Covariance risk premium

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Abstract

Covariance risk premium (CRP), defined as the difference between the historical and the risk-neutral covariance rates (HC and RC) of the implied volatility changes and the market index returns, is positively and significantly related to future stock market returns at horizons from 1 month to 24 months. This paper empirically documents that CRP has significant in-sample, and out-of-sample predictive ability, generates sizable economic value for a mean-variance investor and outperforms many well-known predictors. In addition, CRP can predict cross-sectional stock returns at the portfolio level.

Keywords: Covariance risk premium; return predictability; implied volatility.

JEL Classifications: G13, G12.

1 Introduction

The expected excess return on the market, or equity risk premium (ERP) has important implications in many fundamental areas of finance (e.g., Cochrane, 2008). Predicting the future market returns has significant interest in the empirical asset pricing literature.[1] In this paper, we introduce a new stock market return predictor, covariance risk premium (CRP), defined as the difference between the historical and the risk-neutral covariance rates (HC and RC) of the implied volatility changes and the market index returns. We show that CRP is a strong predictor that positively predicts future stock market returns. To our knowledge, this is the first empirical evidence that CRP contains useful information regarding future market returns.

We first construct the covariance rate between the implied volatility change and market index returns under the risk-neutral measure from equity options. According to the no-arbitrage formula proposed by Carr and Wu (2020), which is based on a new option pricing framework, the degree to which the implied variance level deviates from the at-the-money implied variance level at each strike and moneyness level is determined by the variance and covariance of the implied volatility change. Conversely, RC between the stock market returns and the implied volatility change could be extracted from the option market data. We then measure HC over the previous month by the summation of daily covariances between the variations in the stock market index and the implied volatility. When RC differs from the market observation, the difference between HC and RC can be viewed as a potential source of risk premium. Therefore, we define the difference as CRP. For the

[1] A large literature has focused on the market return predictability. For instance, Welch and Goyal (2008) examine the predictive ability of a set of 14 well-known macroeconomic variables for predicting the equity premium. Huang et al. (2015) propose a new investor sentiment index aligned for predicting the aggregate stock market return. Rapach et al. (2016) find that short interest is a strong predictor of future aggregate excess stock returns and outperforms all of 14 popular predictors. In a recent paper, Chen et al. (2021) show that short selling efficiency contains significant and robust forecasting signals for aggregate stock returns.

return predictability analysis, we focus on over-lapping monthly return and construct the monthly time-series of CRP by using the end-of-month HC and RC.

We propose a hypothesis that CRP can positively predict future stock market returns based on a conceptual model. Then using S&P 500 index and its option data from 1996 to 2019, we undertake an extensive empirical investigation of CRP's predictive performance for forecasting future market returns. First, we consider the predictive ability of CRP in comparison to the five predictors extracted from the no-arbitrage formula, 14 economic variables from Welch and Goyal (2008) and financial variable of variance risk premium (VRP). We evaluate the in-sample and out-of-sample predictive performance of each predictor based on univariate ordinary least squares (OLS) regressions for 1, 3, 6, 9, 12 and 24-month return horizons. Second, we test the economic significance of return predictability using a mean–variance utility function. Third, we consider 25 standard Fama-French portfolios sorted on market capitalisation (size) and book-to-market (BM) (e.g., Fama and French, 1993) and examine whether CRP predict cross-sectional stock returns at the portfolio level rather than the aggregate market return portfolio (e.g., Huang et al., 2015). Finally, we conduct a serial of robustness checks. We consider whether CRP's return predictability is not affected by the 2008-2009 financial crisis, whether the out-of-sample predictive ability of CRP is robust to a rolling window and whether the economic significance of CRP's predictive ability is robust to alternative risk aversion coefficients.

Our empirical analyses unveil a number of findings. First, in-sample results reveal that CRP can positively and significantly predict future stock market returns at forecasting horizons from one to 24 months over the 1996–2019 sample period. The regression coefficient of CRP with a 1-month forecasting horizon is 14.95 with a t-statistic of 3.29 and the adjusted R^2 is 3.6%. The predictive ability of CRP persists over two years. At the 24-month forecasting horizon, the regression coefficient is 4.25 with a t-statistic of 2.54 and the R^2 is 4.46%. CRP outperforms the other predictors since it exhibits the statistically significant regression coefficients and large adjusted R^2 values across all forecasting horizons. CRP remains statistically significant after controlling for other comparative predictors, indicating that it contains distinct information relevant to predicting future market returns.

Second, for out-of-sample results, we find that CRP has positive out-of-sample R^2 statistics of 4.57%, 6.82%, 4.3%, 4.67%, 3.13% and 12.87% at horizons of one to 24 months, respectively. Compared with the other predictors, CRP performs better as it is the only predictor to produce significantly positive out-of-sample R^2 at all horizons. In addition, we examine the economic significance of CRP's predictive ability and find that CRP generates the substantially positive and large certainty equivalent (CE) gains over the historical average forecast up to 24 months, which implies that CRP can produce economically significant profits for a mean-variance investor at any forecast horizon. The CE gains of CRP vary from 3% at the 24-month horizon to 9.61% at the 3-month horizon. While for other forecasting variables except for TBL and VRP, they do not reveal substantial economic values for investors. Although TBL and VRP provide positive CE gains across all horizons, its CE gains are generally lower than CPR's. Therefore, CRP is not only statistically significant, but also economically significant in providing sizable CE gains for a mean-variance investor.

Third, CRP can predict most of the standard 25 size and BM sorted Fama-French portfolio returns. In particular, it predicts 23 out of 25 portfolio returns at the 24-month forecasting horizon. When the stocks are sorted by BM, the t-statistic value of CRP generally becomes smaller as the firm BM becomes higher for each size sorted portfolio at each forecasting horizon. When the stocks are sorted by size, the t-statistic value of CRP generally becomes larger as the firm size increases especially for low BM sorted portfolio at each forecasting horizon. In general, CRP exhibits stronger predictive power in terms of forecasting the returns of lower BM and larger size firms.

Finally, we implement several analyses for robustness checks. We show that: (a) CRP's in-sample predictive ability for forecasting future stock market returns holds when excluding the sample of data corresponding to the global financial crisis. The financial crisis does not drive CRP's return predictability; (b) the out-of-sample predictive performance of CRP is robust to alternative prediction approach; (c) the economic significance of CRP's return predictability holds when we consider alternative risk aversion coefficients.

Our empirical work contributes to the literature on the stock market return predictability, especially using information extracted from option markets for forecasting future market returns. For instance, Bollerslev et al. (2009) show that the variance risk premium (VRP) predicts market returns for up to a few months horizon. After that, there is a variety of studies on return predictability of VRP (e.g., Drechsler and Yaron, 2011; Bollerslev et al., 2015; Feunou et al., 2018). For recent studies, Fan et al. (2021) study the market return predictability of option-implied moment risk premia embedded in the conventional VRP. Cao et al. (2020) and Han and Li (2021) examine the predictive ability of the call-put implied volatility spread for forecasting stock market returns. Avino et al. (2020) show that the dividend growth rate implied by the option market has implications for the predictability of stock market returns. In this paper, we contribute to a growing literature on time series predictability of stock market returns by introducing a new and robust predictor CRP and show that the predictor contains substantial information regarding future stock market returns.

The rest of the paper is organized as follows. Section 2 presents a conceptual model that links CRP to ERP and proposes a hypothesis. Section 3 describes the construction of RC and HC and the measure of CRP. Section 4 presents the data. Section 5 provides the empirical results on the CRP's predictive power for forecasting stock market returns and portfolio returns. Section 6 discusses robustness checks. Section 8 concludes.

2 A conceptual model

Before testing the return predictability of CRP, we introduce a conceptual model to show the link between CRP and ERP and then propose a hypothesis. In this model, we first specify the dynamics processes of a stock market index, the implied volatility of the market index option and the correlation between stock market returns and the implied volatility variations. Then using a pricing kernel, we present the expressions for ERP and CRP, respectively. Finally, we link ERP with CRP by the correlation coefficient. Through the conceptual model, our study attempt to theoretically explore the potential correlation between ERP and CRP.

2.1 Pricing kernel and ERP

In our conceptual model, we first consider a stock market index with price process S_t. Under a given probability space $(\Omega, \mathcal{F}, \mathbb{P})$ and the complete filtration $\{\mathcal{F}_t\}_{t\geq 0}$, S_t is proposed to have the following dynamics under the statistical measure $\mathbb{P}$

$$\frac{dS_t}{S_t} = \mu_{S,t}dt + \sqrt{V_t}dW^{\mathbb{P}}_{S,t}, \tag{1}$$

where $\mu_{S,t}$ is the instantaneous expected stock market returns, V_t denotes the instantaneous variance rate of market returns and $W_{S,t}$ is a standard Brownian motion that measures the stock market return risk.

In terms of measuring the uncertainty of stock market returns, the traditional option pricing literature, e.g., Heston (1993), specify the risk-neutral dynamics of the variance (V_t) of stock market returns. However, we measure the uncertainty of the return risk by implied volatilities derived from option prices and do not consider V_t in this paper contributing a risk premium. The main advantage of using option market information is that option prices are forward looking by nature. In addition, option implied volatilities in different strikes and maturities are more observable than the instantaneous variance rate for investors.

Therefore, in line with Carr and Wu (2016), we specify the risk-neutral dynamics of the option implied volatility across different strikes and maturities.

$$\frac{dI_t}{I_t} = \mu_{I,t}dt + \omega_t dW^{\mathbb{P}}_{I,t}, \tag{2}$$

where dI_t is the dynamics of the option's implied volatility, $\mu_{I,t}$ is the annualized expected rate of implied volatility change, ω_t is the volatility of the implied volatility change and $\omega_t > 0$, and $W_{I,T}$ is a standard Brownian motion that is independent with $W_{S,t}$ and measures the implied volatility risk. Both Brownian shocks on the market index and the implied volatilities are correlated with a correlation parameter ρ

$$\mathbb{E}^{\mathbb{P}}[dW^{\mathbb{P}}_{S,t}dW^{\mathbb{P}}_{I,t}] = \rho_t dt. \tag{3}$$

We assume the dynamics process of the correlation between stock market returns and the implied volatility variations following:

$$d\rho_t = \alpha_t dt + \beta_t dW^{\mathbb{P}}_{\rho,t}, \tag{4}$$

where $W_{\rho,t}$ is a Brownian motion that is independent of $W_{S,t}$ and $W_{I,T}$ and measures the correlation risk. We choose $\{\alpha_t, \beta_t\}$ such that $\rho_t \in [-1, 1]$. Empirically, the correlation parameter ρ is negative, as documented by Carr and Wu (2017) and Hibbert et al. (2008), the correlation estimates between the index return and changes in the implied volatility level are all strongly negative.

Under the specifications in equations (1)-(4), the three Brownian motions, $W_{S,t}$, $W_{I,t}$ and $W_{\rho,t}$, measure the return risk, implied volatility risk and correlation risk, respectively. This reveals that the dynamics of stock market returns is driven by the three sources of risks. We assume that the market price of return and implied volatility risks are $a\sqrt{V_t}$ and $b\sqrt{V_t}$, respectively, proportional to the square root of the variance rate, following Egloff et al. (2010) and Zhou and Zhu (2012). We also assume that the market price of the diffusion correlation risk $W_{\rho,t}$ is $c\rho_t$, proportional to the correlation coefficient. Hence, the pricing kernel dynamics is

$$\frac{dM_t}{M_t} = -rdt - a\sqrt{V_t}dW^{\mathbb{P}}_{S,t} - b\sqrt{V_t}dW^{\mathbb{P}}_{I,t} - c\rho_t dW^{\mathbb{P}}_{\rho,t}, \tag{5}$$

where a, b and c are constants. Empirically, as shown in Egloff et al. (2010), the market price of the return risk is positive ($a > 0$). It means that the investors require higher future market returns as compensation for higher return risk. Bakshi et al. (2003) find that the price of return volatility risk is negative in index option markets. We follow their findings and make a similar assumption that the market price of the implied volatility risk is negative ($b < 0$), so that investors demand a negative compensation for the implied volatility risk.

We define ERP as the difference between expectations of the stock market returns under the statistical measure $\mathbb{P}$ and the risk-neutral probability measure $\mathbb{Q}$. Following Benzoni et al. (2011), we apply Itô's Lemma and get ERP

$$ERP = \frac{1}{dt}\left(\mathbb{E}^{\mathbb{P}}\left[\frac{dS_t}{S_t}\right] - \mathbb{E}^{\mathbb{Q}}\left[\frac{dS_t}{S_t}\right]\right) = -\frac{1}{dt}\mathbb{E}^{\mathbb{P}}\left[\frac{dM_t}{M_t}\frac{dS_t}{S_t}\right] \tag{6}$$

Using the definition of the pricing kernel, we obtain the following expression

$$ERP = aV_t + bV_t\rho_t. \tag{7}$$

For $a > 0$, $b < 0$ and $\rho_t < 0$, ERP should be positive. The specification in equation (7) shows that ERP is driven by three risk sources, the return risk, the implied volatility risk and the correlation risk. In particular, the first term of the right side reflects the compensation for the shock on the market index. The second term represents a confounding of a risk premium on both sources of risks, the implied volatility risk and correlation risk. As discussed above, investors require negative compensations for bearing the implied volatility risk. The compensations can be regarded as the risk premium of the implied volatility.

For the correlation risk or called covariance risk, investors also demand a compensation for being exposed to unexpected changes in the covariance between stock market return and the changes in the implied volatility. The compensation is CRP. We will define CRP under the definitions of the correlation process and the pricing kernel, and construct a theoretical link between the ERP and CRP in the next subsection.

2.2 Linking CRP to ERP

Under the specifications of the dynamics of the stock market return and the implied volatility change, the process of the covariance rate between the two dynamics can be defined a

$$C_t = \frac{1}{dt} Cov^{\mathbb{P}} \left(\frac{dS_t}{S_t}, \frac{dI_t}{I_t} \right) = \frac{1}{dt} Cov^{\mathbb{P}} \left(\sqrt{V_t} dW^{\mathbb{P}}_{S,t}, \omega_t dW^{\mathbb{P}}_{I,t} \right) = \sqrt{V_t} \omega_t \rho_t. \tag{8}$$

Obviously, the covariance rate is negative since the stock market index and the implied volatility usually have the opposite movement directions. Hibbert et al. (2008) explain the negative return-implied volatility relation using characteristics of market behavior, that is, high return and low risk or volatility. For option markets, option investors bid up put prices for hedging the downward risk during a market crash. The more negative the market index return is, the more the implied volatility increases, and the more negative the covariance rate becomes. This suggests that the higher implied volatility is associated with more negative covariance rate.

When RC differs from the market observation, the difference can be viewed as a potential source of risk premium. Similar to VRP, we define the difference between the ex-post HC and the ex ante RC as a measure of CRP. We regard $\sqrt{V_t}$ and ω_t as constants when assuming that the variations of $\sqrt{V_t}$ and ω_t are smaller than the variation of ρ_t,

$$\begin{aligned} CRP =& \frac{1}{dt} \left[\mathbb{E}^{\mathbb{P}}(dC_t) - \mathbb{E}^{\mathbb{Q}}(dC_t) \right] = \sqrt{V_t} \omega_t \cdot \frac{1}{dt} \left[\mathbb{E}^{\mathbb{P}}(d\rho_t) - \mathbb{E}^{\mathbb{Q}}(d\rho_t) \right] \\ =& - \sqrt{V_t} \omega_t \frac{1}{dt} Cov^{\mathbb{P}} \left(\frac{dM_t}{M_t}, d\rho_t \right) = \sqrt{V_t} \omega_t \cdot c \rho_t \beta_t. \end{aligned} \tag{9}$$

We assume that the market price of the correlation risk is positive ($c < 0$ as $\rho_t < 0$). For $\omega_t > 0$ and $\beta_t > 0$, the CRP is always positive. This implies a lower statistical covariance level than RC in absolute magnitude. Risk-averse investors are averse to the variations in return-volatility covariance and require a positive premium for the covariance risk.

Comparing both expressions, CRP and ERP, we find that they can be linked by the correlation coefficient and CRP might has direct implications on the ERP. Thus, we derive the following result according to equations (7) and (9)

$$ERP = e + f \cdot CRP, \tag{10}$$

where

$$e = a_t V_t, f = \frac{b_t \sqrt{V_t}}{\omega_t \beta_t c} > 0.$$

This equation provides a direct relationship between ERP and CRP. According to the analysis above, for $b_t < 0$, $c < 0$, $\omega_t > 0$ and $\beta_t > 0$, the slope parameter f must be positive, so that CRP should be positively related to ERP. In other words, higher risk premium of covariance between stock market returns and the changes in the implied volatility yield higher expected stock market returns next period. CRP should serve as a useful predictor for forecasting the future excess stock market returns. Here, we propose the following hypothesis.

Hypothesis: CRP positively predicts ERP.

3 Measuring CRP

Our hypothesis that CRP positively predicts ERP is directly motivated by equation (10). To measure CRP and investigate the conjecture empirically, we first define two covariance measures: RC and HC.

To construct RC between stock markt returns and the implied volatility variations in the risk-neutral measure, we let I_t denote the implied volatility of a European option at time t and let A_t denote the at-the-money implied volatility of a European option at time t. According to Carr and Wu (2020) formula, which is a no-arbitrage formula based on a new option pricing framework, the degree to which the implied variance level I_t^2 deviates from the at-the-money implied variance level at each strike and moneyness level A_t^2 is determined by the variance and covariance of the implied volatility change. This formula is expressed as:

$$I_t^2 - A_t^2 = 2\gamma_t z_+ + \omega_t^2 z_+ z_-, \tag{11}$$

where ω_t^2 denotes the risk-neutral conditional variance of the implied volatility percentage change, γ_t is the RC between the implied volatility percentage change and stock market return, and the terms $z_{+-} = (k \pm \frac{1}{2} I_t^2 \tau)$, where τ is the time to maturity and $k = \ln(K/S_t)$ is the relative strike, represent the convexity-adjusted moneyness of the call under the risk-neutral measure. ω_t^2 and γ_t jointly determine the shape of the implied volatility smile and they could be regarded as the curvature and slope of the implied volatility smile respectively.

Conversely, we can extract RC from the option market data. In particular, RC can be estimated by performing a cross-sectional regression of the implied variance difference from the at-the-money level $(I_t^2 - A_t^2)$ on the two convexity-adjusted moneyness measures $2z_+$ and $z_+ z_-$ at each date and maturity.[2]

We then measure HC between the variations in the stock market index and the implied volatility. Let $\Delta \ln I_t$ denote the log percentage implied volatility change at time t and let R_t denote the log stock market return at time t. We verify that our empirical findings are hold using the simple implied volatility change and simple return. The ex-post historical covariance is calculated according to the following equation:

$$HC_t = \frac{252}{p} \sum_{i=1}^{p} (\Delta \ln I_{t-i}) R_{t-i}, \tag{12}$$

[2]The estimation of RC is under the local commonality assumption on the movements of the implied volatilities across moneyness following Carr and Wu (2020).

where p is the number of the observations in a rolling window when calculating the covariance rate. The historical covariance is annualized according to the 252/trading day convention.

To estimate the objective expectation of HC, one also can use a statistical forecast of HC, which is similar to estimating the realized variance when measuring VRP. As shown by Zhou (2018), for asset return predictability exercises, especially from a real-world trader's perspective, it is more appropriate to use the simple lag HC because it is available in real time and there is no modeling assumption involved. Therefore, we use the ex-post HC as a proxy for the physical expectation of HC.[3] Correspondingly, CRP can be defined as[4]

$$CRP_t = HC_t - RC_t, \tag{13}$$

4 Data

Our data come from several sources. We use the Standard & Poor's (S&P) 500 index to present the US stock market index. The S&P 500 index data are obtained from OptionMetrics and the sample period is from January 4, 1996 to December 31, 2019. The stock market return is computed as the continuously compounded log return on the S&P 500 index minus the risk-free rate that is the one-month Treasury bill rate from the Kenneth R. French Data Library. Besides, we use S&P 500 index options to measure CRP. The option data are obtained from OptionMetrics and the sample period is the same as the period of S&P 500 index. We process the option data set as follows: we first discard options with zero bid price, zero ask price and implied volatility less than 0.01 and then delete options

[3]Both HCs are highly correlated with a correlation of 0.90 when estimating the expectation of HC using a linear forecast of HC (e.g., Drechsler and Yaron, 2011; Zhou, 2018).

[4]We define CRP as HC minus RC following the definition of VRP in Carr and Wu (2009). CRP also can be defined the other way, RC minus HC, like the definition of VRP in Bollerslev et al. (2009). This will result in all the signs being reversed, but does not affect the conclusions shown below.

with less than seven days to expiration. In terms of the portfolio returns forecasts, we use the monthly returns of 25 standard Fama-French portfolios sorted on size and BM, which are available via the Kenneth French Data Library's website.

4.1 The CRP measure

We first construct three interpolated time-series of implied volatility level, log implied volatility change and log index return.[5] According to equation (11), the daily RC can be extracted based on the interpolated time-series of implied volatility level at each date and maturity. Here, we only consider the extracted covariance rate at a fixed one-month maturity, consistent with the Volatility Index (VIX) which is the market's expectation for volatility over the coming 30 days. For HC, we use both time-series of the interpolated implied volatility change and index return and summate the previous 21 trading days' daily HCs to quantify the total HC over the previous month. Thus, CRP can be easily obtained by equation (13). For the return predictability analysis in the following section, we focus on over-lapping monthly return and construct the monthly time-series of CRP by using the end-of-month HC and RC.

Table 1 reports the summary statistics of the annualized RC and HC. Both average covariance rates are negative across all maturities, in line with the negatively skewed implied volatility smile on the S&P 500 index. Across maturities, both covariance estimates decline with maturity. Furthermore, the covariances show a high time series persistence with high correlation estimates over 0.976. Comparing the two covariances, we find that RC are more negative than HC, suggesting that CRP should be positive.

< Insert Table 1 about here >

[5] They are obtained by interpolation based on a bivariate Gaussian kernel at each maturity moneyness grid. A maturity moneyness grid is defined as $(\tau,\, x)$, where the time to maturity (τ) is 1, 2, 3, 6 and 12 months and the moneyness is $x = 0, \pm 0.5, \pm 1, \pm 1.5, \pm 2$, following Carr and Wu (2020).

We show the summary statistics for the monthly time series of CRP in Table 2. CRP has a positive mean of 0.105 and a skewness of -1.217, which provides an empirical support for the theoretical finding that CRP is positive. Meanwhile, the series of CRP exhibit a first-order autocorrelation of 0.22, showing low time series persistence.

< Insert Table 2 about here >

Figure 1 plots the monthly time series of CRP. CRP is on average positive but displays occasional negative spikes. These large spikes may be caused by downward volatility jumps correlated with the resolution of policy uncertainty as proposed by Amengual and Xiu (2018). The downward and upward spikes appear during the periods associated with the economic or market-specific shocks. For example, CRP exhibits the sharpest spike in the 2011 European debt crisis.

< Insert Figure 1 about here >

4.2 Other predictors

We compare the predictive power of CRP with a set of 20 variables proposed in the literature. When we measure RC, the risk-neutral variance of the implied volatility change also could be extracted from the no-arbitrage formula in equation (11). Correspondingly, we can construct the historical variance rate of the implied volatility change and define the volatility variance risk premium as the difference between the historical and the risk-neutral variance rates following the definition of CRP. The volatility variance risk premium is

$$VVRP = HVV - RVV, \tag{14}$$

where $VVRP$ is the volatility variance risk premium, HVV and RVV are historical and risk-neutral variance rates of the implied volatility change, respectively.[6] Thus, we consider the five comparative predictors, $VVRP$, HVV, RVV, HC and RC.

Second, we include 14 standard economic predictors from Welch and Goyal (2008), such as dividend-price ratio (DP), dividend yield (DY), earnings-price ratio (EP), dividend-payout ratio (DE), stock Variance (SVAR), book-to-market ratio (BM), net equity expansion (NTIS), treasury bill rate (TBL), long-term yield (LTY), long-term return (LTR), term spread (TMS), default yield spread (DFY), default return spread (DFR) and inflation (INFL).

Finally, we add VRP since it is a well-known strong predictor with significant predictive power for short-term returns. VRP is defined as the difference between the annualized realized return variance and the squared Chicago Board Options Exchange (CBOE) VIX index. We just use the simple lagged realized variance following Zhou (2018). In accordance with the historical covariance rates that are constructed based on the daily index returns, the ex post realized variance are also computed using daily index returns rather than the high-frequency intraday return data. The end-of-month VIX data are obtained from the CBOE website from January 1996 to December 2019.

Table 2 also reports summary statistics of market excess returns and other comparative predictors from January 1996 to December 2019, containing 288 monthly observations. The monthly market excess return is 0.387% with the skewness -0.851 and the kurtosis 4.620, suggesting the high non-normality of the return distribution. While most of standard economic predictors are highly persistent with first-order autocorrelations of over 0.9%. VRP has a negative mean (-0.012) and low persistence (0.436). Table 2 also shows that

[6] RVV is the ω^2 in equation (11) and it can be estimated by performing a cross-sectional regression based on the interpolated time-series of implied volatility level at each date and maturity, similar to RC. For HVV, we calculate daily HVV by using both time-series of the interpolated implied volatility change and index return, and then summate the previous 21 trading days' daily HCs to quantify the total HVV over the previous month, the same way as measuring HC.

the correlations between CRP and other predictors are generally low, suggesting that the information content of CRP is different from other predictors. CRP is negatively correlated with VRP, which indicates that high values of CRP are associated with low VRP.

< Insert Table 2 about here >

5 Empirical results

In this section, we conduct empirical tests and investigate whether our findings are consistent with the proposed hypothesis that CRP constructed in Section 3 positively predict ERP. We start by examining the stock market return predictability of CRP in sample, and then we turn our attention to the out-of-sample evidence. We also test the economic value of market return predictability. As a extension, we further examine whether CRP predict portfolio stock returns rather than the aggregate market return portfolio.

5.1 In-sample evidence

We run the in-sample predictive regression:

$$r_{t:t+h} = \alpha + \beta X_t + \epsilon_{t:t+h}, \tag{15}$$

where $r_{t:t+h} = (r_{t+1} + ... + r_{t+h})/h$, for $h = 1, 3, 6, 9, 12, 24$ month, represents the log return on a stock market index in excess of the risk-free interest rate from $t+1$ to $t+h$ and X_t denotes a set of predictor variables at time t.

The in-sample results of univariate predictive regressions for all predictors at horizons ranging from one month to 24 months are given in Table 3. We demonstrate the estimate of the coefficient as well as adjusted R^2 statistics and the Newey and West (1987) t-statistics. CRP can positively and significantly predict future stock market returns for up to 24 months over the 1996-2019 sample period. The regression coefficient of CRP with a 1-month forecasting horizon is 14.95, indicating a 1% increase in CRP is associated with an 14.95% increase in market excess returns over the following month. The adjusted R^2 is 3.6%. The predictive ability of CRP persists over two years. At the 24-month forecasting horizon, the regression coefficient is 4.25 with a t-statistic of 2.54 and the R^2 is 4.46%. This means that CRP contains substantial information about future market returns. Our empirical results provides supportive evidence for the hypothesis that CRP positively predicts the ERP .

For the comparative predictors of the first type ($VVRP$, HVV, RVV, HC and RC), they underperform CRP in predicting market excess returns at all horizons. Only RC and HC show some in-sample predictive power. RC has strong predictive performance at longer horizons (from 6 months to 24 months). In particular, at 24-month forecasting horizon, the t-statistic and adjusted R^2 of RC are larger than those of CRP. HC only exhibits significant predictive ability at short horizon (1 month) with a t-statistic and an adjusted R^2 lower than CRP's. However, RC and HC do not show substantially significant in-sample predictive ability across all horizons so that they underperform CRP.

Turning to the 14 standard variables from Welch and Goyal (2008), all variables except for DY do not exhibit significant predictive power at all forecasting horizons. DY shows weaker predictive ability than CRP for forecasting 1-month and 3-month stock market returns with lower t-statistics and R^2 statistics. For instance, the t-statistics of DY is 1.67 for the 1-month horizon, and 1.95 for the 3-month horizon. While the t-statistics of CRP are 3.29 and 2.74, respectively. In contrast, DY seems to perform better than CRP for forecasting 6- to 24-month stock market returns with significantly larger t-statistics and R^2 statistics. The results might be caused by high autocorrelation and overlapping effects, consistent with Cao et al. (2020) and Han and Li (2021). $SVAR$ only has a significant regression coefficient at the 1-month forecasting horizon. Among remaining standard predictors, some of them exhibit significant coefficients and extremely large R^2 statistics at longer horizons, such as DP, BM and TBL. These results come from high autocorrelation and overlapping effects. At the three-month horizon, the coefficient for IVS is 0.26 in column (4) with a Newey-West t-statistic of 4.

As we known, VRP is a strong predictor with significant predictive power for short-term returns (Bollerslev et al., 2009). From Table 3, we find that VRP can significantly predict 1-month, 3-month, 6-month and 9-month stock market returns. Specially VRP has a largest in-sample R^2 statistics of 8.35% with a t-statistic of -6.76 compare with other predictors. However, as the forecasting horizon extends to a longer period, VRP cannot show any predictive ability. Therefore, consistent with previous literature, we get the same finding that VRP can significantly predict market returns for up to 9 months, but fail to forecast 12-month- and 24-month-ahead market returns.

Overall, CRP outperforms the other predictors in sample as it exhibits the statistically significant regression coefficients and large adjusted R^2 values across all forecasting horizons.

< Insert Table 3 about here >

We test whether the CRP contains information that is not included in other forecasting variables. We run the bivariate predictive regression

$$r_{t:t+h} = \alpha + \beta_1 CRP_t + \beta_2 X_t + \epsilon_{t:t+h}, \tag{16}$$

where X_t is one of the alternative variables. We add one control variable at a time and report the regression results in Table 4.

CRP remains statistically significant after controlling for other comparative predictors except for VRP, indicating that it contains distinct information relevant to predicting future market returns. For example, when we run the bivariate regression including both CRP and RC at 1-month forecasting horizon, CRP has a coefficient of 15.22 with a t-statistic of 3.20, compared to the coefficient of 1.13 with a t-statistic of 0.21 on RC. Both statistics of CRP are similar to those in the univariate predictive regressions. Thus, CRP continues to exhibit significant predictive power for stock market returns after controlling for other predictors with the exception of VRP.

When we control for VRP, we find that the coefficients of CRP is still significant with the exception of the three-month and six-month horizons. For the three-month and six-month horizons, the values of adjusted R^2 values after including VRP are usually larger than the R^2s of CRP and VRP in the univariate regressions. For example, the three-month R^2 including VRP is 9.38%, while the R^2 of CRP and VRP in the univariate predictive regresstions are 6.64% and 8.35%. This indicates that we can obtain better predictive performance when combining the two predictors: CRP and VRP.

< Insert Table 4 about here >

5.2 Out-of-sample evidence

Many studies argue that out-of-sample tests alleviate concerns about in-sample over-fitting and finite sample biases (e.g., Welch and Goyal, 2008; Kelly and Pruitt, 2013). In this subsection, we examine the predictive performance of CRP for future stock market returns based on out-of-sample tests.

We choose the first half of the total sample as our initial training sample and use the training sample to estimate the return-forecasting regression shown in equation (16). Then we use the estimated coefficients of the predictive regression and the last observation of the forecasting variable to predict the next-period excess return. We repeat these steps on the basis of a sequence of expanding windows and finally obtain a series of out-of-sample excess return forecasts. A expanding estimation window means that the estimation sample always starts in 1996:01 and additional observations are used as they become available.

Following Campbell and Thompson (2008) and Rapach et al. (2010), we use out-of-sample R^2 to evaluate the performance of out-of-sample forecasts. The out-of-sample R^2 is given by

$$R^2_{OS} = 1 - \frac{\sum_{t=n}^{N-1}(r_{t,t+h} - \hat{r}_{t,t+h|t})^2}{\sum_{t=n}^{N-1}(r_{t,t+h} - \overline{r}_{t,t+h|t})^2}, \tag{17}$$

where h is the forecast horizon (e.g., 1, 3, 6, 9, 12 and 24 months), n is the number of observations for the initial forecast, N is the total number of observations, $\hat{r}_{t,t+h|t}$ is the return forecast estimated using all observations except those overlapping with $r_{t,t+h}$ and $\overline{r}_{t,t+h|t}$ is the historical average of excess returns calculated by using all observations except those overlapping with $r_{t,t+h}$. A positive R^2_{OS} implies the predictive regression has a lower average mean-squared forecast error than the historical mean benchmark and outperforms the benchmark.

We use the Clark and West (2007) adjusted mean squared prediction error statistic to test whether the out-of-sample R^2 statistic is significantly greater than zero.

$$f_{t,t+h} = (r_{t,t+h} - \overline{r}_{t,t+h|t})^2 - [(r_{t,t+h} - \hat{r}_{t,t+h|t})^2 - (\overline{r}_{t,t+h} - \hat{r}_{t,t+h|t})^2]. \tag{18}$$

We regress the time series of the variable $f_{t,t+h}$ on a constant and compute one-sided p-values for the corresponding R^2_{OS} statistic.

The out-of-sample R^2 of all forecasting variables across all horizons are reported in Table 5. Obviously, CRP is the only variable that produce positive and significant out-of-sample R^2 values over horizons up to 24 months compared with the other predictors. CRP has positive out-of-sample R^2 statistics of 4.57%, 6.82%, 4.3%, 4.67%, 3.13% and 12.87% at horizons of one to 24 months, respectively. Looking at the following five comparative predictors, only RC and HC provide positive and significant out-of-sample R^2 at the

24-month (12.85%) and 1-month (0.51%) horizons, respectively. In terms of 14 classic predictors, none of them have positive and significant out-of-sample R^2 across all horizons. Although some variables (e.g., BM, TBL, TMS and $INFL$) has extreme high out-of-sample R^2 at longer horizons, they do not have significantly positive out-of-sample R^2 at shorter horizons. For example, BM produces monotonically increasing positive out-of-sample R^2 statistics varying from 6.20% at 6-month horizon to 52.89% at 24-month horizon. VRP only has significant out-of-sample predictive power for up to three months (2.73% and 13.34%, respectively), similar to the in sample results of VRP. Overall, CRP shows substantial and significant out-of-sample predictive ability, which is consistent with the performance in-sample results. It outperforms all the other forecasting variables in out-of-sample tests.

< Insert Table 5 about here >

5.3 Economic value of return predictability

In line with Campbell and Thompson (2008) and Ferreira and Santa-Clara (2011), we measure the economic value of stock market returns forecasts by computing the certainty equivalent (CE) return for a mean-variance investor who tries to allocate between the risky stock and risk-free asset. In particular, we construct trading strategies based on return forecasts to allocate the optimal weight w_t to the stock and the remainder to the risk-free asset at the end of the horizon h. Here, $w_t = \hat{r}_{t,t+h}/\theta\hat{\sigma}^2_{t,t+h}$, where θ is the coefficient of relative risk aversion, $\hat{r}_{t,t+h}$ and $\hat{\sigma}_{t,t+h}$ are the expected risky stock excess return and volatility. Thus, the portfolio return at the end of each time horizon is

$$rp_{t,t+h} = w_t r_{t,t+h} + rf_{t,t+h}, \tag{19}$$

where $r_{t,t+h}$ is the stock excess return and $rf_{t,t+h}$ is the risk-free rate. The CE return is defined as

$$CE = \overline{rp} - 0.5\theta\sigma^2(rp), \tag{20}$$

where $\overline{rp}$ is the sample mean of portfolio returns and $\sigma^2(rp)$ is the sample variance of portfolio returns. We define CE gains as the differences between the CE of forecasts generated by our regression model and the historical average forecast benchmark. In line with Rapach et al. (2016), we consider the coefficient of risk aversion: $\theta = 3$ and restrict w_t to lie between -0.5 and 1.5.

Table 6 reports the economic value of return predictability assessed by the CE gain. We find that CRP still outperforms the other forecasting variables as it generates the substantially positive and large CE gains over the historical average forecast up to 24 months. This implies that CRP can produce economically significant profits for a mean-variance investor at any forecast horizon. For example, the 1-month annualized CE gain for CRP is 4.79%, meaning that the investor would be willing to pay 479 basis points to have access to the information in our regression model forecasts compared to the historical average forecast. The CE gain reaches its highest at 3-month horizon (9.61%) and then decreases gradually until 24-month horizon. the Besides CRP, both TBL and VRP provide positive CE gains across all horizons, but their CE gains are generally lower than CRP's. Turning to the remaining variables, several of them perform well from 3-month to 24-month horizons (e.g., DP, DY and TMS), while several variables perform well in shorter horizons (e.g., EP, DE and LTY). However, these variables do not reveal substantial economic values for investors.

Overall, CRP predicts stock market returns at all horizons out of sample with economic significance. The average CE gains in Table 6 provide stronger support for stock market return predictability.

< Insert Table 6 about here >

5.4 Forecasting portfolio returns

We have revealed significant predictive ability of CRP for forecasting the aggregate market return portfolio. In this subsection, to further elucidate the economic source of the predictability of CRP, we examine whether CRP can predict cross-sectional stock returns at the portfolio level.[7]

We consider 25 standard Fama-French portfolios sorted on size and BM (Fama and French, 1993). The monthly returns on the 5 size decile portfolios are denoted by Small, 2, 3, 4, Large in ascending order and the monthly returns on the 5 BM decile portfolios are denoted by Low BM, 2, 3, 4, High BM in ascending order as well. The monthly returns of 25 portfolios are available via the Kenneth French Data Library's website[8]. We report the estimation results of predictive regressions using 25 portfolio returns at different horizons in Table 7.

First, CRP can predict most of Fama-French portfolio returns as it significantly forecasts 83 out of 150 portfolio returns in all forecasting horizons. The predictive performance of CRP for 25 portfolio returns at 24-month horizon is better than that at the other horizons. There are 23 (out of 25) portfolios where the slope coefficients are significant at 24-month horizon. While there are only 7 (out of 25) portfolios where the coefficients are significant at 6-month horizon. Furthermore, for other forecasting horizons, the number of portfolios with significant return predictability is similar.

[7]In addition to aggregate stock returns, there are an ample literature using a wide range of portfolios sorted by market capitalization, book-to-market value, or industry to examine return predictability. Some papers estimate in-sample predictive regressions for characteristics portfolios (e.g., Huang et al., 2015). While other studies emphasize out-of-sample return predictability for characteristics portfolios (e.g., Rapach and Zhou, 2013).

[8]Kenneth French's website is https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Second, CRP is a stronger predictor for low BM portfolios than high BM portfolios, regardless of the size of portfolios or forecasting horizons. More specifically, the predictive ability of CRP generally becomes weaker from low BM portfolios to high BM portfolios. For example, for the large size portfolio at one-month horizon, the t-statistic value of CRP becomes smaller from 4.24 to 1.23. The findings imply that CRP shows stronger predictive power in terms of forecasting the returns of stocks with high growth opportunity (lower BM).

Finally, in general, CRP exhibits better predictive performance for portfolio returns of larger size firms, particularly for firms with lower BM. In Panels A-E, for low BM sorted portfolios, the t-statistic value of CRP generally becomes larger as the firm size increases. However, in Panel F, the t-statistic value of CRP does not show a observable trend with increasing firm size.

In sum, CRP can predict most of Fama-French portfolio returns. In particular, it predicts 23 out of 25 portfolio returns at the 24-month forecasting horizon. considering the size and BM characteristics of a firm, CRP shows stronger predictive power in terms of forecasting the returns of lower BM and larger size firms.

< Insert Table 7 about here >

6 Robustness checks

In this section, we conduct a serial of robustness checks of the main findings. First, we study the impact of the 2008-2009 financial crisis on CRP's return predictability. Second, we examine the out-of-sample predictive ability of CRP using a rolling window. Finally, we measure CE gains under alternative risk aversion coefficients.

6.1 Does financial crisis matter?

Our sample period includes the 2008-2009 financial crisis period. The global financial crisis is considered the second largest economic crisis in history after the Great Depression of the 1930s. Naturally, we would investigate whether CRP's return predictability is driven by the financial crisis. Following Chen et al. (2021), we consider a sample of data that excludes the financial crisis period from July 2008 to January 2009. We perform the in-sample return predictability of CRP with the forecast horizons from 1 month to 24 months. If the in-sample predictability results for the period that excludes the financial crisis are consistent with the full-sample period, then the predictive ability of CRP is not driven by the financial crisis.

Table 8 reports the in-sample predictability of CRP during the period excluding the 2008-2009 finacial crisis. We find that the coefficients of CRP is still highly significant across all horizons, although the t-statistics are relatively smaller than those in Table 3. The in-sample R^2 statistics are positive and large across different horizons (from %3.05 for 1 month to %2.67 for 24 months). Therefore, we ensure that the substantial and significant predictive ability of CRP for forecasting future stock market returns hold when excluding the sample of data corresponding to the global financial crisis. The financial crisis does not drive CRP's return predictability.

< Insert Table 8 about here >

6.2 Out-of-sample tests with different windows

We have performed out-of-sample tests using a expanding window and found that CRP outperforms all the other forecasting variables with positive and significant out-of-sample R^2 values over all horizons in Section 5. Next, following Huang and Kilic (2019) and Chen et al. (2021), we further examine whether our findings are robust to using a rolling window. We first choose the first half of the total sample as our initial training sample, namely from January 1996 to December 2007 (144 observations). We use a rolling window of fixed size the same as the initial sample size to generate predictions.

Table 9 presents the out-of-sample test results at horizons from 1 month to 24 months based on a rolling estimation window. The results imply that CRP outperforms the historical mean benchmark with positive and significant out-of-sample R^2 at horizons from 1 month to 24 months. This finding is consisted with the results based on a expanding window presented in Subsection 5.3. We also find that CRP exhibits larger out-of-sample R^2 statistics with rolling windows than expanding windows from 3-month to 24-month ahead forecasts. Overall, the out-of-sample predictive ability of CRP is robust to alternative prediction approach.

< Insert Table 9 about here >

6.3 Alternative risk aversion coefficients

For measuring the economic value of stock market return predictability above, we assume that a mean-variance investor has a coefficient of risk aversion of three. Next, we will consider different values for the risk aversion parameter and investigate whether CE gain results are robust to alternative risk aversion coefficients.

Table 10 presents CE gains for different values of risk aversion (2 and 5, which represent a high and low risk position for an investor, respectively.) and different investment horizons (1, 3, 6, 9, 12 and 24 months). CRP still produces substantially positive and large CE gains over the historical average forecast across different investment horizons, regardless of the degree of risk aversion. We also find the same finding that although TBL and VRP

produce positive CE gains, their CE gains are generally lower than CRP's. Our findings are therefore robust to different risk aversion coefficients.

< Insert Table 10 about here >

7 Conclusion

This paper proposes a new stock market return predictor, covariance risk premium (CRP), and explores its implications for the predictability of stock market returns. We define CRP as the difference between the historical and the risk-neutral covariance rates (HC and RC) of the implied volatility changes and the market index returns. We first propose a hypothesis that CRP can positively predict future stock market returns based on a conceptual model. We then conduct empirical tests to confirm this hypothesis.

We shows that CRP positively and significantly predicts future stock market returns at horizons from one to 24 months over the 1996–2019 sample period both in-sample and out-of-sample. Its predictive power outperforms many well-known predictors and it also reveals substantial and sizable economic value for a mean-variance investor. In addition, CRP can predict most of 25 size and BM sorted Fama-French portfolio returns. Our findings are robust to a series of alternative specifications, including excluding the global financial crisis period, the rolling method for out-of-sample tests and alternative risk aversion coefficients.

Overall, our study highlights the importance of CRP for the predictability of stock market returns, both theoretically and empirically. The empirical findings of this study provide useful insights to investors seeking to maximize returns.

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Table 1: Estimates of covariance rates

This table reports summary statistics for the term structures of RC and HC between the implied volatility variations and the stock market returns. RC is the risk-neutral covariance rate and HC is the historical covariance rate. The statistics include mean, standard deviation, minimum, maximum and daily autocorrelation. RC is extracted from a no-arbitrage formula proposed by Carr and Wu (2020). HC is calculated within a 21-business-day rolling window. The sample period is from January 1996 to December 2019.

Maturity	1	2	3	6	12
Panel A: RC					
Mean	-0.149	-0.109	-0.091	-0.067	-0.048
Std.dev.	0.062	0.043	0.034	0.023	0.016
Min	-0.600	-0.399	-0.307	-0.208	-0.133
Max	-0.038	-0.032	-0.030	-0.012	0.000
AR(1)	0.976	0.983	0.986	0.989	0.990
Panel B: HC					
Mean	-0.046	-0.039	-0.035	-0.028	-0.023
Std.dev.	0.070	0.061	0.055	0.046	0.039
Min	-0.623	-0.577	-0.542	-0.473	-0.412
Max	0.044	0.032	0.028	0.020	0.014
AR(1)	0.985	0.986	0.987	0.988	0.988

Table 2: Summary statistics of predictive variables

This table provides descriptive statistics for the monthly time series of stock market excess returns and predictive variables as well as their correlations with the covariance risk premium. RC is the risk-neutral covariance rate between the implied volatility variations and the stock market returns. RVV is the risk-neutral variance rate of the implied volatility change. Both RC and RVV are obtained from the equation (11). HC and HV are the historical covariance and variance rates of the implied volatility change with a 21-trading-day rolling window. CRP is the covariance risk premium defined as the difference between HC and RC of the implied volatility variations and the stock market returns. $VVRP$ is the volatility variance risk premium defined as the difference between the historical and the risk-neutral variance rates of the implied volatility change. The detailed descriptions of the 14 standard predictors are shown in Welch and Goyal (2008). VRP is the variance risk premium defined as the difference between the annualized realized return variance and the CBOE VIX index. The sample period is from January 1996 to December 2019.

	Mean	Std.dev.	Skewness	Kurtosis	Min	Max	AR(1)	Corr.CRP
Returns (%)	0.387	4.310	-0.851	4.620	-18.656	10.231		
CRP	0.105	0.057	-1.217	8.820	-0.229	0.288	0.220	1.000
VVRP	-0.782	0.599	0.453	3.656	-2.441	1.812	0.482	-0.199
RC	-0.150	0.060	-1.636	8.257	-0.495	-0.043	0.753	-0.234
RVV	1.060	0.512	0.008	2.833	0.000	2.652	0.597	-0.078
HC	-0.046	0.072	-3.910	23.381	-0.533	0.028	0.341	0.600
HVV	0.274	0.274	5.573	49.710	0.057	3.143	0.060	-0.579
DP	-4.011	0.202	-0.107	4.245	-4.524	-3.281	0.975	0.065
DY	-4.006	0.202	-0.224	4.105	-4.531	-3.295	0.975	0.131
EP	-3.151	0.366	-2.162	9.571	-4.836	-2.566	0.975	-0.150
DE	-0.861	0.419	3.384	16.311	-1.244	1.380	0.983	0.162
SVAR	0.003	0.005	6.724	63.950	0.000	0.058	0.698	-0.308
BM	0.266	0.070	-0.179	2.256	0.121	0.441	0.961	0.033
NTIS	0.000	0.019	-0.643	2.910	-0.058	0.031	0.977	0.076
TBL	0.022	0.020	0.442	1.617	0.000	0.062	0.993	-0.186
LTY	0.044	0.015	0.023	1.910	0.016	0.073	0.979	-0.188
LTR	0.006	0.030	0.115	5.196	-0.112	0.144	-0.003	-0.161
TMS	0.022	0.013	-0.058	2.012	-0.006	0.045	0.969	0.077
DFY	0.010	0.004	3.076	15.466	0.006	0.034	0.962	0.083
DFR	0.000	0.018	-0.458	9.033	-0.098	0.074	0.017	0.385
INFL	0.002	0.003	-0.897	7.683	-0.019	0.012	0.479	-0.029
VRP	-0.012	0.034	5.440	50.550	-0.102	0.334	0.436	-0.574

Table 3: Univariate return predictability

The table reports the estimated regression coefficients, Newey and West (1987) t-statistics and R^2 statistics of the predictability regressions for one- to 12-month excess returns on the S&P 500 index. The definitions of predictors are the same as those in Table 2. The sample period is from January 1996 to December 2019. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	1-month			*3-month*			*6-month*		
	β	t	$R^2(\%)$	β	t	$R^2(\%)$	β	t	$R^2(\%)$
CRP	14.95***	(3.29)	3.60	11.76***	(2.74)	6.64	7.20**	(2.49)	4.32
VVRP	0.05	(0.10)	-0.35	-0.02	(-0.04)	-0.35	-0.24	(-0.57)	0.20
RC	-2.28	(-0.34)	-0.25	-5.58	(-1.00)	1.36	-5.92**	(-2.09)	3.13
RVV	-0.35	(-0.54)	-0.18	0.08	(0.14)	-0.33	0.45	(0.80)	1.03
HC	7.81**	(1.99)	1.37	3.54	(0.84)	0.66	0.45	(0.21)	-0.33
HVV	-0.96	(-1.20)	0.02	0.18	(0.34)	-0.32	0.41	(1.43)	0.00
DP	2.70	(1.30)	1.25	2.78	(1.63)	4.52	3.00**	(2.45)	9.83
DY	2.94*	(1.67)	1.55	2.92*	(1.95)	5.01	3.10***	(2.80)	10.50
EP	0.70	(0.56)	0.00	0.37	(0.35)	-0.06	0.23	(0.26)	-0.16
DE	0.09	(0.09)	-0.34	0.36	(0.44)	0.00	0.52	(0.90)	0.97
SVAR	-127.00*	(-1.95)	1.79	-82.67	(-1.48)	2.25	-15.68	(-0.44)	-0.19
BM	4.33	(1.22)	0.15	5.98**	(2.05)	2.37	7.83***	(3.23)	8.03
NTIS	20.89	(0.99)	0.52	24.72	(1.24)	3.13	24.49	(1.40)	5.78
TBL	-9.85	(-0.83)	-0.13	-11.40	(-1.06)	0.48	-13.61	(-1.39)	1.78
LTY	-23.29	(-1.55)	0.27	-21.29	(-1.53)	1.11	-21.49	(-1.60)	2.25
LTR	8.07	(1.16)	-0.03	0.41	(0.06)	-0.35	2.91	(0.86)	-0.15
TMS	-5.22	(-0.24)	-0.33	1.67	(0.08)	-0.35	8.00	(0.44)	-0.07
DFY	-76.86	(-0.67)	0.19	-43.69	(-0.42)	0.15	4.27	(0.06)	-0.35
DFR	18.10	(0.77)	0.20	7.05	(0.50)	-0.12	7.73	(0.72)	0.16
INFL	41.56	(0.53)	-0.24	45.76	(0.52)	0.04	-54.49	(-1.09)	0.65
VRP	-27.59***	(-3.23)	4.32	-22.25***	(-6.76)	8.35	-11.29***	(-4.06)	3.67

Table 3: Univariate return predictability (cont'd)

The table reports the estimated regression coefficients, Newey and West (1987) t-statistics and R^2 statistics of the predictability regressions for one- to 12-month excess returns on the S&P 500 index. The definitions of predictors are the same as those in Table 2. The sample period is from January 1996 to December 2019. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	9-month			*12-month*			*24-month*		
	β	t	R^2(%)	β	t	R^2(%)	β	t	R^2(%)
CRP	5.42***	(2.99)	3.40	4.37***	(2.83)	2.76	4.25**	(2.54)	4.46
VVRP	-0.33	(-0.87)	1.11	-0.44	(-1.25)	2.94	-0.22	(-1.32)	1.01
RC	-4.71**	(-2.24)	2.79	-3.88**	(-2.20)	2.37	-4.31***	(-2.83)	5.71
RVV	0.53	(1.04)	2.36	0.64	(1.43)	4.71	0.26	(1.31)	1.10
HC	0.10	(0.08)	-0.36	-0.02	(-0.01)	-0.37	-0.70	(-0.79)	-0.17
HVV	0.21	(0.86)	-0.23	0.06	(0.24)	-0.36	-0.23	(-0.50)	-0.17
DP	3.10***	(3.32)	15.20	3.15***	(4.16)	20.11	3.21***	(6.73)	38.12
DY	3.21***	(3.76)	16.24	3.25***	(4.69)	21.42	3.24***	(7.51)	38.90
EP	0.31	(0.40)	0.14	0.32	(0.51)	0.35	0.07	(0.15)	-0.33
DE	0.48	(1.09)	1.27	0.48	(1.48)	1.69	0.69***	(3.19)	7.33
SVAR	8.16	(0.36)	-0.30	11.80	(0.64)	-0.19	17.09	(1.30)	0.27
BM	8.18***	(3.73)	12.70	7.99***	(3.83)	15.57	7.00***	(4.18)	21.60
NTIS	22.03	(1.40)	6.63	19.17	(1.43)	6.33	5.90	(0.77)	0.71
TBL	-15.59*	(-1.72)	3.65	-18.61**	(-2.15)	6.97	-26.14***	(-3.27)	25.75
LTY	-19.63	(-1.55)	2.69	-18.92	(-1.53)	3.21	-23.90**	(-2.15)	9.46
LTR	2.76	(1.05)	-0.10	0.94	(0.40)	-0.33	0.45	(0.25)	-0.37
TMS	16.38	(1.04)	1.31	26.26*	(1.91)	5.02	42.86***	(3.82)	24.83
DFY	21.84	(0.39)	-0.04	34.17	(0.83)	0.65	59.39***	(2.71)	5.14
DFR	7.01	(1.07)	0.24	6.05	(1.20)	0.21	4.05	(1.21)	0.05
INFL	-66.33	(-1.46)	1.74	-65.53**	(-1.99)	2.25	-40.24*	(-1.91)	1.37
VRP	-4.77**	(-1.99)	0.66	-3.07	(-1.28)	0.18	-1.72	(-0.89)	-0.08

Table 4: Bivariate return predictability: controlling for other known predictors

This table reports the bivariate return predictability regression results of VRP for one- to 24-month horizons, controlling for other known predictors. The definitions of control variables are the same as those in Table 2. We add one control predictor to the regression of CRP at a time and report estimated coefficients, Newey and West (1987) t-statistics and R^2 statistics. The sample period is from January 1996 to December 2019. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	1-month					*3-month*					*6-month*				
	CRP β	CRP t	β	t	R^2(%)	CRP β	CRP t	β	t	R^2(%)	CRP β	CRP t	β	t	R^2(%)
VVRP	15.71***	(3.47)	0.36	(0.75)	3.50	12.25***	(3.13)	0.23	(0.51)	6.58	6.99***	(2.62)	-0.10	(-0.25)	4.07
RC	15.22***	(3.20)	1.13	(0.21)	3.29	10.99**	(2.13)	-3.16	(-0.63)	6.83	6.08*	(1.89)	-4.53*	(-1.70)	5.90
RVV	14.80***	(3.15)	-0.23	(-0.38)	3.34	11.86***	(2.66)	0.18	(0.30)	6.43	7.54**	(2.51)	0.53	(0.98)	5.90
HC	14.09**	(2.41)	1.13	(0.21)	3.29	14.15***	(3.35)	-3.16	(-0.63)	6.83	10.61***	(3.19)	-4.53*	(-1.70)	5.90
HVV	18.46***	(3.14)	1.27	(1.27)	3.70	18.36***	(3.64)	2.39***	(3.02)	10.74	12.46***	(3.39)	1.90***	(3.03)	9.05
DP	14.40***	(2.85)	2.44	(1.32)	4.57	11.18**	(2.30)	2.59*	(1.70)	10.51	6.55**	(1.98)	2.90**	(2.57)	13.48
DY	13.84***	(2.68)	2.43	(1.49)	4.54	10.60**	(2.14)	2.54*	(1.78)	10.29	5.89*	(1.76)	2.89***	(2.67)	13.27
EP	15.98***	(3.52)	1.07	(0.92)	4.08	12.40***	(2.80)	0.66	(0.67)	7.21	7.60**	(2.57)	0.41	(0.48)	4.60
DE	15.24***	(3.16)	-0.24	(-0.24)	3.32	11.63**	(2.48)	0.10	(0.13)	6.34	6.76**	(2.15)	0.37	(0.64)	4.63
SVAR	12.78***	(2.75)	-81.75	(-1.22)	4.07	10.55***	(2.81)	-45.41	(-0.83)	7.02	7.47**	(2.59)	10.26	(0.31)	4.04
BM	14.78***	(3.19)	3.91	(1.22)	3.67	11.50***	(2.63)	5.64**	(2.19)	8.74	6.85**	(2.35)	7.61***	(3.40)	11.92
NTIS	14.49***	(3.33)	17.60	(0.98)	3.88	11.16***	(3.02)	22.09	(1.29)	9.08	6.56**	(2.57)	23.05	(1.41)	9.38
TBL	14.81***	(3.09)	-2.17	(-0.18)	3.27	11.39**	(2.54)	-5.60	(-0.52)	6.50	6.53**	(2.18)	-10.13	(-1.04)	5.12
LTY	14.34***	(3.07)	-13.03	(-0.89)	3.45	11.15**	(2.55)	-13.55	(-0.99)	6.88	6.44**	(2.24)	-16.70	(-1.26)	5.50
LTR	16.04***	(3.45)	12.96*	(1.85)	4.07	12.09***	(2.92)	4.05	(0.69)	6.53	7.60**	(2.58)	5.06	(1.51)	4.60
TMS	15.15***	(3.29)	-10.68	(-0.54)	3.37	11.82***	(2.71)	-3.03	(-0.16)	6.33	7.10**	(2.39)	4.83	(0.27)	4.08
DFY	15.53***	(3.52)	-95.21	(-0.97)	4.09	12.11***	(2.83)	-58.00	(-0.64)	7.20	7.23**	(2.42)	-4.57	(-0.07)	3.99
DFR	15.02***	(3.54)	-0.63	(-0.03)	3.26	12.81***	(3.10)	-8.91	(-0.77)	6.64	7.36***	(2.63)	-1.32	(-0.13)	3.99
INFL	15.03***	(3.33)	48.67	(0.79)	3.42	11.84***	(2.85)	51.08	(0.71)	6.80	7.11**	(2.33)	-50.65	(-1.15)	4.84
VRP	8.39*	(1.75)	-19.41*	(-1.91)	4.81	6.30	(1.57)	-16.12***	(-3.27)	9.38	5.03	(1.54)	-6.39*	(-1.71)	4.84

Table 4: Bivariate return predictability: controlling for other known predictors (cont'd)

This table reports the bivariate return predictability regression results of VRP for one- to 24-month horizons, controlling for other known predictors. The definitions of control variables are the same as those in Table 2. We add one control predictor to the regression of CRP at a time and report estimated coefficients, Newey and West (1987) t-statistics and R^2 statistics. The sample period is from January 1996 to December 2019. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	9-month					*12-month*					*24-month*				
	CRP β	CRP t	β	t	R^2(%)	CRP β	CRP t	β	t	R^2(%)	CRP β	CRP t	β	t	R^2(%)
VVRP	4.94***	(2.81)	-0.23	(-0.62)	3.77	3.63**	(2.44)	-0.37	(-1.05)	4.66	4.04**	(2.45)	-0.18	(-1.07)	4.95
RC	4.49**	(2.57)	-3.76*	(-1.83)	4.94	3.58**	(2.44)	-3.18*	(-1.69)	4.13	3.18**	(2.27)	-3.66**	(-2.52)	8.16
RVV	5.83***	(2.95)	0.59	(1.18)	6.33	4.86***	(2.79)	0.68	(1.54)	8.06	4.50**	(2.57)	0.29	(1.55)	5.94
HC	8.25***	(3.00)	-3.76*	(-1.83)	4.94	6.75***	(3.12)	-3.18*	(-1.69)	4.13	6.84***	(3.12)	-3.66**	(-2.52)	8.16
HVV	8.94***	(3.48)	1.28**	(2.49)	6.31	6.72***	(3.39)	0.86**	(2.09)	4.28	5.25***	(2.96)	0.48	(0.80)	4.77
DP	4.73**	(2.23)	3.02***	(3.44)	17.74	3.65**	(2.20)	3.07***	(4.27)	21.89	3.41**	(2.47)	3.14***	(7.05)	40.82
DY	4.03*	(1.88)	3.07***	(3.63)	17.98	2.94*	(1.74)	3.15***	(4.51)	22.53	2.72**	(2.04)	3.15***	(7.39)	40.63
EP	5.86***	(3.19)	0.44	(0.60)	4.08	4.79***	(3.00)	0.43	(0.71)	3.65	4.43***	(2.70)	0.16	(0.39)	4.41
DE	4.97***	(2.60)	0.37	(0.84)	4.01	3.89**	(2.56)	0.39	(1.20)	3.77	3.42**	(2.31)	0.61***	(2.96)	10.06
SVAR	6.22***	(3.04)	29.91	(1.38)	3.85	5.16***	(3.11)	29.88*	(1.65)	3.42	5.19***	(2.95)	34.26**	(2.42)	6.50
BM	5.04***	(2.76)	8.03***	(3.83)	15.66	3.98***	(2.63)	7.88***	(3.92)	17.97	3.88***	(2.71)	6.90***	(4.26)	25.55
NTIS	4.84***	(2.70)	20.82	(1.36)	9.26	3.85**	(2.36)	18.07	(1.36)	8.33	4.11**	(2.41)	4.65	(0.62)	4.76
TBL	4.53**	(2.46)	-13.44	(-1.49)	5.92	3.21**	(2.24)	-17.33**	(-2.01)	8.53	2.34**	(2.03)	-25.36***	(-3.20)	27.70
LTY	4.68***	(2.65)	-16.36	(-1.30)	5.10	3.62**	(2.49)	-16.59	(-1.34)	5.06	3.15**	(2.16)	-21.85*	(-1.95)	12.01
LTR	5.75***	(3.09)	4.37	(1.62)	3.71	4.53***	(2.97)	2.20	(0.94)	2.62	4.41***	(2.67)	1.78	(0.99)	4.33
TMS	5.12***	(2.77)	14.31	-0.93	4.32	3.83***	(2.61)	24.92*	(1.88)	7.22	3.21**	(2.54)	41.82***	(3.94)	27.87
DFY	5.33***	(2.84)	15.98	(0.29)	3.23	4.19***	(2.72)	30.09	(0.75)	3.19	3.90***	(2.60)	56.04***	(2.91)	8.99
DFR	5.38***	(2.69)	0.41	(0.06)	3.05	4.28***	(2.65)	0.77	(0.15)	2.41	4.42**	(2.40)	-1.34	(-0.34)	4.13
INFL	5.30***	(2.81)	-64.33	(-1.45)	5.03	4.23***	(2.78)	-64.47**	(-1.99)	4.93	4.19***	(2.60)	-40.09*	(-1.90)	5.83
VRP	5.67**	(2.25)	0.72	(0.22)	3.07	4.95**	(2.25)	1.68	(0.58)	2.52	5.54**	(2.46)	3.50	-1.53	4.92

Table 5: Out-of-sample return predictability

This table shows the results of out-of-sample predictive regressions based on a expanding estimation window when we choose the first half of the total sample as our initial training sample. The definitions of predictive variables are the same as those in Table 2. We report the out-of-sample R^2 statistics at horizons from one to 24 months. The sample period is from January 1996 to December 2019. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	1-month	*3-month*	*6-month*	*9-month*	*12-month*	*24-month*
CRP	4.57**	6.82**	4.30**	4.67***	3.13***	12.87***
VVRP	-2.00	-5.84	-6.46	-10.00	-9.59	-6.43
RC	-3.75	-11.47	1.67	0.43	-0.44	12.85**
RVV	-1.53	-4.96	-6.76	-10.59	-7.72	-5.21
HC	0.51*	-7.61	-2.00	-2.92	-6.42	-3.05
HVV	-0.20	-2.41	0.14	-0.25	-0.28	-1.29
DP	-3.83	-12.68	-14.67	-17.15	-19.12	-13.40
DY	-2.66	-9.07	-11.15	-11.88	-11.89	2.91
EP	-5.92	-23.38	-40.38	-50.81	-50.32	-59.25
DE	-6.30	-38.85	-63.80	-48.31	-8.36	-97.67
SVAR	-2.93	-10.68	-4.42	-6.32	-10.29	-17.50
BM	-0.94	-0.59	6.20**	10.69**	14.60***	52.89***
NTIS	-0.74	-4.09	-8.53	-18.24	-44.93	-213.62
TBL	-0.73	-2.89	-4.36	0.00	10.39***	62.87***
LTY	-0.32	-2.12	-4.78	-8.83	-14.29	-17.04
LTR	-0.89	-1.78	-0.58	-0.21	-0.51	-0.72
TMS	-0.50	-1.89	-2.90	0.28	6.92**	30.31***
DFY	-3.85	-34.22	-105.17	-123.77	-78.18	-20.89
DFR	-4.62	-7.35	-4.79	-2.63	-4.03	-5.95
INFL	-1.29	-4.77	-0.23	0.32	3.12***	2.51**
VRP	2.73*	13.34*	4.22	-1.90	-9.88	-9.27

Table 6: Economic value of return predictability

This table reports the annualized certainty equivalent return (CE) gain (in percent), the difference between the CE of forecasts generated by our regression model and the historical average forecast benchmark. The definitions of predictive variables are the same as those in Table 2. The sample period is from January 1996 to December 2019.

	1-month	*3-month*	*6-month*	*9-month*	*12-month*	*24-month*
CRP	4.79	9.61	8.99	4.62	3.36	3.00
VVRP	-3.18	-4.05	-2.18	-3.05	-4.05	-1.21
RC	-5.13	-0.03	2.55	0.41	-0.73	0.70
RVV	-1.70	-3.68	-3.25	-4.24	-4.84	-1.77
HC	-2.95	-4.15	0.93	-0.44	-1.11	-1.84
HVV	-1.38	-1.05	0.46	-0.30	-0.65	0.35
DP	-1.98	2.18	7.18	4.93	4.33	5.71
DY	-1.66	3.32	7.09	4.91	4.33	5.71
EP	1.72	3.30	1.64	-1.73	-2.00	-6.20
DE	1.81	4.22	2.29	-5.50	-4.10	-4.48
SVAR	-1.06	-2.78	1.06	-1.11	-2.33	-4.48
BM	-0.57	-0.26	5.11	4.00	3.16	4.96
NTIS	-2.27	-0.66	1.06	-1.91	-4.61	-5.86
TBL	0.71	3.26	0.67	0.84	2.53	5.71
LTY	2.67	4.55	5.71	-1.04	-4.77	-3.68
LTR	-1.68	-1.17	0.03	-0.65	-0.90	-0.67
TMS	-0.28	0.25	0.29	1.94	3.21	3.93
DFY	1.67	3.95	9.25	7.72	4.34	-2.96
DFR	-1.18	-1.53	2.35	2.01	0.03	-1.37
INFL	-2.27	-4.76	3.82	-0.22	-0.49	-0.14
VRP	4.81	6.37	6.05	3.12	1.95	1.32

Table 7: Fama-French portfolio return predictability

The table reports estimation results of the univariate regressions using returns of 25 Fama-French portfolios sorted by size and book-to-market (BM) for CRP at different horizons from one to 12 months. The monthly returns of 25 portfolios are available via the Kenneth French Data Library's website. CRP is the covariance risk premium defined as the difference between HC and RC of the implied volatility variations and the stock market returns. This table reports the slope coefficients and Newey and West (1987) t-statistics. The sample period is from January 1996 to December 2019. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	Low BM		2		3		4		High BM	
	Panel A: Forecasting 1-month return									
Small	1.40**	(2.22)	1.21**	(2.14)	1.06*	(1.93)	0.59	(1.02)	0.78	(1.33)
2	1.61***	(2.96)	1.27**	(2.40)	0.79	(1.36)	0.64	(1.15)	0.64	(1.15)
3	1.36**	(2.46)	1.08*	(1.93)	0.90	(1.53)	0.88	(1.52)	0.56	(0.93)
4	1.54***	(2.99)	1.11**	(2.01)	1.15*	(1.94)	0.86*	(1.76)	0.71	(1.23)
Large	1.43***	(4.24)	1.03***	(3.13)	0.79*	(1.95)	0.96*	(1.77)	0.80	(1.23)
	Panel B: Forecasting 3-month return									
Small	1.12**	(1.99)	0.91*	(1.97)	0.86**	(1.98)	0.71	(1.54)	0.88*	(1.71)
2	1.05**	(2.26)	0.87**	(2.03)	0.47	(1.19)	0.51	(1.29)	0.82	(1.50)
3	0.98**	(2.23)	0.86**	(2.02)	0.57	(1.48)	0.61	(1.43)	0.61	(1.51)
4	1.14***	(2.71)	0.69*	(1.93)	0.72	(1.62)	0.69*	(1.69)	0.78	(1.46)
Large	0.99***	(3.08)	0.79**	(2.43)	0.65*	(1.78)	1.02*	(1.67)	0.45	(0.93)
	Panel C: Forecasting 6-month return									
Small	0.66*	(1.89)	0.47	(1.58)	0.47*	(1.75)	0.41	(1.34)	0.50	(1.46)
2	0.64**	(2.13)	0.40	(1.54)	0.15	(0.59)	0.30	(1.12)	0.40	(1.14)
3	0.58**	(2.09)	0.44	(1.60)	0.21	(0.91)	0.32	(1.15)	0.26	(0.97)
4	0.69**	(2.41)	0.35	(1.50)	0.37	(1.37)	0.34	(1.34)	0.51	(1.50)
Large	0.57***	(2.64)	0.47**	(2.10)	0.34	(1.42)	0.58	(1.47)	0.03	(0.12)

Table 7: Fama-French portfolio return predictability (cont'd)

The table reports estimation results of the univariate regressions using returns of 25 Fama-French portfolios sorted by size and book-to-market (BM) for CRP at different horizons from one to 12 months. The monthly returns of 25 portfolios are available via the Kenneth French Data Library's website. CRP is the covariance risk premium defined as the difference between HC and RC of the implied volatility variations and the stock market returns. This table reports the slope coefficients and Newey and West (1987) t-statistics. The sample period is from January 1996 to December 2019. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	Low BM		2		3		4		High BM	
	Panel D: Forecasting 9-month return									
Small	0.57**	(2.00)	0.43*	(1.90)	0.39**	(1.99)	0.33*	(1.75)	0.36	(1.64)
2	0.58**	(2.55)	0.35**	(2.07)	0.10	(0.62)	0.23	(1.36)	0.25	(1.15)
3	0.53**	(2.57)	0.35**	(1.99)	0.13	(0.91)	0.24	(1.35)	0.14	(0.77)
4	0.63***	(2.67)	0.27*	(1.79)	0.24	(1.40)	0.22	(1.35)	0.38*	(1.68)
Large	0.46***	(3.09)	0.32**	(2.19)	0.24	(1.59)	0.32	(1.29)	-0.05	(-0.25)
	Panel E: Forecasting 12-month return									
Small	0.48*	(1.83)	0.37*	(1.72)	0.31*	(1.70)	0.24	(1.43)	0.20	(1.04)
2	0.50**	(2.49)	0.27*	(1.86)	0.01	(0.09)	0.14	(1.03)	0.12	(0.65)
3	0.40**	(2.18)	0.28**	(2.00)	0.05	(0.48)	0.14	(0.97)	0.06	(0.36)
4	0.55**	(2.53)	0.18	(1.50)	0.17	(1.26)	0.15	(1.08)	0.24	(1.23)
Large	0.39***	(2.81)	0.22**	(2.04)	0.15	(1.32)	0.22	(1.21)	-0.07	(-0.36)
	Panel F: Forecasting 24-month return									
Small	0.60***	(2.78)	0.57***	(2.88)	0.48***	(2.74)	0.42***	(2.75)	0.32*	(1.88)
2	0.53***	(2.90)	0.40***	(2.69)	0.16	(1.37)	0.29***	(2.61)	0.35**	(2.20)
3	0.32**	(2.05)	0.38***	(2.65)	0.17*	(1.73)	0.29**	(2.12)	0.24*	(1.80)
4	0.49***	(2.71)	0.27**	(2.20)	0.31**	(2.23)	0.30**	(2.09)	0.42**	(2.25)
Large	0.33**	(2.49)	0.27**	(2.58)	0.24**	(2.13)	0.39**	(2.27)	0.21	(1.27)

Table 8: Return predictability excluding financial crisis

This table reports the in-sample predictability of CRP during the period excluding the 2008-2009 finacial crisis. CRP is the covariance risk premium defined as the difference between HC and RC. HC is the historical covariance the implied volatility change with a 21-trading-day rolling window. RC is the risk-neutral covariance rate between the implied volatility variations and the stock market returns. The finacial crisis period is 200807-200901. The initial sample period is from January 1996 to December 2019.

	1-month	*3-month*	*6-month*	*9-month*	*12-month*	*24-month*
β	13.82***	8.04**	4.98**	4.07**	3.33**	3.08*
t	(3.37)	(2.58)	(2.11)	(2.39)	(2.34)	(1.94)
$R^2(\%)$	3.05	3.43	2.60	2.51	2.11	2.67

Table 9: Out-of-sample results with a rolling window

This table shows the results of out-of-sample predictive regressions based on a rolling estimation window when we choose the first half of the total sample as our initial training sample. The definitions of predictive variables are the same as those in Table 2. We report the out-of-sample R^2 statistics at horizons from one to 24 months. The sample period is from January 1996 to December 2019. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	1-month	*3-month*	*6-month*	*9-month*	*12-month*	*24-month*
CRP	4.41**	7.77**	5.86**	6.43***	5.57***	14.29***
VVRP	-4.01	-10.03	-10.25	-12.58	-14.12	-6.55
RC	-4.29	-11.44	3.37	3.61	3.80	18.25**
RVV	-3.54	-9.17	-10.22	-14.66	-14.05	-3.95
HC	0.43*	-8.85	-1.39	-1.35	-3.95	0.99
HVV	-0.71	-2.85	-0.23	0.08	-0.31	-1.35
DP	-5.45	-18.00	-22.64	-22.49	-19.63	-10.01
DY	-3.64	-13.53	-17.63	-15.47	-10.98	6.62**
EP	-5.52	-19.99	-31.94	-36.69	-33.79	-50.13
DE	-6.27	-38.60	-64.31	-52.68	-15.11	-67.04
SVAR	-2.70	-13.58	-2.72	-1.95	-3.79	-2.46
BM	-0.81	-1.22	1.55**	3.85**	8.68***	46.16***
NTIS	0.68	0.40	-0.40	-5.43	-21.48	-130.02
TBL	-0.06	-0.93	0.01	8.31***	22.27***	69.34***
LTY	2.58***	5.28***	4.40***	7.44***	15.07***	42.05***
LTR	-0.55	-2.48	-1.02	-0.62	-0.86	-1.72
TMS	-0.62	-2.66	-3.98	-1.48	4.15*	26.61***
DFY	-2.90	-29.53	-88.89	-90.18	-39.59	13.53*
DFR	-4.86	-8.41	-5.56	-3.51	-3.65	-9.21
INFL	-1.68	-5.19	-0.35	0.25*	3.06**	2.25*
VRP	3.31**	14.38*	5.10*	-1.26	-9.14	-9.02

Table 10: CE gains for alternative risk aversion coefficients

This table reports the annualized CE gain (in percent) for alternative risk aversion coefficients, including 2 and 5. The CE gain is defined as the difference between the CE of forecasts generated by our regression model and the historical average forecast benchmark. The definitions of predictive variables are the same as those in Table 2. The sample period is from January 1996 to December 2019.

	Risk aversion coefficient is 2						Risk aversion coefficient is 5					
	1-month	*3-month*	*6-month*	*9-month*	*12-month*	*24-month*	*1-month*	*3-month*	*6-month*	*9-month*	*12-month*	*24-month*
CRP	5.33	10.59	8.03	4.28	3.02	2.56	2.46	8.54	9.36	6.15	4.33	3.79
VVRP	-3.71	-2.35	-2.16	-3.21	-4.15	-1.57	-1.99	-5.54	-2.60	-2.42	-3.23	-0.79
RC	-4.47	1.85	1.95	0.29	-0.67	0.53	-4.40	-1.18	2.53	0.91	-0.13	1.35
RVV	-1.79	-2.47	-3.76	-4.57	-5.15	-2.07	-1.30	-4.53	-2.24	-3.14	-3.75	-1.45
HC	-2.46	-3.08	0.77	-0.39	-1.09	-1.96	-1.75	-4.26	0.78	-0.31	-1.05	-1.38
HVV	-2.20	0.58	0.16	-0.19	-0.55	0.42	-0.74	-2.21	0.92	-0.04	-0.49	0.34
DP	0.94	2.89	6.31	4.33	3.92	5.08	-5.01	1.24	7.50	6.62	5.77	6.94
DY	1.65	4.14	6.30	4.33	3.92	5.08	-3.86	2.46	7.59	6.52	5.80	6.97
EP	2.94	4.01	0.26	-1.95	-1.82	-6.59	0.71	1.94	2.38	-0.29	-1.32	-5.34
DE	2.40	5.79	1.54	-5.71	-4.11	-5.05	1.21	2.93	3.15	-4.63	-3.34	-3.39
SVAR	0.36	-2.01	0.80	-0.74	-1.87	-4.77	-2.57	-2.73	1.59	-1.03	-2.13	-3.59
BM	-0.66	1.11	4.65	3.65	2.78	4.37	-0.55	-1.67	4.99	5.14	4.55	6.15
NTIS	-2.00	-0.09	0.04	-2.79	-5.19	-6.34	-1.71	-0.73	2.05	0.16	-2.83	-4.97
TBL	1.68	3.39	0.08	0.44	2.21	5.08	0.13	3.02	1.55	1.83	3.81	6.97
LTY	4.02	4.50	4.06	-1.82	-5.30	-4.27	1.09	4.75	7.24	1.65	-2.92	-2.53
LTR	-2.01	-0.60	-0.07	-0.48	-0.69	-0.70	-1.08	-1.21	0.47	-0.36	-0.66	-0.65
TMS	-0.14	0.80	0.98	1.67	3.15	3.47	-0.39	-0.41	-1.56	2.06	3.80	4.66
DFY	2.34	4.77	9.07	7.36	4.28	-3.32	1.17	3.25	8.32	7.68	4.64	-2.22
DFR	-0.56	0.45	1.97	1.72	-0.30	-1.83	-1.78	-2.94	1.54	2.53	0.89	-0.61
INFL	-2.65	-3.54	3.26	-0.39	-0.71	-0.51	-1.49	-5.06	3.71	0.33	0.57	0.54
VRP	7.06	7.82	5.11	2.86	1.87	1.09	2.59	5.30	5.20	3.52	2.39	1.48

Figure 1: Time series of CRP

This figure shows the monthly time series of CRP. CRP is the covariance risk premium defined as the difference between HC and RC. HC is the historical covariance the implied volatility change with a 21-trading-day rolling window. RC is the risk-neutral covariance rate between the implied volatility variations and the stock market returns. The sample period is from Janurary 1996 to December 2019.