# The Information Content of Forward Moments*

Panayiotis C. Andreou[†,‡] Anastasios Kagkadis[§] Dennis Philip[‡]
Abderrahim Taamouti[‡]

July 2019

*We would like to thank Geert Bekaert (the Editor), two anonymous referees, Kevin Aretz, Charlie Cai, Chris Florakis, Feng Jiao, Alex Kostakis, Dimitrios Koutmos, Ivilina Popova, Alex Taylor, as well as conference and seminar participants at Lancaster University, Manchester University, Liverpool University, CFE 2016, FMA Applied Finance 2017, EFMA 2017, and FMA 2017, for their useful comments. We are also grateful to Seth Pruitt for sharing his codes with us, and to Robert Shiller, Hao Zhou, Amit Goyal and Marie Hoerova for making their data publicly available. An earlier version of the paper was circulated under the title "Forward Moments and Risk Premia Predictability".

†Department of Commerce, Finance and Shipping, Cyprus University of Technology, 140, Ayiou Andreou Street, 3603 Lemesos, Cyprus; Email: benz@pandreou.com

‡Durham University Business School, Mill Hill Lane, Durham DH1 3LB, UK; Emails: dennis.philip@durham.ac.uk, abderrahim.taamouti@durham.ac.uk

§Department of Accounting and Finance, Lancaster University Management School, Lancaster LA1 4YX, UK; Email: a.kagkadis@lancaster.ac.uk

**Abstract**

We estimate the term structures of risk-neutral forward variance and skewness, and examine their predictive power for equity market excess returns and variance. We use Partial Least Squares to extract a single predictive factor from each term structure that is motivated by the theoretical implications of affine no-arbitrage models. The empirical analysis shows that an increased forward variance factor, FVF (forward skewness factor, FSF) corresponds to a more negatively sloped forward variance (more U-shaped forward skewness) term structure, and significantly forecasts higher future market excess returns and variance. More importantly, FSF exhibits predictive power for market returns that is stronger than, and incremental to, that provided by FVF. However, it does not outperform FVF in terms of excess variance predictability.

*JEL Classification:* G10, G11, G12

*Keywords:* Forward moments; Implied volatility surface; Partial least squares; Predictability of stock returns; Equity premium; Variance premium

# 1 Introduction

The extant literature on stock return predictability underscores the limited forecasting power of stock market risk-neutral variance as captured by the VIX. It also qualifies the variance risk premium – the difference between conditional variance under risk-neutral and physical measures – as a successful predictor (see, for example, Bollerslev et al., 2009; Bekaert and Hoerova, 2014; and Feunou et al., 2018). However, in a new strand of literature, Bakshi et al. (2011) and Luo and Zhang (2017) demonstrate how different measures of risk-neutral *forward* variance can jointly provide significant forecasting ability for future market returns.

In addition, several recent studies have highlighted the importance of considering the *skewness* of investor expectations in order to capture equity premium variations more accurately. Colacito et al. (2016) and Bekaert and Engstrom (2017) build theoretical asset pricing models that incorporate time-varying skewness in the consumption growth process. They are able to show that these models provide a better data fit than similar models that do not explicitly allow for interactions between consumption growth skewness and the equity premium. The main intuition behind these two models is that periods of low (high) skewness are disliked (desirable) by investors, hence leading to a more countercyclical equity premium. In an empirical context, Chabi-Yo and Loudis (2019) show that incorporating higher-order risk-neutral moments in the construction of lower and upper bounds for the conditional equity premium improves out-of-sample predictability of excess market returns.

Motivated by the aforementioned theoretical and empirical developments in the literature, in this paper we use option prices to create risk-neutral forward skewness[1] (hereafter, forward skewness) measures, in addition to risk-neutral forward variance (hereafter, forward variance) measures. In turn, we explore the joint information content of forward moments for stock market excess returns and variance.

Our predictability analysis is motivated by the implications of affine no-arbitrage mod-

[1]Note that we use the risk-neutral forward third moment throughout the paper as a measure of risk-neutral forward skewness.

els. In particular, we show theoretically that the term structures of forward variance and forward skewness can be used to recover the risk factor(s) that drive the equity and variance risk premia. We therefore use the estimated forward variances and skewnesses separately in order to extract each time one predictive factor that can proxy for the latent factor driving the economy. We follow Kelly and Pruitt (2013, 2015) to obtain the factors used in the predictability exercise. Unlike the standard Principal Component method, the Partial Least Squares technique condenses the cross-section of a set of predictors according to its covariance with the predicted variable. In other words, we extract the factor (i.e., the linear combination) from each forward variance and forward skewness term structure that is most relevant for forecasting purposes.

Our results show that both the forward variance and the forward skewness factors exhibit statistically and economically significant in-sample forecasting power for one- to twelve-month-ahead market returns. The forward skewness factor typically exhibits stronger performance. For example, a 1-standard deviation increase in the forward variance (skewness) factor is associated with a 10.20% (13.34%) annualized excess quarterly return. The predictive power of the two factors remains intact after controlling for the simple risk-neutral moments and a wide range of alternative predictors. Given that both factors exhibit significant forecasting power for stock market returns, we further test the in-sample predictive power of the forward skewness factor orthogonalized on the forward variance factor. The empirical evidence shows that the orthogonalized forward skewness factor exhibits significant forecasting power for all but one horizon (the one-month horizon). Thus, a significant proportion of the information content of the forward skewness factor is unique, and is not captured by the forward variance factor.

To understand the economic nature of the forward moments factors, we regress each factor on the respective underlying forward moments. We find that the forward variance factor mainly reflects changes in the slope of the forward variance term structure, while a more negatively sloped term structure is associated with higher future market returns.

Similarly, the forward skewness factor mostly captures changes in the curvature of the forward skewness term structure. And a more U-shaped term structure predicts higher future market returns. By conducting the predictability analysis with a multivariate model that includes the underlying forward variances (or skewnesses) instead of the estimated factors, we further find that the documented factors' predictive power is mostly driven by the changes in shape of each term structure at the longer horizons.

In an out-of-sample analysis, we also observe the strong predictive power of the forward moments factors for excess stock returns, and the incremental forecasting information embedded in the forward skewness factor. In particular, a predictive model with either factor clearly outperforms the historical average model across most horizons examined. More importantly, the forward skewness factor typically exhibits stronger out-of-sample performance than the forward variance factor. Its inclusion in a predictive model that would otherwise include only the forward variance factor provides additional predictive power for excess returns. An asset allocation exercise demonstrates that the market-timing strategies based on the forward moments factors perform markedly better than a strategy that relies on the historical average model, but do not outperform a buy-hold strategy. However, incorporating the information content of the forward moments factors in a trading strategy significantly reduces the downside risk associated with the market portfolio.

Finally, we empirically test whether the forward variance and forward skewness factors that are designed to predict stock market returns can also predict stock market excess variance across multiple horizons. Consistent with our theoretical motivation, that the equity and variance risk premia exhibit the same factor structure, we find that the forward moments factors also exhibit significant and similar in- and out-of-sample forecasting power for excess variance. Moreover, this forecasting power continues to be significant when we control for other strong predictors, such as the stock market conditional variance and the VIX. For the equity market excess variance, we find that the forward variance factor exhibits slightly stronger forecasting power. Furthermore, when investigating whether the forward skewness factor provides predictive information on top of what is already captured by the forward variance factor, we find no supportive in- or out-of-sample evidence.

The remainder of this paper is structured as follows. Section 2 presents the theoretical framework, while Section 3 outlines our data and the construction of the main variables. Section 4 discusses the empirical evidence from the stock market return predictability, and Section 5 reports the results from the stock market excess variance predictability. Section 6 concludes.

# 2 Theoretical Motivation

This section describes the theoretical motivation of the paper. Using Feunou et al.'s (2014) affine reduced-form framework, we show that it is possible to use the term structures of risk-neutral forward variance and skewness to pinpoint the risk factors that drive the equity premium.

## 2.1 Affine reduced-form framework

We assume an economy driven by $K$ state variables, say, $X_t$, which satisfies the following properties: 1) the joint distribution of the one-period-ahead excess market log returns, $r_{t+1}$, and $X_{t+1}$ belongs to the family of affine jump-diffusion continuous-time models; 2) the (log) risk-free rate $r_{f,t}$ is an affine function of $X_t$; and 3) the stochastic discount factor is an exponential affine function of $X_{t+1}$ and $r_{t+1}$ (see, for example, Gouriéroux and Monfort, 2007; and Christoffersen et al., 2010).

Several recent asset pricing models, such as the affine model of Lettau and Wachter (2011), are consistent with the above environment. Affine long-run risk models based on Epstein-Zin-Weil preferences, such as the models of Bansal and Yaron (2004), Eraker (2008), Bollerslev et al. (2009), and Drechsler and Yaron (2011), also fit this framework (see also Appendix A2 in Feunou et al., 2014). However, we note that these models remain approximations of the true models because their affine feature relies on a first-order Taylor approximation. In a recent paper, Pohl et al. (2018) show that the asset pricing models that consider Epstein-Zin-Weil preferences exhibit economically significant non-linearities. Thus, use of the Campbell–Shiller log-linearization may lead to numerical errors, which in turn can affect the magnitude of the equity premium or of the return predictability. Finally, affine habit models, such as the models of Bekaert et al. (2009) and Bekaert et al. (2019) are also consistent with the above framework. For those models log-linearization is also needed but it is implemented after a quasi-affine pricing function is derived.

Under properties (1)-(3), Feunou et al. (2014) (see their Appendices A1 and A4) show that the cumulant-generating functions of excess returns over an investment horizon $\tau$, $r_{t,t+\tau} \equiv \sum_{j=1}^{\tau} r_{t+j}$, under the physical measure, $\mathbb{P}$, and the risk-neutral measure, $\mathbb{Q}$, are given by:

$$\log E_t^{\mathbb{P}} \left[ \exp \left( u \ r_{t,t+\tau} \right) \right] = \mathscr{F}_{r,0}^{\mathbb{P}} \left( u; \tau \right) + X_t^{\top} \mathscr{F}_{r,X}^{\mathbb{P}} \left( u; \tau \right), \tag{1}$$

$$\log E_t^{\mathbb{Q}} \left[ \exp \left( u \ r_{t,t+\tau} \right) \right] = \mathscr{F}_{r,0}^{\mathbb{Q}} \left( u; \tau \right) + X_t^{\top} \mathscr{F}_{r,X}^{\mathbb{Q}} \left( u; \tau \right), \tag{2}$$

where $\mathscr{F}_{r,0}^{\mathbb{M}} \left( u; \tau \right)$ and $\mathscr{F}_{r,X}^{\mathbb{M}} \left( u; \tau \right)$ for $\mathbb{M} = \mathbb{P}$, $\mathbb{Q}$, are functions of the argument $u$ and the parameters of the underlying model.[2] Subsequently, by taking the first derivative of the cumulant-generating function under the $\mathbb{P}$ measure with respect to its argument $u$, the equity premium over an investment horizon $\tau$ can be stated as:

$$EP_t \left( \tau \right) = E_t^{\mathbb{P}} \left[ r_{t,t+\tau} \right] = \beta_{ep,0} \left( \tau \right) + \beta_{ep} \left( \tau \right)^{\top} X_t, \tag{3}$$

where the coefficients $\beta_{ep,0} \left( \tau \right)$ and $\beta_{ep} \left( \tau \right)$ are functions of the parameters of the underlying model. Our main focus here is the estimation of the risk-return trade-off in (3). In this

[2]To avoid heavy notation, we focus throughout only on the horizon parameter $\tau$, which is the main parameter of interest.

equation, the coefficient $\beta_{ep}(\tau)$ characterizes the returns required by investors to bear the risk associated with variations in $X_t$. If the risk factors $X_t$ are observable, then $\beta_{ep,0}(\tau)$ and $\beta_{ep}(\tau)$ could be estimated directly via ordinary least squares (OLS). However, $X_t$ is latent, which makes estimating Equation (3) infeasible.

Moreover, taking the second derivative of the cumulant-generating function in (2), we note that the risk-neutral variance of excess returns over any horizon $\tau$ is an affine function of $X_t$:

$$Var_t^{\mathbb{Q}}(\tau) = Var_t^{\mathbb{Q}}[r_{t,t+\tau}] = \beta_{vr,0}(\tau) + \beta_{vr}(\tau)^{\top} X_t, \tag{4}$$

where the coefficients $\beta_{vr,0}(\tau)$ and $\beta_{vr}(\tau)$ are functions of the parameters of the underlying model. Equation (4) indicates that the risk-neutral variance at different maturities displays a factor structure with dimension $K$. Similarly, taking the third derivative of the cumulant-generating function in (2), we show that the risk-neutral skewness (third moment) of excess returns over any horizon $\tau$ is an affine function of $X_t$:

$$Skw_t^{\mathbb{Q}}(\tau) = Skw_t^{\mathbb{Q}}[r_{t,t+\tau}] = \beta_{skw,0}(\tau) + \beta_{skw}(\tau)^{\top} X_t, \tag{5}$$

where again $\beta_{skw,0}(\tau)$ and $\beta_{skw}(\tau)$ are functions of the parameters of the underlying model.[3]

## 2.2 Forward moments and the risk factors

Within the context of the above framework, we show that forward variance and skewness are also affine functions of risk factors $X_t$. Because the forward variance (skewness) can be written as the difference between the risk-neutral variance (skewness) of two different maturities, it follows that it is also an affine function of $X_t$. We can then invert the system of equations that links the forward variance (skewness) to $X_t$ in order to express the latter as an affine function of the former.

[3]Note that the second cumulant corresponds to the variance, while the third cumulant corresponds to the third moment and provides a measure of skewness.

First, we recall the definitions of forward variance and forward skewness for the period $\tau_1$ to $\tau_2$ estimated at time $t$ :

$$Var_t^{\mathbb{Q}}(\tau_1, \tau_2) = Var_t^{\mathbb{Q}}[r_{t+\tau_1, t+\tau_2}],$$
$$Skw_t^{\mathbb{Q}}(\tau_1, \tau_2) = Skw_t^{\mathbb{Q}}[r_{t+\tau_1, t+\tau_2}].$$

Next, we show that the above forward variance (skewness) can be written as the difference between the risk-neutral variance (skewness) of maturity $\tau_2$ and that of maturity $\tau_1$. To do this, we use Neuberger's (2012) Aggregation Property (see Equation (2) in his Section 2.2), which requires that a real-valued function $g(.)$ of an adapted process $Y$ satisfy, for any times $0 \leq t \leq \tau_1 \leq \tau_2 \leq T$:

$$E_t [g(Y_{\tau_2} - Y_t)] = E_t [g(Y_{\tau_2} - Y_{\tau_1})] + E_t [g(Y_{\tau_1} - Y_t)]. \tag{6}$$

Assuming that the forward asset price $F$ is a martingale, Neuberger (2012) and Kozhan et al. (2013) show that the function $g^V(\delta f) \equiv 2\left(e^{\delta f} - 1 - \delta f\right)$, with $\delta f$ denoting the log change of the forward asset price, converges to the second moment of returns. Therefore, we can consider the following quantity as a measure of risk-neutral variance:

$$G_{t,\tau_2}^V = 2E_t^{\mathbb{Q}}\left[\frac{F_{\tau_2,\tau_2}}{F_{t,\tau_2}} - 1 - \ln\left(\frac{F_{\tau_2,\tau_2}}{F_{t,\tau_2}}\right)\right], \tag{7}$$

where $F_{t,\tau_2}$ is the forward price of the asset at time $t$ with maturity $\tau_2$, and $F_{\tau_2,\tau_2}$ is the forward price of the asset at maturity $\tau_2$. Similarly, the function $g^S(\delta f) \equiv 6\left(\delta f e^{\delta f} - 2e^{\delta f} + \delta f + 2\right)$ approximates the third moment of returns locally, and hence the following quantity can be regarded as a measure of risk-neutral skewness:

$$G_{t,\tau_2}^S = 6E_t^{\mathbb{Q}}\left[\frac{F_{\tau_2,\tau_2}}{F_{t,\tau_2}}\ln\left(\frac{F_{\tau_2,\tau_2}}{F_{t,\tau_2}}\right) - 2\frac{F_{\tau_2,\tau_2}}{F_{t,\tau_2}} + \ln\left(\frac{F_{\tau_2,\tau_2}}{F_{t,\tau_2}}\right) + 2\right]. \tag{8}$$

Neuberger (2012) shows that the functions $g^V(\delta f)$ and $g^S(\delta f)$ exhibit the Aggregation Property. This means that, under the $\mathbb{Q}$ measure, we can write for any $0 \leq t \leq \tau_1 \leq \tau_2 \leq T$:

$$E_t^{\mathbb{Q}}\left[g^V\left(\ln(F_{\tau_2,\tau_2})-\ln(F_{t,\tau_2})\right)\right] = E_t^{\mathbb{Q}}\left[g^V\left(\ln(F_{\tau_2,\tau_2})-\ln(F_{\tau_1,\tau_2})\right)\right] + E_t^{\mathbb{Q}}\left[g^V\left(\ln(F_{\tau_1,\tau_1})-\ln(F_{t,\tau_1})\right)\right], \tag{9}$$

where the first and third terms in the above equation are equal to $G_{t,\tau_2}^V$ and $G_{t,\tau_1}^V$, respectively, and $E_t^{\mathbb{Q}}\left[g^V\left(\ln(F_{\tau_2,\tau_2})-\ln(F_{\tau_1,\tau_2})\right)\right] = FV_{t,\tau_1,\tau_2}$, with $FV_{t,\tau_1,\tau_2}$ being a measure of the time $t$ forward variance between $\tau_1$ and $\tau_2$. By rearranging Equation (9), we obtain:

$$FV_{t,\tau_1,\tau_2} = G_{t,\tau_2}^V - G_{t,\tau_1}^V. \tag{10}$$

Similarly, by the Aggregation Property of the function $g^S(\delta f)$, we obtain:

$$FS_{t,\tau_1,\tau_2} = G_{t,\tau_2}^S - G_{t,\tau_1}^S, \tag{11}$$

where $FS_{t,\tau_1,\tau_2} = E_t^{\mathbb{Q}}\left[g^S\left(\ln(F_{\tau_2,\tau_2})-\ln(F_{\tau_1,\tau_2})\right)\right]$ can be viewed as a measure of the time $t$ forward skewness (third moment) between maturities $\tau_1$ and $\tau_2$.

Note that, for any maturity $\tau$, we have $G_{t,\tau}^V = Var_t^{\mathbb{Q}}(\tau)$, which is an affine function of $X_t$ as expressed in Equation (4). Thus, by combining the results in Equations (4) and (10), the forward variance is an affine function of $X_t$ :

$$FV_{t,\tau_1,\tau_2} = \beta_{vr,0}(\tau_1,\tau_2) + \beta_{vr}(\tau_1,\tau_2)^\top X_t, \tag{12}$$

where $\beta_{vr,0}(\tau_1,\tau_2) = \beta_{vr,0}(\tau_2) - \beta_{vr,0}(\tau_1)$ and $\beta_{vr}(\tau_1,\tau_2) = \beta_{vr}(\tau_2) - \beta_{vr}(\tau_1)$. Similarly, since $G_{t,\tau}^S = Skw_t^{\mathbb{Q}}(\tau)$, by combining the results in Equations (5) and (11), we can obtain that the forward skewness is an affine function of $X_t$ :

$$FS_{t,\tau_1,\tau_2} = \beta_{skw,0}(\tau_1,\tau_2) + \beta_{skw}(\tau_1,\tau_2)^\top X_t, \tag{13}$$

where $\beta_{skw,0}(\tau_1,\tau_2) = \beta_{skw,0}(\tau_2) - \beta_{skw,0}(\tau_1)$ and $\beta_{skw}(\tau_1,\tau_2) = \beta_{skw}(\tau_2) - \beta_{skw}(\tau_1)$.

Finally, we show how the term structures of forward variance and skewness can be used to recover $X_t$. Stacking the terms of Equations (12) and (13) across horizons $\tau = \tau_1, \tau_2, ..., \tau_q$, we obtain:

$$
\begin{aligned}
FV_t &= B_{vr,0} + B_{vr} X_t, \\
FS_t &= B_{skw,0} + B_{skw} X_t,
\end{aligned}
$$

where $FV_t = \left(FV_{t,\tau_1,\tau_2}, ..., FV_{t,\tau_{q-1},\tau_q}\right)^\top$, $FS_t = \left(FS_{t,\tau_1,\tau_2}, ..., FS_{t,\tau_{q-1},\tau_q}\right)^\top$, the $(q-1) \times 1$ vectors $B_{vr,0}$ and $B_{skw,0}$ stack the constants $\beta_{vr,0}(\tau_i, \tau_{i+1})$ and $\beta_{skw,0}(\tau_i, \tau_{i+1})$ for $i = 1, ..., q-1$, respectively, and the $(q-1) \times K$ matrices $B_{vr}$ and $B_{skw}$ stack the corresponding coefficients $\beta_{vr}(\tau_i, \tau_{i+1})$ and $\beta_{skw}(\tau_i, \tau_{i+1})$ for $i = 1, ..., q-1$. We typically have more observations along the term structure than the underlying factors, i.e., $(q-1) > K$. Accordingly, we can write:

$$
\begin{aligned}
X_t &= -\bar{B}_{vr} B_{vr,0} + \bar{B}_{vr} FV_t, \\
X_t &= -\bar{B}_{skw} B_{skw,0} + \bar{B}_{skw} FS_t,
\end{aligned}
\tag{14}
$$

where the $K \times (q-1)$ matrices $\bar{B}_{vr} = \left(B_{vr}^\top B_{vr}\right)^{-1} B_{vr}^\top$ and $\bar{B}_{skw} = \left(B_{skw}^\top B_{skw}\right)^{-1} B_{skw}^\top$ are the left inverse of $B_{vr}$ and $B_{skw}$, respectively. Hence, Equation (14) shows that the forward variance and skewness term structures can be used separately as signals for the underlying risk factors.

In the next section, we use Kelly and Pruitt's (2013, 2015) Partial Least Squares methodology. We extract $X_t$ after measuring the elements of $FV_t$ ($FS_t$) from option prices following Bakshi and Madan (2000) and Carr and Madan (2001). Once we have estimated an empirical proxy for $X_t$ from the measures of forward variance (skewness), we can use it in the context of stock return predictability, i.e., to estimate our equation of interest in (3) with the ex-post market excess return serving as a proxy for the unobservable equity premium.

In summary, we provide a framework within which the risk-neutral forward moments of market returns exhibit the same factor structure as the equity premium. This means it will be possible to extract a latent factor from each term structure of forward variance or skewness, and use it for forecasting purposes. Therefore, unlike Bakshi et al. (2011), we provide a theoretical justification for why forward moments exhibit predictive power for future market returns. Furthermore, while both studies estimate forward moments using option prices, our paper relies on the alternative variance and skewness definitions of Neuberger (2012). These definitions satisfy the Aggregation Property and can account for the presence of jumps in the asset price process. In contrast, Bakshi et al. (2011) rely on the exponential claims on integrated variance of Carr and Lee (2008), and construct the forward variances similarly to the way forward interest rates are estimated. As a result, their approach cannot account for price jumps.

# 3 Data and Variables

This section provides details on the estimation of the main and alternative predictive variables used here, as well as on the summary statistics.

## 3.1 Options data and forward moments factors

To measure the term structure of aggregate market forward moments, we use S&P 500 index options data from OptionMetrics. More specifically, we utilize the volatility surface file that provides a smoothed implied volatility surface for a given range of standardized deltas and maturities. We discard in-the-money options, i.e., options with an absolute value of delta that is higher than 0.5. Our sample period is January 1996-August 2015, and we estimate the monthly time series of forward moments by using data on the penultimate trading day of each month.[4]

On a given day, we estimate risk-neutral variance and skewness for three, six, nine, and twelve months ahead. Neuberger (2012) and Kozhan et al. (2013) show that Equations (7)-

[4]We use the one-day lag rule to account for the fact that, until March 4, 2008, the data provided by OptionMetrics stem from closing prices recorded two minutes after the closure of the stock market (Battalio and Schultz, 2006). Moreover, this procedure gives real-time investors the necessary time to analyze the options data.

(8) can be replicated exactly by positioning out-of-the-money (OTM) call and put options, as per Bakshi and Madan (2000) and Carr and Madan (2001):

$$RNV_t^\tau = \frac{2}{B_t^\tau}\left[\int_0^{F_t^\tau} \frac{P_t^\tau\left[K\right]}{K^2}dK + \int_{F_t^\tau}^{\infty} \frac{C_t^\tau\left[K\right]}{K^2}dK\right], \tag{15}$$

$$RNS_t^\tau = \frac{6}{B_t^\tau}\left[\int_{F_t^\tau}^{\infty} \frac{K - F_t^\tau}{K^2 F_t^\tau}C_t^\tau\left[K\right]dK - \int_0^{F_t^\tau} \frac{F_t^\tau - K}{K^2 F_t^\tau}P_t^T\left[K\right]dK\right], \tag{16}$$

where $B_t^\tau = e^{-r(\tau - t)}$ is the price of a risk-free bond, $F_t^\tau$ is the forward S&P 500 index level of maturity $\tau$ at time $t$, and $P_t^\tau\left[K\right]$ and $C_t^\tau\left[K\right]$ are the prices of a put and a call option, respectively, with strike price $K$ and time to maturity $\tau - t$.[5] Once we have the estimates of constant maturity risk-neutral moments, we use Equations (10) and (11) to create forward variance and skewness estimates for three to six ($\text{FV}_{3m,6m}$ and $\text{FS}_{3m,6m}$), six to nine ($\text{FV}_{6m,9m}$ and $\text{FS}_{6m,9m}$), and nine to twelve ($\text{FV}_{9m,12m}$ and $\text{FS}_{9m,12m}$) months ahead. We retain the three-month-ahead risk-neutral variance (RNV) and skewness (RNS), and use them as control variables in the subsequent empirical analysis.

We rely on Kelly and Pruitt's (2013, 2015) Partial Least Squares (PLS) methodology to extract one factor from the vector FV (FS) that stacks the forward variance (forward skewness) across different maturities. The main characteristic of this method is that it extracts the factor structure from a set of predictive variables according to its covariance with the forecasted variable. In other words, we can identify a primary factor that drives the set of predictive variables but is also relevant for forecasting the target variable.

To implement PLS, we first run time series regressions of the following form:

[5] Note that these formulas require a continuum of option prices, while the available data is only discrete. In order to obtain an accurate approximation of the integrals, we therefore follow Buss and Vilkov (2012) and DeMiguel et al. (2013), among others. For each cross-section of implied volatilities, we interpolate the range of available moneyness levels by using a smoothing cubic spline with a smoothing parameter of 0.99. We extrapolate outside this range by using the respective boundary values. We thus obtain a set of 1,000 implied volatilities that cover the moneyness range from 0.0001 to 3. Finally, these implied volatilities are transformed into option prices, and the trapezoidal approximation is used for computing the integrals in Equations (15) and (16).

$$\tilde{m}_{i,t} = \phi_{i,0} + \phi_i r_{t,t+1} + \epsilon_{i,t}, \tag{17}$$

where $\tilde{m}_{i,t}$ corresponds to each element $i$ of the vector of forward variance FV (forward skewness FS) at a given time $t$, and $r_{t,t+1}$ is the subsequent one-month-ahead excess market return. This is used as a proxy for the unobservable factor $X_t$, and $\phi_i$ is the loading of each forward moment (forward variance or forward skewness) to that factor. As a second step, we run $T$ cross-sectional regressions:

$$\tilde{m}_{i,t} = \varphi_t + X_t \widehat{\phi}_i + \varepsilon_{i,t}, \tag{18}$$

where $\widehat{\phi}_i$ is the estimated coefficient from the first step for each of the forward moments. Intuitively, by regressing the forward moments at each time period on the corresponding factor loadings from the first-step regressions, we obtain the estimated predictive factor $\widehat{X}_t$.[6] Hereafter, we denote the time series of the factor extracted from FV as FVF, and the time series of the factor extracted from FS as FSF.[7]

The forward variance (skewness) factor, estimated using the PLS procedure described above, represents the linear combination of forward variances (skewnesses) that provides the highest forecasting power for future market returns. In order to better understand the economic nature of the two forward moments factors, we regress each one on the respective

[6]In principle, we could also use the Kalman filter to estimate the latent factor X. In this case, Equation (18) could be seen as the Measurement equation. However, the State equation must be specified too. If we assume there is no dynamic in the latent factor process, i.e., if the State equation is given by an i.i.d. disturbance term, then this specification underlines the principal component framework. If we consider a dynamic model for the latent factor process (e.g., an Autoregressive model), then the state-space system – the dynamic model of the latent factor and the Measurement equation in (18) – can be estimated using the Kalman filter based on the available information. In our case, this is given by the forward variances or skewnesses. However, we use the PLS method as it helps extract the latent factors that best explain the one-month-ahead market return.

[7]It is important to note that the factors estimated with PLS change depending on the proxy variable considered. To avoid imposing an overfitting bias on our analysis, we use the FVF and FSF that are designed to predict the one-month-ahead excess market return throughout.

forward moments. FVF is therefore represented by:

$$FVF = 43FV_{3m,6m} + 19FV_{6m,9m} - 66FV_{9m,12m}, \tag{19}$$

which can be interpreted as a slope factor, because it mainly captures changes in the slope of the forward variance term structure. Also, we note that a Principal Component Analysis on forward variances reveals that the second principal component has a 0.92 correlation with FVF. Similarly, FSF is represented by:

$$FSF = 15FS_{3m,6m} - 131FS_{6m,9m} + 104FS_{9m,12m}, \tag{20}$$

which can be seen as a curvature factor, because it mainly reflects changes in the curvature of the forward skewness term structure. A Principal Component Analysis on forward skewnesses shows that the third principal component exhibits a 0.99 correlation with FSF.[8]

## 3.2 Other control variables

The remainder of the predictor variables include the variance risk premium (VP, Bekaert and Hoerova, 2014), the aggregate dividend-price ratio (d-p, Fama and French, 1988), the market dividend-payout ratio (d-e, Lamont, 1998), the default spread (DEF, Fama and French, 1989), the relative short-term risk-free rate (RREL, Campbell, 1991), stock market variance (SVAR, Guo, 2006), and tail risk (TAIL, Kelly and Jiang, 2014).

More precisely, VP is the difference between the squared VIX index and the conditional one-month-ahead S&P 500 index variance, estimated as a linear combination of squared VIX, and monthly, weekly and daily realized variances. d-p is the difference between the log

[8]In the Online Appendix, we also investigate the forecasting power of the second principal component of the forward variance term structure, and the forecasting power of the third principal component of the forward skewness term structure. As expected, given the high correlation between the two components and the respective PLS factors, these predictability results are similar to those presented here. This finding alleviates potential concerns that the information content of the forward moments is an artifact of the PLS method.

aggregate annual dividends and the log level of the S&P 500 index, while d-e is the difference between the log aggregate annual dividends and annual earnings. DEF is the difference between BAA and AAA corporate bond yields from Moody's. RREL is the difference between the three-month T-bill rate and its moving average over the preceding twelve months. SVAR is the sum of squared daily returns of the S&P 500 index. Finally, TAIL captures the probability of extreme negative market returns, and is constructed by applying a power law estimator to the entire NYSE/AMEX/NASDAQ cross-section of daily returns (share codes 10 and 11) within a given month. Data on monthly market prices, dividends, and earnings come from Robert Shiller's website. All interest rate data come from the FRED database of the Federal Reserve Bank of St. Louis. The variance premium data are obtained from Marie Hoerova's website, while the stock market variance data are obtained from Amit Goyal's website.

### 3.3 Summary statistics

The top panel of Table 1 provides descriptive statistics for the predictive variables used in this study. Note that FVF exhibits positive skewness and high excess kurtosis, while FSF exhibits slightly negative skewness and even higher kurtosis. Both variables exhibit modest first-order autocorrelation coefficients (0.64 and 0.53, respectively). RNV and RNS, on the other hand, exhibit more extreme higher moments and are also more persistent, with autocorrelation coefficients of 0.86 and 0.75, respectively. VP, SVAR and TAIL are also modestly autocorrelated, while the remainder of the predictors are highly persistent, with autocorrelation coefficients close to unity.

Figure 1 plots the estimated forward variance and forward skewness factors, together with the risk-neutral variance and risk-neutral skewness. The top panels show that both FVF and FSF exhibited several spikes during the Asian financial crisis and the Russian default. They were also quite volatile during the dot-com bubble. Both factors subsequently remained relatively stable, but experienced high volatility again during the Lehman Brothers' collapse and the ensuing European sovereign debt crisis. In general, we observe that FVF and FSF exhibit similarities across time, but their highs and lows can differ in both timing and magnitude. The bottom panels show that RNV and RNS exhibit very similar but opposite patterns. More importantly, we observe that the RNV pattern differs dramatically from that of FVF. We observe the same pattern for RNS and FSF.

The above relations are also apparent in the bottom panel of Table 1, which presents the correlation coefficients among the predictive variables. As expected, FVF and FSF are positively correlated (0.62), while RNV and RNS are very highly negatively correlated (-0.96).[9] The correlation between FVF and RNV is 0.10, and between FSF and RNS it is 0.05. It is, therefore, apparent that the information embedded in our forward moments factors differs greatly from that contained in the risk-neutral moments. FVF and FSF also exhibit very low correlations with the remainder of the predictors; the highest is the correlation between FVF and VP (0.31).

# 4 Stock Market Return Predictability

## 4.1 In-sample analysis

To gauge the predictive power of the estimated forward moments factors, we run multiple-horizon regressions of excess stock market returns of the following form:

$$r_{t,t+h} = \alpha_h + \boldsymbol{\beta}_h' \mathbf{z}_t + \varepsilon_{t,t+h}, \tag{21}$$

where $r_{t,t+h} = \left(\frac{1200}{h}\right)[r_{t+1} + r_{t+2} + ... + r_{t+h}]$ is the annualized $h$-month excess return of the CRSP value-weighted index, and $\mathbf{z}_t$ is the vector of predictors, which contains the forward moments factors FVF and FSF, the risk-neutral moments RNV and RNS, and the rest of the control variables discussed in Section 3.2. The regression analysis covers the January

[9] Recall that our skewness measure is the third moment, and is not scaled by variance. The respective correlation coefficient presented in Neuberger (2012) is -0.95.

1996-August 2015 period, and considers forecasting horizons of one, two, three, six, nine, and twelve months ahead. To avoid spurious statistical inferences stemming from overlapping observations, we use Hodrick (1992) t-statistics.[10] The beta coefficients in the subsequent tables have been scaled and can be interpreted as the percentage annualized excess market return caused by a 1-standard deviation increase in each regressor.

The univariate predictive regression results for the forward variance and forward skewness factors are reported in the first columns of Tables 2 and 3, respectively. Note that both FVF and FSF exhibit significant forecasting power, but FSF provides somewhat stronger performance than FVF. Furthermore, both factors are highly significant until the six-month horizon, but FSF continues to be significant at either the 5% or 1% significance level until the twelve-month horizon. The slope coefficients are also economically significant. For example, a 1-standard deviation increase in FVF – corresponding to a more negatively sloped forward variance term structure – predicts an annualized excess quarterly return of 10.20%. A 1-standard deviation increase in FSF – corresponding to a more U-shaped forward skewness term structure – predicts an annualized excess quarterly return of 13.34%. The economic significance gradually tapers off for horizons longer than three months ahead. The $R^2$ values show a similar hump-shaped pattern.[11] For each factor, we also test for joint statistical significance across horizons using Ang and Bekaert's (2007) $\chi^2$ test. We obtain a 0.039 p-value for the FVF, and 0.021 for FSF. Therefore, both FVF and FSF provide strong joint predictive power across all horizons considered.

Additionally, we investigate whether FSF contains any further predictive information for market returns that is not captured by FVF. We examine the predictive power of the

[10] In the Online Appendix, we provide additional statistical results using Newey and West (1987) t-statistics with a lag length equal to the maximum of 3 or (horizon $\times$ 2). We also present t-statistics stemming from a circular block bootstrap that accounts for the sampling error induced by the PLS procedure. The results are similar to those reported here.

[11] For example, the three-month-ahead $R^2$ of FVF is a sizable 8.77%, which gradually decreases for longer horizons. The three-month-ahead $R^2$ of FSF takes a high value of 14.99%, before gradually decreasing for horizons up to one year ahead. However, the long-horizon $R^2$s may be upwardly biased because of the autocorrelation of the predictor variable. Thus, in the Online Appendix, we compare the actual long-horizon $R^2$s with the implied long-horizon $R^2$s estimated following Boudoukh et al. (2008). We find that the actual long-horizon $R^2$s are generally higher than the implied ones, and for FSF the difference is substantial.

forward skewness factor orthogonalized on the forward variance factor (denoted as $\text{FSF}_{\perp}$). The univariate regression results are in the first column of Table 4. They show that $\text{FSF}_{\perp}$ is significant at either the 1% or 5% level in all cases, except for the shortest horizon of one month.[12] The joint predictability $\chi^2$ test provides a p-value of 0.136. However, when we exclude the one-month horizon, the evidence of joint predictability across horizons becomes stronger, with a p-value of 0.094. Overall, our empirical evidence demonstrates that, except for the short one-month horizon, FSF contains important information about future market returns on top of the information that is already captured by FVF.

Next, we assess the robustness of the two forward moments factors and the orthogonalized forward skewness factor to the presence of RNV, RNS, and our set of alternative economic predictors discussed in Section 3.2. The results of bivariate regressions with FVF, FSF, or $\text{FSF}_{\perp}$, and each of the alternative predictive variables, are in Tables 2, 3, and 4, respectively. We observe that FVF preserves its significance for horizons of up to six months ahead in all but one case (the VP model at the six-month horizon). Similarly, and consistent with our univariate analysis, FSF remains significant at either the 5% or 1% level in all but one case (the d-p model at the twelve-month horizon). Finally, we observe that the significance of $\text{FSF}_{\perp}$ remains largely unaffected by the inclusion of any of the alternative predictors in the forecasting model. From the remainder of the variables considered, only VP, d-p and RREL exhibit some occasionally modest predictive power. Overall, we find that the information content of the forward moments factors and the incremental information content of the forward skewness factor are not subsumed by any of the alternative predictors examined here.

The above empirical evidence, along with the economic interpretation of the forward moments factors in Equations (19)-(20), imply that a more negatively sloped forward variance term structure and a more U-shaped forward skewness term structure are associated with

[12] $\text{FSF}_{\perp}$ also provides sizable $R^2$s. For example, its three-month horizon $R^2$ takes a value of 6.81%. Similarly to the case for FSF, it gradually decreases for longer horizons. Moreover, as shown in the Online Appendix, these long-horizon $R^2$s are radically higher than the implied $R^2$s estimated following Boudoukh et al. (2008).

higher future market returns. However, it is still possible that the relative movements between certain forward variances or skewnesses are more important for forecasting purposes. To investigate this notion, we perform a predictability analysis using the actual forward moments as predictors instead of the estimated factors. Tables 5 and 6 report the results. When examining each forward variance separately, we find that all exhibit positive but insignificant predictive power for future market returns. Similarly, when examining each forward skewness separately, we find that all exhibit negative but insignificant predictive power.

In contrast, when we include all forward variances together in a multivariate model, we find that $\mathrm{FV}_{6m,9m}$ and $\mathrm{FV}_{9m,12m}$ become highly significant, while $\mathrm{FV}_{3m,6m}$ remains insignificant. Similarly, when we examine a multivariate model with the three forward skewnesses combined, we find that $\mathrm{FS}_{6m,9m}$ and $\mathrm{FS}_{9m,12m}$ become highly significant, while $\mathrm{FS}_{3m,6m}$ remains insignificant. The signs of the coefficients are in line with the evidence presented in Table 2 and Equation (19) with respect to the forward variance factor FVF, and in Table 3 and Equation (20) with respect to the forward skewness factor FSF.[13] Overall, the empirical evidence in Tables 5 and 6 corroborates the conclusions we draw with the forward moments factors. It also suggests that the movements in the long-horizon segments of the forward variance and forward skewness term structures are responsible for the forecasting ability of FVF and FSF.

## 4.2 Out-of-sample analysis

Note that, while the in-sample predictability tests exhibit higher statistical power (Inoue and Kilian, 2004), an examination of the out-of-sample (OS) predictive power of the forward moments factors is of particular importance. First, OS predictability tests avoid potential overfitting problems (Goyal and Welch, 2003, 2008). Second, their forecasts only employ

[13]Recall that, as shown in Tables 2 and 3, FVF and FSF are both positive stock return predictors. Equation (19) shows that $\mathrm{FV}_{6m,9m}$ ($\mathrm{FV}_{9m,12m}$) contributes positively (negatively) to the FVF factor. Consistent with this, Table 5 demonstrates that it also positively (negatively) predicts future stock returns. In an analogous manner, Equation (20) shows that $\mathrm{FS}_{6m,9m}$ ($\mathrm{FS}_{9m,12m}$) contributes negatively (positively) to the FSF factor, and Table 6 demonstrates that, as expected, it also negatively (positively) predicts future stock returns.

data available to investors in real time. Third, they are not affected by the small-sample biases of the PLS method, as discussed in Kelly and Pruitt (2013). Therefore, in this section, we evaluate the OS performance of the forward moments factors for one-, two-, three-, six-, nine-, and twelve-month horizons.

Following Goyal and Welch (2003, 2008), Campbell and Thompson (2008), and Kelly and Pruitt (2013), among others, we estimate the model in Equation (21) recursively using observations from 1 to $s$, where $s < T$, and $T$ is the total number of monthly observations. Next, based on the estimated parameters, and for each time period $s = s_0, ..., T-h$, where $h$ is the forecasting horizon, we form the OS forecasts for the expected excess market return using the concurrent values of the predictive variables examined:

$$\widehat{r}_{s,s+h} = \widehat{\alpha}_s + \widehat{\boldsymbol{\beta}}_s' \mathbf{z}_s. \tag{22}$$

We thus create $T_{OS} = T - s - h + 1$ number of OS forecasts beginning from January 2000. It is important to note that, when the predictive variable is one of the forward moments factors, the PLS method is recursively performed. Each time, it only uses data that are known at time $s$. We compare the OS forecasts of each predictive model to those of a restricted model that only has a constant as a regressor, and thus captures the recursively estimated historical average (HAV). We also investigate the incremental OS forecasting power of FSF by comparing the model with both FVF and FSF to a model that includes only FVF. The OS predictive performance of each model is then assessed via the OS $R^2$ of Goyal and Welch (2008), the MSE-F test of McCracken (2007), and the MSE-adjusted test of Clark and West (2007). Appropriate critical values based on Monte Carlo simulations for McCracken's (2007) MSE-F test are provided by the author.

Table 7 gives results for the OS predictive models. Note that FVF exhibits positive $R^2_{OS}$ values for horizons up to six months ahead, ranging from 0.45% to 2.30%. Moreover, the outperformance of the unrestricted model based on FVF for those horizons is statistically significant overall. In a similar vein, FSF exhibits positive and even larger $R^2_{OS}$ values, ranging from 0.72% to 4.08%, for all horizons up to nine months ahead. The outperformance of the FSF model compared to the HAV model for those horizons is also statistically significant in the majority of cases. The above results from the univariate OS predictability tests corroborate the in-sample empirical evidence presented in Section 4.1. Both forward moments factors exhibit significant forecasting power for future market returns, with FSF typically having stronger power than FVF.

Next, we observe that, when compared to the FVF model, the bivariate model that includes both FVF and FSF exhibits consistently positive $R^2_{OS}$ values. Its outperformance is significant at the 5% level in all cases for horizons up to nine months ahead. This finding again corroborates the conclusion in Section 4.1 that FSF contains significant incremental forecasting power for future market returns over FVF. Finally, VP is the only alternative predictor that exhibits consistently good OS forecasting performance, albeit typically weaker than that of the forward moments factors. RNS and d-p also exhibit occasionally positive $R^2_{OS}$s but the statistical significance of the respective models remains limited. Therefore, we conclude that the OS forecasting power of the forward moments factors is stronger than that of the simple risk-neutral moments or of the alternative stock return predictors.

## 4.3 Asset allocation

In this section, we gauge the economic significance of the documented out-of-sample predictive power of the forward moments factors. Following Campbell and Thompson (2008) and Ferreira and Santa-Clara (2011), among others, we create a market-timing strategy that relies on the OS forecasting power of the estimated factors and the alternative predictors. We focus on horizons from one to three months ahead, because the empirical evidence from the previous sections suggests that the forecasting ability of the forward moments factors is concentrated primarily within short horizons.

We consider a mean-variance investor who allocates wealth every month between the market index and the risk-free asset. At the end of each month $s$, the investor makes a forecast for the future excess market return using the procedure described in Section 4.2.[14] (S)he then forms an estimate of the market return variance using all available data up to time $s$. Based on these estimates, the investor forms the portfolio weights as follows:

$$\omega_s = \frac{\widehat{r}_{s,s+h}}{\gamma \widehat{\sigma}^2_{s,s+h}}, \tag{23}$$

where $\widehat{r}_{s,s+h}$ is the OS forecast of the excess stock market return, $\gamma$ is the risk aversion coefficient, set equal to 3, and $\widehat{\sigma}^2_{s,s+h}$ is the estimate of the variance of the stock market return, computed as the historical variance for the period 1 to $s$. Following Campbell and Thompson (2008), we impose realistic leverage values by constraining the portfolio weight on the market index $\omega_s$ to lie between 0 and 1.5.

The realized return from the above market-timing strategy can thus be represented by:

$$R_{p;s,s+h} = \omega_s R_{m;s,s+h} + (1 - \omega_s) R_{f;s,s+h}, \tag{24}$$

where $R_{m;s,s+h}$ denotes the simple market return, and $R_{f;s,s+h}$ denotes the return of the riskless asset. Iterating this procedure forward, we create a series of realized portfolio returns based on the OS forecasting power of each forecasting model. We then compare each strategy with a strategy based on the recursively estimated historical average (HAV) and a strategy that buys and holds the market portfolio (BH).

For each trading strategy, we estimate the Sharpe ratio (SR), the certainty equivalent return in excess of the HAV and the BH strategies ($\Delta$CER-HAV and $\Delta$CER-BH, respectively), and the maximum drawdown (MD). $\Delta$CER essentially represents the change in the investor's utility that results from the choice to follow the predictive regression strategy instead of the benchmark strategy. Maximum drawdown represents the maximum loss an investor can incur when entering the strategy at any time during its implementation period. All measures except MD are in annualized terms.

[14] In this section, the term return refers to simple returns, not logarithmic returns.

The results from the asset allocation exercise are in Table 8. We observe that the FVF trading strategy exhibits Sharpe ratios ranging from 0.25 to 0.32, while those for the FSF strategy range from 0.21 to 0.36. Regardless of the horizon examined, these Sharpe ratios are consistently higher than the respective ratios of the HAV strategy, which range from 0.07 to 0.10. In the same vein, both the FVF and FSF strategies exhibit consistently positive $\Delta$CER-HAVs. The BH strategy performs much better than the HAV strategy, providing Sharpe ratios that range between 0.34 and 0.36. These values are always at least as high as the Sharpe ratios of the forward moments strategies. Similarly, the FVF strategy provides a positive $\Delta$CER-BH only for the one-month horizon, while the FSF strategy exhibits a negative $\Delta$CER-BH for the one-month horizon, but positive $\Delta$CER-BHs for longer horizons. Collectively, the results show that the two forward moments strategies always perform better than the HAV strategy, but not better than the BH strategy. However, it is noteworthy that FVF and FSF exhibit the consistently lowest maximum drawdown values (in absolute terms) across the examined strategies. Therefore, even when they do not outperform the BH strategy, they can help mitigate its downside risk.

The strategies based on FVF and FSF compare well to those based on the alternative predictors. More specifically, d-p and RREL are the only variables that generally outperform the forward moments factors and the HAV and BH strategies. The d-e strategy also exhibits good performance, but it underperforms the forward moments strategies at the two- and three-month horizons. The two risk-neutral moments and the rest of the alternative predictors always provide inferior economic gains than FVF and FSF. Moreover, all the alternative predictors exhibit higher MD values (in absolute terms) than FVF or FSF. Overall, the results show that the forward moments factors outperform most of the alternative predictors in terms of economic significance.

# 5 Stock Market Excess Variance Predictability

A series of recent papers, including Bollerslev et al. (2009), Bekaert and Hoerova (2014), and Bollerslev et al. (2014), have investigated the predictive power of the variance risk premium for future market returns. And Feunou et al. (2014) show that, within the framework provided in Section 2.1, the variance risk premium over an investment horizon $\tau$, $VP(\tau)$, should be an affine function of the same state variables, $X_t$, that drive the equity premium:

$$VP_t(\tau) = Var_t^{\mathbb{Q}}[r_{t,t+\tau}] - Var_t^{\mathbb{P}}[r_{t,t+\tau}] = \beta_{vp,0}(\tau) + \beta_{vp}(\tau)^{\top} X_t. \tag{25}$$

In light of this finding, this section investigates whether the forward moments factors used in the previous sections, which are designed to predict market returns, can also exhibit significant forecasting power for the ex-post excess variance of the equity market. This is estimated as the difference between the risk-neutral variance extracted from S&P 500 index option prices, and the S&P 500 index realized variance of the respective horizon. Realized variance data come from Hao Zhou's website. In the predictability exercise, we consider three variables as alternative predictors of excess variance. These are the squared VIX (VIX$^2$), the conditional variance estimate of Bekaert and Hoerova (2014) (CV), and the lagged excess variance of each forecasting horizon (LagEV).[15] Conditional variance data are obtained from Marie Hoerova's website.

Similarly to Sections 4.1 and 4.2, we focus on one-, two-, three-, six-, nine-, and twelve-month horizon predictive regressions. Results from in-sample predictability tests are in Table 9. The top panel reports univariate results for FVF, FSF and the orthogonalized forward skewness factor, FSF$_{\perp}$, while the middle (bottom) panel reports bivariate results for a model that includes FVF (FSF) and each of the alternative predictors. We report Newey and West (1987) t-statistics with a lag length equal to the maximum of 3 or (horizon $\times$ 2). Hodrick

[15] For example, when examining two-month-ahead predictability, the excess variance of January-February is used to predict the excess variance of March-April, the excess variance of February-March is used to predict the excess variance of April-May, and so on.

(1992) t-statistics rely heavily on an assumption of no autocorrelation in non-overlapping observations, and hence are not suitable for excess variance predictability.[16]

The first rows in the top panel show that, similarly to excess market returns, FVF is a strong predictor of excess market variance. In particular, it is always significant at either the 5% or 1% significance level for horizons up to six months ahead. A similar significance, albeit lower for short horizons, and slightly higher but marginally significant for longer horizons, is also apparent for FSF. For both factors, the regression coefficients are economically significant. For example, a 1-standard deviation increase in FVF (FSF) forecasts an annualized monthly excess variance of 1.20% (0.93%). The $R^2_{OS}$s achieve their maximum values at the one-month horizon, and gradually taper off as the horizon increases. In the final rows of the top panel, we assess the incremental forecasting power of the forward skewness factor by presenting in-sample regression results for $\text{FSF}_{\perp}$. Note that $\text{FSF}_{\perp}$ does not provide any statistical significance. We thus conclude that, while both FVF and FSF provide significant in-sample forecasting power for excess variance, FSF does not contain any predictive information beyond what is already captured by FVF.

The middle panel reports the bivariate results for FVF. We observe that both $\text{VIX}^2$ and CV exhibit strong predictive power especially at long horizons. The forecasting power of FVF is reduced in these models (especially when $\text{VIX}^2$ is the alternative predictor) but remains largely significant. LagEV exhibits only limited predictive power and only at the 1-month horizon. Consequently, its inclusion in the predictive model hardly affects the significance of FVF. The bottom panel reports the respective results for FSF. Similarly to the case of FVF, the predictive power of FSF is weakened when considering the bivariate model with $\text{VIX}^2$ but remains statistically significant. On the other hand, FSF becomes even stronger predictor when combined with CV. Finally, controlling for LagEV reduces the forecasting power of FSF at the 1-month horizon but leaves it unaffected at longer horizons.

Table 10 shows that the forward moments factors are also strong out-of-sample predictors

[16]The one-month-ahead excess variance has a first-order autocorrelation of 0.27, which is statistically significant.

for excess variance. The $R^2_{OS}$ values are positive and significant at the 5% level in all cases for horizons up to six months ahead. Similarly to that for the in-sample analysis, FVF provides stronger OS performance for short horizons, while FSF offers some OS predictive power for the nine- and twelve-month horizons. However, we observe that the performance of a predictive bivariate model, which relies on both FVF and FSF together, shows little or no improvement compared to a FVF-only model. Additionally, the OS performance of the bivariate model is not significantly better than that of the FVF model. This evidence is in line with the results in Table 9. It provides further confirmation that, while both factors are successful predictors of excess variance, FSF does not provide any additional predictive information over FVF. $\text{VIX}^2$ is the only alternative variable that provides significant OS predictive power. Its performance becomes very strong at long horizons, but it is clearly lower than that of FVF and FSF for horizons of one up to three months ahead. Therefore, we conclude that the forward moments factors are the strongest excess variance predictors at short horizons.

# 6 Conclusion

In this paper, we create forward skewnesses for the stock market, in addition to forward variances, and we explore the joint information content of forward moments for stock market excess returns and excess variance. Our predictability analysis is motivated within the context of affine jump-diffusion models, where the forward moments exhibit a factor structure, and both the equity and variance risk premia are affine functions of the same state variables. To this end, we use the Partial Least Squares methodology to extract a single factor from each term structure that is most relevant for forecasting the one-month-ahead market return. We find that the estimated forward variance factor mainly captures the slope of the forward variance term structure, while the estimated forward skewness factor is related mainly to the curvature of the forward skewness term structure.

Empirically, we show that both factors exhibit strong in- and out-of-sample predictive power for stock market returns. In particular, a more negatively sloped forward variance term structure and a more U-shaped forward skewness term structure are associated with higher future returns. We also find that the documented predictive pattern is driven by movements in the long-horizon segments of the respective term structures. Understanding the economic determinants of the above relations would require a theoretical model where the underlying risk factors are explicitly specified. This is beyond the scope of the paper and is left for future research.

Further evidence shows that the two forward moments factors are robust to and outperform, in terms of predictive power, the risk-neutral variance and skewness, as well as a wide range of traditional predictors. More importantly, we document that the forward skewness factor provides stronger forecasting ability for market returns than the forward variance factor. It also captures important predictive information that is not included in the forward variance factor. Therefore, our study contributes to the literature investigating the asset pricing implications of investors' skewness expectations by highlighting the unique information content of the equity premium that is encapsulated in the term structure of forward skewness.

Finally, we document that the same forward moments factors that are designed to predict market returns also exhibit strong predictive power for market excess variance. However, the forward skewness factor typically performs worse than the forward variance factor. It also does not provide any incremental forecasting power over what is offered by the forward variance factor.

# References


[1] Ang, A., and G. Bekaert. 2007. Stock return predictability: Is it there? Review of Financial Studies 20, 651-707.

[2] Bakshi, G., and D. Madan. 2000. Spanning and derivative-security valuation. Journal of Financial Economics 55, 205-238.

[3] Bakshi, G., G. Panayotov, and G. Skoulakis. 2011. Improving the predictability of real economic activity and asset returns with forward variances inferred from option portfolios. Journal of Financial Economics 100, 475-495.

[4] Bansal, R., and A. Yaron. 2004. Risks for the long run: A potential resolution of asset pricing puzzles. Journal of Finance 59, 1481-1509.

[5] Battalio, R., and P. Schultz. 2006. Options and the bubble. Journal of Finance 61, 2071-2102.

[6] Bekaert, G., and E. Engstrom. 2017. Asset return dynamics under habits and bad environment-good environment fundamentals. Journal of Political Economy 125, 713-760.

[7] Bekaert, G., E. Engstrom, and Y. Xing. 2009. Risk, uncertainty, and asset prices. Journal of Financial Economics 91, 59-82.

[8] Bekaert, G., E. Engstrom, and N. R. Xu. 2019. The time variation in risk appetite and uncertainty. Working paper.

[9] Bekaert, G., and M. Hoerova. 2014. The VIX, the variance premium and stock market volatility. Journal of Econometrics 183, 181-192.

[10] Bollerslev, T., J. Marrone, L. Xu, and H. Zhou. 2014. Stock return predictability and variance risk premia: Statistical inference and international evidence. Journal of Financial and Quantitative Analysis 49, 633-661.

[11] Bollerslev, T., G. Tauchen, and H. Zhou. 2009. Expected stock returns and variance risk premia. Review of Financial Studies 22, 4463-4492.

[12] Boudoukh, J., M. Richardson, and R. Whitelaw. 2008. The myth of long-horizon predictability. Review of Financial Studies 21, 1577-1605.

[13] Buss, A., and G. Vilkov. 2012. Measuring equity risk with option-implied correlations. Review of Financial Studies 25, 3113-3140.

[14] Campbell, J. Y. 1991. A variance decomposition for stock returns. Economic Journal 101, 157-179.

[15] Campbell, J. Y., and S. Thompson. 2008. Predicting excess stock returns out of sample: Can anything beat the historical average? Review of Financial Studies 21, 1509-1531.

[16] Carr, P., and R. Lee. 2008. Robust replication of volatility derivatives. Working paper.

[17] Carr, P., and D. Madan. 2001. Optimal positioning in derivative securities. Quantitative Finance 1, 19-37.

[18] Chabi-Yo, F., and J. A. Loudis. 2019. The conditional expected market return. Journal of Financial Economics, forthcoming.

[19] Christoffersen, P., R. Elkamhi, B. Feunou, and K. Jacobs. 2010. Option valuation with conditional heteroskedasticity and nonnormality. Review of Financial Studies 23, 2139-2183.

[20] Clark, T., and K. West. 2007. Approximately normal tests for equal predictive accuracy in nested models. Journal of Econometrics 138, 291-311.

[21] Colacito, R., E. Ghysels, J. Meng, and W. Siwasarit. 2016. Skewness in expected macro fundamentals and the predictability of equity returns: Evidence and theory. Review of Financial Studies 29, 2069-2109.

[22] DeMiguel, V., Y. Plyakha, R. Uppal, and G. Vilkov. 2013. Improving portfolio selection using option-implied volatility and skewness. Journal of Financial and Quantitative Analysis 48, 1813-1845.

[23] Drechsler, I. and A. Yaron. 2011. What's vol got to do with it. Review of Financial Studies 24, 1-45.

[24] Eraker, B. 2008. Affine general equilibrium models. Management Science 54, 2068-2080.

[25] Fama, E., and K. R. French. 1988. Dividend yields and expected stock returns. Journal of Financial Economics 22, 3-25.

[26] Fama, E., and K. R. French. 1989. Business conditions and expected returns on stocks and bonds. Journal of Financial Economics 25, 23-49.

[27] Ferreira, M. A., and P. Santa-Clara. 2011. Forecasting stock market returns: The sum of the parts is more than the whole. Journal of Financial Economics 100, 514-537.

[28] Feunou, B., J.-S. Fontaine, A. Taamouti, and R. Tédongap. 2014. Risk premium, variance premium, and the maturity structure of uncertainty. Review of Finance 18, 219-269.

[29] Feunou, B., M. R. Jahan-Parvar, and C. Okou. 2018. Downside variance risk premium. Journal of Financial Econometrics 16, 341-383.

[30] Gouriéroux, C., and A. Monfort. 2007 Econometric specification of stochastic discount factor models. Journal of Econometrics 136, 509-530.

[31] Goyal, A., and I. Welch. 2003. Predicting the equity premium with dividend ratios. Management Science 49, 639-654.

[32] Goyal, A., and I. Welch. 2008. A comprehensive look at the empirical performance of equity premium prediction. Review of Financial Studies 21, 1455-1508.

[33] Guo, H. 2006. On the out-of-sample predictability of stock returns. Journal of Business 79, 645-670.

[34] Hodrick, R. J. 1992. Dividend yields and expected stock returns: Alternative procedures for inference and measurement. Review of Financial Studies 2, 357-386.

[35] Inoue, A., and L. Kilian. 2004. In-sample or out-of-sample tests of predictability: Which one should we use? Econometric Reviews 23, 371-402.

[36] Kelly, B., and H. Jiang. 2014. Tail risk and asset prices. Review of Financial Studies 27, 2841-2871.

[37] Kelly, B., and S. Pruitt. 2013. Market expectations in the cross-section of present values. Journal of Finance 68, 1721-1756.

[38] Kelly, B., and S. Pruitt. 2015. The three-pass regression filter: A new approach to forecasting using many predictors. Journal of Econometrics 186, 294-316.

[39] Kozhan, R., A. Neuberger, and P. Schneider. 2013. The skew risk premium in the equity index market. Review of Financial Studies 26, 2174-2203.

[40] Lamont, O. 1998. Earnings and expected returns. Journal of Finance 53, 1563-1587.

[41] Lettau, M. and J. A. Wachter. 2011. The term structures of equity and interest rates. Journal of Financial Economics 101, 90-113.

[42] Luo, X., and J. E. Zhang. 2017. Expected stock returns and forward variance. Journal of Financial Markets 34, 95-117.

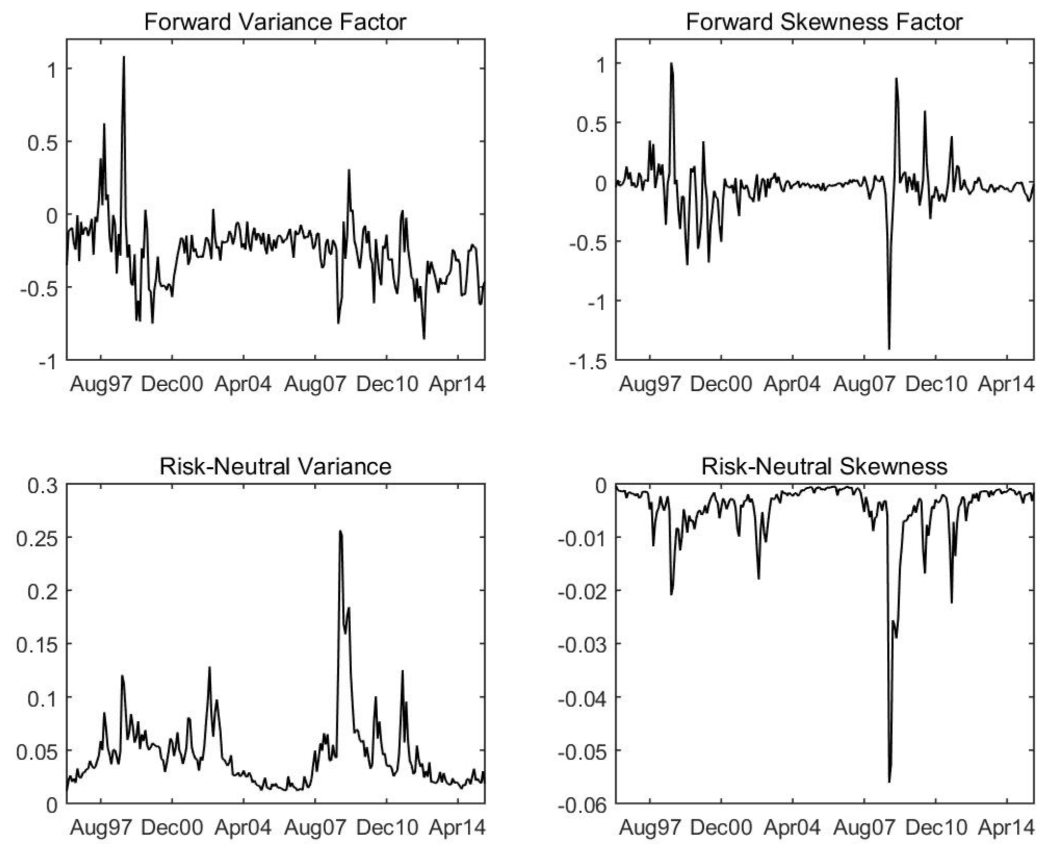
[43] McCracken, M. 2007. Asymptotics for out of sample tests of Granger causality. Journal of Econometrics 140, 719-752.

[44] Neuberger, A. 2012. Realized skewness. Review of Financial Studies 25, 3423-3455.

[45] Newey, W., and K. West. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703-708.

[46] Pohl W., K. Schmedders, and O. Wilms. 2018. Higher-order effects in asset-pricing models with long-run risks. Journal of Finance 73, 1061-1111.

Figure 1: Forward moments factors and risk-neutral moments




This figure plots the monthly time series of the forward variance factor, forward skewness factor, risk-neutral variance and risk-neutral skewness for the period January 1996 to August 2015.

Table 1: Summary statistics

| | FVF | FSF | RNV | RNS | VP | d-p | d-e | DEF | RREL | SVAR | TAIL |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Descriptive statistics | | | | | | | | | | | |
| Mean | -0.25 | -0.04 | 0.05 | -0.01 | 18.64 | -4.03 | -0.88 | 0.01 | -0.00 | 0.00 | 0.42 |
| Median | -0.24 | -0.03 | 0.04 | -0.00 | 13.92 | -4.02 | -1.01 | 0.01 | -0.00 | 0.00 | 0.42 |
| Maximum | 1.09 | 1.01 | 0.26 | -0.00 | 88.59 | -3.32 | 1.38 | 0.03 | 0.01 | 0.06 | 0.51 |
| Minimum | -0.86 | -1.41 | 0.01 | -0.06 | -2.65 | -4.50 | -1.24 | 0.01 | -0.03 | 0.00 | 0.29 |
| St. Dev. | 0.22 | 0.21 | 0.04 | 0.01 | 16.26 | 0.22 | 0.46 | 0.00 | 0.01 | 0.01 | 0.04 |
| Skewness | 1.18 | -0.14 | 2.80 | -4.55 | 1.95 | 0.09 | 3.21 | 2.97 | -0.96 | 6.27 | -0.47 |
| Kurtosis | 9.74 | 17.05 | 14.22 | 30.46 | 7.65 | 3.78 | 14.06 | 13.94 | 4.39 | 54.92 | 3.41 |
| $\rho(1)$ | 0.64 | 0.53 | 0.86 | 0.75 | 0.70 | 0.98 | 0.98 | 0.96 | 0.97 | 0.70 | 0.55 |
| Correlation coefficients | | | | | | | | | | | |
| FVF | 1.00 | | | | | | | | | | |
| FSF | 0.62 | 1.00 | | | | | | | | | |
| RNV | 0.10 | -0.03 | 1.00 | | | | | | | | |
| RNS | -0.09 | 0.05 | -0.96 | 1.00 | | | | | | | |
| VP | 0.31 | 0.28 | 0.77 | -0.70 | 1.00 | | | | | | |
| d-p | 0.07 | 0.18 | 0.26 | -0.33 | 0.14 | 1.00 | | | | | |
| d-e | 0.13 | 0.11 | 0.58 | -0.50 | 0.53 | 0.47 | 1.00 | | | | |
| DEF | -0.04 | -0.03 | 0.69 | -0.68 | 0.47 | 0.60 | 0.74 | 1.00 | | | |
| RREL | -0.03 | 0.02 | -0.44 | 0.35 | -0.39 | -0.16 | -0.44 | -0.41 | 1.00 | | |
| SVAR | -0.01 | -0.26 | 0.83 | -0.86 | 0.41 | 0.29 | 0.38 | 0.59 | -0.34 | 1.00 | |
| TAIL | 0.10 | 0.05 | -0.44 | 0.44 | -0.25 | -0.03 | -0.10 | -0.30 | 0.01 | -0.44 | 1.00 |

This table reports descriptive statistics (top panel) and the correlation coefficients (bottom panel) of the forecasting variables used in the study. The forecasting variables are the forward variance factor (FVF), the forward skewness factor (FSF), risk-neutral variance (RNV), risk-neutral skewness (RNS), the variance premium (VP), the dividend-price ratio (d-p), the dividend-payout ratio (d-e), the default spread (DEF), the relative short-term risk-free rate (RREL), stock market variance (SVAR), and tail risk (TAIL). The sample period is January 1996-August 2015. $\rho(1)$ is the first-order autocorrelation coefficient.

Table 2: In-sample predictive power of forward variance factor for equity market excess returns

| | Univariate Model | Bivariate Models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | RNV | RNS | VP | d-p | d-e | DEF | RREL | SVAR | TAIL |
| | | | | | 1-month horizon | | | | | |
| FVF | 11.85 | 12.04 | 11.84 | 10.41 | 11.43 | 11.90 | 11.77 | 12.07 | 11.84 | 11.68 |
| | ( 2.63)*** | ( 2.59)** | ( 2.63)*** | ( 2.27)** | ( 2.53)** | ( 2.61)*** | ( 2.62)*** | ( 2.67)*** | ( 2.63)*** | ( 2.60)*** |
| Z | | -1.69 | -0.20 | 4.58 | 5.59 | -0.34 | -2.17 | 7.35 | -8.86 | 1.76 |
| | | (-0.29) | (-0.04) | ( 0.87) | ( 1.12) | (-0.06) | (-0.38) | ( 1.87)* | (-1.24) | ( 0.40) |
| $R^2$ (%) | 4.48 | 4.57 | 4.48 | 5.08 | 5.47 | 4.48 | 4.63 | 6.20 | 6.98 | 4.58 |
| | | | | | 2-month horizon | | | | | |
| FVF | 10.52 | 10.48 | 10.33 | 9.17 | 10.04 | 10.44 | 10.47 | 10.74 | 10.51 | 10.69 |
| | ( 2.96)*** | ( 2.90)*** | ( 2.91)*** | ( 2.54)** | ( 2.83)*** | ( 2.92)*** | ( 2.94)*** | ( 3.01)*** | ( 2.96)*** | ( 3.01)*** |
| Z | | 0.46 | -2.32 | 4.32 | 6.15 | 0.66 | -1.39 | 7.50 | -5.15 | -1.61 |
| | | ( 0.09) | (-0.49) | ( 0.93) | ( 1.26) | ( 0.13) | (-0.25) | ( 1.93)* | (-0.98) | (-0.43) |
| $R^2$ (%) | 6.35 | 6.36 | 6.66 | 7.32 | 8.51 | 6.37 | 6.46 | 9.57 | 7.87 | 6.50 |
| | | | | | 3-month horizon | | | | | |
| FVF | 10.20 | 10.13 | 10.08 | 8.60 | 9.69 | 10.02 | 10.19 | 10.42 | 10.18 | 10.37 |
| | ( 3.40)*** | ( 3.31)*** | ( 3.34)*** | ( 2.70)*** | ( 3.25)*** | ( 3.32)*** | ( 3.39)*** | ( 3.47)*** | ( 3.40)*** | ( 3.51)*** |
| Z | | 0.66 | -1.44 | 5.11 | 6.28 | 1.34 | -0.22 | 7.61 | -4.93 | -1.62 |
| | | ( 0.13) | (-0.29) | ( 1.15) | ( 1.29) | ( 0.28) | (-0.04) | ( 1.92)* | (-1.00) | (-0.48) |
| $R^2$ (%) | 8.77 | 8.81 | 8.94 | 10.75 | 12.07 | 8.92 | 8.77 | 13.64 | 10.82 | 8.99 |
| | | | | | 6-month horizon | | | | | |
| FVF | 6.14 | 5.81 | 5.75 | 4.31 | 5.46 | 5.76 | 6.22 | 6.32 | 6.13 | 6.29 |
| | ( 2.46)** | ( 2.24)** | ( 2.25)** | ( 1.56) | ( 2.19)** | ( 2.26)** | ( 2.51)** | ( 2.53)** | ( 2.47)** | ( 2.67)*** |
| Z | | 3.53 | -4.94 | 5.96 | 7.51 | 2.74 | 1.95 | 7.52 | -0.04 | -1.29 |
| | | ( 0.81) | (-1.13) | ( 1.75)* | ( 1.62) | ( 0.66) | ( 0.40) | ( 1.78)* | (-0.01) | (-0.45) |
| $R^2$ (%) | 5.67 | 7.53 | 9.32 | 10.52 | 14.10 | 6.78 | 6.24 | 14.19 | 5.67 | 5.92 |
| | | | | | 9-month horizon | | | | | |
| FVF | 4.04 | 3.72 | 3.69 | 2.72 | 3.32 | 3.66 | 4.15 | 4.23 | 4.06 | 3.91 |
| | ( 1.82)* | ( 1.62) | ( 1.63) | ( 1.12) | ( 1.51) | ( 1.61) | ( 1.88)* | ( 1.90)* | ( 1.83)* | ( 1.90)* |
| Z | | 3.42 | -4.53 | 4.31 | 8.04 | 2.79 | 2.61 | 7.42 | 1.49 | 1.10 |
| | | ( 0.97) | (-1.35) | ( 1.55) | ( 1.83)* | ( 0.76) | ( 0.61) | ( 1.69)* | ( 0.42) | ( 0.42) |
| $R^2$ (%) | 3.56 | 6.08 | 8.00 | 7.22 | 17.53 | 5.22 | 5.04 | 15.53 | 4.04 | 3.82 |
| | | | | | 12-month horizon | | | | | |
| FVF | 3.35 | 3.09 | 3.07 | 2.25 | 2.59 | 2.96 | 3.49 | 3.51 | 3.37 | 3.08 |
| | ( 1.42) | ( 1.28) | ( 1.28) | ( 0.89) | ( 1.11) | ( 1.23) | ( 1.49) | ( 1.49) | ( 1.43) | ( 1.41) |
| Z | | 2.86 | -3.68 | 3.59 | 8.30 | 2.87 | 3.26 | 6.45 | 1.61 | 2.19 |
| | | ( 0.96) | (-1.34) | ( 1.46) | ( 1.96)* | ( 0.84) | ( 0.86) | ( 1.49) | ( 0.56) | ( 0.90) |
| $R^2$ (%) | 3.14 | 5.41 | 6.91 | 6.41 | 22.26 | 5.40 | 6.11 | 14.79 | 3.86 | 4.46 |

This table reports the in-sample results for predictive regressions of the CRSP value-weighted index excess return. The univariate models include the forward variance factor (FVF); the bivariate models include the FVF and each of the alternative predictors Z used in the study. The alternative forecasting variables are risk-neutral variance (RNV), risk-neutral skewness (RNS), the variance premium (VP), the dividend-price ratio (d-p), the dividend-payout ratio (d-e), the default spread (DEF), the relative short-term risk-free rate (RREL), stock market variance (SVAR), and tail risk (TAIL). The sample period is January 1996-August 2015. Reported coefficients indicate the percentage of annualized excess return resulting from a 1-standard deviation increase in each predictor variable. Hodrick (1992) t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: In-sample predictive power of forward skewness factor for equity market excess returns

| | Univariate Model | Bivariate Models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | RNV | RNS | VP | d-p | d-e | DEF | RREL | SVAR | TAIL |
| | 1-month horizon | | | | | | | | | |
| FVF | 12.55 | 12.55 | 12.66 | 11.22 | 11.75 | 12.56 | 12.48 | 12.38 | 11.01 | 12.42 |
| | ( 2.21)** | ( 2.22)** | ( 2.23)** | ( 1.97)* | ( 1.98)** | ( 2.20)** | ( 2.20)** | ( 2.19)** | ( 2.02)** | ( 2.19)** |
| Z | | -0.01 | -1.94 | 4.67 | 4.27 | -0.14 | -2.27 | 6.67 | -6.11 | 2.24 |
| | | (-0.00) | (-0.35) | ( 0.92) | ( 0.82) | (-0.03) | (-0.40) | ( 1.72)* | (-0.87) | ( 0.51) |
| $R^2$ (%) | 5.02 | 5.02 | 5.14 | 5.66 | 5.58 | 5.02 | 5.18 | 6.43 | 6.13 | 5.18 |
| | 2-month horizon | | | | | | | | | |
| FVF | 12.93 | 12.99 | 13.15 | 11.84 | 12.06 | 12.86 | 12.89 | 12.76 | 12.41 | 13.00 |
| | ( 2.87)*** | ( 2.88)*** | ( 2.89)*** | ( 2.61)*** | ( 2.61)*** | ( 2.86)*** | ( 2.86)*** | ( 2.84)*** | ( 2.69)*** | ( 2.87)*** |
| Z | | 1.95 | -3.94 | 3.81 | 4.70 | 0.63 | -1.42 | 6.86 | -2.07 | -1.24 |
| | | ( 0.39) | (-0.83) | ( 0.84) | ( 0.94) | ( 0.13) | (-0.25) | ( 1.77)* | (-0.38) | (-0.33) |
| $R^2$ (%) | 9.59 | 9.81 | 10.47 | 10.35 | 10.81 | 9.61 | 9.70 | 12.28 | 9.82 | 9.67 |
| | 3-month horizon | | | | | | | | | |
| FVF | 13.34 | 13.40 | 13.51 | 12.09 | 12.45 | 13.20 | 13.33 | 13.16 | 12.90 | 13.41 |
| | ( 3.51)*** | ( 3.53)*** | ( 3.55)*** | ( 3.05)*** | ( 3.17)*** | ( 3.44)*** | ( 3.51)*** | ( 3.47)*** | ( 3.39)*** | ( 3.52)*** |
| Z | | 2.12 | -3.05 | 4.35 | 4.74 | 1.23 | -0.24 | 6.97 | -1.74 | -1.29 |
| | | ( 0.44) | (-0.62) | ( 0.99) | ( 0.95) | ( 0.26) | (-0.04) | ( 1.77)* | (-0.35) | (-0.38) |
| $R^2$ (%) | 14.99 | 15.37 | 15.77 | 16.45 | 16.82 | 15.12 | 14.99 | 19.08 | 15.23 | 15.13 |
| | 6-month horizon | | | | | | | | | |
| FVF | 8.47 | 8.62 | 8.82 | 6.97 | 7.21 | 8.18 | 8.53 | 8.28 | 9.03 | 8.54 |
| | ( 3.36)*** | ( 3.48)*** | ( 3.58)*** | ( 2.39)** | ( 2.66)*** | ( 3.10)*** | ( 3.43)*** | ( 3.30)*** | ( 3.88)*** | ( 3.46)*** |
| Z | | 4.37 | -5.90 | 5.31 | 6.64 | 2.62 | 1.95 | 7.14 | 2.18 | -1.05 |
| | | ( 1.02) | (-1.37) | ( 1.52) | ( 1.39) | ( 0.63) | ( 0.40) | ( 1.70)* | ( 0.48) | (-0.36) |
| $R^2$ (%) | 10.81 | 13.68 | 16.04 | 14.71 | 17.20 | 11.83 | 11.38 | 18.48 | 11.48 | 10.97 |
| | 9-month horizon | | | | | | | | | |
| FVF | 5.71 | 5.85 | 6.02 | 4.63 | 4.28 | 5.41 | 5.79 | 5.51 | 6.50 | 5.63 |
| | ( 2.94)*** | ( 3.06)*** | ( 3.16)*** | ( 2.03)** | ( 2.10)** | ( 2.64)*** | ( 3.03)*** | ( 2.86)*** | ( 3.50)*** | ( 3.02)*** |
| Z | | 3.98 | -5.18 | 3.84 | 7.53 | 2.69 | 2.61 | 7.16 | 3.10 | 1.21 |
| | | ( 1.15) | (-1.56) | ( 1.34) | ( 1.67)* | ( 0.72) | ( 0.61) | ( 1.63) | ( 0.87) | ( 0.45) |
| $R^2$ (%) | 7.09 | 10.53 | 12.90 | 10.04 | 18.98 | 8.65 | 8.57 | 18.25 | 9.05 | 7.41 |
| | 12-month horizon | | | | | | | | | |
| FVF | 4.38 | 4.49 | 4.63 | 3.44 | 2.86 | 4.07 | 4.47 | 4.21 | 5.11 | 4.23 |
| | ( 2.49)** | ( 2.59)** | ( 2.67)*** | ( 1.71)* | ( 1.62) | ( 2.23)** | ( 2.58)** | ( 2.42)** | ( 2.95)*** | ( 2.55)** |
| Z | | 3.29 | -4.19 | 3.30 | 7.99 | 2.82 | 3.24 | 6.25 | 2.86 | 2.30 |
| | | ( 1.13) | (-1.55) | ( 1.31) | ( 1.86)* | ( 0.82) | ( 0.85) | ( 1.45) | ( 0.98) | ( 0.91) |
| $R^2$ (%) | 5.37 | 8.40 | 10.26 | 8.17 | 22.60 | 7.56 | 8.30 | 16.30 | 7.51 | 6.84 |

This table reports the in-sample results for predictive regressions of the CRSP value-weighted index excess return. The univariate models include the forward skewness factor (FSF); the bivariate models include the FSF and each of the alternative predictors Z used in the study. The alternative forecasting variables are risk-neutral variance (RNV), risk-neutral skewness (RNS), the variance premium (VP), the dividend-price ratio (d-p), the dividend-payout ratio (d-e), the default spread (DEF), the relative short-term risk-free rate (RREL), stock market variance (SVAR), and tail risk (TAIL). The sample period is January 1996-August 2015. Reported coefficients indicate the percentage of annualized excess return resulting from a 1-standard deviation increase in each predictor variable. Hodrick (1992) t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: In-sample predictive power of orthogonalized forward skewness factor for equity market excess returns

| | Univariate Model | Bivariate Models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | RNV | RNS | VP | d-p | d-e | DEF | RREL | SVAR | TAIL |
| | | | | | 1-month horizon | | | | | |
| FVF | 6.62 | 6.67 | 6.93 | 5.80 | 5.65 | 6.58 | 6.60 | 6.24 | 4.22 | 6.64 |
| | ( 1.25) | ( 1.26) | ( 1.31) | ( 1.11) | ( 1.02) | ( 1.24) | ( 1.25) | ( 1.19) | ( 0.80) | ( 1.26) |
| Z | | 0.45 | -2.21 | 7.21 | 5.46 | 1.02 | -2.58 | 6.63 | -7.53 | 2.99 |
| | | ( 0.08) | (-0.40) | ( 1.43) | ( 1.05) | ( 0.20) | (-0.45) | ( 1.71)* | (-1.03) | ( 0.68) |
| $R^2$ (%) | 1.40 | 1.40 | 1.55 | 3.03 | 2.31 | 1.43 | 1.61 | 2.79 | 3.02 | 1.68 |
| | | | | | 2-month horizon | | | | | |
| FVF | 8.19 | 8.51 | 8.80 | 7.45 | 7.19 | 8.13 | 8.18 | 7.81 | 7.28 | 8.18 |
| | ( 2.01)** | ( 2.03)** | ( 2.08)** | ( 1.85)* | ( 1.71)* | ( 2.00)** | ( 2.00)** | ( 1.92)* | ( 1.65) | ( 2.01)** |
| Z | | 2.61 | -4.43 | 6.33 | 5.67 | 1.77 | -1.73 | 6.75 | -2.87 | -0.43 |
| | | ( 0.51) | (-0.91) | ( 1.42) | ( 1.13) | ( 0.36) | (-0.31) | ( 1.75)* | (-0.51) | (-0.11) |
| $R^2$ (%) | 3.84 | 4.23 | 4.95 | 6.11 | 5.63 | 4.02 | 4.02 | 6.45 | 4.27 | 3.85 |
| | | | | | 3-month horizon | | | | | |
| FVF | 8.99 | 9.33 | 9.49 | 8.18 | 8.00 | 8.91 | 8.99 | 8.61 | 8.24 | 8.99 |
| | ( 2.51)** | ( 2.59)** | ( 2.61)*** | ( 2.29)** | ( 2.14)** | ( 2.48)** | ( 2.51)** | ( 2.42)** | ( 2.22)** | ( 2.51)** |
| Z | | 2.84 | -3.61 | 6.84 | 5.67 | 2.38 | -0.56 | 6.84 | -2.37 | -0.44 |
| | | ( 0.58) | (-0.73) | ( 1.62) | ( 1.13) | ( 0.51) | (-0.10) | ( 1.74)* | (-0.46) | (-0.13) |
| $R^2$ (%) | 6.81 | 7.48 | 7.89 | 10.70 | 9.44 | 7.29 | 6.84 | 10.74 | 7.24 | 6.83 |
| | | | | | 6-month horizon | | | | | |
| FVF | 6.04 | 6.61 | 6.90 | 5.23 | 4.80 | 5.92 | 6.05 | 5.66 | 6.67 | 6.03 |
| | ( 2.82)*** | ( 3.30)*** | ( 3.42)*** | ( 2.30)** | ( 2.04)** | ( 2.71)*** | ( 2.83)*** | ( 2.69)*** | ( 3.39)*** | ( 2.81)*** |
| Z | | 4.85 | -6.32 | 6.64 | 7.18 | 3.32 | 1.72 | 7.06 | 1.99 | -0.43 |
| | | ( 1.13) | (-1.47) | ( 2.05)** | ( 1.50) | ( 0.81) | ( 0.35) | ( 1.68)* | ( 0.43) | (-0.14) |
| $R^2$ (%) | 5.49 | 8.98 | 11.40 | 12.03 | 13.02 | 7.16 | 5.94 | 12.98 | 6.03 | 5.52 |
| | | | | | 9-month horizon | | | | | |
| FVF | 4.14 | 4.66 | 4.90 | 3.57 | 2.78 | 4.03 | 4.16 | 3.75 | 5.11 | 4.16 |
| | ( 2.61)*** | ( 3.14)*** | ( 3.26)*** | ( 2.07)** | ( 1.59) | ( 2.48)** | ( 2.63)*** | ( 2.43)** | ( 3.27)*** | ( 2.62)*** |
| Z | | 4.32 | -5.49 | 4.71 | 7.86 | 3.15 | 2.46 | 7.11 | 3.06 | 1.63 |
| | | ( 1.26) | (-1.66)* | ( 1.77)* | ( 1.74)* | ( 0.86) | ( 0.57) | ( 1.62) | ( 0.83) | ( 0.60) |
| $R^2$ (%) | 3.73 | 7.74 | 10.17 | 8.49 | 16.77 | 5.90 | 5.05 | 14.70 | 5.57 | 4.31 |
| | | | | | 12-month horizon | | | | | |
| FVF | 2.99 | 3.40 | 3.59 | 2.50 | 1.57 | 2.88 | 3.00 | 2.66 | 3.87 | 3.03 |
| | ( 2.33)** | ( 2.82)*** | ( 2.89)*** | ( 1.77)* | ( 1.16) | ( 2.18)** | ( 2.33)** | ( 2.15)** | ( 2.95)*** | ( 2.34)** |
| Z | | 3.53 | -4.40 | 3.96 | 8.27 | 3.17 | 3.11 | 6.22 | 2.78 | 2.61 |
| | | ( 1.21) | (-1.62) | ( 1.67)* | ( 1.92)* | ( 0.93) | ( 0.82) | ( 1.44) | ( 0.92) | ( 1.01) |
| $R^2$ (%) | 2.51 | 5.95 | 7.83 | 6.84 | 21.06 | 5.31 | 5.22 | 13.31 | 4.45 | 4.42 |

This table reports the in-sample results for predictive regressions of the CRSP value-weighted index excess return. The univariate models include the orthogonalized forward skewness factor ($FSF_{\perp}$); the bivariate models include the $FSF_{\perp}$ and each of the alternative predictors Z used in the study. The alternative forecasting variables are risk-neutral variance (RNV), risk-neutral skewness (RNS), the variance premium (VP), the dividend-price ratio (d-p), the dividend-payout ratio (d-e), the default spread (DEF), the relative short-term risk-free rate (RREL), stock market variance (SVAR), and tail risk (TAIL). The sample period is January 1996-August 2015. Reported coefficients indicate the percentage of annualized excess return resulting from a 1-standard deviation increase in each predictor variable. Hodrick (1992) t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: In-sample predictive power of forward variances for equity market excess returns

| | 1-month horizon | 2-month horizon | 3-month horizon | 6-month horizon | 9-month horizon | 12-month horizon |
|---|---|---|---|---|---|---|
| | | | Univariate models | | | |
| $FV_{3m,6m}$ | 2.54 | 3.61 | 3.89 | 5.60 | 4.37 | 3.47 |
| | ( 0.52) | ( 0.77) | ( 0.84) | ( 1.40) | ( 1.32) | ( 1.18) |
| $R^2$ (%) | 0.21 | 0.75 | 1.27 | 4.72 | 4.16 | 3.37 |
| $FV_{6m,9m}$ | 2.14 | 3.58 | 4.09 | 5.75 | 4.48 | 3.49 |
| | ( 0.44) | ( 0.76) | ( 0.89) | ( 1.45) | ( 1.36) | ( 1.19) |
| $R^2$ (%) | 0.15 | 0.74 | 1.41 | 4.99 | 4.36 | 3.42 |
| $FV_{9m,12m}$ | 0.82 | 2.18 | 2.57 | 4.82 | 3.86 | 3.02 |
| | ( 0.17) | ( 0.47) | ( 0.56) | ( 1.20) | ( 1.15) | ( 1.01) |
| $R^2$ (%) | 0.02 | 0.27 | 0.56 | 3.49 | 3.24 | 2.56 |
| | | | Multivariate models | | | |
| $FV_{3m,6m}$ | 40.07 | 20.91 | 10.23 | 6.70 | 4.56 | 6.65 |
| | ( 1.25) | ( 0.90) | ( 0.49) | ( 0.41) | ( 0.30) | ( 0.44) |
| $FV_{6m,9m}$ | 68.51 | 89.92 | 106.71 | 68.71 | 45.74 | 32.19 |
| | ( 1.20) | ( 2.13)** | ( 3.03)*** | ( 3.01)*** | ( 2.70)*** | ( 2.27)** |
| $FV_{9m,12m}$ | -106.77 | -107.78 | -113.52 | -70.05 | -46.08 | -35.52 |
| | (-2.28)** | (-2.98)*** | (-3.80)*** | (-3.08)*** | (-2.51)** | (-1.95)* |
| $R^2$ (%) | 5.13 | 9.34 | 15.53 | 14.37 | 10.23 | 7.89 |

This table reports the in-sample results for predictive regressions of the CRSP value-weighted index excess return. The univariate models include each forward variance; the multivariate models include the combination of all three forward variances. The sample period is January 1996-August 2015. Reported coefficients indicate the percentage of annualized excess return resulting from a 1-standard deviation increase in each predictor variable. Hodrick (1992) t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: In-sample predictive power of forward skewnesses for equity market excess returns

| | 1-month horizon | 2-month horizon | 3-month horizon | 6-month horizon | 9-month horizon | 12-month horizon |
|---|---|---|---|---|---|---|
| | | | Univariate models | | | |
| $FS_{3m,6m}$ | -2.98 | -4.11 | -4.11 | -6.35 | -5.14 | -4.09 |
| | (-0.57) | (-0.85) | (-0.84) | (-1.50) | (-1.54) | (-1.43) |
| $R^2$ (%) | 0.28 | 0.97 | 1.43 | 6.07 | 5.76 | 4.69 |
| $FS_{6m,9m}$ | -4.21 | -5.28 | -5.30 | -7.13 | -5.49 | -4.29 |
| | (-0.84) | (-1.08) | (-1.09) | (-1.75)* | (-1.67)* | (-1.50) |
| $R^2$ (%) | 0.57 | 1.60 | 2.37 | 7.65 | 6.55 | 5.15 |
| $FS_{9m,12m}$ | -2.09 | -3.08 | -3.03 | -5.69 | -4.49 | -3.52 |
| | (-0.42) | (-0.65) | (-0.63) | (-1.36) | (-1.33) | (-1.19) |
| $R^2$ (%) | 0.14 | 0.55 | 0.77 | 4.87 | 4.39 | 3.46 |
| | | | Multivariate models | | | |
| $FS_{3m,6m}$ | 4.12 | 1.82 | 1.44 | -0.39 | -4.29 | -4.71 |
| | ( 0.18) | ( 0.11) | ( 0.10) | (-0.03) | (-0.44) | (-0.50) |
| $FS_{6m,9m}$ | -77.44 | -79.32 | -81.59 | -53.09 | -34.69 | -26.12 |
| | (-2.06)** | (-2.71)*** | (-3.31)*** | (-3.40)*** | (-3.04)*** | (-2.74)*** |
| $FS_{9m,12m}$ | 70.23 | 73.33 | 75.98 | 47.01 | 33.87 | 26.79 |
| | ( 2.28)** | ( 2.91)*** | ( 3.54)*** | ( 2.93)*** | ( 2.42)** | ( 1.88)* |
| $R^2$ (%) | 5.33 | 10.63 | 16.55 | 17.09 | 13.11 | 10.36 |

This table reports the in-sample results for predictive regressions of the CRSP value-weighted index excess return. The univariate models include each forward skewness; the multivariate models include the combination of all three forward skewnesses. The sample period is January 1996-August 2015. Reported coefficients indicate the percentage of annualized excess return resulting from a 1-standard deviation increase in each predictor variable. Hodrick (1992) t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Out-of-sample predictability of equity market excess returns

| | $R^2_{OS}$ | MSE-F | MSE-Adj | $R^2_{OS}$ | MSE-F | MSE-Adj | $R^2_{OS}$ | MSE-F | MSE-Adj |
|---|---|---|---|---|---|---|---|---|---|
| | 1-month horizon | | | 2-month horizon | | | 3-month horizon | | |
| FVF vs HAV | 1.93 | 3.70** | 1.63* | 1.93 | 3.66** | 1.63* | 2.30 | 4.34** | 1.84** |
| FSF vs HAV | 0.72 | 1.37* | 0.89 | 3.06 | 5.87** | 2.14** | 4.08 | 7.83** | 2.08** |
| FVF & FSF vs FVF | 2.66 | 5.13** | 1.68** | 1.76 | 3.34** | 1.98** | 3.05 | 5.78** | 1.81** |
| RNV vs HAV | -3.83 | -6.93 | -0.54 | -7.33 | -12.70 | -0.58 | -12.74 | -20.80 | -0.90 |
| RNS vs HAV | -5.62 | -10.00 | -0.75 | -14.38 | -23.39 | -0.35 | -23.79 | -35.36 | -0.78 |
| VP vs HAV | -0.22 | -0.42 | 0.93 | -1.19 | -2.18 | 1.21 | 1.02 | 1.89** | 1.99** |
| d-p vs HAV | -0.33 | -0.62 | 0.54 | -1.40 | -2.58 | 0.35 | -2.64 | -4.73 | 0.27 |
| d-e vs HAV | -7.23 | -12.68 | -0.13 | -19.34 | -30.14 | -0.56 | -34.49 | -47.19 | -0.95 |
| DEF vs HAV | -4.53 | -8.14 | 0.43 | -10.53 | -17.72 | 0.40 | -23.53 | -35.05 | 0.06 |
| RREL vs HAV | -0.55 | -1.03 | 0.24 | -1.33 | -2.44 | 0.28 | -3.39 | -6.04 | 0.14 |
| SVAR vs HAV | -4.96 | -8.88 | 0.45 | -8.58 | -14.70 | -0.79 | -12.09 | -19.84 | -1.79 |
| TAIL vs HAV | -1.46 | -2.71 | -0.27 | -3.01 | -5.43 | -1.51 | -5.44 | -9.50 | -1.79 |
| | 6-month horizon | | | 9-month horizon | | | 12-month horizon | | |
| FVF vs HAV | 0.45 | 0.81* | 1.16 | -1.00 | -1.69 | 0.70 | -4.05 | -6.46 | 0.07 |
| FSF vs HAV | 3.13 | 5.75** | 1.64* | 3.52 | 6.28** | 1.62* | -0.02 | -0.03 | 0.95 |
| FVF & FSF vs FVF | 6.70 | 12.79** | 2.65** | 2.48 | 4.38** | 1.75** | 0.94 | 1.58** | 0.77 |
| RNV vs HAV | -1.61 | -2.82 | 0.69 | -1.79 | -3.03 | -0.16 | -3.47 | -5.57 | -1.31 |
| RNS vs HAV | 0.80 | 1.43* | 1.50* | 2.21 | 3.88** | 1.18 | -0.08 | -0.13 | 0.76 |
| VP vs HAV | 4.92 | 9.21** | 1.86** | 1.71 | 2.99** | 1.13 | 0.11 | 0.19 | 0.72 |
| d-p vs HAV | -0.74 | -1.31 | 0.59 | 2.46 | 4.33** | 0.95 | 5.06 | 8.85** | 1.32* |
| d-e vs HAV | -80.88 | -79.59 | -1.71 | -111.43 | -90.65 | -1.59 | -111.18 | -87.39 | -0.97 |
| DEF vs HAV | -64.34 | -69.69 | -0.59 | -66.00 | -68.38 | -0.86 | -34.73 | -42.79 | -1.22 |
| RREL vs HAV | -13.10 | -20.62 | -0.20 | -43.96 | -52.52 | -0.74 | -83.24 | -75.41 | -1.04 |
| SVAR vs HAV | -6.99 | -11.63 | -1.37 | -6.34 | -10.25 | -1.90 | -7.67 | -11.82 | -1.61 |
| TAIL vs HAV | -9.58 | -15.57 | -1.54 | -10.40 | -16.20 | -0.72 | -19.22 | -26.77 | -0.95 |

This table reports the results of out-of-sample predictability of the CRSP value-weighted index excess return. The total sample period is January 1996-August 2015, and the forecasting period begins in January 2000. The forecasting variables are the two forward moments factors (FVF and FSF), risk-neutral variance (RNV), risk-neutral skewness (RNS), the variance premium (VP), the dividend-price ratio (d-p), the dividend-payout ratio (d-e), the default spread (DEF), the relative short-term risk-free rate (RREL), stock market variance (SVAR), and tail risk (TAIL). For the univariate models, the benchmark is the historical average model (HAV); for the bivariate model with FVF and FSF, the benchmark is the FVF model. For each forecasting model, we report the out-of-sample coefficient of determination $R^2_{OS}$, the MSE F-statistic of McCracken (2007), and the MSE-adjusted test of Clark and West (2007). ** and * denote significance at the 5% and 10% levels, respectively.

Table 8: Market-timing strategies

| | SR | ΔCER-HAV (%) | ΔCER-BH (%) | MD (%) | SR | ΔCER-HAV (%) | ΔCER-BH (%) | MD (%) | SR | ΔCER-HAV (%) | ΔCER-BH (%) | MD (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1-month horizon | | | | 2-month horizon | | | | 3-month horizon | | | |
| HAV | 0.10 | | | -45.43 | 0.09 | | | -41.30 | 0.07 | | | -39.02 |
| BH | 0.34 | | | -51.45 | 0.36 | | | -47.00 | 0.36 | | | -44.42 |
| FVF | 0.32 | 2.70 | 0.07 | -29.56 | 0.29 | 2.44 | -0.47 | -28.14 | 0.25 | 2.16 | -0.90 | -27.71 |
| FSF | 0.21 | 0.99 | -1.64 | -38.37 | 0.36 | 3.27 | 0.36 | -30.85 | 0.36 | 3.42 | 0.36 | -28.72 |
| RNV | -0.08 | -3.45 | -6.08 | -58.12 | -0.05 | -2.88 | -5.80 | -53.66 | -0.11 | -3.21 | -6.27 | -55.53 |
| RNS | -0.07 | -2.61 | -5.24 | -57.08 | -0.03 | -2.25 | -5.16 | -52.64 | -0.05 | -1.67 | -4.74 | -50.26 |
| VP | 0.13 | -0.45 | -3.09 | -57.41 | 0.19 | 0.46 | -2.46 | -40.36 | 0.20 | 0.89 | -2.17 | -41.42 |
| d-p | 0.43 | 3.84 | 1.20 | -62.42 | 0.40 | 3.35 | 0.43 | -61.18 | 0.43 | 3.99 | 0.93 | -58.75 |
| d-e | 0.33 | 2.81 | 0.17 | -41.48 | 0.23 | 1.85 | -1.07 | -41.24 | 0.12 | 0.63 | -2.43 | -41.09 |
| DEF | 0.13 | 0.59 | -2.05 | -42.47 | 0.17 | 1.25 | -1.67 | -37.03 | 0.20 | 1.84 | -1.22 | -32.61 |
| RREL | 0.35 | 2.95 | 0.31 | -46.54 | 0.32 | 2.81 | -0.10 | -46.96 | 0.40 | 3.87 | 0.81 | -39.13 |
| SVAR | 0.08 | -1.30 | -3.93 | -53.69 | 0.01 | -2.09 | -5.00 | -49.66 | -0.06 | -2.56 | -5.62 | -52.83 |
| TAIL | 0.04 | -0.59 | -3.22 | -52.64 | 0.00 | -0.88 | -3.79 | -44.62 | -0.01 | -0.77 | -3.83 | -41.86 |

This table reports the results of market-timing strategies based on the out-of-sample predictability of the CRSP value-weighted index excess return. The total sample period is January 1996-August 2015, and the forecasting period begins in January 2000. The forecasting variables are the two forward moments factors (FVF and FSF), risk-neutral variance (RNV), risk-neutral skewness (RNS), the variance premium (VP), the dividend-price ratio (d-p), the dividend-payout ratio (d-e), the default spread (DEF), the relative short-term risk-free rate (RREL), stock market variance (SVAR), and tail risk (TAIL). SR stands for the Sharpe ratio. ΔCER-HAV is the certainty equivalent return in excess of the historical average (HAV) strategy, and ΔCER-BH is the certainty equivalent return in excess of the buy-and-hold (BH) strategy. MD denotes maximum drawdown. All measures of performance, except MD, are in annualized terms.

Table 9: In-sample predictive power of forward moments factors for equity market excess variance

| | 1-month horizon | 2-month horizon | 3-month horizon | 6-month horizon | 9-month horizon | 12-month horizon |
|---|---|---|---|---|---|---|
| Univariate models | | | | | | |
| FVF | 1.20 | 1.08 | 1.00 | 0.73 | 0.50 | 0.35 |
| | ( 2.68)*** | ( 3.26)*** | ( 3.34)*** | ( 2.39)** | ( 1.85)* | ( 1.48) |
| $R^2$ (%) | 8.39 | 6.83 | 6.07 | 3.75 | 1.94 | 1.01 |
| FSF | 0.93 | 0.80 | 0.82 | 0.76 | 0.58 | 0.50 |
| | ( 2.43)** | ( 2.35)** | ( 2.58)** | ( 2.77)*** | ( 1.94)* | ( 1.79)* |
| $R^2$ (%) | 5.00 | 3.77 | 4.09 | 4.06 | 2.62 | 2.14 |
| $\text{FSF}_{\perp}$ | 0.23 | 0.17 | 0.26 | 0.40 | 0.35 | 0.37 |
| | ( 0.90) | ( 0.64) | ( 0.98) | ( 1.73)* | ( 1.25) | ( 1.26) |
| $R^2$ (%) | 0.31 | 0.17 | 0.41 | 1.14 | 0.96 | 1.18 |
| Bivariate models with FVF | | | | | | |
| FVF | 1.10 | 0.93 | 0.83 | 0.56 | 0.31 | 0.15 |
| | ( 1.95)* | ( 2.21)** | ( 2.29)** | ( 1.57) | ( 0.99) | ( 0.50) |
| $\text{VIX}^2$ | 0.71 | 1.05 | 1.24 | 1.35 | 1.46 | 1.57 |
| | ( 1.25) | ( 2.51)** | ( 3.25)*** | ( 4.26)*** | ( 5.70)*** | ( 7.63)*** |
| $R^2$ (%) | 11.25 | 13.17 | 15.20 | 16.27 | 18.17 | 21.52 |
| FVF | 1.20 | 1.08 | 1.00 | 0.74 | 0.51 | 0.36 |
| | ( 2.56)** | ( 2.93)*** | ( 3.02)*** | ( 2.14)** | ( 1.59) | ( 1.18) |
| CV | 0.23 | 0.62 | 0.80 | 0.91 | 1.03 | 1.16 |
| | ( 0.37) | ( 1.31) | ( 1.96)* | ( 2.79)*** | ( 3.74)*** | ( 5.34)*** |
| $R^2$ (%) | 8.70 | 9.08 | 9.94 | 9.48 | 10.14 | 12.37 |
| FVF | 0.99 | 1.10 | 1.01 | 0.67 | 0.42 | 0.34 |
| | ( 2.81)*** | ( 3.08)*** | ( 3.29)*** | ( 2.29)** | ( 1.62) | ( 1.52) |
| LagEV | 0.89 | -0.10 | -0.03 | -0.56 | -0.46 | -0.24 |
| | ( 1.94)* | (-0.22) | (-0.07) | (-1.54) | (-0.98) | (-0.50) |
| $R^2$ (%) | 12.70 | 6.88 | 6.06 | 5.84 | 3.54 | 1.59 |
| Bivariate models with FSF | | | | | | |
| FSF | 0.93 | 0.80 | 0.83 | 0.78 | 0.59 | 0.52 |
| | ( 2.07)** | ( 2.11)** | ( 2.59)** | ( 2.57)** | ( 2.00)** | ( 1.81)* |
| $\text{VIX}^2$ | 0.87 | 1.18 | 1.36 | 1.43 | 1.50 | 1.60 |
| | ( 1.98)** | ( 3.87)*** | ( 4.95)*** | ( 6.98)*** | ( 8.34)*** | ( 8.88)*** |
| $R^2$ (%) | 9.36 | 11.96 | 15.23 | 18.29 | 20.16 | 23.58 |
| FSF | 1.00 | 0.94 | 1.00 | 0.96 | 0.80 | 0.74 |
| | ( 2.95)*** | ( 2.89)*** | ( 3.34)*** | ( 3.14)*** | ( 2.43)** | ( 2.25)** |
| CV | 0.41 | 0.79 | 0.98 | 1.08 | 1.17 | 1.29 |
| | ( 0.78) | ( 2.15)** | ( 3.20)*** | ( 4.85)*** | ( 5.61)*** | ( 7.28)*** |
| $R^2$ (%) | 5.95 | 7.31 | 9.72 | 11.87 | 12.89 | 15.76 |
| FSF | 0.56 | 0.87 | 0.90 | 0.73 | 0.54 | 0.51 |
| | ( 1.69)* | ( 2.40)** | ( 2.60)** | ( 2.93)*** | ( 1.91)* | ( 1.82)* |
| LagEV | 0.90 | -0.21 | -0.24 | -0.58 | -0.49 | -0.27 |
| | ( 1.87)* | (-0.41) | (-0.54) | (-1.59) | (-1.07) | (-0.57) |
| $R^2$ (%) | 8.87 | 4.01 | 4.43 | 6.39 | 4.47 | 2.79 |

This table reports the in-sample results for predictive regressions of the S&P 500 index excess variance. The top panel shows univariate predictive regression results for the forward variance factor (FVF), the forward skewness factor (FSF), and the orthogonalized forward skewness factor ($\text{FSF}_{\perp}$). The middle and bottom panels show bivariate predictive regression results for FVF and FSF, respectively. The alternative forecasting variables are the squared VIX ($\text{VIX}^2$), the conditional variance (CV), and the lagged excess variance of each horizon (LagEV). The sample period is January 1996-August 2015. Reported coefficients indicate the percentage of annualized excess variance resulting from a 1-standard deviation increase in each predictor variable. Newey-West (1987) t-statistics with lag length equal to the maximum of 3 or (horizon × 2) are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 10: Out-of-sample predictability of equity market excess variance

| | 1-month horizon | 2-month horizon | 3-month horizon | 6-month horizon | 9-month horizon | 12-month horizon |
|---|---|---|---|---|---|---|
| | $R^2_{OS}$ | MSE-F | MSE-Adj | $R^2_{OS}$ | MSE-F | MSE-Adj |
| | 1-month horizon | | | 2-month horizon | | |
| FVF vs HAV | 5.55 | 11.04** | 2.22** | 6.18 | 12.26** | 2.48** |
| FSF vs HAV | 3.12 | 6.05** | 1.73** | 4.74 | 9.26** | 2.47** |
| FVF & FSF vs FVF | 0.58 | 1.09* | 1.15 | -0.10 | -0.19 | 0.05 |
| $VIX^2$ vs HAV | -5.81 | -10.33 | 0.02 | -2.96 | -5.35 | 1.36* |
| CV vs HAV | -28.54 | -41.74 | -0.96 | -23.28 | -35.12 | -0.60 |
| LagEV vs HAV | -73.88 | -79.88 | 1.40* | -24.78 | -36.94 | -0.72 |
| | 3-month horizon | | | 6-month horizon | | |
| FVF vs HAV | 6.12 | 11.99** | 2.47** | 3.25 | 5.98** | 1.79** |
| FSF vs HAV | 5.85 | 11.44** | 2.60** | 3.19 | 5.86** | 2.03** |
| FVF & FSF vs FVF | -0.10 | -0.18 | 0.15 | -0.51 | -0.90 | -0.20 |
| $VIX^2$ vs HAV | 0.96 | 1.79** | 2.33** | 4.80 | 8.98** | 2.19** |
| CV vs HAV | -13.45 | -21.82 | 0.66 | -9.24 | -15.06 | 1.42* |
| LagEV vs HAV | -9.22 | -15.53 | -0.93 | -12.24 | -19.41 | -1.23 |
| | 9-month horizon | | | 12-month horizon | | |
| FVF vs HAV | 0.98 | 1.71** | 1.08 | -0.18 | -0.30 | 0.59 |
| FSF vs HAV | 2.52 | 4.45** | 1.60* | 1.64 | 2.77** | 1.39* |
| FVF & FSF vs FVF | -1.76 | -2.98 | -0.88 | 0.34 | 0.57 | 0.79 |
| $VIX^2$ vs HAV | 10.41 | 19.99** | 1.86** | 14.52 | 28.21** | 1.72** |
| CV vs HAV | -1.74 | -2.94 | 1.35* | 0.48 | 0.81* | 1.37* |
| LagEV vs HAV | -44.13 | -52.66 | -1.12 | -58.59 | -61.33 | -1.38 |

This table reports the results of out-of-sample predictability of the S&P 500 index excess variance. The total sample period is January 1996-August 2015, and the forecasting period begins in January 2000. The forecasting variables are the two forward moments factors (FVF and FSF), the squared VIX ($VIX^2$), the conditional variance (CV), and the lagged excess variance of each horizon (LagEV). For the univariate models, the benchmark is the historical average model (HAV); for the bivariate model with FVF and FSF, the benchmark is the FVF model. For each forecasting model, we report the out-of-sample coefficient of determination $R^2_{OS}$, the MSE F-statistic of McCracken (2007), and the MSE-adjusted test of Clark and West (2007). ** and * denote significance at the 5% and 10% levels, respectively.

# Online Appendix to "The Information Content of Forward Moments"

Panayiotis C. Andreou[*,†] Anastasios Kagkadis[‡] Dennis Philip[†]
Abderrahim Taamouti[†]

July 2019

[*]Department of Commerce, Finance and Shipping, Cyprus University of Technology, 140, Ayiou Andreou Street, 3603 Lemesos, Cyprus; Email: benz@pandreou.com

[†]Durham University Business School, Mill Hill Lane, Durham DH1 3LB, UK; Emails: dennis.philip@durham.ac.uk, abderrahim.taamouti@durham.ac.uk

[‡]Department of Accounting and Finance, Lancaster University Management School, Lancaster LA1 4YX, UK; Email: a.kagkadis@lancaster.ac.uk

**Abstract**

This Online Appendix provide additional results not presented in the main paper.

# 1 Predictability Tests Using Principal Components

Our main predictability results are conducted with the forward moments factors extracted using the PLS procedure. In this section, we investigate the robustness of our results to this technique by using Principal Components instead of the PLS factors. As mentioned in the main paper, we find that FVF is highly correlated (correlation coefficient of 0.92) with the second principal component of the forward variance term structure (FVPC), while FSF is highly correlated (correlation coefficient of 0.99) with the third principal component of the forward skewness term structure (FSPC). Therefore, we perform the predictability analysis using the respective principal components.

Table 1 shows that the results using principal components are qualitatively similar to those utilizing the PLS factors. A slight difference is that the FVPC is statistically less significant than the FVF especially at long horizons. For FSPC and $\text{FSPC}_{\perp}$ (orthogonalized FSPC to FVPC) the results are quantitatively very close to those obtained using FSF and $\text{FSF}_{\perp}$, respectively. These findings alleviate potential concerns that the information content of the forward moments is an artifact of the PLS method.

# 2 Robustness Results for In-Sample Predictability

In this section, we provide additional statistical results for the in-sample predictive power of the forward moments factors. First, it is important to take into consideration the sampling error induced by the PLS procedure. To this end, we follow Kelly and Pruitt (2011) and calculate additional t-statistics based on a circular block bootstrap technique. In particular, we perform the PLS procedure using a series of 1,000 pseudo-samples generated by resampling the forward moments and the stock market returns. The reported t-statistics are based on the sampling distribution of the estimated predictive regression coefficients across pseudo-samples. To account for the presence of autocorrelation in our data, our pseudo-samples are generated using blocks with length equal to 12.

Table 2 reports the results for the forward variance factor (FVF), Table 3 reports the results for the forward skewness factor (FSF), and Table 4 reports the results for the orthogonalized forward skewness factor ($FSF_{\perp}$). It can be seen that the statistically significant predictive power is preserved for all three variables when using bootstrap t-statistics. In the case of FVF the bootstrap t-statistics are somewhat smaller in magnitude than the Hodrick (1992) t-statistics, while in the case of FSF and $FSF_{\perp}$ they are quantitatively very similar to the Hodrick (1992) t-statistics. Overall, the predictive power of the forward moments factors, and especially of the forward skewness factor, appears to be robust to the sampling error induced by the PLS procedure.

Second, we present results with Newey-West (1987) t-statistics utilizing a lag length equal to the maximum of 3 or (horizon $\times$ 2) as in Bekaert and Hoerova (2014). Tables 5-7 of this report show that the Newey-West (1987) t-statistics are very similar to the Hodrick (1992) t-statistics.

# 3 Implied Long-Horizon $R^2$s

In the in-sample predictability results presented in the main paper, we report the $R^2$ values from all the horizons examined. However, the long-horizon $R^2$s may be upwardly biased because of the autocorrelation of the forward moments factors. For example, Boudoukh et al. (2008) show that under some assumptions the long-horizon $R^2$s ($R_h^2$) are mechanically related to the one-period ahead $R^2$ ($R_1^2$) as follows:

$$E\left(R_h^2 | R_1^2\right) = \left[\frac{1 + \frac{\phi\left(1-\phi^{h-1}\right)}{1-\phi}}{h}\right]^2 R_1^2, \tag{1}$$

where $\phi$ stands for the autocorrelation coefficient of the predictor and $h$ denotes the forecasting horizon. To this end, following Boudoukh et al. (2008), we estimate the long-horizon $R^2$s implied by the one-month-ahead $R^2$ and compare them with the actual long-horizon $R^2$

estimates.

Table 8 presents the results. As shown in Table 2 of the main paper, FVF is significant for horizons up to 6 months ahead. For those horizons, the actual $R^2$s are higher than the implied $R^2$s even though the difference is not always substantial. For FSF and $\text{FSF}_\perp$, the actual long-horizon $R^2$s are consistently much higher than the implied long-horizon $R^2$s. We conclude that, especially for FSF and $\text{FSF}_\perp$, the long-horizon $R^2$s are not just mechanically driven by the one-month $R^2$s.

# References

[1] Bekaert, G. and M. Hoerova. 2014. The VIX, the variance premium and stock market volatility. Journal of Econometrics 183, 181-192.

[2] Boudoukh, J., M. Richardson and R. F. Whitelaw. 2008.The myth of long-horizon predictability. Review of Financial Studies 21, 1577-1605.

[3] Hodrick, R. J. 1992. Dividend yields and expected stock returns: alternative procedures for inference and measurement. Review of Financial Studies 2, 357-386.

[4] Kelly, B. and S. Pruitt. 2011. Market expectations in the cross-section of present values. Working paper.

[5] Newey, W. and K. West. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703-708.

Table 1: In-sample predictive power of forward moments factors and forward moments principal components for equity market excess returns

| | 1-month horizon | 2-month horizon | 3-month horizon | 6-month horizon | 9-month horizon | 12-month horizon |
|---|---|---|---|---|---|---|
| | | | Forward variance | | | |
| FVF | 11.85 | 10.52 | 10.20 | 6.14 | 4.04 | 3.35 |
| | ( 2.63)*** | ( 2.96)*** | ( 3.40)*** | ( 2.46)** | ( 1.82)* | ( 1.42) |
| $R^2$ (%) | 4.48 | 6.35 | 8.77 | 5.67 | 3.56 | 3.14 |
| FVPC | 9.27 | 7.11 | 6.12 | 3.53 | 2.32 | 2.14 |
| | ( 2.25)** | ( 2.25)** | ( 2.21)** | ( 1.52) | ( 1.07) | ( 0.93) |
| $R^2$ (%) | 2.74 | 2.90 | 3.15 | 1.88 | 1.17 | 1.28 |
| | | | Forward skewness | | | |
| FSF | 12.55 | 12.93 | 13.34 | 8.47 | 5.71 | 4.38 |
| | ( 2.21)** | ( 2.87)*** | ( 3.51)*** | ( 3.36)*** | ( 2.94)*** | ( 2.49)** |
| $R^2$ (%) | 5.02 | 9.59 | 14.99 | 10.81 | 7.09 | 5.37 |
| FSPC | 12.52 | 12.88 | 13.28 | 8.43 | 5.66 | 4.33 |
| | ( 2.19)** | ( 2.85)*** | ( 3.49)*** | ( 3.34)*** | ( 2.94)*** | ( 2.51)** |
| $R^2$ (%) | 4.99 | 9.52 | 14.87 | 10.71 | 6.96 | 5.25 |
| | | | Orthogonalized forward skewness | | | |
| $\text{FSF}_\perp$ | 6.62 | 8.19 | 8.99 | 6.04 | 4.14 | 2.99 |
| | ( 1.25) | ( 2.01)** | ( 2.51)** | ( 2.82)*** | ( 2.61)*** | ( 2.33)** |
| $R^2$ (%) | 1.40 | 3.84 | 6.81 | 5.49 | 3.73 | 2.51 |
| $\text{FSPC}_\perp$ | 10.32 | 11.35 | 12.07 | 7.76 | 5.22 | 3.89 |
| | ( 1.81)* | ( 2.55)** | ( 3.17)*** | ( 3.26)*** | ( 2.98)*** | ( 2.69)*** |
| $R^2$ (%) | 3.39 | 7.39 | 12.27 | 9.07 | 5.93 | 4.24 |

This table reports the in-sample results for predictive regressions of the CRSP value-weighted index excess return. The predictive variables are the forward variance factor (FVF) and second principal component (FVPC), the forward skewness factor (FSF) and third principal component (FSPC), and the orthogonalized forward skewness factor ($\text{FSF}_\perp$) and third principal component ($\text{FSPC}_\perp$). The sample period is January 1996-August 2015. Reported coefficients indicate the percentage of annualized excess return resulting from a 1-standard deviation increase in each predictor variable. Hodrick (1992) t-statistics are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 2: In-sample predictive power of forward variance factor for equity market excess returns – Bootstrap t-stats

| | Univariate Model | Bivariate Models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | RNV | RNS | VP | d-p | d-e | DEF | RREL | SVAR | TAIL |
| | | | | | 1-month horizon | | | | | |
| FVF | 11.85 | 12.04 | 11.84 | 10.41 | 11.43 | 11.90 | 11.77 | 12.07 | 11.84 | 11.68 |
| | ( 2.43)** | ( 2.36)** | ( 2.31)** | ( 2.00)** | ( 2.38)** | ( 2.50)** | ( 2.52)** | ( 2.70)*** | ( 2.95)*** | ( 2.39)** |
| Z | | -1.69 | -0.20 | 4.58 | 5.59 | -0.34 | -2.17 | 7.35 | -8.86 | 1.76 |
| | | (-0.34) | (-0.05) | ( 1.12) | ( 1.00) | (-0.05) | (-0.38) | ( 1.93)* | (-1.77)* | ( 0.50) |
| $R^2$ (%) | 4.48 | 4.57 | 4.48 | 5.08 | 5.47 | 4.48 | 4.63 | 6.20 | 6.98 | 4.58 |
| | | | | | 2-month horizon | | | | | |
| FVF | 10.52 | 10.48 | 10.33 | 9.17 | 10.04 | 10.44 | 10.47 | 10.74 | 10.51 | 10.69 |
| | ( 2.36)** | ( 2.11)** | ( 2.08)** | ( 1.88)* | ( 2.33)** | ( 2.42)** | ( 2.36)** | ( 2.62)*** | ( 2.37)** | ( 2.35)** |
| Z | | 0.46 | -2.32 | 4.32 | 6.15 | 0.66 | -1.39 | 7.50 | -5.15 | -1.61 |
| | | ( 0.10) | (-0.58) | ( 1.24) | ( 1.18) | ( 0.12) | (-0.26) | ( 1.95)* | (-1.31) | (-0.54) |
| $R^2$ (%) | 6.35 | 6.36 | 6.66 | 7.32 | 8.51 | 6.37 | 6.46 | 9.57 | 7.87 | 6.50 |
| | | | | | 3-month horizon | | | | | |
| FVF | 10.20 | 10.13 | 10.08 | 8.60 | 9.69 | 10.02 | 10.19 | 10.42 | 10.18 | 10.37 |
| | ( 2.16)** | ( 1.97)** | ( 1.91)* | ( 1.72)* | ( 2.29)** | ( 2.30)** | ( 2.16)** | ( 2.51)** | ( 2.32)** | ( 2.32)** |
| Z | | 0.66 | -1.44 | 5.11 | 6.28 | 1.34 | -0.22 | 7.61 | -4.93 | -1.62 |
| | | ( 0.16) | (-0.34) | ( 1.67)* | ( 1.32) | ( 0.25) | (-0.04) | ( 1.96)* | (-1.28) | (-0.59) |
| $R^2$ (%) | 8.77 | 8.81 | 8.94 | 10.75 | 12.07 | 8.92 | 8.77 | 13.64 | 10.82 | 8.99 |
| | | | | | 6-month horizon | | | | | |
| FVF | 6.14 | 5.81 | 5.75 | 4.31 | 5.46 | 5.76 | 6.22 | 6.32 | 6.13 | 6.29 |
| | ( 1.92)* | ( 1.63) | ( 1.52) | ( 1.48) | ( 2.00)** | ( 1.94)* | ( 1.84)* | ( 2.15)** | ( 1.68)* | ( 1.86)* |
| Z | | 3.53 | -4.94 | 5.96 | 7.51 | 2.74 | 1.95 | 7.52 | -0.04 | -1.29 |
| | | ( 1.27) | (-1.94)* | ( 2.37)** | ( 1.90)* | ( 0.58) | ( 0.44) | ( 1.75)* | (-0.01) | (-0.46) |
| $R^2$ (%) | 5.67 | 7.53 | 9.32 | 10.52 | 14.10 | 6.78 | 6.24 | 14.19 | 5.67 | 5.92 |
| | | | | | 9-month horizon | | | | | |
| FVF | 4.04 | 3.72 | 3.69 | 2.72 | 3.32 | 3.66 | 4.15 | 4.23 | 4.06 | 3.91 |
| | ( 1.60) | ( 1.40) | ( 1.26) | ( 1.11) | ( 1.77)* | ( 1.66)* | ( 1.58) | ( 1.79)* | ( 1.40) | ( 1.58) |
| Z | | 3.42 | -4.53 | 4.31 | 8.04 | 2.79 | 2.61 | 7.42 | 1.49 | 1.10 |
| | | ( 1.22) | (-1.83)* | ( 1.71)* | ( 2.33)** | ( 0.66) | ( 0.63) | ( 1.54) | ( 0.58) | ( 0.40) |
| $R^2$ (%) | 3.56 | 6.08 | 8.00 | 7.22 | 17.53 | 5.22 | 5.04 | 15.53 | 4.04 | 3.82 |
| | | | | | 12-month horizon | | | | | |
| FVF | 3.35 | 3.09 | 3.07 | 2.25 | 2.59 | 2.96 | 3.49 | 3.51 | 3.37 | 3.08 |
| | ( 1.59) | ( 1.39) | ( 1.37) | ( 1.07) | ( 2.00)** | ( 1.58) | ( 1.64) | ( 1.68)* | ( 1.35) | ( 1.44) |
| Z | | 2.86 | -3.68 | 3.59 | 8.30 | 2.87 | 3.26 | 6.45 | 1.61 | 2.19 |
| | | ( 1.06) | (-1.55) | ( 1.56) | ( 2.73)*** | ( 0.92) | ( 1.01) | ( 1.48) | ( 0.63) | ( 0.88) |
| $R^2$ (%) | 3.14 | 5.41 | 6.91 | 6.41 | 22.26 | 5.40 | 6.11 | 14.79 | 3.86 | 4.46 |

This table reports the in-sample results for predictive regressions of the CRSP value-weighted index excess return. The univariate models include the forward variance factor (FVF); the bivariate models include the FVF and each of the alternative predictors Z used in the study. The alternative forecasting variables are risk-neutral variance (RNV), risk-neutral skewness (RNS), the variance premium (VP), the dividend-price ratio (d-p), the dividend-payout ratio (d-e), the default spread (DEF), the relative short-term risk-free rate (RREL), stock market variance (SVAR), and tail risk (TAIL). The sample period is January 1996-August 2015. Reported coefficients indicate the percentage of annualized excess return resulting from a 1-standard deviation increase in each predictor variable. T-statistics from a circular block bootstrap with block length equal to 12 are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: In-sample predictive power of forward skewness factor for equity market excess returns – Bootstrap t-stats

| | Univariate Model | Bivariate Models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | RNV | RNS | VP | d-p | d-e | DEF | RREL | SVAR | TAIL |
| | 1-month horizon | | | | | | | | | |
| FSF | 12.55 | 12.55 | 12.66 | 11.22 | 11.75 | 12.56 | 12.48 | 12.38 | 11.01 | 12.42 |
| | ( 2.73)*** | ( 2.55)** | ( 2.38)** | ( 2.14)** | ( 2.53)** | ( 2.76)*** | ( 2.77)*** | ( 2.99)*** | ( 2.80)*** | ( 2.81)*** |
| Z | | -0.01 | -1.94 | 4.67 | 4.27 | -0.14 | -2.27 | 6.67 | -6.11 | 2.24 |
| | | (-0.00) | (-0.51) | ( 1.16) | ( 0.76) | (-0.02) | (-0.39) | ( 2.08)** | (-1.28) | ( 0.61) |
| $R^2$ (%) | 5.02 | 5.02 | 5.14 | 5.66 | 5.58 | 5.02 | 5.18 | 6.43 | 6.13 | 5.18 |
| | 2-month horizon | | | | | | | | | |
| FSF | 12.93 | 12.99 | 13.15 | 11.84 | 12.06 | 12.86 | 12.89 | 12.76 | 12.41 | 13.00 |
| | ( 3.26)*** | ( 2.88)*** | ( 2.58)** | ( 2.60)*** | ( 2.92)*** | ( 3.09)*** | ( 3.28)*** | ( 3.47)*** | ( 3.01)*** | ( 3.23)*** |
| Z | | 1.95 | -3.94 | 3.81 | 4.70 | 0.63 | -1.42 | 6.86 | -2.07 | -1.24 |
| | | ( 0.48) | (-1.09) | ( 1.11) | ( 0.89) | ( 0.11) | (-0.27) | ( 1.99)** | (-0.55) | (-0.41) |
| $R^2$ (%) | 9.59 | 9.81 | 10.47 | 10.35 | 10.81 | 9.61 | 9.70 | 12.28 | 9.82 | 9.67 |
| | 3-month horizon | | | | | | | | | |
| FSF | 13.34 | 13.40 | 13.51 | 12.09 | 12.45 | 13.20 | 13.33 | 13.16 | 12.90 | 13.41 |
| | ( 3.50)*** | ( 2.96)*** | ( 2.75)*** | ( 2.70)*** | ( 3.18)*** | ( 3.30)*** | ( 3.14)*** | ( 3.81)*** | ( 3.17)*** | ( 3.38)*** |
| Z | | 2.12 | -3.05 | 4.35 | 4.74 | 1.23 | -0.24 | 6.97 | -1.74 | -1.29 |
| | | ( 0.57) | (-0.88) | ( 1.45) | ( 0.94) | ( 0.23) | (-0.05) | ( 2.01)** | (-0.56) | (-0.48) |
| $R^2$ (%) | 14.99 | 15.37 | 15.77 | 16.45 | 16.82 | 15.12 | 14.99 | 19.08 | 15.23 | 15.13 |
| | 6-month horizon | | | | | | | | | |
| FSF | 8.47 | 8.62 | 8.82 | 6.97 | 7.21 | 8.18 | 8.53 | 8.28 | 9.03 | 8.54 |
| | ( 3.26)*** | ( 2.81)*** | ( 2.40)** | ( 2.67)*** | ( 3.03)*** | ( 3.40)*** | ( 3.08)*** | ( 3.75)*** | ( 2.66)*** | ( 3.23)*** |
| Z | | 4.37 | -5.90 | 5.31 | 6.64 | 2.62 | 1.95 | 7.14 | 2.18 | -1.05 |
| | | ( 1.47) | (-2.20)** | ( 1.95)* | ( 1.66)* | ( 0.53) | ( 0.43) | ( 1.68)* | ( 0.78) | (-0.40) |
| $R^2$ (%) | 10.81 | 13.68 | 16.04 | 14.71 | 17.20 | 11.83 | 11.38 | 18.48 | 11.48 | 10.97 |
| | 9-month horizon | | | | | | | | | |
| FSF | 5.71 | 5.85 | 6.02 | 4.63 | 4.28 | 5.41 | 5.79 | 5.51 | 6.50 | 5.63 |
| | ( 3.06)*** | ( 2.67)*** | ( 2.52)** | ( 2.54)** | ( 2.63)*** | ( 2.92)*** | ( 2.73)*** | ( 2.88)*** | ( 2.55)** | ( 2.95)*** |
| Z | | 3.98 | -5.18 | 3.84 | 7.53 | 2.69 | 2.61 | 7.16 | 3.10 | 1.21 |
| | | ( 1.33) | (-1.93)* | ( 1.44) | ( 2.18)** | ( 0.66) | ( 0.67) | ( 1.48) | ( 1.02) | ( 0.45) |
| $R^2$ (%) | 7.09 | 10.53 | 12.90 | 10.04 | 18.98 | 8.65 | 8.57 | 18.25 | 9.05 | 7.41 |
| | 12-month horizon | | | | | | | | | |
| FSF | 4.38 | 4.49 | 4.63 | 3.44 | 2.86 | 4.07 | 4.47 | 4.21 | 5.11 | 4.23 |
| | ( 2.66)*** | ( 2.72)*** | ( 2.45)** | ( 2.12)** | ( 2.61)*** | ( 2.84)*** | ( 2.59)** | ( 2.65)*** | ( 2.55)** | ( 2.81)*** |
| Z | | 3.29 | -4.19 | 3.30 | 7.99 | 2.82 | 3.24 | 6.25 | 2.86 | 2.30 |
| | | ( 1.14) | (-1.66)* | ( 1.33) | ( 2.61)*** | ( 0.89) | ( 1.02) | ( 1.41) | ( 0.91) | ( 0.88) |
| $R^2$ (%) | 5.37 | 8.40 | 10.26 | 8.17 | 22.60 | 7.56 | 8.30 | 16.30 | 7.51 | 6.84 |

This table reports the in-sample results for predictive regressions of the CRSP value-weighted index excess return. The univariate models include the forward skewness factor (FSF); the bivariate models include the FSF and each of the alternative predictors Z used in the study. The alternative forecasting variables are risk-neutral variance (RNV), risk-neutral skewness (RNS), the variance premium (VP), the dividend-price ratio (d-p), the dividend-payout ratio (d-e), the default spread (DEF), the relative short-term risk-free rate (RREL), stock market variance (SVAR), and tail risk (TAIL). The sample period is January 1996-August 2015. Reported coefficients indicate the percentage of annualized excess return resulting from a 1-standard deviation increase in each predictor variable. T-statistics from a circular block bootstrap with block length equal to 12 are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: In-sample predictive power of orthogonalized forward skewness factor for equity market excess returns – Bootstrap t-stats

| | Univariate Model | Bivariate Models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | RNV | RNS | VP | d-p | d-e | DEF | RREL | SVAR | TAIL |
| | 1-month horizon | | | | | | | | | |
| $FSF_{\perp}$ | 6.62 | 6.67 | 6.93 | 5.80 | 5.65 | 6.58 | 6.60 | 6.24 | 4.22 | 6.64 |
| | ( 1.36) | ( 1.32) | ( 1.23) | ( 1.07) | ( 1.17) | ( 1.39) | ( 1.34) | ( 1.50) | ( 1.14) | ( 1.36) |
| Z | | 0.45 | -2.21 | 7.21 | 5.46 | 1.02 | -2.58 | 6.63 | -7.53 | 2.99 |
| | | ( 0.08) | (-0.43) | ( 1.78)* | ( 0.97) | ( 0.16) | (-0.46) | ( 1.78)* | (-1.19) | ( 0.85) |
| $R^2$ (%) | 1.40 | 1.40 | 1.55 | 3.03 | 2.31 | 1.43 | 1.61 | 2.79 | 3.02 | 1.68 |
| | 2-month horizon | | | | | | | | | |
| $FSF_{\perp}$ | 8.19 | 8.51 | 8.80 | 7.45 | 7.19 | 8.13 | 8.18 | 7.81 | 7.28 | 8.18 |
| | ( 2.43)** | ( 2.25)** | ( 2.07)** | ( 1.89)* | ( 2.10)** | ( 2.42)** | ( 2.36)** | ( 2.37)** | ( 2.20)** | ( 2.39)** |
| Z | | 2.61 | -4.43 | 6.33 | 5.67 | 1.77 | -1.73 | 6.75 | -2.87 | -0.43 |
| | | ( 0.61) | (-1.04) | ( 1.91)* | ( 1.11) | ( 0.31) | (-0.31) | ( 1.74)* | (-0.62) | (-0.14) |
| $R^2$ (%) | 3.84 | 4.23 | 4.95 | 6.11 | 5.63 | 4.02 | 4.02 | 6.45 | 4.27 | 3.85 |
| | 3-month horizon | | | | | | | | | |
| $FSF_{\perp}$ | 8.99 | 9.33 | 9.49 | 8.18 | 8.00 | 8.91 | 8.99 | 8.61 | 8.24 | 8.99 |
| | ( 2.86)*** | ( 2.58)** | ( 2.51)** | ( 2.38)** | ( 2.64)*** | ( 2.85)*** | ( 2.76)*** | ( 2.93)*** | ( 2.43)** | ( 2.77)*** |
| Z | | 2.84 | -3.61 | 6.84 | 5.67 | 2.38 | -0.56 | 6.84 | -2.37 | -0.44 |
| | | ( 0.70) | (-0.85) | ( 2.20)** | ( 1.21) | ( 0.42) | (-0.10) | ( 1.79)* | (-0.50) | (-0.16) |
| $R^2$ (%) | 6.81 | 7.48 | 7.89 | 10.70 | 9.44 | 7.29 | 6.84 | 10.74 | 7.24 | 6.83 |
| | 6-month horizon | | | | | | | | | |
| $FSF_{\perp}$ | 6.04 | 6.61 | 6.90 | 5.23 | 4.80 | 5.92 | 6.05 | 5.66 | 6.67 | 6.03 |
| | ( 2.59)** | ( 2.36)** | ( 2.25)** | ( 2.08)** | ( 2.21)** | ( 2.57)** | ( 2.56)** | ( 2.62)*** | ( 2.50)** | ( 2.52)** |
| Z | | 4.85 | -6.32 | 6.64 | 7.18 | 3.32 | 1.72 | 7.06 | 1.99 | -0.43 |
| | | ( 1.80)* | (-2.80)*** | ( 2.33)** | ( 1.79)* | ( 0.67) | ( 0.38) | ( 1.64) | ( 0.82) | (-0.16) |
| $R^2$ (%) | 5.49 | 8.98 | 11.40 | 12.03 | 13.02 | 7.16 | 5.94 | 12.98 | 6.03 | 5.52 |
| | 9-month horizon | | | | | | | | | |
| $FSF_{\perp}$ | 4.14 | 4.66 | 4.90 | 3.57 | 2.78 | 4.03 | 4.16 | 3.75 | 5.11 | 4.16 |
| | ( 2.21)** | ( 2.39)** | ( 2.38)** | ( 1.91)* | ( 1.96)* | ( 2.25)** | ( 2.20)** | ( 1.91)* | ( 2.41)** | ( 2.39)** |
| Z | | 4.32 | -5.49 | 4.71 | 7.86 | 3.15 | 2.46 | 7.11 | 3.06 | 1.63 |
| | | ( 1.60) | (-2.28)** | ( 1.72)* | ( 2.24)** | ( 0.74) | ( 0.61) | ( 1.45) | ( 1.31) | ( 0.58) |
| $R^2$ (%) | 3.73 | 7.74 | 10.17 | 8.49 | 16.77 | 5.90 | 5.05 | 14.70 | 5.57 | 4.31 |
| | 12-month horizon | | | | | | | | | |
| $FSF_{\perp}$ | 2.99 | 3.40 | 3.59 | 2.50 | 1.57 | 2.88 | 3.00 | 2.66 | 3.87 | 3.03 |
| | ( 1.81)* | ( 2.03)** | ( 2.04)** | ( 1.49) | ( 1.44) | ( 1.84)* | ( 1.95)* | ( 1.61) | ( 2.22)** | ( 1.95)* |
| Z | | 3.53 | -4.40 | 3.96 | 8.27 | 3.17 | 3.11 | 6.22 | 2.78 | 2.61 |
| | | ( 1.33) | (-1.95)* | ( 1.64) | ( 2.64)*** | ( 0.94) | ( 1.01) | ( 1.33) | ( 1.18) | ( 1.04) |
| $R^2$ (%) | 2.51 | 5.95 | 7.83 | 6.84 | 21.06 | 5.31 | 5.22 | 13.31 | 4.45 | 4.42 |

This table reports the in-sample results for predictive regressions of the CRSP value-weighted index excess return. The univariate models include the orthogonalized forward skewness factor ($FSF_{\perp}$); the bivariate models include the $FSF_{\perp}$ and each of the alternative predictors Z used in the study. The alternative forecasting variables are risk-neutral variance (RNV), risk-neutral skewness (RNS), the variance premium (VP), the dividend-price ratio (d-p), the dividend-payout ratio (d-e), the default spread (DEF), the relative short-term risk-free rate (RREL), stock market variance (SVAR), and tail risk (TAIL). The sample period is January 1996-August 2015. Reported coefficients indicate the percentage of annualized excess return resulting from a 1-standard deviation increase in each predictor variable. T-statistics from a circular block bootstrap with block length equal to 12 are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: In-sample predictive power of forward variance factor for equity market excess returns – Newey-West t-stats

| | Univariate Model | Bivariate Models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | RNV | RNS | VP | d-p | d-e | DEF | RREL | SVAR | TAIL |
| | 1-month horizon | | | | | | | | | |
| FVF | 11.85 | 12.04 | 11.84 | 10.41 | 11.43 | 11.90 | 11.77 | 12.07 | 11.84 | 11.68 |
| | ( 3.25)*** | ( 3.14)*** | ( 3.13)*** | ( 2.57)** | ( 2.96)*** | ( 3.17)*** | ( 3.22)*** | ( 3.37)*** | ( 3.54)*** | ( 3.26)*** |
| Z | | -1.69 | -0.20 | 4.58 | 5.59 | -0.34 | -2.17 | 7.35 | -8.86 | 1.76 |
| | | (-0.32) | (-0.04) | ( 0.95) | ( 1.07) | (-0.06) | (-0.38) | ( 1.84)* | (-2.65)*** | ( 0.49) |
| $R^2$ (%) | 4.48 | 4.57 | 4.48 | 5.08 | 5.47 | 4.48 | 4.63 | 6.20 | 6.98 | 4.58 |
| | 2-month horizon | | | | | | | | | |
| FVF | 10.52 | 10.48 | 10.33 | 9.17 | 10.04 | 10.44 | 10.47 | 10.74 | 10.51 | 10.69 |
| | ( 3.59)*** | ( 3.38)*** | ( 3.34)*** | ( 2.77)*** | ( 3.27)*** | ( 3.48)*** | ( 3.55)*** | ( 3.67)*** | ( 3.75)*** | ( 3.65)*** |
| Z | | 0.46 | -2.32 | 4.32 | 6.15 | 0.66 | -1.39 | 7.50 | -5.15 | -1.61 |
| | | ( 0.10) | (-0.53) | ( 1.21) | ( 1.26) | ( 0.13) | (-0.26) | ( 2.03)** | (-1.91)* | (-0.58) |
| $R^2$ (%) | 6.35 | 6.36 | 6.66 | 7.32 | 8.51 | 6.37 | 6.46 | 9.57 | 7.87 | 6.50 |
| | 3-month horizon | | | | | | | | | |
| FVF | 10.20 | 10.13 | 10.08 | 8.60 | 9.69 | 10.02 | 10.19 | 10.42 | 10.18 | 10.37 |
| | ( 3.74)*** | ( 3.54)*** | ( 3.51)*** | ( 2.91)*** | ( 3.51)*** | ( 3.67)*** | ( 3.74)*** | ( 3.80)*** | ( 3.95)*** | ( 3.74)*** |
| Z | | 0.66 | -1.44 | 5.11 | 6.28 | 1.34 | -0.22 | 7.61 | -4.93 | -1.62 |
| | | ( 0.16) | (-0.36) | ( 2.05)** | ( 1.33) | ( 0.30) | (-0.04) | ( 2.19)** | (-2.27)** | (-0.65) |
| $R^2$ (%) | 8.77 | 8.81 | 8.94 | 10.75 | 12.07 | 8.92 | 8.77 | 13.64 | 10.82 | 8.99 |
| | 6-month horizon | | | | | | | | | |
| FVF | 6.14 | 5.81 | 5.75 | 4.31 | 5.46 | 5.76 | 6.22 | 6.32 | 6.13 | 6.29 |
| | ( 2.59)** | ( 2.34)** | ( 2.24)** | ( 1.79)* | ( 2.71)*** | ( 2.60)*** | ( 2.66)*** | ( 2.59)** | ( 2.59)** | ( 2.49)** |
| Z | | 3.53 | -4.94 | 5.96 | 7.51 | 2.74 | 1.95 | 7.52 | -0.04 | -1.29 |
| | | ( 1.76)* | (-2.75)*** | ( 3.06)*** | ( 2.02)** | ( 0.88) | ( 0.59) | ( 2.16)** | (-0.02) | (-0.48) |
| $R^2$ (%) | 5.67 | 7.53 | 9.32 | 10.52 | 14.10 | 6.78 | 6.24 | 14.19 | 5.67 | 5.92 |
| | 9-month horizon | | | | | | | | | |
| FVF | 4.04 | 3.72 | 3.69 | 2.72 | 3.32 | 3.66 | 4.15 | 4.23 | 4.06 | 3.91 |
| | ( 1.80)* | ( 1.57) | ( 1.54) | ( 1.10) | ( 2.08)** | ( 1.71)* | ( 1.89)* | ( 1.75)* | ( 1.74)* | ( 1.80)* |
| Z | | 3.42 | -4.53 | 4.31 | 8.04 | 2.79 | 2.61 | 7.42 | 1.49 | 1.10 |
| | | ( 1.82)* | (-3.27)*** | ( 1.86)* | ( 2.51)** | ( 1.31) | ( 1.07) | ( 1.93)* | ( 1.13) | ( 0.39) |
| $R^2$ (%) | 3.56 | 6.08 | 8.00 | 7.22 | 17.53 | 5.22 | 5.04 | 15.53 | 4.04 | 3.82 |
| | 12-month horizon | | | | | | | | | |
| FVF | 3.35 | 3.09 | 3.07 | 2.25 | 2.59 | 2.96 | 3.49 | 3.51 | 3.37 | 3.08 |
| | ( 1.52) | ( 1.33) | ( 1.32) | ( 0.91) | ( 2.19)** | ( 1.40) | ( 1.67)* | ( 1.45) | ( 1.47) | ( 1.56) |
| Z | | 2.86 | -3.68 | 3.59 | 8.30 | 2.87 | 3.26 | 6.45 | 1.61 | 2.19 |
| | | ( 1.54) | (-2.90)*** | ( 1.60) | ( 2.93)*** | ( 1.92)* | ( 1.85)* | ( 1.94)* | ( 1.22) | ( 0.86) |
| $R^2$ (%) | 3.14 | 5.41 | 6.91 | 6.41 | 22.26 | 5.40 | 6.11 | 14.79 | 3.86 | 4.46 |

This table reports the in-sample results for predictive regressions of the CRSP value-weighted index excess return. The univariate models include the forward variance factor (FVF); the bivariate models include the FVF and each of the alternative predictors Z used in the study. The alternative forecasting variables are risk-neutral variance (RNV), risk-neutral skewness (RNS), the variance premium (VP), the dividend-price ratio (d-p), the dividend-payout ratio (d-e), the default spread (DEF), the relative short-term risk-free rate (RREL), stock market variance (SVAR), and tail risk (TAIL). The sample period is January 1996-August 2015. Reported coefficients indicate the percentage of annualized excess return resulting from a 1-standard deviation increase in each predictor variable. Newey-West (1987) t-statistics with lag length equal to the maximum of 3 or (horizon × 2) are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: In-sample predictive power of forward skewness factor for equity market excess returns – Newey-West t-stats

| | Univariate Model | Bivariate Models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | RNV | RNS | VP | d-p | d-e | DEF | RREL | SVAR | TAIL |
| | 1-month horizon | | | | | | | | | |
| FSF | 12.55 | 12.55 | 12.66 | 11.22 | 11.75 | 12.56 | 12.48 | 12.38 | 11.01 | 12.42 |
| | ( 3.13)*** | ( 3.17)*** | ( 3.03)*** | ( 2.39)** | ( 2.46)** | ( 3.06)*** | ( 3.16)*** | ( 3.30)*** | ( 2.76)*** | ( 3.14)*** |
| Z | | -0.01 | -1.94 | 4.67 | 4.27 | -0.14 | -2.27 | 6.67 | -6.11 | 2.24 |
| | | (-0.00) | (-0.63) | ( 0.95) | ( 0.85) | (-0.03) | (-0.48) | ( 1.83)* | (-1.82)* | ( 0.70) |
| $R^2$ (%) | 5.02 | 5.02 | 5.14 | 5.66 | 5.58 | 5.02 | 5.18 | 6.43 | 6.13 | 5.18 |
| | 2-month horizon | | | | | | | | | |
| FSF | 12.93 | 12.99 | 13.15 | 11.84 | 12.06 | 12.86 | 12.89 | 12.76 | 12.41 | 13.00 |
| | ( 4.42)*** | ( 4.48)*** | ( 4.28)*** | ( 3.49)*** | ( 3.59)*** | ( 4.45)*** | ( 4.28)*** | ( 4.39)*** | ( 3.87)*** | ( 4.47)*** |
| Z | | 1.95 | -3.94 | 3.81 | 4.70 | 0.63 | -1.42 | 6.86 | -2.07 | -1.24 |
| | | ( 0.64) | (-1.46) | ( 1.11) | ( 1.07) | ( 0.15) | (-0.34) | ( 2.08)** | (-0.88) | (-0.54) |
| $R^2$ (%) | 9.59 | 9.81 | 10.47 | 10.35 | 10.81 | 9.61 | 9.70 | 12.28 | 9.82 | 9.67 |
| | 3-month horizon | | | | | | | | | |
| FSF | 13.34 | 13.40 | 13.51 | 12.09 | 12.45 | 13.20 | 13.33 | 13.16 | 12.90 | 13.41 |
| | ( 5.12)*** | ( 5.04)*** | ( 4.83)*** | ( 4.02)*** | ( 4.04)*** | ( 5.11)*** | ( 5.08)*** | ( 5.35)*** | ( 4.66)*** | ( 5.13)*** |
| Z | | 2.12 | -3.05 | 4.35 | 4.74 | 1.23 | -0.24 | 6.97 | -1.74 | -1.29 |
| | | ( 0.90) | (-1.41) | ( 1.85)* | ( 1.15) | ( 0.34) | (-0.06) | ( 2.28)** | (-1.05) | (-0.69) |
| $R^2$ (%) | 14.99 | 15.37 | 15.77 | 16.45 | 16.82 | 15.12 | 14.99 | 19.08 | 15.23 | 15.13 |
| | 6-month horizon | | | | | | | | | |
| FSF | 8.47 | 8.62 | 8.82 | 6.97 | 7.21 | 8.18 | 8.53 | 8.28 | 9.03 | 8.54 |
| | ( 6.00)*** | ( 6.19)*** | ( 5.10)*** | ( 4.72)*** | ( 5.98)*** | ( 6.93)*** | ( 6.46)*** | ( 4.90)*** | ( 5.24)*** | ( 6.09)*** |
| Z | | 4.37 | -5.90 | 5.31 | 6.64 | 2.62 | 1.95 | 7.14 | 2.18 | -1.05 |
| | | ( 2.77)*** | (-5.12)*** | ( 2.83)*** | ( 1.93)* | ( 0.97) | ( 0.64) | ( 2.11)** | ( 1.35) | (-0.42) |
| $R^2$ (%) | 10.81 | 13.68 | 16.04 | 14.71 | 17.20 | 11.83 | 11.38 | 18.48 | 11.48 | 10.97 |
| | 9-month horizon | | | | | | | | | |
| FSF | 5.71 | 5.85 | 6.02 | 4.63 | 4.28 | 5.41 | 5.79 | 5.51 | 6.50 | 5.63 |
| | ( 3.41)*** | ( 4.20)*** | ( 4.18)*** | ( 2.25)** | ( 3.94)*** | ( 3.23)*** | ( 3.78)*** | ( 2.72)*** | ( 4.00)*** | ( 3.29)*** |
| Z | | 3.98 | -5.18 | 3.84 | 7.53 | 2.69 | 2.61 | 7.16 | 3.10 | 1.21 |
| | | ( 2.10)** | (-3.68)*** | ( 1.57) | ( 2.49)** | ( 1.32) | ( 1.10) | ( 1.89)* | ( 1.85)* | ( 0.45) |
| $R^2$ (%) | 7.09 | 10.53 | 12.90 | 10.04 | 18.98 | 8.65 | 8.57 | 18.25 | 9.05 | 7.41 |
| | 12-month horizon | | | | | | | | | |
| FSF | 4.38 | 4.49 | 4.63 | 3.44 | 2.86 | 4.07 | 4.47 | 4.21 | 5.11 | 4.23 |
| | ( 3.16)*** | ( 3.72)*** | ( 3.75)*** | ( 1.82)* | ( 4.96)*** | ( 2.85)*** | ( 3.79)*** | ( 2.43)** | ( 3.77)*** | ( 2.89)*** |
| Z | | 3.29 | -4.19 | 3.30 | 7.99 | 2.82 | 3.24 | 6.25 | 2.86 | 2.30 |
| | | ( 1.70)* | (-2.88)*** | ( 1.39) | ( 2.89)*** | ( 1.85)* | ( 1.81)* | ( 1.88)* | ( 1.73)* | ( 0.95) |
| $R^2$ (%) | 5.37 | 8.40 | 10.26 | 8.17 | 22.60 | 7.56 | 8.30 | 16.30 | 7.51 | 6.84 |

This table reports the in-sample results for predictive regressions of the CRSP value-weighted index excess return. The univariate models include the forward skewness factor (FSF); the bivariate models include the FSF and each of the alternative predictors Z used in the study. The alternative forecasting variables are risk-neutral variance (RNV), risk-neutral skewness (RNS), the variance premium (VP), the dividend-price ratio (d-p), the dividend-payout ratio (d-e), the default spread (DEF), the relative short-term risk-free rate (RREL), stock market variance (SVAR), and tail risk (TAIL). The sample period is January 1996-August 2015. Reported coefficients indicate the percentage of annualized excess return resulting from a 1-standard deviation increase in each predictor variable. Newey-West (1987) t-statistics with lag length equal to the maximum of 3 or (horizon × 2) are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: In-sample predictive power of orthogonalized forward skewness factor for equity market excess returns – Newey-West t-stats

| | Univariate Model | Bivariate Models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | RNV | RNS | VP | d-p | d-e | DEF | RREL | SVAR | TAIL |
| | 1-month horizon | | | | | | | | | |
| $FSF_{\perp}$ | 6.62 | 6.67 | 6.93 | 5.80 | 5.65 | 6.58 | 6.60 | 6.24 | 4.22 | 6.64 |
| | ( 1.52) | ( 1.60) | ( 1.57) | ( 1.27) | ( 1.04) | ( 1.50) | ( 1.56) | ( 1.54) | ( 0.91) | ( 1.56) |
| Z | | 0.45 | -2.21 | 7.21 | 5.46 | 1.02 | -2.58 | 6.63 | -7.53 | 2.99 |
| | | ( 0.08) | (-0.50) | ( 1.47) | ( 0.96) | ( 0.19) | (-0.45) | ( 1.71)* | (-1.58) | ( 0.84) |
| $R^2$ (%) | 1.40 | 1.40 | 1.55 | 3.03 | 2.31 | 1.43 | 1.61 | 2.79 | 3.02 | 1.68 |
| | 2-month horizon | | | | | | | | | |
| $FSF_{\perp}$ | 8.19 | 8.51 | 8.80 | 7.45 | 7.19 | 8.13 | 8.18 | 7.81 | 7.28 | 8.18 |
| | ( 2.39)** | ( 2.50)** | ( 2.48)** | ( 2.16)** | ( 1.77)* | ( 2.42)** | ( 2.37)** | ( 2.32)** | ( 1.81)* | ( 2.38)** |
| Z | | 2.61 | -4.43 | 6.33 | 5.67 | 1.77 | -1.73 | 6.75 | -2.87 | -0.43 |
| | | ( 0.60) | (-1.13) | ( 1.76)* | ( 1.15) | ( 0.38) | (-0.34) | ( 1.90)* | (-0.78) | (-0.16) |
| $R^2$ (%) | 3.84 | 4.23 | 4.95 | 6.11 | 5.63 | 4.02 | 4.02 | 6.45 | 4.27 | 3.85 |
| | 3-month horizon | | | | | | | | | |
| $FSF_{\perp}$ | 8.99 | 9.33 | 9.49 | 8.18 | 8.00 | 8.91 | 8.99 | 8.61 | 8.24 | 8.99 |
| | ( 2.72)*** | ( 2.79)*** | ( 2.71)*** | ( 2.49)** | ( 2.01)** | ( 2.73)*** | ( 2.73)*** | ( 2.75)*** | ( 2.32)** | ( 2.71)*** |
| Z | | 2.84 | -3.61 | 6.84 | 5.67 | 2.38 | -0.56 | 6.84 | -2.37 | -0.44 |
| | | ( 0.81) | (-1.07) | ( 2.78)*** | ( 1.22) | ( 0.60) | (-0.12) | ( 2.05)** | (-0.83) | (-0.20) |
| $R^2$ (%) | 6.81 | 7.48 | 7.89 | 10.70 | 9.44 | 7.29 | 6.84 | 10.74 | 7.24 | 6.83 |
| | 6-month horizon | | | | | | | | | |
| $FSF_{\perp}$ | 6.04 | 6.61 | 6.90 | 5.23 | 4.80 | 5.92 | 6.05 | 5.66 | 6.67 | 6.03 |
| | ( 4.55)*** | ( 5.04)*** | ( 4.39)*** | ( 4.49)*** | ( 3.22)*** | ( 5.05)*** | ( 4.78)*** | ( 3.82)*** | ( 3.86)*** | ( 4.65)*** |
| Z | | 4.85 | -6.32 | 6.64 | 7.18 | 3.32 | 1.72 | 7.06 | 1.99 | -0.43 |
| | | ( 2.77)*** | (-4.67)*** | ( 3.78)*** | ( 1.96)* | ( 1.19) | ( 0.49) | ( 1.98)** | ( 1.16) | (-0.16) |
| $R^2$ (%) | 5.49 | 8.98 | 11.40 | 12.03 | 13.02 | 7.16 | 5.94 | 12.98 | 6.03 | 5.52 |
| | 9-month horizon | | | | | | | | | |
| $FSF_{\perp}$ | 4.14 | 4.66 | 4.90 | 3.57 | 2.78 | 4.03 | 4.16 | 3.75 | 5.11 | 4.16 |
| | ( 2.57)** | ( 3.48)*** | ( 3.74)*** | ( 2.11)** | ( 2.49)** | ( 2.45)** | ( 2.90)*** | ( 2.07)** | ( 3.14)*** | ( 2.41)** |
| Z | | 4.32 | -5.49 | 4.71 | 7.86 | 3.15 | 2.46 | 7.11 | 3.06 | 1.63 |
| | | ( 2.43)** | (-4.20)*** | ( 2.24)** | ( 2.48)** | ( 1.56) | ( 0.90) | ( 1.81)* | ( 2.01)** | ( 0.57) |
| $R^2$ (%) | 3.73 | 7.74 | 10.17 | 8.49 | 16.77 | 5.90 | 5.05 | 14.70 | 5.57 | 4.31 |
| | 12-month horizon | | | | | | | | | |
| $FSF_{\perp}$ | 2.99 | 3.40 | 3.59 | 2.50 | 1.57 | 2.88 | 3.00 | 2.66 | 3.87 | 3.03 |
| | ( 2.39)** | ( 3.13)*** | ( 3.31)*** | ( 1.68)* | ( 1.74)* | ( 2.10)** | ( 2.85)*** | ( 1.92)* | ( 2.97)*** | ( 2.15)** |
| Z | | 3.53 | -4.40 | 3.96 | 8.27 | 3.17 | 3.11 | 6.22 | 2.78 | 2.61 |
| | | ( 2.01)** | (-3.45)*** | ( 1.94)* | ( 2.84)*** | ( 2.15)** | ( 1.50) | ( 1.81)* | ( 1.95)* | ( 1.02) |
| $R^2$ (%) | 2.51 | 5.95 | 7.83 | 6.84 | 21.06 | 5.31 | 5.22 | 13.31 | 4.45 | 4.42 |

This table reports the in-sample results for predictive regressions of the CRSP value-weighted index excess return. The univariate models include the orthogonalized forward skewness factor ($FSF_{\perp}$); the bivariate models include the $FSF_{\perp}$ and each of the alternative predictors Z used in the study. The alternative forecasting variables are risk-neutral variance (RNV), risk-neutral skewness (RNS), the variance premium (VP), the dividend-price ratio (d-p), the dividend-payout ratio (d-e), the default spread (DEF), the relative short-term risk-free rate (RREL), stock market variance (SVAR), and tail risk (TAIL). The sample period is January 1996-August 2015. Reported coefficients indicate the percentage of annualized excess return resulting from a 1-standard deviation increase in each predictor variable. Newey-West (1987) t-statistics with lag length equal to the maximum of 3 or (horizon × 2) are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Implied long-horizon $R^2$ estimates

| | 2-month horizon | 3-month horizon | 6-month horizon | 9-month horizon | 12-month horizon |
|---|---|---|---|---|---|
| | | | Actual estimates | | |
| FVF | 6.35 | 8.77 | 5.67 | 3.56 | 3.14 |
| FSF | 9.59 | 14.99 | 10.81 | 7.09 | 5.37 |
| $FSF_\perp$ | 3.84 | 6.81 | 5.49 | 3.73 | 2.51 |
| | | | Implied estimates | | |
| FVF | 6.02 | 6.27 | 5.00 | 3.70 | 2.85 |
| FSF | 5.88 | 5.49 | 3.62 | 2.51 | 1.89 |
| $FSF_\perp$ | 1.47 | 1.27 | 0.76 | 0.51 | 0.39 |

This table reports the implied long-horizon $R^2$ estimates from the one-month actual $R^2$ estimates under the null of no long-horizon predictability using the methodology of Boudoukh, Richardson, and Whitelaw (2008). For comparison, the table also presents the actual long-horizon $R^2$ estimates. FVF is the forward variance factor, FSF is the forward skewness factor, and $FSF_\perp$ is the orthogonalized forward skewness factor.