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Moment Risk Premia and Stock Return Predictability

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Abstract

We study the predictive power of option-implied moment risk premia embedded in the conventional variance risk premium. We find that although the second-moment risk premium predicts market returns in short horizons with positive coefficients, the third-moment (fourth-moment) risk premium predicts market returns in medium horizons with negative (positive) coefficients. Combining the higher-moment risk premia with the second-moment risk premium improves the stock return predictability over multiple horizons, both in sample and out of sample. The finding is economically significant in an asset-allocation exercise and survives a series of robustness checks.

I. Introduction

The issue of whether stock market returns are predictable has been one of the most discussed topics in financial economics. Until a few decades ago, the widespread view was that market returns are unpredictable if the market is efficient. It has now been generally accepted that expected returns are time varying and partially predictable even in an efficient market (see, e.g., Campbell and Shiller (1988), Fama and French (1989), Kothari and Shanken (1997), and Cochrane (2008)). Ample empirical evidence has shown that variables, including financial ratios and macroeconomic variables, can predict the variation of stock returns over business-cycle and multiyear horizons. More recent articles uncover that predictors extracted from options data forecast market returns at horizons as short as a few months. This article

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contributes to the literature on the time-series predictability of stock market returns over short horizons by exploiting new predictive information in equity index options.

A typical example of a short-term predictor extracted from the option market is the variance risk premium (see, e.g., Bollerslev, Tauchen, and Zhou (2009)), which has been shown to strongly predict the market return over horizons of up to 6 months. In fact, the conventional variance risk premium, defined as the difference between the squared Volatility Index (VIX) and the realized return variance, is a quasi-variance risk premium (QVRP) because it not only has a second-order component, the pure variance risk premium (PVRP), but also contains higher moment premium components. In this article, we seek to investigate the predictability of moment risk premia embedded in QVRP over different forecasting horizons.

Following Bakshi and Madan (2000) and Bakshi, Kapadia, and Madan (2003), we compute the risk-neutral moments of returns using portfolios of out-of-the-money (OTM) European call and put options. Matching the risk-neutral moments with their realized counterparts, we calculate the PVRP, the risk premium on the third moment of returns (M3RP), and the risk premium on the fourth moment of returns (M4RP) in a model-free fashion.

Using the S&P 500 index and its option data from 1990 to 2019, we investigate the predictability of the market return afforded by the option-implied moment risk premia over different horizons using predictive regressions. We find that higher-moment risk premia, M3RP and M4RP, are similar to each other but have different statistical features from the second-moment risk premium, PVRP. In particular, PVRP and M3RP are only moderately correlated, and their means have different signs. By contrast, M3RP and M4RP contain overlapping information and are highly correlated. This evidence suggests that much information in the higher-moment risk premia is unspanned by PVRP, and aggregating them may lead to substantial information losses. As a consequence, there is room for potential improvement in predicting the market equity return using options by considering these moment risk premia separately.

We evaluate the predictability of each moment risk premium using predictive regressions for 1- to 24-month excess returns on the S&P 500 index both in sample and out of sample (OOS). We have three main findings. First, we find that the predictive performance of PVRP dominates that of QVRP at all horizons, with higher t-statistics and larger in-sample and OOS R^2s. This confirms that PVRP, a cleaner measure of the variance risk premium after removing the higher-moment risk premia from QVRP, is a better predictor than the conventional variance risk premium.

Second, we find that although PVRP predicts short-term market returns, M3RP and M4RP predict medium-term market returns. At 6- to 24-month horizons, M3RP (M4RP) predicts market returns with highly significant coefficients and higher in-sample and OOS R^2s than PVRP. We show that M3RP remains statistically significant after controlling for the stock return predictors in Welch and Goyal (2008) and short-term predictors, such as aggregate short interest in Rapach, Ringgenberg, and Zhou (2016), average skewness in Jondeau, Zhang, and Zhu (2019), and left jump probability in Andersen, Fusari, and Todorov (2015).

Finally, combining moment risk premia improves both the in-sample and OOS predictability of QVRP over multiple horizons. In particular, the adjusted R^2s of the joint regressions with PVRP and M3RP are 9.7%, 6.1%, and 4.5% at 6-, 9-, and

12-month horizons, in contrast to 3.7%, 0.9%, and 0.3% for the univariate regressions with QVRP. The OOS R^2s of the forecast combination with PVRP and M3RP are 10.9%, 6.9%, and 4.5% at 6-, 9-, and 12-month horizons, compared with 2.0%, –2.4%, and –7.9% in the univariate regressions with QVRP. Our main findings survive various robustness checks.

We further examine the economic value of the predictability offered by the moment risk premia via an asset-allocation experiment. The different predictability contained in moment risk premia can be exploited by forming strategic portfolios. Consistent with our findings on the predictive regressions, the portfolios formed on PVRP result in a higher certainty equivalent in the shorter term, and those formed on M3RP or M4RP result in a higher certainty equivalent in the longer term. In addition, portfolios that combine the predictability from PVRP and M3RP (M4RP) generate higher OOS utility gains in medium horizons than those based on QVRP alone.

Our article is related to the literature that studies option-implied moments and different measures of risk-neutral variance. Martin (2017) proposes an option-implied variance of simple returns and relates it to the lower bound of the expected market return. Kozhan, Neuberger, and Schneider (2013) construct a measure of the skewness risk premium, which can be interpreted as the profit to a dynamic trading strategy. In a similar spirit, Bondarenko (2014) defines an alternative variance risk premium, which is robust to sampling frequencies and price discontinuities. Another related article is Ait-Sahalia, Karaman, and Mancini (2018), who identify a large and time-varying jump component by comparing the variance swaps rates and the VIX and postulate a parametric model that generates the empirical patterns of these price jumps.

Our article contributes to the literature on return predictability from the variance risk premium and components of the variance risk premium. Since the seminal work by Bollerslev et al. (2009), who show that the variance risk premium predicts market returns for up to a few months' horizon, many articles investigate how different components of the variance risk premium contribute to the return prediction. For instance, Bollerslev, Todorov, and Xu (2015) decompose the total variance into its continuous- and jump-variance components and find that much of the predictability in the variance risk premium may be attributed to the jump tail component. Feunou, Jahan-Parvar, and Okou (2018) study the predictability of the downside variance risk premium. Kilic and Shaliastovich (2019) show that the good and bad variance risk premiums can jointly predict stock and bond returns. Buss, Schönleber, and Vilkov (2019) identify a correlation risk premium in the variance risk premium and find considerable predictability in the correlation risk premium. Whereas these articles analyze components within the variance risk premium, we focus on the higher-moment risk premia, which, although embedded in the QVRP, is beyond the second-moment risk premium. We show that higher-moment risk premia contain complementary predictive power to the second-moment risk premium.

Our article also contributes to the literature on the predictability of higher moments of returns. Many articles have shown that skewness is related to future stock returns (see, e.g., Chang, Christoffersen, and Jacobs (2013), Conrad, Dittmar, and Ghysels (2013), Amaya, Christoffersen, Jacobs, and Vasquez (2015), and Stilger, Kostakis, and Poon (2017)). Most of these articles focus on the individual stock level. An exception is Jondeau et al. (2019), who use a weighted average of realized skewness of individual stocks to predict market returns.

Whereas Jondeau et al. use realized skewness to predict returns in the next month, we use the option-implied higher-moment risk premia, which have a natural forward-looking component, to predict the market return over 1- to 24-month horizons.

The rest of the article is organized as follows: Section II defines the QVRP and moment risk premia. Section III explains the data used in the empirical analysis. Section IV reports the predictive regression results for the market return on the moment risk premia, along with a series of robustness checks. Section V studies the OOS predictability of moment risk premia in terms of OOS R^2s and asset-allocation implications. Section VI concludes.

II. Separating the Moment Risk Premia

The conventional variance risk premium is defined based on the Chicago Board of Options Exchange (CBOE) VIX, such as in Bollerslev et al. (2009) and Bekaert and Hoerova (2014). The CBOE VIX is a popular measure of investors' fear, which is constructed from a portfolio of OTM S&P 500 index call and put options. If the call and put options have a continuum of strike prices from 0 to ∞, VIX_t^2 is defined as follows:

$$\text{(1)} \qquad \text{VIX}_t^2 \equiv \frac{2}{T-t}\int_0^\infty \frac{\Theta_t(K,T)}{K^2}dK,$$

where $\Theta_t(K,T)$ denotes the time t value of an OTM option with strike price $K > 0$ and maturity T. Puts are used for low strikes ($K \leq F_t(T)$) and calls are used for high strikes ($K \geq F_t(T)$) because OTM options are more liquid than in-the-money options. Here, $F_t(T)$ is the forward price of the underlying asset at time t with maturity T.

As noted by Carr and Wu (2009), when used as the option-implied expectation of stock volatility, the VIX given by equation (1) has an approximation error induced by return discontinuities. As a matter of fact, Kozhan et al. (2013) show that VIX_t^2 is the risk-neutral expectation of $g(r(t,T))$:

$$\text{(2)} \qquad \text{VIX}_t^2 = \frac{1}{T-t}\mathbb{E}_t^Q[g(r(t,T))],$$

with $g(r) \equiv 2(e^r - 1 - r)$. Here, $r(t,T)$ denotes the log return on the forward prices from t to T: $r(t,T) = \log F_T(T) - \log F_t(T)$. Note that we define $r(t,T)$ using forward prices rather than the spot prices to avoid complications with interest rates and dividends, similar to Bondarenko (2014).[1]

Let $\{t, t+\Delta, \ldots, t+N\Delta\}$ be a partition of $[t,T]$, and denote $r(t+i\Delta, t+(i+1)\Delta)$ as r_i for simplicity. To obtain a coherent realized counterpart for VIX^2, we consider the following expression:

$$\text{(3)} \qquad \text{QRV}_T \equiv \frac{1}{T-t}\sum_{i=1}^N g(r_i) = \frac{1}{T-t}\sum_{i=1}^N 2(e^{r_i} - 1 - r_i).$$

[1]Returns thus defined are excess returns. In other words, the expectation under which equation (2) is evaluated is the forward Q-measure.

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We denote the quantity defined in equation (3) as the *quasi-realized variance* (QRV) because the function $g(r)$ differs from r^2 only in higher-order terms. To see this, we apply Taylor expansion to $g(r)$ and get

$$g(r) = r^2 + \frac{1}{3}r^3 + \frac{1}{12}r^4 + o\left(r^4\right). \tag{4}$$

Taking the difference between the squared VIX and QRV gives the QVRP:

$$\text{QVRP}_t \equiv \text{VIX}_t^2 - \mathbb{E}_t[\text{QRV}_T]. \tag{5}$$

We use the word *quasi* to distinguish our definition of the variance risk premium from those in the prevailing literature. Many articles use different formulations of realized variance other than QRV as the realized counterpart of VIX^2. For instance, Carr and Wu (2009) use the realized squared simple returns $(1/(T-t)\sum_{i=1}^{N}(e^{r_i})^2)$, and Bollerslev et al. (2009) use the realized squared log returns $(1/(T-t)\sum_{i=1}^{N}r_i^2)$.

The higher-order terms in equation (4) are nontrivial when returns can jump. The empirical literature has presented strong evidence of jumps in the S&P 500 index return (e.g., Bakshi, Cao, and Chen (1997), Andersen, Benzoni, and Lund (2002), Pan (2002), Eraker, Johannes, and Polson (2003), and Christoffersen, Jacobs, and Ornthanalai (2012), among others). If the higher-order terms on the right-hand side of equation (4) are nonnegligible, QRV serves as the only consistent realized counterpart of VIX^2, regardless of the presence of jumps. This internal consistency between the option-implied moments and their realized counterparts in QVRP facilitates the identification of the higher-order risk premiums within QVRP, as follows:

$$\begin{aligned}
\text{QVRP}_t &\equiv \text{VIX}_t^2 - \mathbb{E}_t[\text{QRV}_T] \\
&= \underbrace{\frac{1}{T-t}\left(\mathbb{E}_t^Q\left[r(t,T)^2\right] - \mathbb{E}_t\left[\sum_{i=1}^{N} r_i^2\right]\right)}_{\text{PVRP}_t} \\
&\quad + \underbrace{\frac{1}{3}\frac{1}{T-t}\left(\mathbb{E}_t^Q\left[r(t,T)^3\right] - \mathbb{E}_t\left[\sum_{j=1}^{N} r_i^3\right]\right)}_{\text{M3RP}_t} \\
&\quad + \underbrace{\frac{1}{12}\frac{1}{T-t}\left(\mathbb{E}_t^Q\left[r(t,T)^4\right] - \mathbb{E}_t\left[\sum_{j=1}^{N} r_i^4\right]\right)}_{\text{M4RP}_t} \\
&\quad + \frac{1}{T-t}\sum_{i=5}^{\infty}\frac{2}{i!}\left(\mathbb{E}_t^Q\left[r(t,T)^i\right] - \mathbb{E}_t\left[\sum_{j=1}^{N} r_i^j\right]\right) \\
&\approx \text{PVRP}_t + \frac{1}{3}\text{M3RP}_t + \frac{1}{12}\text{M4RP}_t.
\end{aligned}$$

PVRP, M3RP, and M4RP represent risk premiums associated with the second, third, and fourth moments of returns, respectively. In the Supplementary Material, we derive the moments of returns in a jump-diffusion model as an example to illustrate the potential sources of higher moments.

The risk-neutral components in the moment risk premia can be constructed by using the quadratic, cubic, and quartic contracts introduced by Bakshi et al. (2003). We denote them as the implied variance (IV), the implied third moment (IM3), and the implied fourth moment (IM4):

(6) $$\mathrm{IV}_t = \frac{1}{T-t}\mathbb{E}_t^Q\left[r(t,T)^2\right] = \frac{2}{T-t}\int_0^{\infty}\frac{1+\log(F_t/K)}{K^2}\Theta_t(K,T)dK,$$

(7) $$\begin{aligned}\mathrm{IM3}_t &= \frac{1}{T-t}\mathbb{E}_t^Q\left[r(t,T)^3\right]\\ &= \frac{1}{T-t}\int_0^{\infty}\frac{6\log(K/F_t) - 3(\log(K/F_t))^2}{K^2}\Theta_t(K,T)dK,\end{aligned}$$

(8) $$\begin{aligned}\mathrm{IM4}_t &= \frac{1}{T-t}\mathbb{E}_t^Q\left[r(t,T)^4\right]\\ &= \frac{1}{T-t}\int_0^{\infty}\frac{12(\log(F_t/K))^2 - 4(\log(K/F_t))^3}{K^2}\Theta_t(K,T)dK.\end{aligned}$$

The realized variance (RV), realized third moment (RM3), and realized fourth moment (RM4), corresponding to IV, IM3, and IM4, are, respectively, as follows:

(9) $$\mathrm{RV}_t \equiv \frac{1}{T-t}\sum_{j=1}^{N} r_i^2,\ \mathrm{RM3}_t \equiv \frac{1}{T-t}\sum_{j=1}^{N} r_i^3,\ \mathrm{RM4}_t \equiv \frac{1}{T-t}\sum_{j=1}^{N} r_i^4.$$

The PVRP, the M3RP, and the M4RP are defined as the differences between the risk-neutral and physical expectation of realized moments of log returns:

(10) $$\begin{aligned}\mathrm{PVRP}_t &= \mathrm{IV}_t - \mathbb{E}_t[\mathrm{RV}_T],\\ \mathrm{M3RP}_t &= \mathrm{IM3}_t - \mathbb{E}_t[\mathrm{RM3}_T],\\ \mathrm{M4RP}_t &= \mathrm{IM4}_t - \mathbb{E}_t[\mathrm{RM4}_T].\end{aligned}$$

Here, we use the term *risk premium* to indicate that the variables in equation (10) are differences between Q- and P-expectations.[2] In the next section, we show how to construct QVRP, PVRP, M3RP, and M4RP empirically using option prices and stock returns.

III. Data Source and Risk Premiums

A. Data Source and Variable Construction

We use the S&P 500 index option data from the CBOE, starting from Jan. 1990 and ending in July 2019. Our data sample includes the highest closing bid and the

[2]Strictly speaking, these moment risk premia are not profits from a trading strategy and hence do not qualify as risk premiums in the economic sense, as pointed out by Kozhan et al. (2013).

lowest closing ask prices of all call and put options, strike prices, and expiration dates. We obtain monthly 1-month risk-free rates from the CRSP. These rates are based on the Treasury bill that has a minimum of 30 days to maturity and is the closest to 30 days to maturity. We obtain monthly dividends rates of the S&P 500 index from Compustat, which are the anticipated annual dividend rates.

We apply standard filters to select the option sample. First, we delete all options with 0 open interest, 0 bid prices, and missing implied volatility. Second, following the literature on model-free implied volatility (e.g., Jiang and Tian (2005) and Carr and Wu (2009)), we only keep OTM and at-the-money options. A put (call) option is regarded as OTM if the strike price is lower (higher) than the forward price. The 1-month forward price at time t is defined as $F_t = S_t e^{(r_{f,t}-q_t)\tau}$. Here, S_t is the S&P 500 index spot price, $\tau = 1/12$ denotes the time to maturity of 1 month, $r_{f,t}$ is the risk-free rate, and q_t is the dividend rate at time t. Third, we only keep options with less than 365 days of expiry. After applying the filters, we have 5,503,043 option-day data points. Similar to the construction of the VIX provided by the CBOE, we work with the best bid and ask closing quotes. The option price is the average of the highest closing bid and the lowest closing ask prices.

At the end of each month, we construct the annualized VIX^2, IV, IM3, and IM4 using the discrete versions of equations (1), (6), (7), and (8):

(11)
$$\begin{aligned}
\text{VIX}_t^2 &\approx \frac{1}{T-t}\sum_{i=2}^{m_{t,\tau}}[f(t,T,K_i)+f(t,T,K_{i-1})]\Delta K_i,\\
\text{IV}_t &\approx \frac{1}{T-t}\sum_{i=2}^{m_{t,\tau}}[f_v(t,T,K_i)+f_v(t,T,K_{i-1})]\Delta K_i,\\
\text{IM3}_t &\approx \frac{1}{T-t}\sum_{i=2}^{m_{t,\tau}}[f_3(t,T,K_i)+f_3(t,T,K_{i-1})]\Delta K_i,\\
\text{IM4}_t &\approx \frac{1}{T-t}\sum_{i=2}^{m_{t,\tau}}[f_4(t,T,K_i)+f_4(t,T,K_{i-1})]\Delta K_i,
\end{aligned}$$

where $\Delta K_i = K_i - K_{i-1}$. Here, $m_{t,\tau}$ is the number of available OTM options on day t with maturity $\tau = T-t$ after we filter the options data. Therefore, $m_{t,\tau}$ varies by date t and maturity τ. f, f_v, f_3, and f_4 are defined as follows:

$$\begin{aligned}
f(t,T,K_i) &= \frac{\Theta_t(K_i,T)}{K_i^2},\\
f_v(t,T,K_i) &= \frac{1+\log(F_t/K_i)}{K_i^2}\Theta_t(K_i,T),\\
f_3(t,T,K_i) &= \frac{6\log(K_i/F_t)-3(\log(K_i/F_t))^2}{2K_i^2}\Theta_t(K_i,T),\\
f_4(t,T,K_i) &= \frac{12(\log(F_t/K_i))^2-4(\log(K_i/F_t))^3}{2K_i^2}\Theta_t(K_i,T),
\end{aligned}$$

where F_t denotes the forward price, and $\Theta_t(K,T)$ denotes the time t value of an out-of-the-money option with strike price K and maturity $T \geq t$. Following the construction of VIX provided by the CBOE, we select two maturities of options: the shortest maturity with more than 30 days of expiry and the longest maturity with less than 30 days and more than 7 days of expiry. The annualized VIX^2 in equation (11) is then calculated for these two maturities. Next, we interpolate the 30-day VIX^2 using the VIX^2 of the two maturities with linear interpolation. The same procedure applies to the calculation of IV, IM3, and IM4 with 30 days of expiration.

Following the recent literature (e.g., Bollerslev et al. (2009), Buss et al. (2019), among others), to approximate the expectations under the physical measure, we use daily S&P 500 index prices to calculate quasi realized variance QRV, realized variance (RV), realized third moment (RM3), and realized fourth moment (RM4) for each calendar month. In accordance with the risk-neutral moments that are constructed based on the forward prices, the realized moments are also computed using forward prices. Specifically, we assume that the risk-free rate and dividend rate are constant within a month. Given month t, we denote the forward price on the nth day of the month as F_t^n. Here, the subscript t denotes the month, and the superscript n denotes the day of the month. F_t^n is calculated as

$$F_t^n = S_t^n \exp\left(\left(r_{f,t} - q_t\right)(N_t - n)/(12N_t)\right),$$

where S_t^n is the spot price on day n of month t; $r_{f,t}$ and q_t are the annualized risk-free rate and dividend rate of month t, respectively; and N_t is the number of trading days in month t. We calculate daily excess log returns as

$$r_t^{n+1} = \log\left(F_t^{n+1}\right) - \log\left(F_t^n\right).$$

Realized moments are then computed as

$$\text{QRV} = \sum_{i=1}^{N} 2(e^{r_i} - 1 - r_i), \text{RV}_t = \sum_{i=1}^{N} \left(r_t^i\right)^2,$$

$$\text{RM3}_t = \sum_{i=1}^{N} \left(r_t^i\right)^3, \text{RM4}_t = \sum_{i=1}^{N} \left(r_t^i\right)^4.$$

Notice that the implied moments (VIX, IV, IM3, and IM4) are calculated using OTM options at the last trading day of the month, but the realized moments (QRV, RV, RM3, and RM4) are calculated with daily returns *within* the month t. In other words, we use the realized moments of $t-1$ as an estimator for the expected realized moments of t. This formulation has the advantage that the risk premiums are ex ante and model-free. Because both implied and realized moments are available at time t without relying on any specific model, this facilitates the return-forecasting exercise in Section IV.

B. Summary Statistics of Moment Risk Premia

Table 1 reports the summary statistics of risk-neutral moments, realized moments, and moment risk premia. The summary statistics of the risk-neutral moments, VIX^2, IV, IM3, and IM4, and those of the realized moments, QRV, RV,

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TABLE 1

Summary Statistics of Moment Risk Premia

Panel A of Table 1 reports the mean, standard deviation, median, 5% quantile (P5), and 95% quantile (P95) of risk-neutral and realized moments. Risk-neutral moments include the squared Volatility Index (VIX^2), implied variance (IV), implied third moment (IM3), and implied fourth moment (IM4). Realized moments include the quasi-realized variance (QRV), realized variance (RV), realized third moment (RM3), and realized fourth moment (RM4). Panel B reports the mean, standard deviation, median, 5% quantile (P5), 95% quantile (P95), and autocorrelation coefficient (AR(1)) of the moment risk premia: quasi-variance risk premium (QVRP), pure variance risk premium (PVRP), third-moment risk premium (M3RP), and fourth-moment risk premium (M4RP). Moment risk premia are the differences between the risk-neutral and realized moments. Panel C reports the correlation matrix among moment risk premia. All variables are denoted in percentage per annum. The sample period is Jan. 1990–July 2019.

Panel A. Risk-Neutral and Realized Moments

	VIX^2	IV	IM3	IM4
Mean	3.86	4.02	−0.51	0.23
Std. Dev.	3.77	4.06	1.14	0.93
Median	2.75	2.79	−0.24	0.06
P5	1.05	1.08	−1.80	0.01
P95	9.64	10.08	−0.04	0.79
	QRV	RV	RM3	RM4
Mean	2.91	2.91	-7.15×10^{-3}	4.10×10^{-3}
Std. Dev.	5.07	5.07	0.09	0.03
Median	1.54	1.54	9.02×10^{-4}	3.23×10^{-4}
P5	0.41	0.41	−0.07	2.13×10^{-5}
P95	8.93	8.97	0.04	9.28×10^{-3}

Panel B. Moment Risk Premia

	QVRP	PVRP	M3RP	M4RP
Mean	0.95	1.10	−0.51	0.23
t-stat.	7.05	8.61	−8.33	4.78
Median	0.90	1.00	−0.23	0.06
P5	−1.45	−1.23	−1.72	0.01
P95	3.96	4.25	−0.04	0.79
AR(1)	0.38	0.34	0.55	0.46

Panel C. Correlation Matrix

	QVRP	PVRP	M3RP	M4RP
QVRP	1.00	0.99	0.47	−0.55
PVRP	0.99	1.00	0.36	−0.45
M3RP	0.47	0.36	1.00	−0.98
M4RP	−0.55	−0.45	−0.98	1.00

RM3, and RM4, are reported in Panel A. Comparing risk-neutral and realized moments, we observe that the sample means of risk-neutral moments are larger in magnitude than those of their realized counterparts. The risk-neutral and realized third moments are both negative. IM3 is larger in magnitude, has a larger standard deviation, and is more left skewed than RM3. IM4 and RM4 follow a similar pattern with an opposite sign. The mean of VIX^2 is slightly lower than that of IV because VIX^2 is a linear combination of IV, IM3, and IM4.

Panel B of Table 1 reports the summary statistics of the moment risk premia. Consistent with the existing literature, QVRP is on average positive, with a mean of 0.95%. M3RP is on average negative, which explains why PVRP has a slightly larger mean than QVRP. All risk premiums are significantly different from 0 at the 1% level. Compared with QVRP and PVRP, M3RP and M4RP have a relatively lower standard deviation and higher autocorrelation.

Panel C of Table 1 reports the correlation matrix among the risk premiums. The correlation between QVRP and PVRP is as high as 0.99, implying that PVRP is the major component of QVRP. There is also substantial comovement between

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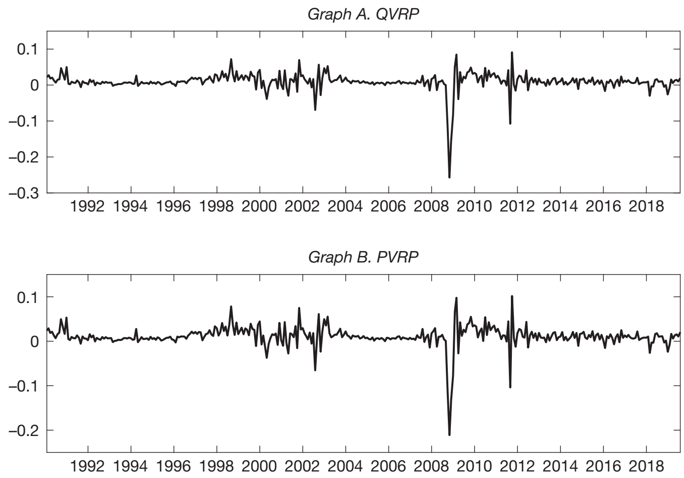
FIGURE 1

Time Series of QVRP and PVRP

Figure 1 shows the time series of the quasi-variance risk premium (QVRP) and the pure variance risk premium (PVRP) from Jan. 1990 to July 2019.



PVRP and higher moment risk premia, with a correlation coefficient of 0.47 for M3RP and −0.55 for M4RP. M3RP and M4RP almost always move in opposite directions, with a correlation coefficient of −0.98.

Figure 1 plots the time series of QVRP and PVRP. The dynamics of QVRP and PVRP are almost indistinguishable. Both QVRP and PVRP fluctuate between positive and negative values and display moderate variations as well as occasional spikes. Despite the fact that both QVRP and PVRP are on average positive, as shown by the summary statistics, there are a couple of extreme negative values in late 2002, 2008, and 2011. These negative spikes may be attributed to the downward volatility jumps, as proposed by Amengual and Xiu (2018), or heightened uncertainty, as proposed by Hu, Pan, Wang, and Zhu (2019), associated with resolutions of policy uncertainties. Figure 2 plots the time series of M3RP and M4RP. Compared with QVRP or PVRP, M3RP and M4RP have fewer fluctuations but sharper spikes. The spikes in M3RP and M4RP coincide with the volatile periods in PVRP.

IV. Predictive Regression Analysis

In this section, we analyze the predictability of stock market returns using the moment risk premia embedded in QVRP. We run predictive regressions of the market return of different horizons on each moment risk premium separately and on multiple moment risk premia jointly. Section IV.A reports the baseline predictive results. Section IV.B reports the prediction results for weighted least squares. In Sections IV.C and IV.D, we control for the established long-term and short-term predictors, respectively.

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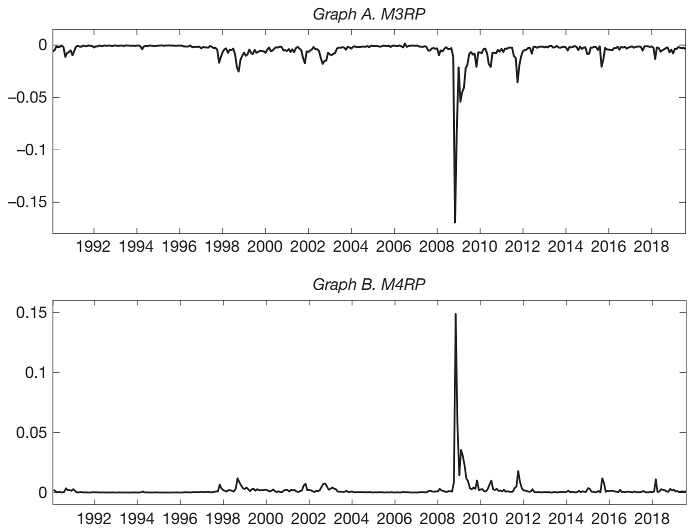
FIGURE 2

Time Series of M3RP and M4RP

Figure 2 shows the time series of the third-moment risk premium (M3RP) and the fourth-moment risk premium (M4RP) from Jan. 1990 to July 2019.



A. Predicting the Market Return

As shown by Bollerslev et al. (2009), Drechsler and Yaron (2011), and Bekaert and Hoerova (2014), the variance risk premium has significant predictive power for future market returns at the quarterly horizon. In this section, we show that although QVRP predicts short-term market returns of up to 6 months, higher-moment risk premia, M3RP and M4RP, predict medium-term market returns of up to 24 months. We also show that at any horizon from 1 to 24 months, separating M3RP and M4RP from PVRP yields better predictive results.

Let $\boldsymbol{X_t}$ be a vector of predictive variables containing end-of-month values. We use the following specification for predictive regressions:

$$R_{t,t+h} = \alpha_h + \beta_h' X_t + \varepsilon_{t,t+h}, \tag{12}$$

where $R_{t,t+h}$ is the market excess return from the first day of next month $t+1$ to the last day of month $t+h$. We use simple excess return on the S&P 500 index as a proxy of market excess return.[3]

As shown in the summary statistics in Table 1, M3RP and M4RP are correlated with PVRP. To investigate the predictive information in higher-moment risk premia

[3]Here, we use the S&P 500 returns instead of aggregate stock market returns because moment risk premia are only available for the former. An important difference from the traditional aggregate market return is that the S&P 500 is a price index, so returns do not include dividends.

orthogonal to PVRP, we first regress M3RP and M4RP on PVRP and a constant to obtain a time series of M3RP and M4RP residuals, denoted as $\text{M3RP}^{\perp}$ and $\text{M4RP}^{\perp}$. We then use the residuals $\text{M3RP}^{\perp}$ and $\text{M4RP}^{\perp}$ as predictors. In the univariate regressions, $X_t = \text{QVRP}_t$, PVRP_t, $\text{M3RP}_t^{\perp}$, or $\text{M4RP}_t^{\perp}$, respectively. In the joint regressions, we consider $X_t = \left(\text{PVRP}_t, \text{M3RP}_t^{\perp}\right)'$ and $\left(\text{PVRP}_t, \text{M4RP}_t^{\perp}\right)'$. We use Newey–West standard errors to correct for the autocorrelation and heteroscedasticity in error terms.

The predictive regression results are reported in Table 2, including univariate regressions using QVRP, PVRP, $\text{M3RP}^{\perp}$, and $\text{M4RP}^{\perp}$, respectively, and multivariate regressions using PVRP and $\text{M3RP}^{\perp}$, and PVRP and $\text{M4RP}^{\perp}$ jointly. Consistent with the literature, in the univariate regressions of QVRP (first column of each horizon), the coefficients on QVRP are positive and highly significant for horizons of up to 6 months. QVRP achieves a maximum adjusted R^2 of over 9% at the 3-month horizon. The predictive power of QVRP tapers off as the prediction horizon gets longer. As a cleaner measure of the variance risk premium, PVRP has better predictive performance than QVRP in all horizons, with larger t-statistics and R^2s.

The predictive power of the higher-moment risk premia (the third and fourth columns of each horizon) has a different pattern. The coefficients on $\text{M3RP}^{\perp}$ are negative across all horizons. At the short end (1 month and 3 months), the predictive regressions on $\text{M3RP}^{\perp}$ feature small t-statistics and low R^2s. At medium horizons (6–24 months), by contrast, $\text{M3RP}^{\perp}$ is significantly negative. The R^2s of $\text{M3RP}^{\perp}$ from 6 to 24 months range from 3.55% to 5.95%. Univariate regressions of $\text{M4RP}^{\perp}$ exhibit a similar pattern, except that the coefficients on $\text{M4RP}^{\perp}$ are positive. $\text{M3RP}^{\perp}$ and $\text{M4RP}^{\perp}$ share similar levels of predictive coefficients, t-statistics, and R^2s. This is not surprising because M3RP and M4RP are highly correlated, with a linear correlation coefficient of -0.98.

The multivariate predictive regressions reveal interesting findings on the higher-moment risk premia. First, the coefficients on PVRP and $\text{M4RP}^{\perp}$ are always positive, and those on $\text{M3RP}^{\perp}$ are always negative. Because PVRP and $\text{M3RP}^{\perp}$ predict future returns with opposite signs, the predictive power of QVRP is substantially hindered as a result of the negative prediction by M3RP canceling out the positive prediction by PVRP. This could explain why QVRP is not as strong of a predictor as PVRP at short horizons and has less predictive power at medium horizons than M3RP.

Second, different from the univariate regressions, where the higher-moment risk premia are only significant at longer horizons, the $\text{M3RP}^{\perp}$ and $\text{M4RP}^{\perp}$ coefficients are statistically significant at all horizons in the joint regressions. At short horizons, the $\text{M3RP}^{\perp}$ and $\text{M4RP}^{\perp}$ coefficients turn highly statistically significant in the multivariate regressions despite their insignificance in the univariate regressions. The t-statistics of $\text{M3RP}^{\perp}$ are -2.7 in the joint regression for the 1-month horizon and -3.5 for the 3-month horizon. Across all horizons, most of the t-statistics of the $\text{M3RP}^{\perp}$ and $\text{M4RP}^{\perp}$ coefficients in the joint regressions are larger in magnitude than those in the univariate regressions.

Finally, combining higher-moment risk premia and PVRP leads to improvements in R^2s. The R^2s of the joint regressions are always higher than those of the univariate regressions across all horizons. For example, at the 6-month horizon,

TABLE 2

Market Return Predictive Regressions at Different Horizons

Table 2 reports estimated regression coefficients and R^2s of the predictability regressions for 1- to 24-month excess returns on the S&P 500 index. Heteroscedasticity- and autocorrelation-robust *t*-statistics are reported in parentheses. For each horizon, we report the predictive-regression results of the univariate regressions on the quasi-variance risk premium (QVRP), the pure variance risk premium (PVRP), the residual of the third-moment risk premium after regressing on PVRP ($M3RP^{\perp}$), the residual of the fourth-moment risk premium after regressing on PVRP ($M4RP^{\perp}$), the bivariate regression on PVRP and $M3RP^{\perp}$ jointly, and the bivariate regression for PVRP and $M4RP^{\perp}$ jointly. Returns are observed monthly, with the sample period ranging from Jan. 1990 to July 2019.

	1	2	3	4	5	6
Panel A. 1 Month						
QVRP	0.31 (3.76)					
PVRP		0.35 (3.86)			0.35 (3.41)	0.35 (3.50)
$M3RP^{\perp}$			−0.41 (−1.38)		−0.41 (−2.69)	
$M4RP^{\perp}$				0.46 (1.10)		0.46 (2.35)
R^2	3.69	4.28	1.18	0.84	5.45	5.12
Adj. R^2	3.42	4.01	0.90	0.56	4.92	4.58
Panel B. 3 Months						
QVRP	0.85 (6.26)					
PVRP		0.95 (5.30)			0.95 (3.31)	0.95 (3.46)
$M3RP^{\perp}$			−0.96 (−1.37)		−0.96 (−3.49)	
$M4RP^{\perp}$				1.08 (1.22)		1.08 (3.03)
R^2	9.11	10.34	2.09	1.50	12.43	11.84
Adj. R^2	8.85	10.08	1.81	1.22	11.93	11.34
Panel C. 6 Months						
QVRP	0.82 (5.50)					
PVRP		0.99 (5.66)			0.99 (2.79)	0.99 (2.94)
$M3RP^{\perp}$			−2.21 (−2.71)		−2.21 (−3.96)	
$M4RP^{\perp}$				2.57 (2.40)		2.57 (4.04)
R^2	3.93	5.15	5.09	3.95	10.24	9.10
Adj. R^2	3.65	4.88	4.82	3.68	9.73	8.58
Panel D. 9 Months						
QVRP	0.57 (2.24)					
PVRP		0.75 (2.91)			0.75 (2.43)	0.75 (2.45)
$M3RP^{\perp}$			−2.69 (−3.39)		−2.70 (−3.55)	
$M4RP^{\perp}$				3.31 (3.28)		3.32 (4.06)
R^2	1.19	1.86	4.81	4.15	6.68	6.03
Adj. R^2	0.91	1.58	4.53	3.87	6.14	5.49
Panel E. 12 Months						
QVRP	0.47 (1.42)					
PVRP		0.65 (1.98)			0.66 (2.22)	0.66 (2.21)

(continued on next page)

TABLE 2 (continued)

Market Return Predictive Regressions at Different Horizons

	1	2	3	4	5	6
Panel E. 12 Months (continued)						
$M3RP^{\perp}$			−2.96 (−3.39)		−2.96 (−3.37)	
$M4RP^{\perp}$				3.66 (3.40)		3.66 (3.90)
R^2	0.56	0.99	4.06	3.55	5.07	4.57
Adj. R^2	0.27	0.71	3.78	3.27	4.51	4.01
Panel F. 24 Months						
QVRP	0.46 (1.11)					
PVRP		0.72 (1.59)			0.73 (1.45)	0.74 (1.47)
$M3RP^{\perp}$			−4.27 (−2.48)		−4.28 (−2.42)	
$M4RP^{\perp}$				5.31 (2.76)		5.32 (2.85)
R^2	0.20	0.44	3.06	2.70	3.50	3.15
Adj. R^2	−0.10	0.14	2.76	2.40	2.92	2.56

the R^2 of the joint regression with PVRP and $M3RP^{\perp}$ is as high as 9.7%, whereas the univariate regression of QVRP only has an R^2s of 3.7%. A more impressive example is the 9-month predictive results, in which case the joint regression of PVRP and $M3RP^{\perp}$ produces an R^2 of 5.5%, more than 5 times that of QVRP (0.9%).

To compare the predictive power of different moment risk premia over different horizons, we plot the graph of adjusted R^2s as a function of forecasting horizons in Figure 3. Graph A shows the R^2s of the univariate regressions of the moment risk premia. Graph B shows the R^2s of QVRP and the joint regression of PVRP and $M3RP^{\perp}$. Graph A shows that PVRP is a strong predictor at the short end. After reaching its peak at the 3-month horizon, the R^2 tapers off and remains low after 6 months. We see a less bumpy curve in the higher-moment risk premia. The R^2s of $M3RP^{\perp}$ and $M4RP^{\perp}$ are of a similar magnitude. Both of them reach their highest at 6- to 10-month horizons and remain at moderate levels until 24 months. In terms of R^2s, PVRP outperforms the higher-moment risk premia at horizons shorter than 6 months and underperforms them thereafter.

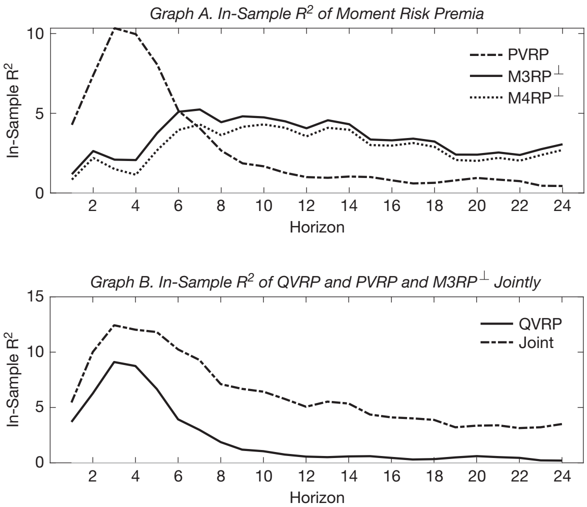
Graph B of Figure 3 illustrates the improvement in prediction power across different horizons when we combine the predictability of moment risk premia. We observe that the R^2s of the joint regression stay above those of QVRP across all horizons. The improvement is more pronounced over longer horizons. The evidence illustrates that the higher moment risk premia contain complementary predictive power to PVRP. As a result, separating the moment risk premia in QVRP and including them in a joint regression will effectively combine the short-term predictability of PVRP and the medium-term predictability of the higher-moment risk premia.

Note that we use the lagged realized moments as proxies for the physical moments in the next month in this section. The advantage of this specification is

FIGURE 3

In-Sample R^2 of Predictive Regressions

Graph A of Figure 3 plots the in-sample R^2 (in percentage) of the predictive regressions for the S&P 500 return afforded by moment risk premia in the univariate regressions, as a function of forecasting horizon (in months). We consider the pure variance risk premium (PVRP), the residual of the third-moment risk premium after regressing on PVRP (M3RP$^{\perp}$), and the residual of the fourth-moment risk premium after regressing on PVRP (M4RP$^{\perp}$). Graph B plots the in-sample R^2 (in percentage) of the predictive regressions for the market equity return afforded by the quasi-variance risk premium (QVRP) in the univariate regression and by PVRP and M3RP$^{\perp}$ in the joint regression, as a function of forecasting horizon (in months).



that both the risk-neutral moments and the lagged realized moments are available ex ante without specifying any forecasting model. However, by using the lagged realized moments, we implicitly assume that the realized moments are random walks. In the Supplementary Material, we discuss two additional robustness checks, in which we use predicted realized moments and intraday moments to construct moment risk premia. The moment risk premia are then used to predict aggregate stock returns.

It is worth noting that the high-frequency second moment and the high-frequency higher moments have different properties. Under reasonable assumptions, utilizing intraday return data provides a more consistent and efficient estimator for the return variance than using daily returns, but this is generally not the case for realized higher moments. As shown by Neuberger (2012), the skewness estimates of long-horizon log returns can be very different from those of the high-frequency log returns because of the leverage effect. For simple returns, the skewness estimates of long-horizon returns will be different from those of short-horizon returns because of compounding, even in the absence of the leverage effect (see Bessembinder (2018)). In the Supplementary Material, we also derive the sources of higher moments of long-horizon log returns in an illustrative example. As shown in the Supplementary Material, our results remain qualitatively similar when using moment risk premia constructed by intraday or predicted moments.

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B. Predicting the Market Returns with Weighted Least Squares

Time-varying market return volatility might create heteroscedasticity in the time series of the error term in the return-predictability regressions. Indeed, Johnson (2019) finds that the return predictability afforded by the conventional variance risk premium is not robust and is driven by several extreme observations with high variance. To deal with potential heteroscedasticity, we consider the weighted least squares (WLS) in addition to OLS in this section.

We estimate the regression coefficients in equation (12) using WLS in 2 steps. In the first step, we estimate $\widehat{\sigma}^2_{t,t+h|t}$, the conditional variance of the market return from t to $t+h$. Following Johnson (2019), we estimate $\widehat{\sigma}_{t,t+h|t}$ using realized variance in the past month and in the past year:

$$\widehat{\sigma}^2_{t,t+h|t} = \widehat{a} + \widehat{b}\sigma^2_{t-1,t} + \widehat{c}\sigma^2_{t-11,t},$$

where $\sigma^2_{t-1,t}$ is the sum of squared daily market returns in the past month, and $\sigma^2_{t-11,t}$ is the sum of squared daily market returns in the past year. $\hat{a}$, $\widehat{b}$, and $\widehat{c}$ are the estimated coefficients in a regression of $\sigma^2_{t,t+h}$ on a constant, $\sigma^2_{t-1,t}$, and $\sigma^2_{t-11,t}$.

In the second step, we estimate the predictive regression for predictor X_t using the following regression:

$$R_{t,t+h}/\widehat{\sigma}_{t,t+h|t} = \alpha_h/\widehat{\sigma}_{t,t+h|t} + \beta'_h X_t/\widehat{\sigma}_{t,t+h|t} + \varepsilon_{t,t+h}. \tag{13}$$

Table 3 reports the WLS predictive regression results. We confirm with Johnson (2019) that the t-statistics of WLS estimators are smaller in absolute value across different horizons. Nevertheless, the predictive coefficients, significance, and R^2s are qualitatively similar to those reported in Table 2.

C. Control for Stock Return Predictors in Welch and Goyal

To relate our findings to the voluminous literature on market return predictability, we consider a set of predictors documented in the previous literature as control variables. Specifically, we consider 11 variables used by Welch and Goyal (2008): dividend–price ratio (DP), dividend yield (DY), log earnings–price ratio (EP), book-to-market ratio (BM), interest rate on a 3-month Treasury bill (TBL), difference between Moody's BAA- and AAA-rated corporate bond yields (DFY), long-term government bond yield (LTY), net equity expansion (NTIS), inflation calculated from the Consumer Price Index (CPI) for all urban consumers (INFL), long-term government bond return (LTR), and the difference between the long-term corporate bond return and the long-term government bond return (DFR).

Because the higher-moment risk premia, M3RP and M4RP, are very similar in terms of predictability, as shown in the baseline results of Table 2, we only report results for the joint regressions of PVRP and M3RP in this section to save space. We report the results of return regressions on PVRP and M3RP for the 1-month (Panel A) and 12-month horizons (Panel B) in Table 4 with each of

TABLE 3

Market Return Predictive Regressions at Different Horizons (WLS)

Table 3 reports estimated regression coefficients and R^2s of the predictability regressions using weighted least squares (WLS) for the 1- to 24-month excess return on the S&P 500 index. Heteroscedasticity- and autocorrelation-robust *t*-statistics are reported in parentheses. For each horizon, we report the predictive-regression results of the univariate regressions on the quasi-variance risk premium (QVRP), the pure variance risk premium (PVRP), the residual of the third-moment risk premium after regressing on PVRP ($M3RP^{\perp}$), the residual of the fourth-moment risk premium after regressing on PVRP ($M4RP^{\perp}$), the bivariate regression on PVRP and $M3RP^{\perp}$ jointly, and the bivariate regression for PVRP and $M4RP^{\perp}$ jointly. Returns are observed monthly, with the sample period ranging from Jan. 1990 to July 2019.

	1	2	3	4	5	6
Panel A. 1 Month						
QVRP	0.33 (3.19)					
PVRP		0.35 (3.13)			0.30 (2.83)	0.30 (2.83)
$M3RP^{\perp}$			−0.57 (−1.92)		−0.30 (−1.73)	
$M4RP^{\perp}$				0.78 (1.71)		0.40 (1.71)
R^2	4.01	4.66	1.16	0.51	5.75	5.45
Adj. R^2	3.73	4.38	0.87	0.22	5.47	4.90
Panel B. 3 Months						
QVRP	0.83 (4.31)					
PVRP		0.89 (3.90)			0.77 (2.52)	0.78 (2.65)
$M3RP^{\perp}$			−1.43 (−2.51)		−0.85 (−2.36)	
$M4RP^{\perp}$				1.90 (2.36)		1.05 (2.63)
R^2	9.50	10.72	1.43	0.48	12.43	11.92
Adj. R^2	9.24	10.46	1.14	0.19	12.17	11.40
Panel C. 6 Months						
QVRP	0.90 (4.72)					
PVRP		1.01 (4.30)			0.78 (2.37)	0.79 (2.31)
$M3RP^{\perp}$			−2.36 (−2.96)		−1.85 (−2.59)	
$M4RP^{\perp}$				3.16 (3.07)		2.43 (3.11)
R^2	3.96	5.21	4.85	3.63	9.85	8.93
Adj. R^2	3.68	4.93	4.57	3.35	9.59	8.39
Panel D. 9 Months						
QVRP	0.72 (2.65)					
PVRP		0.85 (2.95)			0.60 (2.18)	0.59 (1.89)
$M3RP^{\perp}$			−2.53 (−2.55)		−2.16 (−2.14)	
$M4RP^{\perp}$				3.56 (3.18)		3.07 (2.96)
R^2	1.13	1.86	4.74	4.13	6.42	5.97
Adj. R^2	0.83	1.56	4.45	3.85	6.14	5.41
Panel E. 12 Months						
QVRP	0.66 (1.92)					
PVRP		0.8 (2.29)			0.53 (1.82)	0.52 (1.60)

(continued on next page)

TABLE 3 (continued)

Market Return Predictive Regressions at Different Horizons (WLS)

	1	2	3	4	5	6
Panel E. 12 Months (continued)						
M3RP$^{\perp}$			−2.73		−2.43	
			(−2.38)		(−2.05)	
M4RP$^{\perp}$				3.84		3.43
				(3.03)		(2.85)
R^2	0.41	0.87	3.93	3.47	4.75	4.39
Adj. R^2	0.11	0.58	3.64	3.18	4.46	3.81
Panel F. 24 Months						
QVRP	0.69					
	(1.36)					
PVRP		0.91			0.56	0.56
		(1.61)			(1.11)	(1.00)
M3RP$^{\perp}$			−4.16		−3.90	
			(−1.80)		(−1.73)	
M4RP$^{\perp}$				5.64		5.28
				(2.28)		(2.28)
R^2	0.16	0.42	3.02	2.67	3.42	3.11
Adj. R^2	−0.15	0.11	2.71	2.36	3.12	2.50

the 11 predictors as a control variable in each column.[4] Table 4 shows that the coefficients on PVRP and M3RP are both statistically significant in all regressions. In Panel A, only DP has significant coefficients among the 11 control variables. The adjusted R^2s of the 1-month prediction range from 5% to 6.5%, similar to the baseline results.

In Panel B of Table 4, DP is the only significant predictor at the 12-month horizon. The R^2 of the regression with DP as the control variable increases from 5% in the baseline results to 16.5%. Despite insignificance coefficients, BM and NTIS also substantially increase the 12-month adjusted R^2s of the baseline results to 13% and 8%, respectively. This is consistent with Welch and Goyal (2008), who find that these predictors perform better at yearly horizons.

D. Control for Short-Term Predictors

The control predictors considered in Section IV.C are known to contain predictability over multiyear horizons. Because we focus on the short-horizon predictability of moment risk premia, we control for a set of established short–term predictors in this section. We consider short interest (SI) from Rapach et al. (2016) and the cross-sectional book-to-market factor (BM_{KP}) from Kelly and Pruitt (2013), which are shown to contain short-term predictability for market returns. In addition, because M3RP is closely related to jumps and skewness, we consider several jump- or skewness-related predictors: realized signed jumps (RSJ) from Guo, Wang, and Zhou (2019); value-weighted average skewness ($SKEW_{VW}$) and equal-weighted average skewness ($SKEW_{EW}$) from Jondeau et al. (2019); and left-jump probability

[4]The results for 3-, 6-, 9-, 24-month horizons as well as for the joint regression of PVRP and M4RP are qualitatively similar. The results are available from the authors.

TABLE 4

Predictive Regressions Controlling for Predictors in Welch and Goyal

Table 4 reports the regression results of the pure variance risk premium (PVRP), the third-moment risk premium (M3RP), and control variables at the 1-month and 12-month horizons in Panels A and B. In each column, we add one control variable to the regression of PVRP and M3RP; the control variable is specified in the column head of the table. The control variables are defined in Section IV.C. Variables are obtained from Amit Goyal's website (http://www.hec.unil.ch/agoyal/). The Newey–West t-statistics are reported in parentheses. We report R^2 and adjusted R^2 in the last two rows. The sample period is Jan. 1990–Dec. 2018.

	DP	DY	EP	BM	TBL	DFY	LTY	NTIS	INFL	LTR	DFR
Panel A. 1-Month Horizon											
Constant	0.07	−0.01	0.03	−0.02	0.00	0.00	0.00	0.00	0.00	−0.01	0.00
	(2.07)	(−1.64)	(1.00)	(−1.99)	(−0.65)	(0.27)	(0.26)	(−1.40)	(−0.86)	(−1.48)	(−1.42)
M3RP	−0.38	−0.41	−0.55	−0.41	−0.40	−0.56	−0.40	−0.44	−0.36	−0.41	−0.41
	(−2.51)	(−2.72)	(−3.64)	(−2.79)	(−2.61)	(−3.61)	(−2.65)	(−2.81)	(−2.36)	(−2.72)	(−2.71)
PVRP	0.44	0.43	0.46	0.43	0.42	0.43	0.42	0.42	0.44	0.45	0.44
	(3.89)	(3.75)	(4.16)	(3.77)	(3.60)	(3.51)	(3.62)	(3.60)	(3.50)	(3.17)	(3.52)
Control	0.02	0.00	0.01	0.04	−0.06	−0.69	−0.11	0.06	−0.72	0.17	−0.08
	(2.23)	(1.14)	(1.15)	(1.66)	(−0.67)	(−1.18)	(−1.06)	(0.53)	(−1.56)	(1.49)	(−0.68)
R^2	7.27	5.89	6.75	6.47	5.76	5.94	5.89	5.75	5.96	7.05	5.75
Adj. R^2	6.46	5.07	5.93	5.66	4.94	5.12	5.07	4.93	5.14	6.24	4.93
Panel B. 12-Month Horizon											
Constant	0.83	0.02	0.31	−0.13	0.06	0.03	0.06	0.02	0.05	0.03	0.03
	(2.27)	(0.35)	(1.12)	(−1.12)	(1.90)	(0.42)	(0.93)	(0.55)	(1.52)	(0.91)	(1.01)
M3RP	−2.54	−2.94	−3.95	−2.88	−2.68	−2.86	−2.88	−3.65	−2.50	−2.96	−2.98
	(−3.09)	(−3.36)	(−5.15)	(−3.42)	(−3.17)	(−2.86)	(−3.31)	(−3.11)	(−2.80)	(−3.25)	(−3.43)
PVRP	1.33	1.20	1.41	1.25	1.16	1.17	1.17	1.01	1.30	1.21	1.13
	(3.54)	(3.07)	(3.93)	(3.01)	(2.86)	(2.99)	(2.89)	(2.61)	(2.52)	(2.76)	(2.96)
Control	0.20	0.00	0.09	0.57	−0.81	0.51	−0.45	1.74	−6.21	0.28	0.34
	(2.18)	(0.44)	(1.03)	(1.62)	(−0.77)	(0.09)	(−0.39)	(1.10)	(−1.46)	(1.12)	(0.57)
R^2	17.27	5.43	8.87	14.07	6.38	5.11	5.37	9.74	6.56	5.35	5.21
Adj. R^2	16.53	4.58	8.05	13.30	5.54	4.26	4.51	8.93	5.71	4.50	4.36

(LJP), which is the probability of a 10% weekly down move from Andersen et al. (2015).[5]

Table 5 reports the correlation matrix of M3RP and the aforementioned predictors. Although M3RP is related to jumps and skewness, the correlations between M3RP and RSJ, SKEW_{VW}, and SKEW_{EW} are as small as −0.08. The largest absolute correlation (−0.61) is between M3RP and LJP because both are related to option-implied jumps.

Table 6 reports the predictive regression results with these control variables. Similar to Section IV.C, we add one control variable at a time and report the regression results in each column. We report the regression results for 1- (Panel A) and 12-month (Panel B) horizons. The table shows that the predictive coefficients on M3RP remain significantly negative after we include these control variables.

Among these control variables, SI, RSJ, and BM_{KP} have significant coefficients in both the 1- and 12-month horizons, implying that M3RP and these

[5]The book-to-market predictors are calculated with the data and codes from Seth Pruitt's website (https://sethpruitt.net/). Because these factors are data driven, we use different BM factors for different predictive horizons, as implemented by Kelly and Pruitt (2013). Specifically, for each predictive horizon, we first extract BM factors using the Kelly and Pruitt data that date back to 1930. Then we use the BM factors from 1990 onward in the controlled regressions. The LJP series is downloaded from https://tailindex.com/index.html. The number of observations varies in each regression, depending on the availability of the control variables.

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TABLE 5

Correlation Matrix of Short-Term Predictors

Table 5 reports the correlation matrix among the third-moment risk premium (M3RP) and other short-term predictors. We consider short interest (SI) from Rapach et al. (2016), realized signed jump (RSJ) from Guo et al. (2019), value-weighted average skewness ($SKEW_{VW}$) and equal-weighted average skewness ($SKEW_{EW}$) from Jondeau et al. (2019), and left-jump probability (LJP) from Andersen et al. (2015). BM_{KP}^{1m} and BM_{KP}^{12m} are the 1-month and 12-month cross-section book-to-market factors, extracted using the 3-pass-regression filter following Kelly and Pruitt (2013).

	M3RP	SI	RSJ	$SKEW_{VW}$	$SKEW_{EW}$	LJP	BM_{KP}^{1m}	BM_{KP}^{12m}
M3RP	1.00	−0.08	−0.07	−0.07	−0.10	−0.61	0.11	0.00
SI	−0.08	1.00	−0.07	−0.01	−0.04	0.04	−0.11	0.09
RSJ	−0.07	−0.07	1.00	−0.03	−0.05	0.09	0.02	0.01
$SKEW_{VW}$	−0.07	−0.01	−0.03	1.00	0.80	0.02	−0.10	−0.09
$SKEW_{EW}$	−0.10	−0.04	−0.05	0.80	1.00	0.09	−0.27	−0.31
LJP	−0.61	0.04	0.09	0.02	0.09	1.00	−0.01	−0.04
BM_{KP}^{1m}	0.11	−0.11	0.02	−0.10	−0.27	−0.01	1.00	0.69
BM_{KP}^{12m}	0.00	0.09	0.01	−0.09	−0.31	−0.04	0.69	1.00

TABLE 6

Predictive Regressions with Short-Term Control Variables

Table 6 reports the regression results of the third-moment risk premium (M3RP), pure variance risk premium (PVRP), and control variables at 1-month and 12-month horizons in Panels A and B. In each column of the table, we add one control variable to the regression of M3RP and PVRP; the control variable is specified in the first row of the table. The Newey–West *t*-statistics are reported in parentheses. We report R^2 and adjusted R^2 in the last two rows in each panel.

	SI	RSJ	$SKEW_{VW}$	$SKEW_{EW}$	LJP	BM_{KP}
Panel A. 1-Month Horizon						
Constant	0.00	0.00	0.00	0.00	−0.01	0.02
	(−1.56)	(−1.12)	(−0.83)	(−0.52)	(−1.27)	(2.07)
M3RP	−0.43	−0.35	−0.44	−0.44	−0.45	−0.31
	(−2.67)	(−2.29)	(−2.84)	(−2.94)	(−2.70)	(−2.03)
PVRP	0.42	0.38	0.43	0.44	0.44	0.37
	(3.64)	(3.54)	(3.14)	(3.44)	(3.46)	(2.88)
Control	−0.02	0.39	−0.03	−0.03	0.00	0.02
	(−2.21)	(3.14)	(−0.40)	(−0.29)	(0.17)	(2.56)
R^2	7.83	9.81	6.55	6.50	7.34	5.16
Adj. R^2	6.89	8.93	5.67	5.62	6.34	4.01
Panel B. 12-Month Horizon						
Constant	0.03	0.03	0.03	0.06	0.03	0.65
	(0.90)	(0.80)	(0.85)	(1.17)	(0.81)	(5.22)
M3RP	−3.36	−2.90	−3.11	−3.15	−3.82	−3.04
	(−3.83)	(−3.15)	(−3.43)	(−3.48)	(−2.52)	(−3.00)
PVRP	1.02	1.10	1.15	1.09	1.32	1.41
	(2.66)	(2.81)	(2.65)	(2.30)	(2.90)	(3.09)
Control	−0.28	0.79	−0.17	−0.58	−0.02	0.81
	(−1.96)	(2.77)	(−0.61)	(−0.81)	(−0.35)	(4.95)
R^2	20.40	6.50	5.87	6.55	9.82	26.46
Adj. R^2	19.57	5.55	4.95	5.64	8.80	25.53

predictors contain orthogonal information for future market returns. The highest R^2 for both horizons is achieved in the joint regression of M3RP, PVRP, and BM_{KP}. The predictive coefficients on average skewness and LJP are not significant in the joint regression with PVRP and M3RP. Therefore, although the economic intuition of M3RP may partially overlap with the existing jump- or skewness-related variables, the coefficient of M3RP remains significant after controlling for these variables.

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V. Out-of-Sample Performance

Although many variables can significantly predict stock market returns in sample, most of them perform poorly in the OOS tests. Several articles (e.g., Drechsler (2013), Kilic and Shaliastovich (2019), and Buss et al. (2019)) have shown that the predictability of the traditional variance premium survives OOS tests. In this section, we investigate the OOS predictability of moment risk premia. In Section V.A, we report the OOS R^2s of the baseline regressions as well as various regressions in Section IV. We conduct asset-allocation analysis in Section V.B and show that the predictability of moment risk premia can be exploited by investors to improve portfolio performance.

A. Out-of-Sample R^2

For each univariate predictive regression, we calculate the return forecast at time t, using only the data available up to time t:

$$\widehat{R}_{t,t+h} = \widehat{\alpha}_{t,h} + \widehat{\beta}_{t,h} X_t, \quad t \geq T_0,$$

where $\widehat{\alpha}_{t,h}$ and $\widehat{\beta}_{t,h}$ are OLS estimates from the regression in equation (12). We use observations in the first half of the sample as the initial sample and construct the first return forecast. Then we construct the remaining return forecasts using an expanding window until the end of the sample.

As pointed out by Rapach, Strauss, and Zhou (2010), combining forecasts from individual predictors can yield less volatile and more reliable forecasts. It is particularly useful in our case to reduce noisy signals from higher-moment risk premia at short horizons and those from PVRP at longer horizons. We construct our forecast combination of PVRP and M3RP$^{\perp}$ (M4RP$^{\perp}$) as

$$\widehat{R}_{t,t+h}^{\mathrm{PVRP+M3RP}^{\perp}} = w_{h,t}^{\mathrm{PVRP}} \widehat{R}_{t,t+h}^{\mathrm{PVRP}} + w_{h,t}^{\mathrm{M3RP}^{\perp}} \widehat{R}_{t,t+h}^{\mathrm{M3RP}^{\perp}},$$

where $w_{h,t}^{x}$ is the ex ante combining weights on predictor x formed at time t for forecast horizon h,

$$w_{h,t}^{x} = \frac{\left(\mathrm{CSE}_{h,t}^{x}\right)^{-1}}{\left(\mathrm{CSE}_{h,t}^{\mathrm{PVRP}}\right)^{-1} + \left(\mathrm{CSE}_{h,t}^{\mathrm{M3RP}^{\perp}}\right)^{-1}}, \quad t \geq T_0 + 1.$$

$\mathrm{CSE}_{h,t}^{x}$ is the cumulative squared forecast error of the univariate predictive regression with predictor x,

$$\text{(14)} \qquad \mathrm{CSE}_{h,t}^{x} = \sum_{l=T_0}^{t} \left(R_{l,l+h} - \widehat{R}_{l,l+h}^{x}\right)^2, \; x = \mathrm{PVRP}, \mathrm{M3RP}^{\perp}.$$

At time T_0 when the first forecast is made, there is no history of prediction errors to differentiate the two models. Hence, we set the initial weights $w_{T_0,h}^{x}$ to 1/2. The forecast combination of PVRP and M4RP$^{\perp}$ follows a similar procedure.

TABLE 7

OOS R^2 of the Moment Risk Premia

Table 7 reports out-of-sample (OOS) R^2 of the predictability regressions using baseline regression (Panel A) and weighted least squares (WLS) regression (Panel B). For each horizon, we report the OOS R^2s of the univariate regressions for the quasi-variance risk premium (QVRP), the pure variance risk premium (PVRP), the residual of the third-moment risk premium after regressing on PVRP (M3RP$^\perp$), the residual of the fourth-moment risk premium after regressing on PVRP (M4RP$^\perp$), the forecast combination for PVRP and M3RP$^\perp$ (PVRP & M3RP$^\perp$), and forecast combination for PVRP and M4RP$^\perp$ (PVRP & M4RP$^\perp$). The sample period is Jan. 1990–July 2019.

	QVRP	PVRP	M3RP$^\perp$	M4RP$^\perp$	PVRP & M3RP$^\perp$	PVRP & M4RP$^\perp$
Panel A. Baseline Regression						
1 month	2.83	4.24	−5.16	−8.95	1.97	0.84
3 months	14.53	16.32	−14.19	−19.21	10.95	9.76
6 months	1.97	5.29	5.88	1.53	10.89	9.65
9 months	−2.36	0.74	7.07	6.02	6.92	7.12
12 months	−7.86	−3.90	6.06	5.22	4.47	4.69
24 months	−0.48	1.16	−0.20	1.69	1.03	2.05
Panel B. WLS Regression						
1 month	5.81	6.91	−1.47	−4.31	4.43	3.47
3 months	16.32	17.69	−7.03	−12.10	12.71	11.40
6 months	5.56	8.10	8.71	5.56	11.77	11.01
9 months	−1.16	2.39	10.04	8.52	9.54	9.63
12 months	−5.06	−1.09	9.24	7.90	7.41	7.45
24 months	1.32	2.59	0.29	2.30	1.89	2.91

Following Welch and Goyal (2008), we define the OOS R^2 for horizon h and prediction x as

$$\left(\text{OOS } R^2\right)_h^x = 1 - \frac{\text{CSE}_{h,T}^x}{\text{CSE}_{h,T}^{\text{bm}}},$$

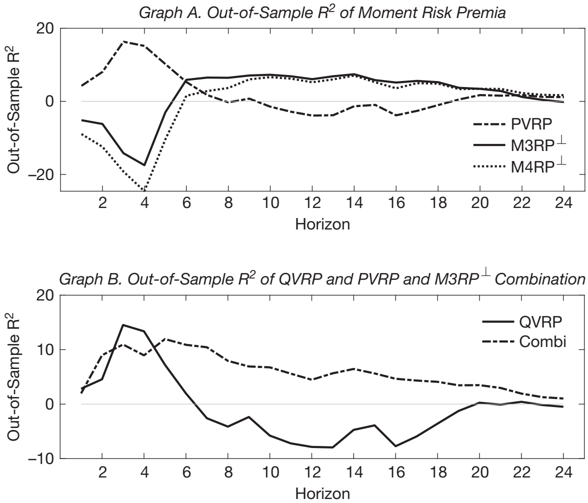
where $\text{CSE}_{h,T}^{\text{bm}}$ is the cumulative squared forecast error of a benchmark prediction, which uses the average excess return from the beginning of the sample through month t as the return forecast for the next period. The OOS R^2 measures the forecast accuracy relative to the historical average return. A positive OOS R^2 implies that the predictor outperforms the naive forecast using the historical mean, and a negative OOS R^2 implies underperformance.

The results of OOS forecasts are reported in Table 7, including univariate regressions using QVRP, PVRP, M3RP$^\perp$, and M4RP$^\perp$, respectively, and forecast combinations using PVRP and M3RP$^\perp$, and PVRP and M4RP$^\perp$. In the baseline regression (Panel A), QVRP and PVRP provide positive OOS R^2s at horizons of up to 6 months in the univariate regressions, with the latter slightly higher. The higher-moment risk premia, M3RP$^\perp$ and M4RP$^\perp$, give positive OOS R^2s from 6 to 24 months. The OOS predictive performance of higher-moment risk premia reaches a peak at the 9-month horizon, with an OOS R^2 of 7.07%. The forecast combinations of PVRP and M3RP$^\perp$ (M4RP$^\perp$) deliver positive OOS R^2s at all horizons, with a maximum of over 10% at the 3-month horizon. In most cases, the OOS R^2s forecast combinations fall between those of the two univariate regressions, with the exception of the 24-month forecasts. Overall, in terms of OOS performance, QVRP and PVRP perform well up to the 6-month horizon, whereas higher-moment risk premia perform well in longer horizons. Forecast combination incorporates the advantages of the two and provides positive OOS R^2s across all horizons.

FIGURE 4

Out-of-Sample R^2 of Predictive Regressions

Graph A of Figure 4 plots the out-of-sample (OOS) R^2 (in percentage) of the predictive regressions for the S&P 500 return afforded by moment risk premia in the univariate regressions, as a function of forecasting horizon (in months). We consider the pure variance risk premium (PVRP), the residual of the third-moment risk premium after regressing on PVRP (M3RP$^{\perp}$), and the residual of the fourth-moment risk premium after regressing on PVRP (M4RP$^{\perp}$). Graph B plots the OOS R^2 (in percentage) of the quasi-variance risk premium (QVRP) in the univariate regression and the forecast combination of PVRP and M3RP$^{\perp}$.



Panel B of Table 7 reports the OOS R^2s of the WLS regressions in Section IV.B. For every t, we reestimate $\widehat{\sigma}^2_{t,t+h}$ using information only up to time t. Then we run WLS regressions of returns from month $h+1$ to month t scaled by $\widehat{\sigma}^2_{t,t+h|t}$ on candidate predictors from the beginning of the sample to month $t-h$ scaled by $\widehat{\sigma}^2_{t,t+h|t}$ to obtain WLS coefficients. The return forecasts are constructed the same way as in an OLS regression, except that the predictive coefficients are WLS estimators. Compared with Panel A, we find that the OOS R^2 for every prediction and every horizon increases when applying WLS. This confirms the finding of Johnson (2019) that predictors perform better OOS using the WLS estimator.

Figure 4 compares the OOS R^2s of predictions over different horizons of the baseline results. Similar to Figure 3, we present the OOS R^2s of moment risk premia in Graph A and the OOS R^2s of QVRP and the forecast combination of PVRP and M3RP$^{\perp}$ in Graph B. Graph A shows that the patterns of the OOS R^2s of moment risk premia are similar to those of the in-sample ones. The OOS R^2 of PVRP is the highest at the 3-month horizon and drops to negative values as the forecasting horizon increases. M3RP$^{\perp}$ and M4RP$^{\perp}$, to the contrary, have negative OOS R^2s at the short end and positive ones at medium horizons. Graph B shows that the forecast combination of PVRP and M3RP$^{\perp}$ substantially improves OOS R^2s at medium horizons. Comparing with PVRP in Graph A, the positive OOS R^2s of the forecast combination at 6 months and beyond mostly come from the higher-moment risk premia.

B. Asset Allocation

In this section, we evaluate the economic gain of moment risk premia from the asset-allocation perspective. Similar to Campbell and Thompson (2007) and Rapach et al. (2010), (2016), we consider a mean-variance investor who allocates her wealth between a stock and a risk-free asset. At the end of month t, she invests w_t of her wealth in the market portfolio and the rest in risk-free assets and holds the portfolio for h months. The optimal weight of the stock is determined by $\mathrm{w}_t = (\widehat{\mathrm{R}}_{t+h}) / (\gamma \widehat{\sigma}^2_{t+h})$, where γ is the investor's relative risk aversion. $\widehat{\mathrm{R}}_{t+h}$ and $\widehat{\sigma}^2_{t+h}$ are the forecast of excess return and return variance h months ahead. VIX^2 is used as the forecast of return variance because it reflects investors' expectations of the return variation in the future. We calculate the certainty equivalent return (CER) for this investor: $\mathrm{CER} = \mathrm{R_p} - 0.5\gamma\sigma_p^2$, where R_p and σ_p^2 are the mean and variance of the portfolio return over the forecasting evaluation period.

We consider the scenario that the portfolio weights are larger than 0 and smaller than 1 (i.e., no short sales or leverage).[6] We annualize the CER so that it can be interpreted as the annual portfolio-management fee that the investor would be willing to pay to have access to the predictive-regression forecast.

The results of the OOS CER are reported in Table 8. We also compute the CER for the buy-and-hold strategy as a benchmark. Similar to the calculation of the OOS

TABLE 8

Out-of-Sample CER Gains

Table 8 reports the annualized certainty equivalent return (CER) in percentage for a mean-variance investor who allocates between S&P 500 index and risk-free assets using a predictive regression based on the predictive variable in the first column. We report results for a relative risk-aversion coefficient γ of 3, 5, and 7. The portfolio weights are constrained to be from 0 to 1. "Buy and hold" corresponds to the investor passively holding the market portfolio. We consider horizons from 1 month to 24 months. We use nonoverlapping returns so that the forecast horizon and rebalancing frequency coincide.

	1 Month	3 Months	6 Months	9 Months	12 Months	24 Months
Panel A. γ = 3						
QVRP	4.06	5.87	6.50	5.96	5.17	4.33
PVRP	4.25	5.90	6.37	5.97	5.24	4.34
$\mathrm{M3RP}^{\perp}$	0.94	5.86	5.89	6.00	5.72	4.27
$\mathrm{M4RP}^{\perp}$	0.68	5.89	6.16	6.04	5.84	5.31
PVRP and $\mathrm{M3RP}^{\perp}$	3.20	6.60	7.05	6.05	5.42	4.01
PVRP and $\mathrm{M4RP}^{\perp}$	3.22	6.54	7.03	6.13	5.61	4.47
Buy and hold	1.72	2.97	3.48	3.04	3.59	2.45
Panel B. γ = 5						
QVRP	2.43	5.17	4.81	4.13	3.46	2.77
PVRP	2.52	5.14	4.76	4.17	3.48	2.79
$\mathrm{M3RP}^{\perp}$	0.57	4.00	4.49	4.33	4.33	2.81
$\mathrm{M4RP}^{\perp}$	0.32	4.01	4.43	4.38	4.28	3.47
PVRP and $\mathrm{M3RP}^{\perp}$	1.84	5.34	5.20	4.28	3.70	2.62
PVRP and $\mathrm{M4RP}^{\perp}$	1.80	5.32	5.10	4.30	3.77	2.91
Buy and hold	−0.33	1.35	1.58	1.07	1.51	−0.38
Panel C. γ = 7						
QVRP	1.71	4.36	3.70	3.00	2.48	1.98
PVRP	1.86	4.31	3.74	3.04	2.49	1.99
$\mathrm{M3RP}^{\perp}$	0.40	2.93	3.51	3.13	3.18	2.01
$\mathrm{M4RP}^{\perp}$	0.23	2.72	3.40	3.16	3.19	2.48
PVRP and $\mathrm{M3RP}^{\perp}$	1.31	4.28	4.02	3.10	2.66	1.87
PVRP and $\mathrm{M4RP}^{\perp}$	1.28	4.27	3.92	3.12	2.70	2.08
Buy and hold	−2.37	−0.28	−0.31	−0.90	−0.57	−3.20

[6]The case that allows short sales ($w_t \in [-1,1]$) gives similar results.

R^2, we employ an expanding window to estimate the predictive-regression parameters. The first half of the sample is used to estimate the first set of regression parameters. In the table, we report the CER of the investment strategy based on QVRP, PVRP, $M3RP^{\perp}$, and $M4RP^{\perp}$ in the univariate predictive regression and forecast combination for PVRP and $M3RP^{\perp}$ and PVRP and $M4RP^{\perp}$.

We consider three levels of the risk-aversion parameter: $\gamma = 3,5,7$. We observe that in most cases, PVRP outperforms QVRP in terms of higher CERs, suggesting that a cleaner PVRP has more economic value for a risk-averse investor than QVRP. QVRP and PVRP perform well up to the 6-month horizon, whereas $M3RP^{\perp}$ and $M4RP^{\perp}$ perform well in longer horizons. When $\gamma = 3$, the forecast combinations yield higher CERs than QVRP from the 3-month to 12-month horizons. All predictors and forecast combinations provide higher CERs than the buy-and-hold strategy. The results are similar for $\gamma = 5$ and $\gamma = 7$.

Overall, the results in this section suggest that different moment risk premia show advantages in terms of CERs across different horizons. Combining predictability in different moment risk premia has substantial economic value for a risk-averse investor.

VI. Conclusion

This article investigates how to use option-implied information to improve market return predictability over short to medium horizons. The conventional variance risk premium has been shown to be a strong predictor for market returns in the recent literature. Because the conventional variance risk premium contains higher moment premia besides the second-moment risk premium, we exploit the predictive power of each moment risk premium separately and jointly.

Using the S&P 500 index and options data, we run predictive regressions of the 1- to 24-month excess returns of the market equity index on moment risk premia. We find that i) PVRP is a better predictor than QVRP, which is contaminated by higher-moment risk premia; ii) PVRP contains short-term predictive power for market returns with statistically significant positive coefficients, whereas M3RP (M4RP) contains medium-term predictive power for market returns with statistically significant negative (positive) coefficients; and iii) when M3RP and M4RP are separated from QVRP, PVRP and M3RP (M4RP) jointly deliver higher in-sample and OOS R^2s than QVRP, across all horizons from 1 to 24 months. The predictability afforded by M3RP (M4RP) survives a series of robustness checks.

Supplementary Material

To view supplementary material for this article, please visit http://dx.doi.org/10.1017/S002210902000085X.

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