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A re-examination of the predictability of stock returns and cash flows via the decomposition of VIX

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ABSTRACT

This paper investigates return and cash flow predictability via the decomposition of VIX. The squared VIX index is decomposed into expected return variations (ERV) and variance risk premium (VRP). Without imposing a strong assumption on the dynamics of the return variations, I examine the predictability via the generalized method of moments (GMM) approach with appropriately chosen instruments. Empirical analysis shows the short-term return predictability of VRP and the short- and long-term cash flow predictability of ERV.

1. Introduction

Campbell and Shiller's (1988) well-known present value decomposition of the dividend–price ratio is:

$$dp_t = \text{constant } + E_t\left[\sum_{j=1}^{\infty}\rho^{j-1}\left(r_{t+j}+\Delta d_{t+j}\right)\right], \tag{1}$$

where dp_t is the log dividend–price ratio, ρ is a constant of approximation (e.g., $\rho = 0.96^{1/12}$ for monthly frequency), r_t is stock returns, and Δd_t is dividend (cash flow) growth rate. Eq. (1) implies that if the current dp_t changes at all, it must predict either future r_t or future Δd_t. Past studies have shown that current dp_t tends to predict only future r_t, not future Δd_t (e.g., Cochrane, 2006, 2011).

Some studies, such as Cochrane (2011), Bollerslev et al. (2015), Maio and Santa-Clara (2015), and Chava et al. (2015), extend predictability regression with information set beyond the dividend–price ratio. This paper investigates to what extent the decomposition of VIX (source: CBOE) helps forecast returns or cash flow growth.

VIX (source: CBOE) represents the option-implied volatility of the S&P 500 index with a one-month horizon, equivalent to expected future S&P 500 return variations under the risk-neutral probability. Squared VIX can be decomposed into expected return variation (henceforth, ERV) and variance risk premium (henceforth, VRP). Mathematically, $ERV_t \equiv E_t\left[RV_{t+1}\right]$ and $VRP_t \equiv VIX_t^2 - E_t\left[RV_{t+1}\right]$, where RV_t is the sum of daily squared returns in month t. Bekaert and Hoerova (2014) argue that ERV and VRP indicate economic uncertainty and risk aversion, respectively.

Past studies have shown that VRP exhibits short-term return predictability (e.g., Bollerslev et al., 2009; Drechsler and Yaron, 2011; Bollerslev et al., 2014; Qiao et al., 2018). On the other hand, Bollerslev et al. (2015) found that an increase in ERV is associated with higher future cash flows using a structural GARCH model.

This paper contributes to the literature by analyzing the return and cash flow predictability of the VIX components in a model-insensitive way. How to decompose VIX depends on how ERV is estimated, and controversy remains. To circumvent this problem, I investigate the predictability of the VIX components via the generalized method of moments (GMM) approach with appropriately selected instruments. Empirical analysis confirms the short-term return predictability of VRP and finds both short- and long-term cash flow predictability of ERV.

2. Data and methodology

I employ monthly S&P 500 index returns for the aggregate market portfolio, and S&P 500 dividend payments for the aggregate cash flows. Monthly dividend payments are available from

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Table 1
Return and cash flow predictability regressions.

Regressors	Monthly Forecasts			Quarterly Forecasts			Annual Forecasts		
(a) Stock returns									
dp	0.186 (1.664)	0.187 (1.723)	0.180 (1.812)	**0.191** **(2.018)**	**0.191** **(2.058)**	**0.185** **(2.394)**	**0.218** **(2.570)**	**0.217** **(2.535)**	**0.217** **(2.543)**
VIX^2		−0.169 (−0.128)			0.099 (0.081)			0.222 (0.693)	
ERV			−0.837 (−0.843)			−0.421 (−0.707)			0.122 (0.459)
VRP			**8.009** **(3.489)**			**6.582** **(3.834)**			**1.554** **(2.371)**
Constant	1.284 (1.780)	1.296 (1.911)	1.170 (1.875)	**1.316** **(2.155)**	**1.309** **(2.258)**	**1.211** **(2.452)**	**1.491** **(2.794)**	**1.475** **(2.693)**	**1.459** **(2.673)**
P-values for the Wald tests			**0.001**			**0.001**			**0.012**
(b) Dividend growth									
dp	−0.004 (−0.496)	−0.008 (−1.397)	−0.008 (−1.448)	−0.002 (−0.173)	−0.014 (−1.572)	−0.014 (−1.664)	−0.011 (−0.526)	−0.016 (−0.675)	−0.017 (−0.722)
VIX^2		**−0.132** **(−2.565)**			**−0.280** **(−4.112)**			**−0.532** **(−3.014)**	
ERV			**−0.138** **(−2.190)**			**−0.287** **(−4.010)**			**−0.554** **(−5.069)**
VRP			0.011 (0.082)			−0.133 (−0.846)			0.008 (0.032)
Constant	−0.025 (−0.464)	−0.037 (−1.069)	−0.041 (−1.181)	−0.008 (−0.116)	−0.065 (−1.166)	−0.069 (−1.293)	−0.054 (−0.408)	−0.050 (−0.340)	−0.065 (−0.438)
P-values for the Wald tests			0.259			0.250			**0.004**

Note: Each predictive regression is estimated via the GMM as explained in Section 2. The numbers in parentheses are t-statistics. Bold entries indicate statistical significance at 5%. The p-values for the Wald tests correspond to the null hypothesis that the coefficients for ERV and VRP are the same.

Robert Shiller's webpage.[1] The sample period spans from January 1990 through December 2018.

The log dividend–price ratio in month t is defined as $dp_t = \ln\left(D_t^{12}/12/P_t\right)$ where $D_t^{12} \equiv D_{t-11} + \cdots + D_t$ is the simple sum of monthly dividends in the past 12 months. The monthly dividend growth rate Δd_t and the log returns r_t are $\Delta d_t = \ln\left(D_t^{12}/D_{t-1}^{12}\right)$ and $r_t = \ln\left(\left(P_t + D_t^{12}/12\right)/P_{t-1}\right)$, respectively. Since monthly dividends from the past 12 months are summed to remove seasonality, each observation shares data over 11 overlapping months.

Since VRP and ERV are not observable, I employ the methodology in Hamilton and Kim (2002).[2] The predictive regression for the h-month horizon is:

$$\begin{aligned} X_{t+h} &= \gamma_0 + \gamma_1 dp_t + \gamma_2 ERV_t + \gamma_3 VRP_t + \varepsilon_{t+h}. \qquad (2) \\ &= \gamma_0 + \gamma_1 dp_t + \gamma_2 E_t\left[RV_{t+1}\right] + \gamma_3\left(VIX_t^2 - E_t\left[RV_{t+1}\right]\right) + \varepsilon_{t+h}, \end{aligned}$$

where X_{t+h} is a predicted variable. Let ν_{t+1} denote error in forecasting RV_{t+1}:

$$\nu_{t+1} = RV_{t+1} - E_t\left[RV_{t+1}\right]. \qquad (3)$$

Then Eq. (3) can be written as

$$X_{t+h} = \gamma_0 + \gamma_1 dp_t + \gamma_2 RV_{t+1} + \gamma_3\left(VIX_t^2 - RV_{t+1}\right) + u_{t+h}. \qquad (4)$$

with $u_{t+h} = \varepsilon_{t+h} + (\gamma_3 - \gamma_2)\,\nu_{t+1}$. Under rational expectations, u_{t+h} should be uncorrelated with any variable known at time t. Thus, Eq. (4) can be estimated by the GMM using instruments dated t or earlier. Similar to Hamilton and Kim (2002), I use instruments such as $\widehat{ERV}_t^D$ $(\equiv RV_t)$, $\widehat{VRP}_t^D$ $(\equiv VIX_t^2 - RV_t)$, and a constant.[3] Following Bekaert and Hoerova (2014), the corresponding weighting function is constructed using the Bartlett-kernel with a lag length of $\max[3, 2 \times h]$. Notably, Bollerslev et al. (2014) use $\widehat{ERV}_t^D$ and $\widehat{VRP}_t^D$ as estimates for ERV_t and VRP_t, respectively, because $E_t\left[RV_{t+1}\right] = RV_t$ under their random walk assumption.

3. Empirical analysis

In Table 1, three specifications for regressors are considered: (1) dp_t alone; (2) both dp_t and VIX_t^2; and (3) dp_t, ERV_t and VRP_t. The third specification for each horizon is estimated using the instruments above. For cash flow predictability (Panel (b)), 12-month lags of dividend growth are included in Eq. (4) in order to control for serial correlation in dividend growth.[4]

Panel (a) in Table 1 shows that like existing studies, future returns are significantly predicted by VRP for all horizons, but not by ERV. Interestingly, Panel (b) shows that ERV strongly predicts future dividend growth with negative coefficients for all horizons, but that cash flow predictability of VRP is absent. Consistent with past studies, dp_t significantly predicts future returns for quarterly and annual horizons, but does not predict dividend growth for every horizon.

Fig. 1 illustrates the regression coefficients for dp_t, ERV_t and VRP_t along 1–24 monthly horizons (for the third specification above) with a 95% confidence interval. The short-term return predictability of VRP can be seen based on its coefficients decreasing with horizon. The cash flow predictability of ERV exhibits a hump-shaped pattern, with a maximum around the 12-month horizon.

Meanwhile, the last row in each panel in Table 1 reports the p-values of Wald tests corresponding to the null hypothesis that the coefficients for ERV and VRP are the same. Strong rejections

[1] http://www.econ.yale.edu/~shiller/data.htm.

[2] They analyze the output predictability of US yield spread by decomposing the spread into the expectation and the term premium components.

[3] The superscript D indicates computation from daily returns.

[4] To save space, these coefficients are not reported in Table 1. In fact, without these lags, the results are qualitatively similar.

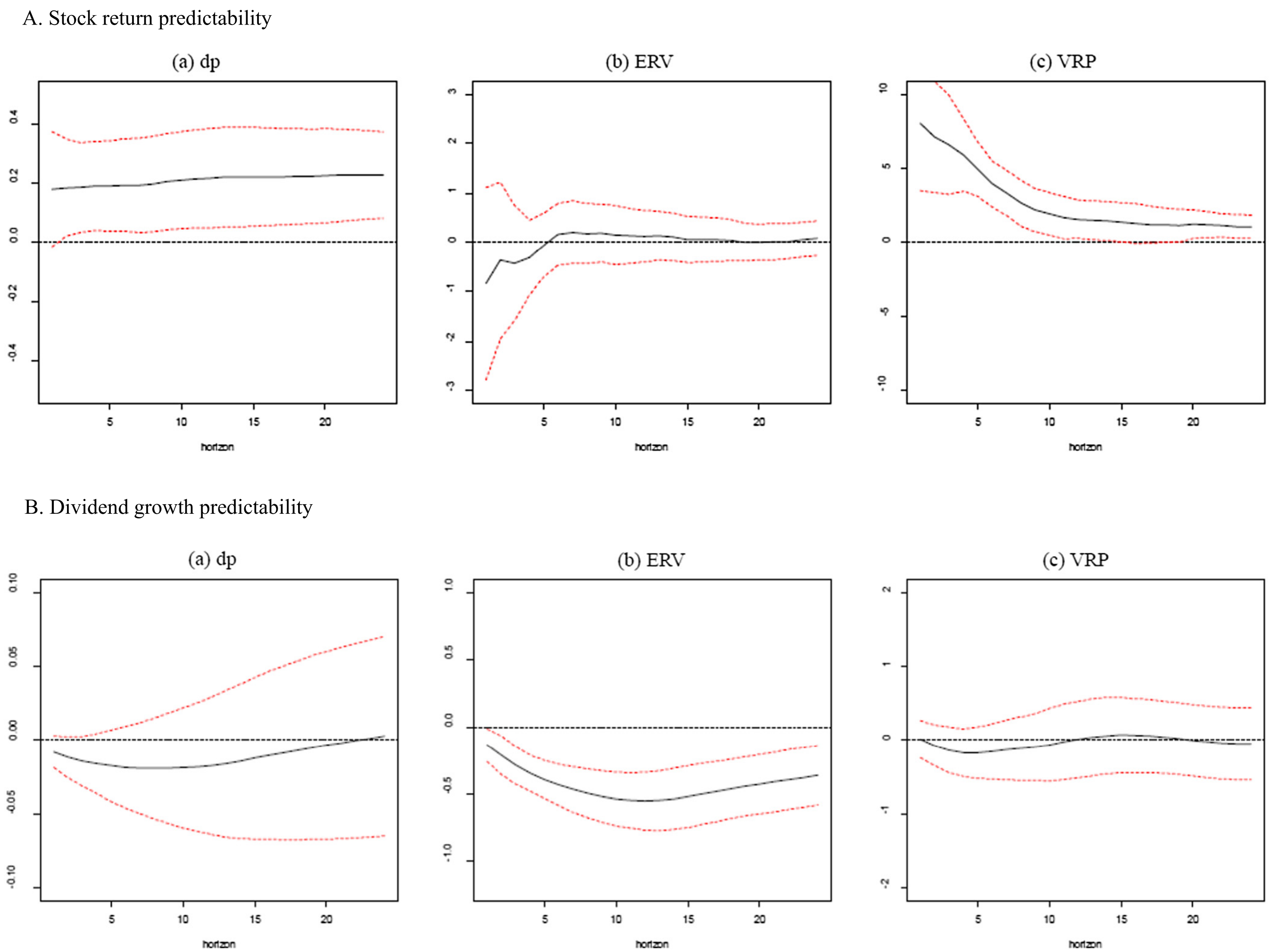

Fig. 1. Return and cash flow growth predictability via dp, ERV, and VRP. Each figure shows the regression coefficients for dp, ERV, and VRP across 1–24 monthly horizons with a 95% confidence interval.

against the null in Panel (a) indicate that the decomposition of VIX is effective for return predictability. However, with regard to cash flow predictability, the decomposition is not as effective because most variations in VIX are attributable to variations in ERV.

I now turn to the long-term return and cash flow predictability of the VIX components. Based on Cochrane (2011) and Chava et al. (2015), I employ the first-order annual vector autoregression (VAR) approach to handle the relatively short-term sample problem.

Based on the related literature, dp_t, ERV_t and VRP_t are set as three state variables in the following first-order VAR process. The annual horizon setting here substantially reduces the concern of serial correlation in dividend growth.

$$\begin{bmatrix} r_{t,t+12} \\ \Delta d_{t,t+12} \end{bmatrix} = B \times \begin{bmatrix} dp_t \\ ERV_t \\ VRP_t \end{bmatrix} + \begin{bmatrix} \varepsilon^{r}_{t+12} \\ \varepsilon^{\Delta d}_{t+12} \end{bmatrix}, \tag{5}$$

$$\begin{bmatrix} dp_{t+12} \\ ERV_{t+12} \\ VRP_{t+12} \end{bmatrix} = \Phi \times \begin{bmatrix} dp_t \\ ERV_t \\ VRP_t \end{bmatrix} + \begin{bmatrix} \varepsilon^{dp}_{t+12} \\ \varepsilon^{ERV}_{t+12} \\ \varepsilon^{VRP}_{t+12} \end{bmatrix} \tag{6}$$

where Φ and B are 2×3 and 3×3 coefficient matrices, respectively and $dp_t = \ln\left(D^{12}_t/P_t\right)$, $\Delta d_{t,t+12} = \ln\left(D^{12}_{t+12}/D^{12}_t\right)$, and $r_{t,t+12} = \ln\left[\left(P_{t+12} + D^{12}_{t+12}\right)/P_t\right]$.[5]

The model-implied long-horizon forecasts are:

$$\begin{bmatrix} r^{LR}_t \\ \Delta d^{LR}_t \end{bmatrix} \equiv \begin{bmatrix} \sum_{j=1}^{\infty} \rho^{j-1} r_{t+12(j-1),t+12j} \\ \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+12(j-1),t+12j} \end{bmatrix} = C \times \begin{bmatrix} dp_t \\ ERV_t \\ VRP_t \end{bmatrix}, \tag{7}$$

where $\rho = 0.96$ and $C \equiv B(I - \rho\Phi)^{-1}$.

The VAR coefficients are not without restrictions. Let $B_{(i,j)}$ ($i = 1, 2$ and $j = 1, 2, 3$) denote the corresponding element from matrix B. The return identity $r_{t+1} = \Delta d_{t+1} - \rho dp_{t+1} + dp_t$ imposes restrictions such as $B_{(1,1)} + \rho B_{(3,1)} - B_{(2,1)} = 1$, $B_{(1,2)} + \rho B_{(3,2)} - B_{(2,2)} = 0$, and $B_{(1,3)} + \rho B_{(3,3)} - B_{(2,3)} = 0$. These restrictions do not hold exactly since the return identity comes from Taylor approximation. Considering this, I estimate both restricted and unrestricted VAR models.[6] The estimation procedure is similar to that used earlier: GMM with the instruments introduced above. Since the long-run coefficients in Eq. (7) are functions of the GMM estimator, the delta method is used to obtain standard errors.

Table 2 shows the estimation result for the restricted VAR and the corresponding model-implied long-run coefficients. As above, VRP and ERV strongly predict annual return and cash flow

[5] These definitions are slightly different from those used previously.

[6] For the restricted model, no estimation is needed for the Δd_t equation in Eq. (5), because it can be derived from the restrictions.

Table 2
Annual VAR model and model-implied long-run coefficients.

Regressors	Dependent Variables for VAR					Model-implied Long-run Coefficients	
	r_{t+12}	Δd_{t+12}	dp_{t+12}	ERV_{t+12}	VRP_{t+12}	$\Sigma\rho^{j-1}r_{t+j}$	$\Sigma\rho^{j-1}\Delta d_{t+j}$
dp_t	**0.214**	−0.056	**0.761**	**−0.041**	0.004	**0.945**	−0.055
	(2.516)	(−1.184)	**(10.239)**	**(−4.307)**	(0.694)	**(4.177)**	(−0.244)
ERV_t	0.109	**−0.955**	**−1.108**	**0.118**	**0.133**	**−1.133**	**−1.133**
	(0.412)	**(−5.641)**	**(−3.550)**	**(3.050)**	**(5.620)**	**(−2.245)**	**(−2.245)**
VRP_t	**1.554**	−0.621	**−2.265**	0.200	**0.158**	−0.847	−0.847
	(2.381)	(−1.228)	**(−3.440)**	(1.815)	**(2.417)**	(−0.925)	(−0.925)

Note: The first-order annual VAR model is estimated via the GMM as explained in Section 3. The numbers in parentheses are t-statistics. Bold entries indicate statistical significance at 5%.

growth, respectively. As for the model-implied long-horizon forecasts, dp_t significantly predicts long-term stock returns, but does not predict long-term dividend growth. More importantly, the long-run dividend growth predictability of ERV is as strong as the short-run predictability, whereas the long-run return predictability coefficient of VRP is insignificant. The estimation results for unrestricted VAR (available upon request) are similar. Pohl et al. (2018) argue that the approximation error introduced by the return identity may be substantial when nonlinear transformation is involved. It seems unlikely for this kind of approximation error to be serious in my case.

In contrast to this paper, Bollerslev et al. (2015) show that an increase in ERV is associated with higher future dividend growth. However, when the same analysis is performed over their sample period (1990:01–2011:11), my results are not affected. It is possible that this contrast is due to the restrictions imposed by their structural GARCH model.

Moreover, as discussed in Guo and Whitelaw (2006), many studies have found a weak or negative relationship between ERV and future market index returns. Guo and Whitelaw (2006) argue that in the context of Merton's (1973) Intertemporal CAPM, the omission of hedge components may be responsible for this seemingly puzzling result. Within the context of their discussion, the insignificant ERV in predicting returns described herein implies that VRP alone is not sufficient to capture the role of hedge components.

4. Robustness check

To verify robustness, I conduct the same analysis for different sample periods.[7] For most samples, roughly the same results are obtained. Exceptions occur for samples without the Global Financial Crisis, where cash flow prediction coefficients for ERV are still negative, but insignificant. It has often been documented that cash flow predictability is insignificant for the postwar sample period due to firms engaging in dividend-smoothing practices (e.g., Chen, 2009; Chen et al., 2012; Zhu et al., 2018). Zhu et al. (2018) argue that after the Global Financial Crisis, the cash flow predictability of many macro variables becomes remarkable because managers' ability to smooth dividends is imperfect over the business cycle.

When conducting empirical analysis for Table 1, I also try to employ two different sets of instruments. First, I use the ERV and VRP measures computed using high-frequency data, taken from Zhou (2018).[8] Second, I estimate those measures via a volatility forecasting model using daily returns and VIX.[9] It turns out that the results are robust to the choice of instruments.[10]

5. Concluding remarks

This paper shows the short-term return predictability of VRP and the short- and long-term cash flow predictability of ERV. As argued by Bekaert and Hoerova (2014), the return predictability of VRP can potentially be explained in terms of the "habit" advocated by Campbell and Cochrane (1999). Their habit-induced counter-cyclical changes in risk aversion generate variations in risk premiums. On the other hand, one candidate theory for the cash flow predictability of ERV may be the long-run risk model (e.g., Bansal and Yaron, 2004). Economic uncertainty, which can be proxied by ERV, is a key variable in the long-run risk model. In a version of the model in Bollerslev et al. (2015), innovations in time-varying volatility and the long-run risk factor are correlated; thus, the long-run risk factor can have a persistent effect on dividend growth. This specification may drive the long-term cash flow predictability of ERV. It would be interesting to develop a version of the long-run risk model that leads to long-run cash flow predictability of economic uncertainty in future research.

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7 The sample periods considered are 1990:01–2005:01 (Bollerslev et al., 2009), 1990:01–2004:05 (Bollerslev et al., 2011), 1990:01–2011:11 (Bollerslev et al., 2015), 1990:01–2016:12 (Zhou, 2018), 1990:01–2010:10 (Bekaert and Hoerova, 2014), and 1996:01–2014:08 (Kilic and Shaliastovich, 2018).

8 He is providing updated VRP and ERV measures through his webpage (https://sites.google.com/site/haozhouspersonalhomepage/).

9 I thank the reviewer for this suggestion. This model is introduced in Eq. (15) in Bollerslev et al. (2015).

10 These results are available upon request.

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