate an AR(1)-GARCH(1,1) model. The common volatility factor estimated from the panel of volatilities is denoted by EM_VF and the corresponding one from returns and spreads is denoted by EM_RF.

Using the AR(1)-GARCH(1,1) univariate filters in panel (i) above, the short-run funding risk volatility factor (SRFUN_VF) explains 65% of the variation of the panel as given by the sum of squared loadings. This factor loads heavily on the following types of spreads: 15Day A2/P2/F2 Nonfinancial Commercial Paper (% Per Annum) -15Day Aa Financial Commercial Paper (% Per Annum), 15Day A2/P2/F2 Nonfinancial Commercial Paper (% Per Annum) -15Day Aa Nonfinancial Commercial Paper (% Per Annum) and 7Day London Interbank Offered Rate (%) -FF.[3] We find that the corresponding SRFUN_RV factor explains also 81% of the variation of the series in this panel.

In the second panel of the corporate risk we extract the common factor from the AR(1)-GARCH(1,1) univariate filters of long-run corporate spreads which is denoted by LRCOR_VF and explains 75% variation of this panel. The LRCOR_VF factor explains 85% of the variation of the panel and loads heavily on the following types of volatility spreads: Merrill Lynch Treasury Master: Effective Yield (%)-10Yr-Tbond, Merrill Lynch Treasury Master: Yield To Worst (%)-10Yr-Tbond, Merrill Lynch Corporate Bonds: Industrials: 1 to 3 Yrs: Effective Yield (%) -3Yr-Tnote and Merrill Lynch Corporate Bonds: Utilities: 1 to

[3]For robustness we also obtain the corresponding factor from the panel of univariate monthly Realized volatilities based on the aggregated squared residuals of the daily AR(1) of the spreads.

3 Yrs: Effective Yield (%) -3Yr-Tnote. Note that the corresponding factor based on the Realized Volatility of the squared residuals of the daily AR(1) of the spreads, LRCOR_RV, also explains 85% of the variation in the panel.

The last panel of the energy and metals commodities returns and spreads volatilities yields a common volatility factor which explains 95% of the variation of this panel of asset volatilities and correlates highly with the volatilities of the following series: S&P GSCI Heating Oil Total Return Index (Dec-31-82=100), No 2 Heating Oil Futures Price: 3-Month Contract Settlement ($/Gal) and S&P GSCI Energy Commodities Total Return Index (12/31/82=100).

We examine the predictive ability of these factors, SRFUN_VF, LRCOR_VF and EM_VF, in explaining the VIX, the Realized Volatility of the S&P 500 (RV_SP500) and the VRP at different horizons. The VIX is the Chicago Board Options Exchange Market Volatility Index, a measure of the implied volatility S&P 500 index options. We model the VIX^2. The monthly RV measure 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 return. For a typical month with 22 trading days, this leaves us with a total of $T = 22 \times 78 = 1716$ five-minute returns. The variance risk premium is a common short-run component of the market risk premia which is not directly observable but an empirical proxy can be constructed from the difference between model-free option-implied variance (VIX^2) and the conditional expectation of model-free realized variance RV_SP500.

5 What drives the VIX, RV_SP500 and VRP?

In this section we focus the discussion on the results related to the two novel volatility factors, the short-run funding risk spread volatility factor, SRFUN_VF, and the energy and metals volatility factor, EM_VF, which predict the VIX^2, RV_SP500 and VRP for alternative forecast horizons, h, and model specifications using in-sample analysis. A number of additional results are discussed and presented in the robustness section 6.

Table 1 presents the estimated linear predictive regression models for the VIX^2 during the period 1999m01 - 2010m12 for alternative forecasting horizons of H = 6, 9 and 12 months. The LS parameter estimates and the Newey West HAC standard errors with fixed bandwidth are reported along with the adjusted R^2 for each model. The following models are specified: Models 1 and 2 in Table 1 represent the benchmark models. In model 1 the VIX^2 follows a simple AR(H) process and in model 2 the VIX^2 is driven by its own lag and that of the volatility of consumption along the lines of models of Drechsler and Yaron (2011). Note that we proxy the volatility of the volatility of consumption using the AR-GARCH fitted values of the monthly per capita consumption on non-durables and services. This series is also used in Drechsler and Yaron (2011) and Bansal and Shaliastovich (2013). Alternative measures of consumption volatility are also addressed in the robustness section. The corresponding single factor model specification for the VIX^2

which is closer to the theory e.g. Drechsler and Yaron (2011) is given by model 7 and includes only the volatility of consumption, DLC_V($-H$). The remaining models considered in table 1 incorporate our new volatility factors , EM_VF($-H$) and or just SRFUN_VF($-H$), with and without VIX$^2(-H)$ in models 3-6 and models 8-9, respectively.

The general results from Table 1 are the following: (i) The three factor model which includes the volatility of consumption, DLC_V($-H$), the energy and metals volatility factor, EM_VF($-H$), and the short-run funding risk, SRFUN_VF($-H$), shows the last two factors are statistically significant and that in general the volatility of the volatility of consumption factor is statistically insignificant in explaining the VIX^2. This result holds for all H considered in Table 1. (ii) The short-run funding risk volatility factor, SRFUN_VF, is statistically significant at the 1% level in almost all forecast horizons, $H = 6, 9$ and 12 and alternative model specifications in Table 1. Most importantly the SRFUN_VF($-H$) factor provides significant gains in terms of adjusted R^2 for all H horizons vis-à-vis the benchmark models 1 and 2 i.e. the AR(1) and single factor consumption volatility models, respectively. (iii) The adjusted R^2 gains from our factors are higher for the shorter horizons of 6 and 9 months compared to those of one year. For example, for $H = 6$ months the benchmark models 1 and 2 yield adjusted R^2 of 6% whereas incorporating the SRFUN_VF factor can improve the adjusted R^2 by on average 35%.

Table 2 examines whether our two factors, SRFUN_VF and EM_VF can predict the RV_SP500 for the sample period 1999m01 - 2010m12. Table 2 has a similar structure to that of Table 1. The difference in Table 2 is that models 1-6 control for the lags of both RV_SP500 and the VIX^2. The general results in Table 2 are the following: (i) The SRFUN_VF and EM_VF factors are both statistically significant at $H = 6$ and 9 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 at 1% and 5% significant levels vis-à-vis the other factors for all H. Interestingly enough the lagged RV_SP500 is only significant for $H = 6$ whereas the SRFUN_VF is significant for all horizons considered from 6 to 12 months. In contrast, the energy and metals factor, EM_VF, appears to be strongly significant for relatively shorter horizons of 6 months and insignificant for horizons (ii) The adjusted R^2 gains from our factors are higher for the shorter horizons of 6 and 9 months and they are relatively small for $H = 12$. For example, for $H = 6$ months the benchmark models 1 yields a low adjusted R^2 of 1% whereas incorporating the SRFUN_VF factor can improve the adjusted R^2 by on average 30% for $H = 6$ and 20% for $H = 9$.

Table 3 presents the predictive regression models for the VRP for the sample period 1999m01 - 2010m12 for forecasting horizons of $H = 6, 9$ and 12 months. The benchmark models include model 1 with the lagged VIX^2 as well as the single factor of the volatility of volatility of consumption, DLC_V($-H$), in the univariate model 7 which is in accordance to the long-run risk models of e.g. Drechsler and Yaron (2011). The benchmark model 2 which includes both VIX$^2(-H)$ and DLC_V$(-H)$ is also considered. The results in Table 3 present some interesting results: (i) In accordance with the theory the VRP can be explained by the single factor model which is the volatility of the volatility of consumption which is approximated by the DLC_V that turns out to be significant in longer horizons of 12 months in explaining the VRP. In particular, in the last panel of Table 3 the DLC_V(-12) factor turns out to be significant even in the presence of other factors such as our two factors and even lagged VIX^2. However, in shorter horizons of $H = 6$ the consumption risk factor becomes insignificant and weakly significant in some models for $H = 6$. (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 only 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 model specifications is SRFUN_VF. This short-run funding risk factor appears to be driving the VRP and it is the factor which also improves adjusted R^2 for all H but especially $H = 6$.

The results in Tables 1 - 3 refer to the sample period until the end of 2010m12 which includes the Lehman Brother collapse during September and October 2008. In Tables 4 - 6 we estimate the same models as those in Tables 1 - 3 but exclude the months of the Lehman brothers collapse using a dummy variable. Table 4 shows the predictive regression model results for the VIX^2 excluding the two months related to the Lehman Brothers collapse. Comparing the results in Tables 1 and 4 with and without the 2008m09 and m10, respectively, we find that overall the results described in Table 1 are qualitatively the same as those with Table 4. Namely, the SRFUN_VF$(-H)$ is still the most strongly significant predictor for all H = 6, 9 and 12 and that 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. The notable difference between the results in Tables 1 and 4 is the fact that excluding the Lehman Brothers collapse improves significantly the adjusted R^2's of the benchmark models 1 and 2 for all H. Yet, including our factors and especially SRFUN_VF$(-H)$ for H = 6 and 9 months doubles the adjusted R^2 of the benchmark models 1 and 2. In Tables 5 and 6 we find that excluding the Lehman effect improves some of the benchmark model adjusted R^2's in models 2 and 1, respectively. Hence the corresponding improvements from adding our factors in the models for the RV_SP500 and VRP are significantly lower when the crisis months are not in the sample. In the RV_SP500 predictive regressions our two proposed factors, SRFUN_VF and RV_SP500 are the two statistically significant factors for H = 6 as reported in Table 5 as well as H = 9 and 12. Another notable difference when predicting the VRP without the Lehman brother months is that for the VRP model a single factor captures its fluctuations at H = 6 months.

In summarizing the above results and most importantly in comparing the adjusted R^2's of different types of corporate risk factors in predicting the VIX^2, RV_SP500 and VRP we report the results in panels A, B and C, in Table 7, respectively, in the period 1999m01-2010m12. The following corporate risk type factors are compared: The two volatility factors, namely the short-run funding volatility factor, SRFUN_VF, the (short- and long-run) corporate volatility factor (COR_VF) as well as the three spreads factors, the short-run funding risk factor (SRFUN_SF), the (short- and long-run) corporate spreads factor and the GZ spread factor (GZ_SPR). The first column panels A-C in Table 7 reports the model specifications and each column refers to one of the above factors included in the models in the first column one at a time. The reported adjusted

R^2's and the corresponding stars denote the level of significance of the corresponding factor. The overall result from Table 7 is that SRFUN_VF provides that highest adjusted R^2 compared to the other factors and it turns out to be the significant factor across model specifications followed by the COR_SF. It is worth noting that while the adjusted R^2 are mildly higher when using the SRFUN_VF instead of the COR_SF predictor for explaining the VIX^2 in panel A, the gains are almost double when using the SRFUN_VF instead of the COR_SF to predict either the RV_SP500 or the VRP in panels B and C, respectively.

6 Revisiting the Equity Return Predictability

The empirical evidence in the previous section suggests that some of the short-run funding risk and corporate risk factors predict the VRP. Consequently in this section we examine whether these factors can also predict the equity returns by improving the in-sample fit of some of the benchmark models and methods in this literature. Hence we revisit some of the traditional equity predictability results by examining whether our factors have any additional predictive ability beyond that of the VRP and some of the most popular predictors of returns, such as the log Price-Dividend ratio, log(P/D) and the Moody's bonds default spread, BAA-AAA which is also directly related with our corporate risk factor. 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 8 presents the LS estimation results and robust standard errors based on the Newey West HAC estimator with a fixed bandwidth value specified to 12 months. The top panel of Table 8 presents the models where VRP is taken as the benchmark predictor in model 1 and the rest of the models 2-7 which include our short-run funding risk factors of spreads (SRFUN_SF) and their volatilities (SRFUN_VF) as well as corporate risk factors based on spreads (COR_SF) and their volatilities (COR_VF). Additional factors included in the models are the Gildchrist and Zakrajšek (2009, 2012) GZ credit spread (GZ_SPR) as well as the orthogonalized factor based on the residuals from the regression of COR_SF and SRFUN_VF. In the predictive models 2-7 these factors are included in addition to VRP, one at a time, in order to compare their relative predictive ability with the benchmark model 1 which includes only the VRP predictor and another benchmark model which includes the VRP and a traditional corporate spread predictor, BAA-AAA. Whilst results show that VRP is significant in all models our risk factors and in particular 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 vis-à-vis the corresponding benchmark models which include as predictors only the VRP (model 1) or the VRP and BAA-AAA (model 2) or other benchmark models which include the VRP and log(P/D) (model 9).

In the second panel of Table 8 we perform the same analysis as above controlling for both the VRP and log(P/D) and examining the predictive ability of our factors in models 9-14. Similarly in models 15-20 we also control for the VRP and the Baltic Dry Index (BDI) growth rate predictor proposed in Bakshi, Panayotov, and Skoulakis (2011) which is related to commodity prices. In these models we obtain similar results to those mentioned above. Namely the SRFUN_VF, the SRFUN_SF and the COR_SF are always statistically significant vis-à-vis the corresponding benchmark models which include as predictors only the VRP and log(P/D) (model 9) or the BDI (model 15). Overall the SRFUN_SF yields the relatively highest improvement in the adjusted R^2 and including this predictor along with the traditional benchmark predictors (VRP, log(P/D), BAA-AAA and BDI) more than doubles the adjusted R^2 vis-à-vis the benchmarks which include any of the above predictors.[4]

7 Robustness

We examine the robustness of the results in Section 5 by performing the following checks:

(i) Comparing the short-run funding spreads (SRFUN_SF) versus volatility of spreads (SRFUN_VF) factors

Given that both the spreads and the volatility of the spreads are considered as alternative risk factors we compare the results of Table 1 replacing the common volatility factor of short-run funding volatility risk, SRFUN_VF, and corporate volatility risk (both long-run corporate bond and short-run funding risk), with the corresponding factors from spreads only, given by SRFUN_SF and COR_SF, respectively. These results are reported in Table B.1. Comparing the results from the two panels (SRFUN_SF and COR_SF) of Table B.1 with the corresponding one from Table 1 for SRFUN_VF we find that for $H = 6$ the common volatility factor, SRFUN_VF, yields a corresponding higher Adj. R^2 compared to either SRFUN_SF or COR_SF, whilst overall their significance is very similar for $H = 6$. Note that higher Adj. R^2 for the SRFUN_VF and similar significance between SRFUN_VF and either SRFUN_SF or COR_SF is also observed for $H = 9$ and 12.

(ii) How many corporate factors affect the VIX^2, RV_SP500 and VRP?

We examine how many corporate factors explain the VIX^2, RV_SP500 and VRP for the period 1999m01 - 2010m12. Given that COR_SF (the factor from the spreads of short-run funding and long-run corporate spreads which correlates highly with GZ spread) appears significant, we examine the number of corporate factors in addition to SRFUN_VF by orthogonalizing the COR_SF and SRFUN_VF factors using a linear regression of COR_SF on SRFUN_VF and obtaining the residuals of this regression which represents the new factor, denoted by CORSF_SRFUNVF. We examine whether this is significant in addition to SRFUN_VF and EM_VF. The IV method is used to estimate these models to correct for the generated regressor, CORSF_SRFUNVF, problem.

In Tables B.2-B.5 we report the predictive regression models for VIX^2, RV_SP500 and VRP, respectively. These tables report both the IV and LS standard errors and show that there is only weak significant evidence

[4]Note that empirical results in Table 8 do not report results for the Energy and Metals volatility factor because this turns out to be an insignificant in-sample predictor.

for $H = 6$ for the additional factor, CORSF_SRFUNVF, for VIX^2 only (as opposed to VRP and RV_SP500) mostly at 10% significance level, for the sample period up to 2010m12 and that of excluding the Lehman Brother effect.

(iii) Reverse Causality analysis

We examine whether the VIX^2 and RV_SP500 also help predict our volatility factors, SRFUN_VF, LRCOR_VF and EM_VF i.e. if there is also reverse causality. 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_SP500$(-H)$ for various H using robust standard errors. Table B.6 reports the corresponding equation where the above hypothesis is tested for the volatility factors. Table B.7 reports the corresponding results for the mean or returns and spreads factors. The general result is that in 1999m01 - 2010m12 the VIX^2 and RV_SP500 do not provide empirical evidence of Granger causing the SRFUN_VF or SRFUN_SF, the EM_VF or EM_RF for $H = 6, 12$ months.

(iv) Consumption Volatility Proxies

The volatility of volatility of consumption is difficult to measure empirically. Alternative 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 the monthly industrial production (IP) or the Chicago Fed National Activity Index (CFNAI) instead of the per capita consumption on non-durables and services growth rates and volatilities based on an AR(1)-GARCH(1,1).

Hence we replace the DLC_V in all models of Section 5 with the corresponding consumption and industrial production proxies of consumption volatility given by the growth rates of consumption or Industrial production and their corresponding AR(1)-GARCH(1,1) volatilities, one at a time, and find that similar results apply for the CFNAI AR-GARCH volatility proxy (CFNAI_V), the consumption (DLC), the IP and the IP volatility proxy (IP and IP_V).

(v) Monthly factors of Realized Volatility Panels

Using monthly RV_SP500 based on daily squared returns instead of the GARCH estimator for each series and extracting the corresponding common factor volatilities from each panel - SRFUN_RV, COR_RV and EM_RV.

(vi) Predictive models of log RV_SP500

There is a large literature on predictive models for RV_SP500 which consider the log RV_SP500 transformation. Our results in Table 2 are robust to both RV_SP500 and log RV_SP500 transformations.

(vii) Static versus Dynamic Factors and Factors of log volatilities

The results are robust to either the static or dynamic factors extracted from our volatility panels. In particular, the static and dynamic factors yield very similar Adj R^2 and significance results when the Lehman brothers effect is excluded from our sample period.

Using the panel of log and non-log GARCH/RV series for extracting volatility factors for the corporate, short-run funding spreads and energy and metals commodities returns we find that the results in Tables 1, 2 and 3 are robust in terms of statistical significance.

(viii) The Ludvigson and Ng volatility factor approach

Ludvigson and Ng (2007) extract the common factors from a large panel of monthly financial assets returns and spreads and then approximate the volatility of this factor by estimating a GARCH or RV model for the factors of returns and spreads. Instead our analysis is based on extracting the common volatility factor from a panel of N volatilities. We compare the results of both approaches. First, we extract the common factor from the panel of spreads and returns, namely, EM_RF for the energy and metals returns and spreads, SRFUN_SF for the short-run funding spreads, LRCOR_SF for the long-run corporate bond spreads. Then we estimate an AR-GARCH model for each of SRFUN_SF, LRCOR_SF and EM_RF and estimate the corresponding Tables 1-3. Our volatility factors COR_VF and SRFUN_VF yield a 0.72 correlation coefficient with the corresponding volatility of the spreads factors for the COR and SRFUN following the Ludvigson and Ng (2007) approach. We find that our results are similar using either approach during the relatively low volatility period up to 2008M8 whereas our factors are significant for the full sample including the crisis up to 2010M12.

8 Conclusions

We extract novel common volatility factors from a cross-section of (i) corporate spread volatilities, (ii) short-run funding risk and (iii) volatilities of energy and metals commodities returns. We find that the VIX, VRP and RV_SP500 can be predicted by new factors, in addition to the Consumption Volatility, namely the Volatility Factor of the Corporate Spreads and in particular the funding risk as well as the energy and metals volatility. We show that our new corporate risk factors can also predict monthly excess returns at short horizons both in-sample and out-of-sample. We plan to test the economic significance of the out-of-sample returns predictability results and most importantly the VIX predictability results by trying to price the VIX futures.

Figure 1: The VIX^2 and the RV of the SP500 returns during the monthly period 1999m01 - 2010m12.

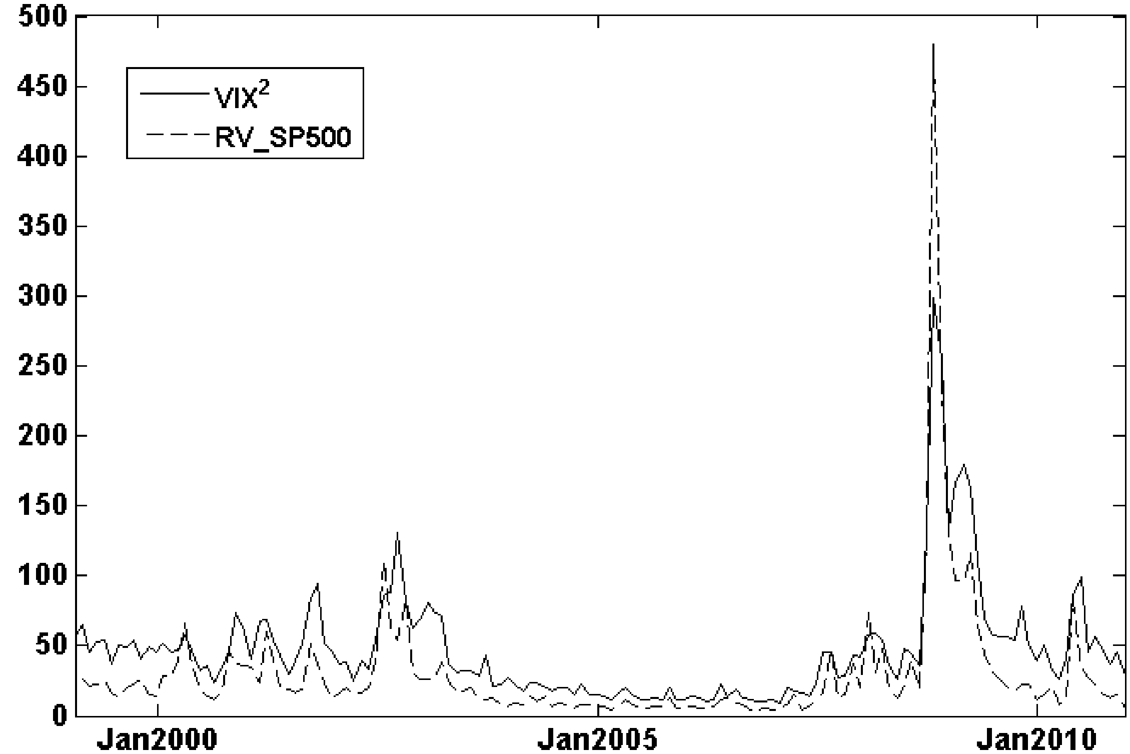

Figure 2: The VRP during the monthly period 1999m01 - 2010m12.

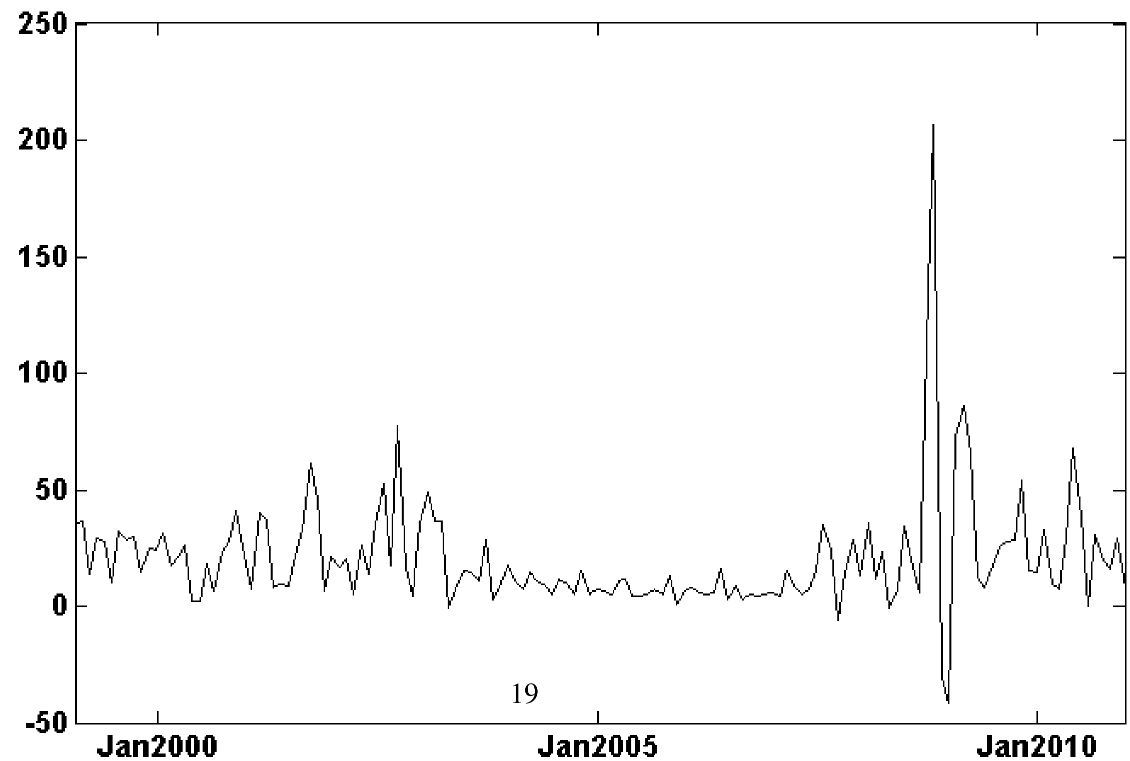

Figure 3: The short-run funding risk/volatility (SRFUN_VF) and corporate risk (short- and long-run) (COR_VF) volatility factors in the monthly period 1999m01 - 2010m12.

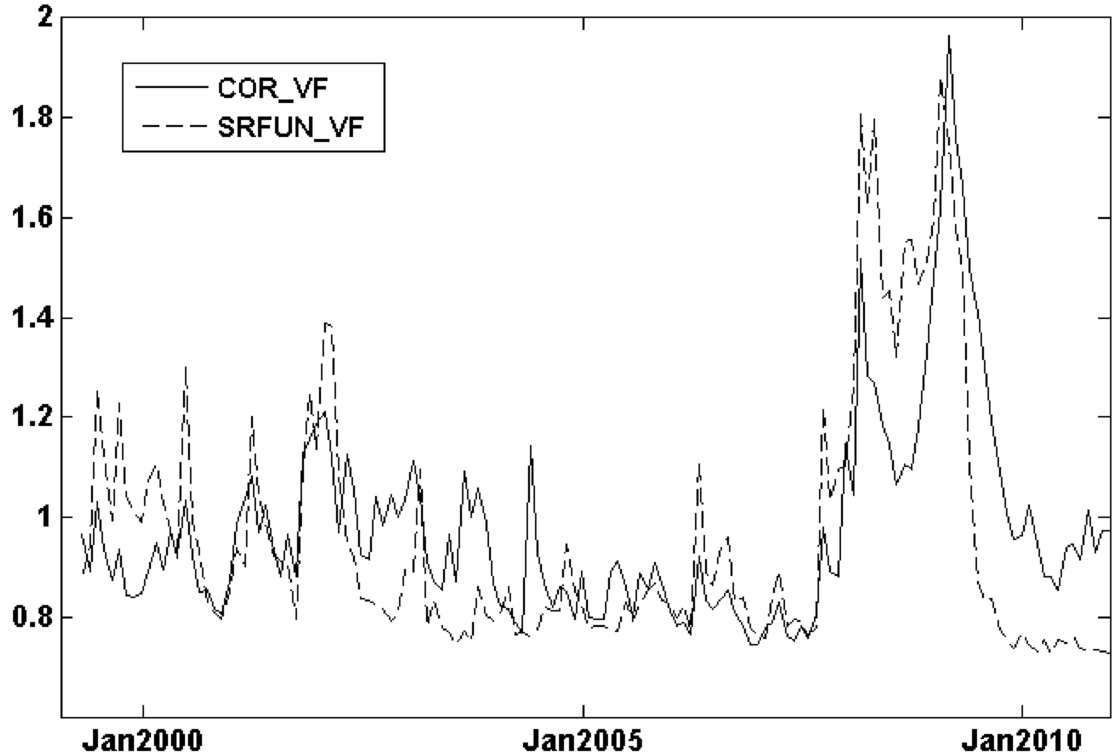

Figure 4: The energy and metals volatility factor (EM_VF) in the monthly period 1999m01 - 2010m12.

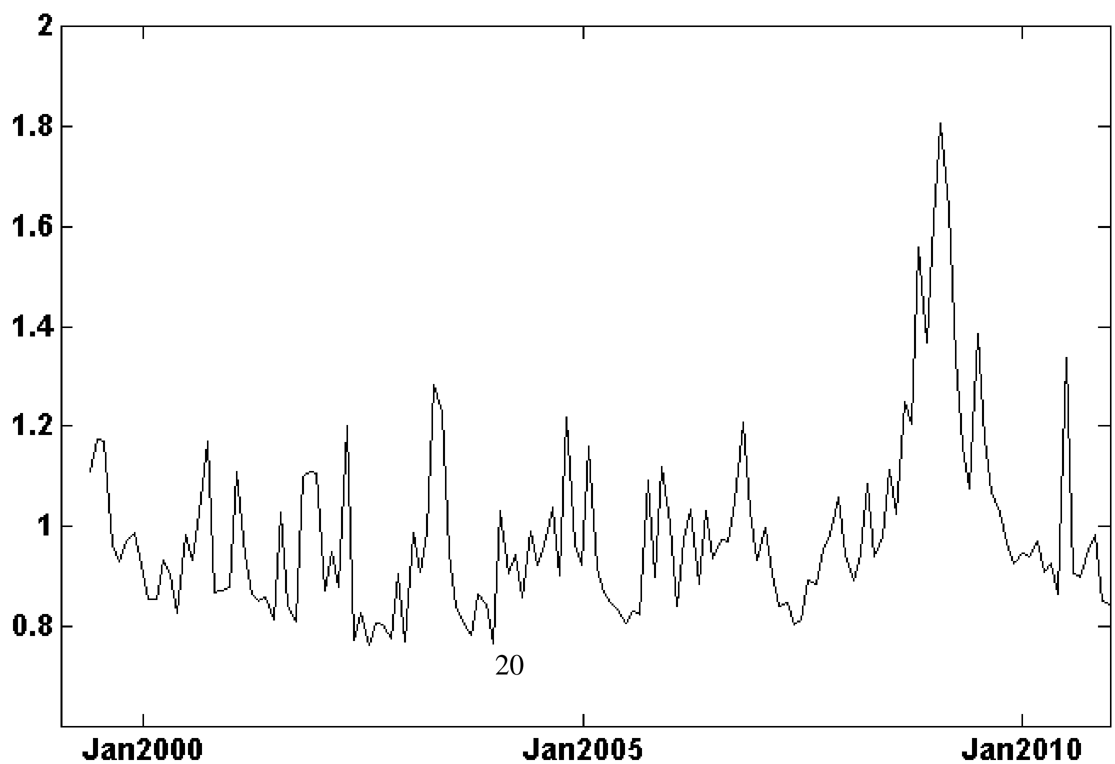

Table 1: Predictive regression models for the VIX^2 for the period 1999m01 - 2010m12

The OLS estimation results are reported and the significance levels are denoted with (***), (**), (*) referring to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) are found in the parentheses. The NW HAC estimator was used and the bandwidth value was specified to 12.

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	-	-4.09	8.10	-	0.34
		-	(6.90)	(2.49)***	-	
	9	-	**-0.99**	**9.51**	**-4.35**	**0.37**
		-	**(5.36)**	**(2.70)*** **	**(2.01)** **	
$H = 9$	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	-	-4.50	7.95	-	0.32
		-	(6.14)	(3.03)***	-	
	9	-	**-0.23**	**9.96**	**-5.96**	**0.38**
		-	**(3.00)**	**(3.29)*** **	**(3.47)* **	
$H = 12$	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	-	-6.26	5.54	-	0.14
		-	(4.53)	(2.50)**	-	
	9	-	**-3.84**	**6.65**	**-3.26**	**0.16**
		-	**(3.46)**	**(2.46)*** **	**(2.00)**	

Table 2: Predictive regression models for the RV_SP500 for the period 1999m01 - 2010m12

The predictive regressions for the monthly RV_SP500 for horizons H = 6, 9 and 12 are reported. The OLS estimation results are reported and the significance levels are denoted with (***), (**), (*) referring to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) are found in the parentheses. The NW HAC estimator was used and the bandwidth value was specified to 12.

Horizon	Model	Predictors					Adj. R^2
		RV_SP500(-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	-	-	-9.76	8.38	-	0.27
		-	-	(7.02)	(3.52)**	-	
	9	-	-	**-5.29**	**10.42**	**-6.29**	**0.31**
		-	-	**(4.32)**	**(3.92)*****	**(3.53)**	
$H=9$	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	-	-	-5.72	6.50	-	0.15
		-	-	(7.92)	(3.29)*	-	
	9	-	-	**-0.52**	**8.94**	**-7.29**	**0.21**
		-	-	**(5.05)**	**(3.50)****	**(3.98)***	
$H=12$	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	-	-	**-0.51**	**3.24**	-	**0.03**
		-	-	**(0.49)**	**(1.99)**	-	
	9	-	-	**-0.31**	**4.14**	**-2.56**	**0.03**
		-	-	**(0.40)**	**(1.80)****	**(1.67)**	

Table 3: Predictive regression models for the VRP for the period 1999m01 - 2010m12

The OLS estimation results are reported and the significance levels are denoted with (***), (**), (*) referring to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) are found in the parentheses. The NW HAC estimator was used and the bandwidth value was specified to 12.

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	-	-0.81	3.10	-	0.14
		-	(3.42)	(1.05)***	-	
	9	-	**1.00**	**3.93**	**-2.57**	**0.16**
		-	**(2.42)**	**(1.18)*** **	**(1.15)** **	
$H=9$	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	-	**1.66**	**1.67**	-	**0.03**
		-	**(1.83)**	**(0.54)*** **	-	
	9	-	**2.29**	**1.96**	**0.82**	**0.03**
		-	**(1.36)* **	**(0.74)*** **	**(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	-	**-0.31**	**2.11**	-	**0.05**
		-	**(0.13)** **	**(0.81)** **	-	
	9	-	**-0.23**	**2.46**	**-1.03**	**0.05**
		-	**(0.11)** **	**(0.91)*** **	**(0.89)**	

Table 4: Predictive regression models for the VIX^2 with a Dummy for the Lehman Brothers effect for the period 1999m01 - 2010m12

The OLS estimation results are reported and the significance levels are denoted with (***), (**), (*) referring to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) are found in the parentheses. The NW HAC estimator was used and the bandwidth value was specified to 12.

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	-	-1.91	6.58	-	0.42
		-	(6.21)	(2.04)***	-	
	9	-	**0.18**	**7.75**	**-3.19**	**0.44**
		-	**(5.33)**	**(2.31)*** **	**(1.54)** **	
$H = 9$	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	-	-3.63	7.37	-	0.50
		-	(5.81)	(2.72)***	-	
	9	-	**0.21**	**9.03**	**-4.81**	**0.54**
		-	**(3.24)**	**(2.93)*** **	**(2.82)* **	
$H = 12$	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	-	**-4.76**	**5.06**	-	**0.35**
		-	**(3.88)**	**(2.26)** **	-	
	9	-	**-2.75**	**6.00**	**-2.71**	**0.35**
		-	**(2.97)**	**(2.31)** **	**(1.88)**	

Table 5: Predictive regression models for the RV_SP500 with a Dummy for the Lehman Brothers effect for the period 1999m01 - 2010m12

The predictive regressions for the monthly RV_SP500 for horizon $H = 6$ are reported. The OLS estimation results are reported and the significance levels are denoted with (***), (**), (*) referring to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) are found in the parentheses. The NW HAC estimator was used and the bandwidth value was specified to 12.

Horizon	Model	Predictors					Adj. R^2
		RV_SP500(-H)	**VIX^2(-H)**	**DLC_V(-H)**	**SRFUN_VF(-H)**	**EM_VF(-H)**	
$H = 6$	1	0.08	0.03	-	-	-	0.01
		(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	-	-	-5.22	5.21	-	0.54
		-	-	(4.56)	(1.91)***	-	
	9	-	-	**-2.75**	**6.59**	**-3.76**	**0.55**
		-	-	**(3.46)**	**(2.15)*** **	**(1.74)** **	

Table 6: Predictive regression models for the VRP with a Dummy for the Lehman Brothers effect for the period 1999m01 - 2010m12

The OLS estimation results are reported and the significance levels are denoted with (***), (**), (*) referring to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) are found in the parentheses. The NW HAC estimator was used and the bandwidth value was specified to 12.

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	-	**1.74**	**1.33**	-	**0.47**
		-	**(2.57)**	**(0.58)****	-	
	9	-	**2.46**	**1.73**	**-1.12**	**0.47**
		-	**(2.44)**	**(0.78)****	**(0.68)**	

Table 7: Summarizing results for alternative corporate factors "COR_X", 1999m01 - 2010m12

Monthly VIX^2, RV_SP500 and VRP Predictive Regressions for alternative corporate factors "COR_X", 1999m01 - 2010m12. The OLS estimation results are reported and the significance levels are denoted with ***, **, * referring to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. The NW HAC estimator was used and the bandwidth value was specified to 12.

Panel A: Monthly VIX^2 Predictive Regressions for alternative corporate factors "COR_X", 1999m01 - 2010m12, $H = 6$

	Volatility Factors		Spreads Factors		
	SRFUN_VF	COR_VF	SRFUN_SF	COR_SF	GZ_SPR
Predictive Regressions	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2
VIX^2(-H)	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
VIX^2(-H), COR_X(-H)	0.34***	0.12	0.16	0.24**	0.14
VIX^2(-H), DLC_V(-H), COR_X(-H)	0.34***	0.12	0.16	0.25**	0.17
VIX^2(-H), DLC_V(-H), COR_X(-H), EM_X(-H)	0.36***	0.12	0.71	0.28**	0.19*
VIX^2(-H), COR_X(-H), EM_X(-H)	0.37***	0.13	0.22*	0.32**	0.16*

Panel B: Monthly RV_SP500 Predictive Regressions for alternative corporate factors "COR_X", 1999m01 - 2010m12, $H = 6$

	Volatility Factors		Spreads Factors		
	SRFUN_VF	COR_VF	SRFUN_SF	COR_SF	GZ_SPR
Predictive Regressions	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2
RV_SP500(-H), VIX^2(-H)	0.01	0.01	0.01	0.01	0.01
RV_SP500(-H), VIX^2(-H) ,DLC_V(-H)	0.01	0.01	0.01	0.01	0.01
RV_SP500(-H), VIX^2(-H), COR_X(-H)	0.29**	0.07	0.07	0.12*	0.05
RV_SP500(-H), VIX^2(-H), DLC_V(-H), COR_X(-H)	0.29**	0.08	0.08	0.14*	0.07
RV_SP500(-H), VIX^2(-H), DLC_V(-H), COR_X(-H), EM_X(-H)	0.32**	0.08	0.08*	0.15*	0.07
RV_SP500(-H), VIX^2(-H), COR_X(-H), EM_X(-H)	0.32**	0.09	0.08*	0.14*	0.06

Panel C: Monthly VRP Predictive Regressions for alternative corporate factors "COR_X", 1999m01 - 2010m12, $H = 6$

	Volatility Factors		Spreads Factors		
	SRFUN_VF	COR_VF	SRFUN_SF	COR_SF	GZ_SPR
Predictive Regressions	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2	Adj.R^2
VIX^2(-H)	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
VIX^2(-H), COR_X(-H)	0.14***	0.05*	0.02	0.07**	0.03
VIX^2(-H), DLC_V(-H), COR_X(-H)	0.13**	0.04*	0.01	0.06**	0.04
VIX^2(-H), DLC_V(-H), COR_X(-H), EM_X(-H)	0.16***	0.05**	0.01	0.08**	0.05*
VIX^2(-H), COR_X(-H), EM_X(-H)	0.16***	0.05**	0.02	0.08**	0.05**

Table 8: Revisiting Equity Return Predictability, 1999m01 - 2010m12

The OLS estimation results are reported and the significance levels are denoted with (***), (**), (*) referring to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) are found in the parentheses. The NW HAC estimator was used and the bandwidth value was specified to 12.

Predictive models for $H = 1$ monthly S&P500 excess returns:

Predictors	1	2	3	4	5	6	7
VRP(-H)	0.56	0.56	0.58	0.50	0.55	0.56	0.55
	(0.11)***	(0.12)***	(0.09)***	(0.15)***	(0.15)***	(0.14)***	(0.15)***
SRFUN_VF(-H)	-	-3.15	-	-	-	-	-3.14
	-	(1.49)**	-	-	-	-	(1.28)**
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)**	-
CORSF_SRFUNVF(-H)	-	-	-	-	-	-	0.75
	-	-	-	-	-	-	(0.60)
Adj. R^2	0.046	0.068	0.040	**0.105**	0.079	0.065	0.072

	8	9	10	11	12	13	14
VRP(-H)	0.55	0.56	0.55	0.63	0.45	0.53	0.53
	(0.13)***	(0.10)***	(0.10)***	(0.08)***	(0.11)***	(0.12)***	(0.11)***
BAA-AAA(-H)	-0.76	-	-	-	-	-	-
	(0.79)	-	-	-	-	-	-
log(P/D)(-H)	-	-1.01	-2.63	-2.83	-5.35	-4.06	-4.20
	-	(2.12)	(1.51)*	(2.11)	(1.93)***	(1.83)**	(1.83)**
SRFUN_VF(-H)	-	-	-3.99	-	-	-	-4.48
	-	-	(1.87)**	-	-	-	(1.71)***
COR_VF(-H)	-	-	-	-3.39	-	-	-
	-	-	-	(1.99)*	-	-	-
SRFUN_SF(-H)	-	-	-	-	-1.94	-	-
	-	-	-	-	(0.61)***	-	-
COR_SF(-H)	-	-	-	-	-	1.46	-
	-	-	-	-	-	(0.40)***	-
CORSF_SRFUNVF(-H)	-	-	-	-	-	-	1.37
	-	-	-	-	-		- (0.37)***
Adj. R^2	0.046	0.042	0.079	0.047	**0.156**	0.106	0.101

	15	16	17	18	19	20
VRP(-H)	0.43	0.44	0.45	0.40	0.44	0.44
	(0.13)***	(0.12)***	(0.12)***	(0.14)***	(0.14)***	(0.14)***
BDI(-H)	4.39	3.76	4.19	3.33	3.55	3.49
	(0.32)***	(1.51)**	(1.36)***	(1.87)*	(1.70)**	(1.65)**
SRFUN_VF(-H)	-	-2.71	-	-	-	-2.74
	-	(1.44)*	-	-	-	(1.30)**
COR_VF(-H)	-	-	-0.87	-	-	-
	-	-	(1.83)	-	-	-
SRFUN_SF(-H)	-	-	-	-1.09	-	-
	-	-	-	(0.41)***	-	-
COR_SF(-H)	-	-	-	-	0.79	-
	-	-	-	-	(0.37)**	-
CORSF_SRFUNVF(-H)	-	-	-	-	-	0.58
	-	-	-	-	-	(0.58)
Adj. R^2	0.077	0.088	0.067	**0.120**	0.095	0.088

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A Data Description Appendix

Table A.1: Summary table of the short-run funding risk series

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

Table A.2: Summary table of the long-run funding risk series

Moody's Corporate Bond Yield (AAA, BBB) - Govt bond corresp. maturity
Moody's BAA-AAA
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): Effective Yield - Govt bond corresp. maturity
Merrill Lynch Corporate Bonds:Financials: (A, AA, AAA, BBB, 1-3Y, 3-5Y, 5-7Y, 7-10Y): Effective Yield - Govt bond corresp. maturity
Merrill Lynch Corporate Bonds:Utilities: (A, AA, AAA, BBB, 1-3Y, 3-5Y, 5-7Y, 7-10Y): Effective Yield - Govt bond corresp. maturity
Merrill Lynch (Treasury, Domestic) Master: (Effective Yield, Yield to Worst, Yield to Maturity) -Govt bond corresp. maturity
Merrill Lynch (Agency, Corporate & Government) Master: (Effective 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, Treasuries Current 10 Year, 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 A.3: Summary table of the energy and metal commodities series

S&P GSCI (Energy Commodities, Crude, Heating and Gas Oil) Index, Total Return and Total Excess Return Index
S&P GSCI (Unleaded Gasoline, Natural Gas, 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
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 Harbour 2 Heating, Natural Gas) Oil Futures Price: 2-Month Contract Settlement
(Light Sweet Crude, No 2 Heating) Oil Futures Price: 3-M Contract Settlement
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: Crude Oil and Benzene
European Free Market Price: Brent Crude Oil
(Cushing OK WTI, Europe Brent, US Gulf Coast Conventional Gasoline Regular) 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

Table A.4: Detailed table of the short-run funding risk series

Index	Definition	Index	Definition
1	15-Day A2/P2/F2 Nonfin. Com. Paper (% Per Annum) -15-Day Aa Fin. Com. Paper (% p.a)	19	15-Day Aa Nonfinancial Commercial Paper (% p.a) -FF
2	15-Day A2/P2/F2 Nonfin. Com. Paper (% p.a) -15-Day Aa Nonfin. Com. Paper (% p.a)	20	6-Month Eurodollar Deposits (London Bid) (% P.A.) -FF
3	7-Day London Interbank Offered Rate (%) -FF	21	6-Month Certificates Of Deposit, Secondary Market (% P.A.) -FF
4	1-Day Aa Nonfinancial Commercial Paper (% Per Annum) -FF	22	One-Year London Interbank Offered Rate (%) -FF
5	1-Day Aa Financial Commercial Paper (% Per Annum) -FF	23	1-Month Eurodollar Deposits (London Bid) (% P.A.) -FF
6	7-Day Aa Nonfinancial Commercial Paper (% Per Annum) -FF	24	1-Month A2/P2/F2 Nonfinancial Commercial Paper (% Per Annum) -FF
7	7-Day Aa Financial Commercial Paper (% Per Annum) -FF	25	3-Month Eurodollar Deposits (London Bid) (% P.A.) -FF
8	1-Day A2/P2/F2 Nonfinancial Commercial Paper (% Per Annum) -FF	26	3-Month London Interbank Offered Rate (%) -FF
9	15-Day Aa Financial Commercial Paper (% Per Annum) -FF	27	3-Month Certificates Of Deposit, Secondary Market (% P.A.) -FF
10	7-Day A2/P2/F2 Nonfin. Com. Paper (% Per Annum) -7-Day Aa Nonfin. Com. Paper (% p.a)	28	6-Month London Interbank Offered Rate (%) -FF
11	1-Month Nonfinancial Commercial Paper (% Per Annum) -FF	29	1-Month London Interbank Offered Rate (%) -FF
12	1-Month Aa Nonfinancial Commercial Paper (% Per Annum) -FF	30	7-Day A2/P2/F2 Nonfin. Com. Paper (% p.a) -7-Day Aa Fin. Com. Paper (% p.a)
13	1-Day A2/P2/F2 Nonfin. Com. Paper (% p.a) -1-Day Aa Fin. Com. Paper (% Per Annum)	31	Overnight London Interbank Offered Rate (%) -FF
14	1-Month Certificates Of Deposit, Secondary Market (% P.A.) -FF	32	Ted 3Month Tbill-3-Month London Interbank Offered Rate (%) -FF
15	7-Day A2/P2/F2 Nonfinancial Commercial Paper (% Per Annum) -FF	33	1-Month A2/P2/F2 Nonfin. Com. Paper (% p.a) -1-Month Aa Nonfin. Com. Paper
16	1-Month Financial Commercial Paper (% Per Annum) -FF	34	15-Day A2/P2/F2 Nonfinancial Commercial Paper (% Per Annum) -FF
17	1-Month Aa Financial Commercial Paper (% Per Annum) -FF	35	1-Month A2/P2/F2 Nonfin. Com. Paper (% p.a) -1-Month Aa Fin. Com. Paper (% p.a)
18	1-Day A2/P2/F2 Nonfin. Com. Paper (% Per Annum) -1-Day Aa Nonfin. Com. Paper (% p.a)		

Table A.5: Detailed table of the long-run corporate risk series

Index	Definition	Index	Definition
1	Merrill Lynch Corporate Master: Effective Yield (%)-Y10-Tbond	38	Merrill Lynch Corporate Bonds: Financials: Bbb Rated: Effective Yield (%)-Y10-Tbond
2	Merrill Lynch Corporate Bonds: A Rated: Effective Yield (%)-Y10-Tbond	39	Merrill Lynch Corporate Bonds: Utilities: 1 To 3 Years: Effective Yield (%) -Y3-Tnote
3	Merrill Lynch Corporate Bonds: Industrials: Effective Yield (%)-Y10-Tbond	40	Merrill Lynch Corporate Bonds: Utilities: Effective Yield (%)-Y10-Tbond
4	Merrill Lynch Corporate Bonds: Industrials: 7 To 10 Years: Effective Yield (%)-Y10-Tbond	41	Merrill Lynch Corporate & Government Master: Yield To Worst (%)-Y10-Tbond
5	Moody'S Seasoned Baa Corporate Bond Yield (% P.A.)-Y10-Tbond	42	Merrill Lynch Corporate Bonds: Financials: Aa Rated: Effective Yield (%)-Y10-Tbond
6	Merrill Lynch Corporate Bonds: Financials: 7 To 10 Years: Effective Yield (%)-Y10-Tbond	43	Merrill Lynch Treasury Master: Yield To Worst (%)-Y10-Tbond
7	Merrill Lynch Corporate Bonds: Financials: Effective Yield (%)-Y10-Tbond	44	Merrill Lynch Asset-Backeds: Automobiles Fixed Rate: Effective Yld(%)-Y10-Tbond
8	Merrill Lynch Corporate Bonds: Bbb Rated: Effective Yield (%)-Y10-Tbond	45	Merrill Lynch High Yield Corporates: Bb Rated: Effective Yield (%)-Y10-Tbond
9	Merrill Lynch High Yield Corporates: B Rated: Effective Yield (%)-Y10-Tbond	46	Merrill Lynch Corporate Bonds: Financials: 1 To 3 Years: Effective Yield (%) -Y3-Tnote
10	Merrill Lynch Corporate Bonds: Industrials: A Rated: Effective Yield (%)-Y10-Tbond	47	Merrill Lynch High Yield Corporates: Cash Pay: Bb Rated: Effective Yield (%)-Y10-Tbond
11	Merrill Lynch Corporate Bonds: Financials: A Rated: Effective Yield (%)-Y10-Tbond	48	Merrill Lynch Corporate Bonds: Industrials: Aa Rated: Effective Yield (%)-Y10-Tbond
12	Merrill Lynch High Yield Corporates: Cash Pay: B Rated: Effective Yield (%)-Y10-Tbond	49	Merrill Lynch Corporate & Government Master: Effective Yield (%)-Y10-Tbond
13	Merrill Lynch Corporate Bonds: Utilities: A Rated: Effective Yield (%)-Y10-Tbond	50	Merrill Lynch Corporate & Government Master: Yield To Maturity (%)-Y10-Tbond
14	Merrill Lynch Corporate Bonds: Financials: 5 To 7 Years: Effective Yield (%) -Y7-Tnote	51	Merrill Lynch Treasury/Agency Master: Aaa Rated: Effective Yield (%)-Y10-Tbond
15	Merrill Lynch Corporate Bonds: Industrials: Bbb Rated: Effective Yield (%)-Y10-Tbond	52	Merrill Lynch Corporate Bonds: Industrials: 3 To 5 Years: Effective Yield (%) -Y5-Tnote
16	Merrill Lynch Broad Market: Yield To Worst (%)-Y10-Tbond	53	Merrill Lynch Corporate Bonds: Utilities: 5 To 7 Years: Effective Yield (%) -Y7-Tnote
17	Merrill Lynch Corporate Bonds: 5 To 7 Years: Effective Yield (%) -Y7-Tnote	54	Merrill Lynch Treasury Master: Effective Yield (%)-Y10-Tbond
18	Merrill Lynch Corporate Bonds: Financials: 3 To 5 Years: Effective Yield (%) -Y5-Tnote	55	Merrill Lynch Corporate Bonds: Utilities: 7 To 10 Years: Effective Yield (%)-Y10-Tbond
19	Merrill Lynch Mortgage Master: Effective Yield (%)-Y10-Tbond	56	Merrill Lynch Corporate Bonds: Industrials: 1 To 3 Years: Effective Yield (%) -Y3-Tnote
20	Merrill Lynch Corporate Bonds: Industrials: 5 To 7 Years: Effective Yield (%) -Y7-Tnote	57	Merrill Lynch Corporate Bonds: Financials: Aaa Rated: Effective Yield (%)-Y10-Tbond
21	Merrill Lynch Domestic Master: Yield To Worst (%)-Y10-Tbond	58	Merrill Lynch Corporate Bonds: Utilities: Bbb Rated: Effective Yield (%)-Y10-Tbond
22	Merrill Lynch Corporate Bonds: 3 To 5 Years: Effective Yield (%) -Y5-Tnote	59	Merrill Lynch Corporate Bonds: Aaa Rated: Effective Yield (%)-Y10-Tbond
23	Merrill Lynch Broad Market: Effective Yield (%)-Y10-Tbond	60	Merrill Lynch Treasury Master: Yield To Maturity (%)-Y10-Tbond
24	Merrill Lynch High Yield Corporate Master Ii: Effective Yield (%)-Y10-Tbond	61	Merrill Lynch Corporate Bonds: Utilities: Aa Rated: Effective Yield (%)-Y10-Tbond
25	Merrill Lynch Corporate Bonds: 1 To 3 Years: Effective Yield (%)-Y3-Tnote	62	Merrill Lynch Corporate Bonds: Utilities: 3 To 5 Years: Effective Yield (%) -Y5-Tnote
26	Merrill Lynch High Yield: Cash Pay: Rated Ccc & Lower: Effective Yield (%)-Y10-Tbond	63	Merrill Lynch Asset-Backeds: Home Equity: Fixed Rate: Effective Yield (%)-Y10-Tbond
27	Merrill Lynch Corporate Bonds: Aa Rated: Effective Yield (%)-Y10-Tbond	64	Merrill Lynch Treasury/Agency Master: Aaa Rated: Yield To Maturity (%)-Y10-Tbond
28	Merrill Lynch Broad Market: Yield To Maturity (%)-Y10-Tbond	65	Merrill Lynch Treasuries: Current 10 Year: Yield To Worst (%)-Y10-Tbond
29	Merrill Lynch High Yield Corporates: Cash Pay: Effective Yield (%)-Y10-Tbond	66	Merrill Lynch Treasuries: Current 10 Year: Yield To Maturity (%)-Y10-Tbond
30	Moody'S Seasoned Aaa Corporate Bond Yield (% P.A.)-Y10-Tbond	67	BAA-AAA
31	Merrill Lynch Domestic Master: Yield To Maturity (%)-Y10-Tbond	68	Merrill Lynch Agency Master: Aaa Rated: Yield To Maturity (%)-Y10-Tbond
32	Merrill Lynch Domestic Master: Effective Yield (%)-Y10-Tbond	69	Merrill Lynch Treasury Master: Yield To Maturity (%)
33	Merrill Lynch Agency Master: Aaa Rated: Effective Yield (%)-Y10-Tbond	70	Merrill Lynch Domestic Master: Yield To Maturity (%)
34	Merrill Lynch Agency Master: Aaa Rated: Yield To Worst (%)-Y10-Tbond	71	Merrill Lynch Treasuries: Current 10 Year: Yield To Maturity (%)
35	Merrill Lynch Corporate Bonds: Industrials: Aaa Rated: Effective Yield (%)-Y10-Tbond	72	Merrill Lynch Treasury/Agency Master: Aaa Rated: Yield To Maturity (%)
36	Merrill Lynch High Yield Corporates: Rated: Ccc & Lower: Effective Yield (%)- Y10-Tbond	73	Merrill Lynch Corporate & Government Master: Yield To Maturity (%)
37	Merrill Lynch Treasury/Agency Master: Aaa Rated: Yield To Worst (%)-Y10-Tbond	74	Merrill Lynch Agency Master: Aaa Rated: Yield To Maturity (%)

Table A.6: Detailed table of the energy and metal Commodities

Index	Definition
1	Lme Lead: Closing 3-Month Forward Price ($/Metric Tonne)
2	S&P GSCI Lead Total Return Index (Dec-30-94=100)
3	S&P GSCI Lead Total Excess Return Index (Dec-30-94=100)
4	S&P GSCI Lead Index (Dec-30-94=100)
5	S&P GSCI Zinc Index (Dec-31=90=100)
6	S&P GSCI Zinc Total Return Index (Dec-31=90=100)
7	S&P GSCI Zinc Total Excess Return Index (Dec-31=90=100)
8	S&P GSCI Precious Metal Nearby Index (Jan-2-73=100)
9	S&P GSCI Precious Metals Total Return Index (Dec-29-72=100)
10	S&P GSCI Silver Total Return Index (Dec-29-72=100)
11	Lme Zinc: Closing Cash Price ($/Metric Tonne)
12	S&P GSCI Silver Total Excess Return Index (Dec-29-72=100)
13	S&P GSCI Biofuel Index (Jan-16-95=100)
14	S&P GSCI Silver Index (Dec-29-72=100)
15	Commodity Prices: Zinc, Special High Grade (Cents/Lb)
16	S&P GSCI Precious Metals Total Excess Return Index (Dec-29-72=100)
17	S&P GSCI Biofuel Total Excess Return Index (Jan-16-95=100)
18	S&P GSCI Biofuel Total Return Index (Jan-16-95=100)
19	Fiber Industrial Materials Price Index: Metals (1990$\bar{1}$00)
20	S&P GSCI Ultra-Light Energy Cpw 8 Total Return Index (Jan=2-70=100)
21	S&P GSCI Ultra-Light Energy Cpw 8 Excess Return Index (Jan=2-70=100)
22	Lme Tin: Closing 3-Month Forward Price ($/Metric Tonne)
23	Philadelphia Semiconductor Index (12/01/93=100)
24	S&P GSCI Gold Index
25	Lme Tin: Closing Cash Price ($/Metric Tonne)
26	S&P GSCI Gold Total Return Index
27	Crb Spot Commodity Price Index: Metals (1967$\bar{1}$00)
28	Gold Futures Price: 6-Month Contract Settlement ($/Troy Oz)
29	S&P GSCI Gold Total Excess Return Index
30	Lme Nickel: Closing Cash Price ($/Metric Tonne)
31	Cash Price: London Gold Bullion, Pm Fix (Us$/Troy Oz)
32	S&P GSCI Industrial Metals Nearby Index (Dec-31-76)
33	S&P GSCI Ultra-Light Energy Index Cpw 8 (Jan=2-70=100)
34	S&P GSCI Industrial Metals Total Return Index (Dec-31-76)
35	S&P GSCI Industrial Metals Total Excess Return Index (Dec-31-76)
36	S&P GSCI Light Energy Cpw 4 Total Excess Return Index (Jan-02-70=100)
37	S&P GSCI Light Energy Cpw 4 Total Return Index (Jan-02-70=100)
38	S&P Gsci Nickel Total Return Index (Dec-31-92=100)
39	Lme Copper, Grade A: Closing Cash Price ($/Metric Tonne)
40	Lme Copper, Grade A: Closing 3-Month Forward Price ($/Metric Tonne)
41	Lme Nickel: Closing 3-Month Forward Price ($/Metric Tonne)
42	S&P GSCI Nickel Index (Dec-31-92=100)
43	Commodity Prices: Benzene ($/Gal)
44	S&P GSCI Copper Index (Dec-30-76=100)
45	S&P GSCI Copper Total Return Index (Dec-30-76=100)
46	S&P GSCI Copper Total Excess Return Index (Dec-30-76=100)
47	Lme Aluminum, 99.7% Purity: Closing 3-Month Forward Price ($Metric/Tonne)
48	S&P GSCI Light Energy Index -Cpw 4 (Jan-02-70=100)
49	Commodity Prices: Hides, Chicago, Heavy Native Steers (Cents/Lb)
50	Commodity Prices: Burlap, NY 10 Oz, 40 (Cents/Yard)
51	Cushing Ok Crude Oil Futures Price: 2-Month Contract Settlement ($/Barrel)
52	Light Sweet Crude Oil Futures Price: 3-Month Contract Settlement ($/Bbl)
53	S&P GSCI Aluminum Total Excess Return Index (Dec-31-90=100)
54	S&P GSCI Aluminum Total Return Index (Dec-31-90=100)
55	S&P GSCI Aluminum Index (Dec-31-90=100)
56	S&P GSCI All Crude Index (Dec-31-86=100)
57	S&P GSCI Brent Crude Total Excess Return Index (Jan-6-99=100)
58	S&P GSCI Energy And Metals Total Excess Return Index (Jan-6-95=100)
59	S&P GSCI Brent Crude Total Return Index (Jan-6-99=100)
60	S&P GSCI Energy And Metals Total Return Index (Jan-6-95=100)
61	S&P GSCI All Crude Total Excess Return Index (Dec-31-86=100)
62	Lme Aluminum, 99.7% Purity: Closing Cash Price ($/Metric Tonne)
63	S&P GSCI All Crude Total Return Index (Dec-31-86=100)
64	S&P GSCI Petroleum Ex-Gasoil Total Excess Return Index (Dec-30-82=100)
65	Cushing Ok Wti Spot Price Fob (Dollars Per Barrel)
66	S&P GSCI Energy And Metals Index (Jan-6-95=100)
67	Light Sweet Crude Oil Futures Price: 1St Expiring Contract Settlement ($/Bbl)
68	S&P GSCI Crude Oil Index
69	S&P GSCI Crude Oil Total Excess Return Index
70	S&P GSCI Crude Oil Total Return Index
71	Domestic Spot Market Price: Crude West Texas Sour, Midland ($/Barrel)
72	Domestic Spot Market Price: West Texas Intermediate, Cushing ($/Barrel)
73	Commodity Prices: Aluminum, Lme Spot ($/Metric Ton)
74	S&P GSCI Energy Commodities Nearby Index (12/31/82$\bar{1}$00)
75	S&P GSCI Energy Commodities Total Return Index (12/31/82=100)
76	S&P GSCI Four Energy Commodities Excess Return Index (Jan-16-95=100)
77	Commodity Prices: Copper Scrap, NY No. 2 (Cents/Lb)
78	S&P GSCI Four Energy Commodities Index (Jan-16-95=100)
79	S&P GSCI Four Energy Commodities Total Return Index (Jan-16-95=100)
80	Commodity Prices: Crude Oil, West Texas Intermediate ($/Barrel)
81	Commodity Prices: Tallow, Chicago Inedible Prime (Cents/Lb)
82	Us Gulf Coast Conventional Gasoline Regular Spot Price Fob (Cents Per Gallon)
83	Domestic Spot Market Price: Crude Louisiana Sweet, St James ($/Barrel)
84	Europe Brent Spot Price Fob (Dollars Per Barrel)
85	S&P GSCI Heating Oil Total Excess Return Index (Dec-31-82=100)
86	S&P GSCI Natural Gas Total Excess Return Index (Dec-31-93=100)
87	S&P GSCI Natural Gas Total Return Index (Dec-31-93=100)
88	Domestic Spot Mkt Price: Alaskan North Slope Oil Delivered Pacific ($/Barrel)
89	S&P GSCI Heating Oil Total Return Index (Dec-31-82=100)
90	Commodity Prices: Steel Scrap, No. 1 Heavy Melting ($/gross Ton)
91	Spot Price: U.S. Gulf Coast Kerosene-Type Jet Fuel F.O.B. (Cents/Gallon)
92	European Free Market Price: Brent Crude Oil ($/Barrel)
93	Mont Belvieu Tx Propane Spot Price Fob (Cents Per Gallon)
94	Random Lengths' Framing Lumber Composite ($/1000 Bd Ft)
95	Unleaded Gas Price, Premium Non-Oxygenated, Ny ($/Gal)
96	S&P GSCI Gasoil Total Excess Return Index
97	New York Harbor No 2 Diesel Low Sulfur Spot Price Fob (Cents Per Gallon)
98	S&P GSCI Gasoil Total Return Index
99	New York Harbor No 2 Heating Oil Spot Price Fob (Cents Per Gallon)
100	Ny Harbor #2 Heating Oil Futures Price: 2-Month Contract Settlement($/Gallon)
101	S&P GSCI Heating Oil Index (Dec-31-82$\bar{1}$00)
102	S&P GSCI Unleaded Gasoline Total Excess Return Index (Dec-31-87=100)
103	S&P GSCI Unleaded Gasoline Total Return Index (Dec-31-87=100)
104	Commodity Prices: Random Lengths' Structural Panel Composite ($/1000 Sq Ft)
105	Us Gulf Coast No 2 Diesel Low Sulfur Spot Price Fob (Cents Per Gallon)
106	S&P GSCI Natural Gas Index (Dec-31-93=100)
107	Natural Gas Futures Price: 1St Expiring Contract Settlement ($/Mmbtu)
108	S&P GSCI Unleaded Gasoline Index (Dec-31-87$\bar{1}$00)
109	Philadelphia Exchange: Gold & Silver Index (Close, 6/7/89=90)
110	Gas Oil Futures Price: 1St Expiring Contract Settlement ($/Metric Ton)
111	Natural Gas Futures Price: 2-Month Contract Settlement ($/Mmbtu)
112	S&P GSCI Gasoil Index
113	Oil Price: Fuel Oil No 2, Ny ($/Gallon)
114	Fiber Industrial Materials Price Index: Crude Oil And Benzene (1990$\bar{1}$00)
115	Los Angeles Ca No 2 Diesel Spot Price Fob (Cents Per Gallon)
116	Lme Aluminum Alloy: Closing 3-Month Forward Price ($/Metric Tonne)
117	No 2 Heating Oil Futures Price: 3-Month Contract Settlement ($/Gal)
118	No 2 Heating Oil Futures Price: 1St Expiring Contract Settlement ($/Gal)
119	Propane Price, Mont Belvieu ($/Gal)
120	Lme Aluminum Alloy: Closing Cash Price ($/Metric Tonne)
121	Unleaded Gas Price, Regular, Non-Oxygenated, Ny ($/Gal)
122	New York Harbor Conventional Gasoline Regular Spot Price Fob (Cents Per Gallon)

B Robustness Appendix

Table B.1: Predictive regression models for the VIX^2 for the period 1999m01 - 2010m12, using the SRFUN_SF and COR_SF factors

The OLS estimation results are reported and the significance levels are denoted with (***), (**), (*) referring to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) are found in the parentheses. The NW HAC estimator was used and the bandwidth value was specified to 12.

Horizon	Model	Predictors				Adj. R^2
		VIX^2(-H)	**DLC_V(-H)**	**SRFUN_SF(-H)**	**EM_RF(-H)**	
$H=6$	1	0.26	-	-	-	0.06
		(0.09)***	-	-	-	
	2	0.28	-1.81	-	-	0.06
		(0.09)***	(4.55)	-	-	
	3	0.06	-	1.32	-	0.16
		(0.20)	-	(0.83)	-	
	4	0.08	-0.75	1.42	-	0.16
		(0.19)	(1.02)	(0.96)	-	
	5	0.12	-0.65	1.65	-3.14	0.17
		(0.17)	(1.02)	(1.02)	(1.59)*	
	6	**0.04**	-	**1.20**	**-0.93**	**0.22**
		(0.20)	-	**(0.72)***	**(0.41)****	
	7	-	3.58	-	-	0.01
		-	(4.12)	-	-	
	8	-	-0.69	1.56	-	0.17
		-	(1.16)	(0.70)**	-	
	9	-	-0.59	1.80	-2.38	0.17
		-	(1.13)	(0.84)**	(2.07)	

Horizon	Model	Predictors				Adj. R^2
		VIX^2(-H)	**DLC_V(-H)**	**COR_SF(-H)**	**EM_RF(-H)**	
$H=6$	1	0.26	-	-	-	0.06
		(0.09)***	-	-	-	
	2	0.28	-1.81	-	-	0.06
		(0.09)***	(4.55)	-	-	
	3	-0.28	-	-2.43	-	0.24
		(0.27)	-	(1.19)**	-	
	4	-0.29	-1.05	-2.66	-	0.25
		(0.27)	(1.11)	(1.32)**	-	
	5	**-0.27**	**-0.94**	**-3.13**	**-4.78**	**0.28**
		(0.26)	**(1.10)**	**(1.36)****	**(1.87)****	
	6	**-0.32**	-	**-2.41**	**-1.03**	**0.32**
		(0.26)	-	**(1.05)****	**(0.47)****	
	7	-	3.58	-	-	0.01
		-	(4.12)	-	-	
	8	-	-1.01	-1.85	-	0.23
		-	(1.00)	(0.71)**	-	
	9	-	-0.90	-2.40	-5.05	0.26
		-	(0.97)	(0.75)***	(2.24)**	

Table B.2: Predictive regression models for the VIX^2 for the period 1999m01 - 2010m12

The OLS estimation results are reported and the significance levels are denoted with (***), (**), (*) referring to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) are found in the parentheses. The NW HAC estimator was used and the bandwidth value was specified to 12.

Horizon	Model	SE	Predictors				
			VIX^2(-H)	**DLC_V(-H)**	**SRFUN_VF(-H)**	**CORSF_SRFUNVF(-H)**	**EM_VF(-H)**
$H = 6$	1		0.26	-	-	-	-
			(0.09)***	-	-	-	-
	2		0.28	-1.81	-	-	-
			(0.09)***	(4.55)	-	-	-
	3		-0.60	-	11.81	-3.33	-
		LS	(0.18)	-	(3.39)**	(0.76)	-
		IV	(0.40)	-	(4.89)**	(1.84)*	-
	4		-0.52	-1.31	11.99	-3.33	-
		LS	(0.19)	(0.75)	(3.62)**	(0.74)	-
		IV	(0.35)	(1.41)	(4.92)**	(1.89)*	-
	5		-0.54	-1.20	14.82	-4.40	-8.02
		LS	(0.17)	(0.70)	(3.70)***	(0.68)*	(1.83)***
		IV	(0.35)	(1.44)	(5.61)***	(2.30)*	(3.59)**
	6		-0.59	-	14.97	-4.53	-8.92
		LS	(0.16)	-	(3.49)***	(0.62)*	(1.97)***
		IV	(0.40)	-	(5.91)**	(2.43)*	(4.87)*
	7		-	3.58	-	-	-
			-	(4.12)	-	-	-
	8		-	-1.11	8.42	-1.41	-
		LS	-	(0.66)	(2.58)***	(0.72)	-
		IV	-	(1.01)	(3.00)***	(0.73)*	-
	9		-	-0.98	11.28	-2.47	-8.53
		LS	-	(0.60)	(2.77)***	(0.43)**	(2.00)***
		IV	-	(0.98)	(3.51)***	(0.94)***	(4.29)**
$H = 9$	1		0.17	-	-	-	-
			(0.10)	-	-	-	-
	2		0.19	-0.82	-	-	-
			(0.12)	(4.42)	-	-	-
	3		-0.25	-	9.67	-0.45	-
		LS	(0.10)	-	(2.89)***	(0.90)	-
		IV	(0.22)	-	(3.63)***	(1.15)	-
	4		-0.24	-0.37	9.72	-0.47	-
		LS	(0.10)	(0.39)	(2.97)***	(0.86)	-
		IV	(0.21)	(0.64)	(3.67)***	(1.18)	-
	5		-0.28	-0.29	12.30	-1.43	-6.58
		LS	(0.09)*	(0.34)	(3.24)***	(0.65)	(2.74)**
		IV	(0.20)	(0.65)	(4.39)***	(1.34)	(3.45)*
	6		-0.29	-	12.35	-1.46	-6.80
		LS	(0.09)*	-	(3.19)***	(0.65)	(2.78)**
		IV	(0.21)	-	(4.45)***	(1.35)	(3.81)*
	7		-	2.98	-	-	-
			-	(4.17)	-	-	-
	8		-	-0.49	8.05	-0.03	-
		LS	-	(0.36)	(2.79)***	(0.92)	-
		IV	-	(0.73)	(3.12)**	(0.95)	-
	9		-	-0.42	10.76	-1.08	-7.78
		LS	-	(0.28)	(3.18)***	(0.59)	(2.90)**
		IV	-	(0.69)	(3.93)***	(1.13)	(4.80)

Table B.3: Predictive regression models for the RV_SP500 for the period 1999m01 - 2010m12

The OLS estimation results are reported and the significance levels are denoted with (***), (**), (*) referring to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) are found in the parentheses. The NW HAC estimator was used and the bandwidth value was specified to 12.

Horizon	Model	SE	Predictors					
			RV_SP500(-H)	**VIX^2(-H)**	**DLC_V(-H)**	**SRFUN_VF(-H)**	**CORSF_SRFUNVF(-H)**	**EM_VF(-H)**
$H = 6$	1		0.13	-0.02	-	-	-	-
			(0.06)**	(0.13)	-	-	-	-
	2		0.11	0.02	-4.21	-	-	-
			(0.08)	(0.15)	(4.36)	-	-	-
	3		0.17	-0.67	-	11.58	-1.42	-
		LS	(0.17)	(0.30)	-	(4.03)**	(0.73)	-
		IV	(0.22)	(0.47)	-	(4.89)**	(0.96)	-
	4		0.17	-0.62	-1.10	11.72	-1.42	-
		LS	(0.17)	(0.33)	(0.54)	(4.21)**	(0.64)	-
		IV	(0.23)	(0.44)	(0.79)	(4.87)**	(0.98)	-
	5		0.16	-0.63	-1.00	14.12	-2.33	-6.82
		LS	(0.17)	(0.30)	(0.45)	(4.56)**	(0.53)	(2.43)**
		IV	(0.23)	(0.45)	(0.80)	(5.70)**	(1.50)	(3.55)
	6		0.16	-0.67	-	14.25	-2.43	-7.57
		LS	(0.16)	(0.28)	-	(4.42)**	(0.54)	(2.53)**
		IV	(0.23)	(0.48)	-	(5.92)**	(1.60)	(4.37)*
	7		-	-	-1.66	-	-	-
			-	-	(4.14)	-	-	-
	8		-	-	-0.92	8.57	0.26	-
		LS	-	-	(0.52)	(3.25)**	(0.90)	-
		IV	-	-	(0.61)	(3.48)**	(0.70)	-
	9		-	-	-0.82	11.01	-0.65	-7.30
		LS	-	-	(0.43)	(3.73)***	(0.51)	(2.80)**
		IV	-	-	(0.54)	(4.16)***	(0.52)	(4.28)*
$H = 9$	1		0.10	-0.02	-	-	-	-
			(0.18)	(0.18)	-	-	-	-
	2		0.07	0.02	-1.30	-	-	-
			(0.19)	(0.19)	(6.69)	-	-	-
	3		0.14	-0.16	-	6.57	1.38	-
		LS	(0.19)	(0.25)	-	(2.62)**	(0.84)	-
		IV	(0.19)	(0.28)	-	(2.51)**	(1.01)	-
	4		0.14	-0.16	0.10	6.55	1.38	-
		LS	(0.19)	(0.26)	(0.53)	(2.76)**	(0.87)	-
		IV	(0.19)	(0.26)	(0.51)	(2.56)**	(1.02)	-
	5		0.15	-0.21	0.17	9.01	0.46	-6.22
		LS	(0.19)	(0.23)	(0.53)	(3.27)***	(0.65)	(3.35)*
		IV	(0.19)	(0.25)	(0.60)	(3.41)***	(0.97)	(3.42)*
	6		0.15	-0.20	-	8.98	0.48	-6.09
		LS	(0.19)	(0.23)	-	(3.19)***	(0.56)	(3.36)*
		IV	(0.19)	(0.28)	-	(3.44)**	(1.01)	(3.55)*
	7		-	-	0.54	-	-	-
			-	-	(6.46)	-	-	-
	8		-	-	0.11	6.36	1.45	-
		LS	-	-	(0.47)	(2.72)**	(0.82)	-
		IV	-	-	(0.50)	(2.63)**	(0.92)	-
	9		-	-	0.16	8.55	0.60	-6.30
		LS	-	-	(0.46)	(3.28)**	(0.45)	(3.31)*
		IV	-	-	(0.58)	(3.22)***	(0.82)	(3.37)*

Table B.4: Predictive regression models for the VRP for the period 1999m01 - 2010m12

The OLS estimation results are reported and the significance levels are denoted with (***), (**), (*) referring to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) are found in the parentheses. The NW HAC estimator was used and the bandwidth value was specified to 12.

Horizon	Model	SE	Predictors				
			VIX^2(-H)	**DLC_V(-H)**	**SRFUN_VF(-H)**	**CORSF_SRFUNVF(-H)**	**EM_VF(-H)**
$H = 6$	1		0.08	-	-	-	-
			(0.05)	-	-	-	-
	2		0.08	0.55	-	-	-
			(0.05)	(2.03)	-	-	-
	3		-0.29	-	4.99	-1.49	-
		LS	(0.08)	-	(1.25)***	(0.26)	-
		IV	(0.18)	-	(1.95)**	(0.76)*	-
	4		-0.27	-0.42	5.05	-1.49	-
		LS	(0.08)	(0.26)	(1.32)***	(0.25)	-
		IV	(0.16)*	(0.66)	(1.97)**	(0.77)*	-
	5		-0.28	-0.37	6.52	-2.05	-4.17
		LS	(0.07)	(0.25)	(1.39)***	(0.20)	(0.88)***
		IV	(0.16)*	(0.70)	(2.44)***	(1.06)*	(1.77)**
	6		-0.30	-	6.56	-2.09	-4.44
		LS	(0.07)	-	(1.34)***	(0.20)	(0.91)***
		IV	(0.18)	-	(2.54)**	(1.12)*	(2.28)*
	7		-	2.04	-	-	-
			-	(2.29)	-	-	-
	8		-	-0.32	3.19	-0.49	-
		LS	-	(0.22)	(0.99)***	(0.38)	-
		IV	-	(0.42)	(1.27)**	(0.33)	-
	9		-	-0.25	4.67	-1.05	-4.44
		LS	-	(0.21)	(1.10)***	(0.26)	(0.93)***
		IV	-	(0.44)	(1.53)***	(0.47)**	(2.14)**
$H = 9$	1		0.07	-	-	-	-
			(0.04)*	-	-	-	-
	2		0.07	1.71	-	-	-
			(0.04)*	(1.54)	-	-	-
	3		-0.19	-	3.09	-1.30	-
		LS	(0.06)	-	(0.81)***	(0.33)*	-
		IV	(0.18)	-	(1.68)*	(1.03)	-
	4		-0.19	-0.20	3.12	-1.31	-
		LS	(0.06)	(0.26)	(0.86)***	(0.36)	-
		IV	(0.16)	(0.53)	(1.71)*	(1.05)	-
	5		-0.20	-0.17	4.04	-1.65	-2.34
		LS	(0.06)	(0.25)	(1.07)***	(0.38)*	(1.35)
		IV	(0.17)	(0.53)	(2.24)*	(1.27)	(2.02)
	6		-0.21	-	4.07	-1.67	-2.47
		LS	(0.06)	-	(1.02)***	(0.36)**	(1.39)
		IV	(0.19)	-	(2.29)*	(1.28)	(2.30)
	7		-	3.19	-	-	-
			-	(1.59)**	-	-	-
	8		-	-0.29	1.82	-0.97	-
		LS	-	(0.22)	(0.64)***	(0.28)	-
		IV	-	(0.59)	(0.97)*	(0.77)	-
	9			-0.27	2.93	-1.40	-3.20
		LS	-	(0.20)	(0.88)**	(0.29)	(1.44)
		IV	-	(0.57)	(1.57)*	(1.09)	(3.02)

Table B.5: Predictive regression models for the VIX^2 with a Dummy for the Lehman Brothers effect for the period 1999m01 - 2010m12

The OLS estimation results are reported and the significance levels are denoted with (***), (**), (*) referring to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) are found in the parentheses. The NW HAC estimator was used and the bandwidth value was specified to 12.

Horizon	Model	SE	Predictors				
			VIX^2(-H)	**DLC_V(-H)**	**SRFUN_VF(-H)**	**CORSF_SRFUNVF(-H)**	**EM_VF(-H)**
$H=6$	1		0.26	-	-	-	-
			(0.08)***	-	-	-	-
	2		0.28	-0.68	-	-	-
			(0.08)***	(4.03)	-	-	-
	3		-0.46	-	9.37	-3.24	-
		LS	(0.17)	-	(2.88)**	(0.69)	-
		IV	(0.38)	-	(4.16)**	(1.95)*	-
	4		-0.42	-1.13	9.60	-3.24	-
		LS	(0.18)	(0.76)	(3.15)**	(0.75)	-
		IV	(0.34)	(1.40)	(4.30)**	(1.99)	-
	5		-0.45	-1.05	12.21	-4.18	-6.94
		LS	(0.17)	(0.72)	(3.27)***	(0.72)**	(1.52)***
		IV	(0.34)	(1.43)	(4.95)**	(2.28)*	(3.01)**
	6		-0.49	-	12.28	-4.28	-7.70
		LS	(0.16)	-	(3.04)***	(0.61)**	(1.65)***
		IV	(0.38)	-	(5.13)**	(2.41)*	(4.17)*
	7		-	4.68	-	-	-
			-	(3.55)	-	-	-
	8		-	-0.96	6.59	-1.69	-
		LS	-	(0.67)	(2.10)***	(0.57)	-
		IV	-	(1.03)	(2.37)***	(0.78)**	-
	9		-	-0.86	9.15	-2.58	-7.29
		LS	-	(0.64)	(2.32)***	(0.39)***	(1.63)***
		IV	-	(1.02)	(2.81)***	(1.01)**	(3.52)**
$H=9$	1		0.17	-	-	-	-
			(0.09)*	-	-	-	-
	2		0.18	-0.04	-	-	-
			(0.11)*	(0.41)	-	-	-
	3		-0.21	-	8.83	-0.35	-
		LS	(0.10)	-	(2.50)***	(0.89)	-
		IV	(0.23)	-	(3.36)***	(1.16)	-
	4		-0.20	-0.28	8.87	-0.37	-
		LS	(0.11)	(0.36)	(2.59)***	(0.90)	-
		IV	(0.22)	(0.63)	(3.42)**	(1.19)	-
	5		-0.24	-0.23	10.99	-1.15	-5.27
		LS	(0.10)	(0.32)	(2.76)***	(0.76)	(1.89)**
		IV	(0.20)	(0.63)	(3.99)***	(1.33)	(2.73)*
	6		-0.25	-	11.03	-1.16	-5.45
		LS	(0.09)	-	(2.70)***	(0.73)	(1.93)**
		IV	(0.22)	-	(4.05)***	(1.35)	(3.13)*
	7		-	0.33	-	-	-
			-	(0.39)	-	-	-
	8		-	-0.38	7.46	0.01	-
		LS	-	(0.32)	(2.46)***	(0.89)	-
		IV	-	(0.72)	(2.78)***	(0.94)	-
	9		-	-0.34	9.68	-0.85	-6.27
		LS	-	(0.27)	(2.70)***	(0.65)	(2.02)**
		IV	-	(0.69)	(3.46)***	(1.14)	(4.10)

Table B.6: Reverse Causality Tests

The OLS estimation results are reported and the significance levels are denoted with (***), (**), (*) referring to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) are found in the parentheses. The NW HAC estimator was used and the bandwidth value was specified to 12.

Sample Period 1999m01-2008m08

	SRFUN_VF		COR_VF		EM_VF	
	$H = 6$	$H = 12$	$H = 6$	$H = 12$	$H = 6$	$H = 12$
SRFUN_VF(-H)	0.471	0.162	-	-	0.108	0.021
	(0.169)***	(0.202)	-	-	(0.107)	(0.081)
COR_VF(-H)	-	-	0.099	-0.187	-	-
	-	-	(0.120)	(0.281)	-	-
EM_VF(-H)	-0.145	-0.207	0.028	-0.091	-0.227	-0.135
	(0.131)	(0.241)	(0.112)	(0.145)	(0.070)***	(0.084)
DLC_V(-H)	-0.509	-0.330	0.024	0.111	-0.143	-0.044
	(0.214)**	(0.159)**	(0.142)	(0.107)	(0.099)	(0.072)
VIX^2(-H)	0.001	-0.001	0.001	0.001	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RV_SP500(-H)	0.001	0.001	0.001	0.001	0.001	0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Adj. R^2	0.203	0.018	0.117	0.049	0.058	0.003

Sample Period 1999m01-2010m12, with a Dummy for the Lehman Brothers effect

	SRFUN_VF		COR_VF		EM_VF	
	$H = 6$	$H = 12$	$H = 6$	$H = 12$	$H = 6$	$H = 12$
SRFUN_VF(-H)	0.604	0.427	-	-	0.354	0.313
	(0.225)***	(0.168)**	-	-	(0.199)*	(0.139)**
COR_VF(-H)	-	-	0.145	0.474	-	-
	-	-	(0.148)	(0.412)	-	-
EM_VF(-H)	-0.280	-0.404	0.144	-0.260	-0.095	-0.099
	(0.133)**	(0.195)**	(0.143)	(0.152)*	(0.079)	(0.142)
DLC_V(-H)	-0.054	-0.028	-0.004	-0.010	0.057	-0.020
	(0.018)***	(0.016)*	(0.020)	(0.025)	(0.020)***	(0.009)**
VIX^2(-H)	-0.003	-0.003	0.000	-0.002	-0.001	-0.002
	(0.002)*	(0.001)**	(0.001)	(0.002)	(0.001)***	(0.001)**
RV_SP500(-H)	0.003	0.002	0.001	0.001	0.001	0.001
	(0.001)***	(0.001)**	(0.001)***	(0.001)	(0.000)***	(0.000)**
Adj. R^2	0.298	0.194	0.285	0.082	0.281	0.184

Table B.7: Reverse Causality Tests, using the SRFUN_SF, COR_SF and EM_RF factors

The OLS estimation results are reported and the significance levels are denoted with (***), (**), (*) referring to rejecting the null hypothesis of insignificant predictors at 1%, 5% and 10% respectively. Standard errors (SE) are found in the parentheses. The NW HAC estimator was used and the bandwidth value was specified to 12.

Sample Period 1999m01-2008m08

	SRFUN_SF		COR_SF		EM_RF	
	$H=6$	$H=12$	$H=6$	$H=12$	$H=6$	$H=12$
SRFUN_SF(-H)	0.245	0.274	-	-	-0.217	-0.106
	(0.096)**	(0.171)	-	-	(0.112)*	(0.197)
COR_SF(-H)	-	-	1.146	0.932	-	-
	-	-	(0.181)***	(0.241)***	-	-
EM_RF(-H)	0.000	0.124	0.042	0.026	0.113	0.023
	(0.088)	(0.080)	(0.044)	(0.042)	(0.074)	(0.074)
DLC_V(-H)	-0.213	-0.420	0.376	1.371	0.529	0.508
	(0.525)	(0.623)	(0.414)	(0.575)**	(0.498)	(0.406)
VIX^2(-H)	-0.004	-0.002	0.010	0.005	-0.006	0.006
	(0.005)	(0.006)	(0.003)***	(0.007)	(0.005)	(0.006)
RV_SP500(-H)	0.006	0.002	0.001	0.010	0.005	-0.007
	(0.007)	(0.005)	(0.004)	(0.004)***	(0.005)	(0.008)
Adj. R^2	0.009	0.019	0.588	0.359	0.006	0.001

Sample Period 1999m01-2010m12, with a Dummy for the Lehman Brothers effect

	SRFUN_SF		COR_SF		EM_RF	
	$H=6$	$H=12$	$H=6$	$H=12$	$H=6$	$H=12$
SRFUN_SF(-H)	0.420	0.337	-	-	-0.009	0.055
	(0.167)**	(0.173)*	-	-	(0.076)	(0.107)
COR_SF(-H)	-	-	0.983	0.681	-	-
	-	-	(0.320)***	(0.353)**	-	-
EM_RF(-H)	-0.050	0.096	0.166	0.093	0.066	0.045
	(0.067)	(0.080)	(0.050)***	(0.059)	(0.086)	(0.060)
DLC_V(-H)	-0.200	-0.248	0.295	0.295	0.023	0.055
	(0.180)	(0.126)*	(0.235)	(0.206)	(0.087)	(0.125)
VIX^2(-H)	-0.006	-0.007	0.019	0.018	0.000	0.003
	(0.004)	(0.006)	(0.007)***	(0.009)**	(0.004)	(0.004)
RV_SP500(-H)	0.003	0.003	-0.007	-0.004	0.002	-0.002
	(0.002)	(0.003)	(0.004)**	(0.004)	(0.003)	(0.003)
Adj. R^2	0.206	0.155	0.520	0.243	0.024	0.027