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State-Space Model and Present Value Model: An Application to the Korean Stock Market*

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Abstract We have applied the state-space model to the Korean stock market under restrictions imposed by the present-value relation. Our main findings are (i) expected stock returns vary over time and have persistent and predictable component, (ii) expected dividend growth rates do not contain persistent and predictable component, (iii) expected stock returns play relatively more important role in explaining variations in the price-dividend ratio, (iv) shocks to expected stock returns are also more crucial in understanding unexpected stock return shocks, and (v) the state-space model does not appear to perform better than the predictive regression in terms of the ability in forecasting stock returns or dividend growth rates.

Keywords expected stock returns, expected dividend growth rates, price-dividend ratio, present-value model, state-space model

JEL Classification G12, C12, C32

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1. INTRODUCTION

According to the dividend discount model in the literature, a stock price is the total present value of future expected dividends. Hence, fluctuations of stock prices result from either fluctuations of expected discount rate or fluctuations of expected future dividends. Regarding this statement, one long-standing question in financial economics is which one, between expected discount rate and expected dividends, plays a more dominant role in explaining fluctuations in stock prices. In order to address this question, economists have proposed various ways to estimate expected stock returns[1] and/or expected dividend growth rates from observable data.[2] For example, Binsbergen and Koijen (2010) and Rytchkov (2008) recently applied the Kalman filtering approach to estimate the expected stock returns and the expected dividend growth rates, treating them as latent variables contained in the price-dividend ratio. This approach is attractive because it has shown how to extract expected stock returns and expected dividend growth rates from data, as well as how to conduct a variety of hypothesis tests explicitly. Employing this new approach, both studies report that changes in expected stock returns are relatively more important in understanding movements of the price-dividend ratio and that expected stock returns and expected dividend growth rates are not constant but vary over time. Also, expected stock returns and expected dividend growth rates are reported to contain persistent and predictable component.[3]

We apply this approach to the Korean stock market. There are reasons why this exercise for the Korean market could be interesting and important. First, previous studies such as Binsbergen and Koijen (2010) and Rytchkov (2008) focus on mainly the US stock market. However, studies like Hjalmarsson (2010), Engsted and Pedersen (2010), and Park (2010) show that stock return predictability differs greatly across countries. In other words, an almost stylized fact that the US stock returns are predictable by the price-dividend ratio is not observed for some other countries. Hence, the findings reported in Binsbergen and Koijen (2010) and Rytchkov (2008) might not hold in the Korean market which is an

[1] Discount rate and (expected) stock returns are interchangeable in this study.

[2] The issue of stock return predictability has been examined in numerous studies. Refer to chapter 20 of Cochrane (2001) for an excellent survey.

[3] Return predictability is an important issue for other financial assets as well as stocks. For example, Hong and Lee (2003) report that suitable nonlinear models can outperform the martingale model in predicting exchange rates. Hong and Li (2005) applied nonparametric model to the term structure and interest rates. The results in these studies imply that there is a predictable component in other assets.

emerging market.

Second but more importantly, Kim and Kim (2004) and Kim and Park (2009) showed that valuation ratios such as the dividend-price ratio and earnings-price ratio have no predictive power for future stock returns in Korea. These results might be interpreted as no stock return predictability in the Korean market, which imply that movements of the price-dividend ratio can be explained by changes in expected dividend growth rates only. However, the results in Kim and Kim (2004) and Kim and Park (2009) could reflect the finding in Lettau and Ludvigson (2005). Lettau and Ludvigson (2005) demonstrated that the dividend-price ratio in the US market contains information about both expected future stock returns and expected future dividend growth rate, but that expectations about both sides did offset each other so that the dividend-price ratio does not have clear predictive power for future stock returns. Since both interpretations (the dividend-price ratio has no information about future stock returns, or the dividend-price ratio contains information for future stock returns but that information cancels out information about future dividend growth rates) are possible for the Korean market based on previous studies, we need to examine what causes no stock return predictability by valuation ratios in Korea. For this purpose, we expect the state-space approach to be particularly useful because we do not need to rely on the predictive regression approach which is sensible only when the price-dividend ratio has predictive power. Unlike the predictive regression approach, the state-space approach allows us to extract expected stock returns and expected dividend growth rates from the price-dividend ratio under the restriction of the present-value model.

In order to address these questions, this paper is organized as follows. Section 2 presents the econometric model under the state-space approach. Section 3 presents empirical results which contain estimations, hypothesis tests, and variance decomposition. Section 3 also compares the state-space and the predictive regression approach in terms of the predictive ability for stock returns or dividend growth rates. Section 4 offers the concluding remarks.

2. THE ECONOMETRIC MODEL

Recently, Binsbergen and Koijen (2010) proposed a latent variables approach within a present-value model to estimate the expected returns and expected dividend growth rates of the aggregate stock market. We employ the Kalman filtering approach to estimate the expected stock returns and the expected dividend growth rates, treating them as latent variables contained in the price-dividend ratio. This new approach is attractive because it has shown how to extract expected stock returns and expected dividend growth rates from data, as well as how to conduct a variety of hypothesis tests (such as whether the expected stock returns and/or the expected dividend growth rates are constant or varying over time, etc.) explicitly. It also allows us to answer which component between the expected stock returns and the expected dividend growth rates is relatively more dominant in explaining movements of the price-dividend ratio.

Following the econometric model in Binsbergen and Koijen (2010), we assume that expected returns and expected dividend growth rates are latent variables with the following stationary autoregressive dynamics:

$$\mu_{t+1} = \delta_0 + \delta_1(\mu_t - \delta_0) + \varepsilon^{\mu}_{t+1} \tag{1}$$

$$g_{t+1} = \gamma_0 + \gamma_1(g_t - \gamma_0) + \varepsilon^{g}_{t+1} \tag{2}$$

where $\mu_t = E_t(r_{t+1})$ is the expected return, $g_t = E_t(\Delta d_{t+1})$ is the expected dividend growth, δ_0 is the mean of the expected return, and γ_0 is the mean of the expected dividend growth. Then, the stock return (r_{t+1}) and the dividend growth rate (Δd_{t+1}) can be written as:

$$r_{t+1} = \delta_0 + \tilde{\mu}_t + \varepsilon^{R}_{t+1} \tag{3}$$

$$\Delta d_{t+1} = \gamma_0 + \tilde{g}_t + \varepsilon^{D}_{t+1} \tag{4}$$

where $\tilde{\mu}_{t+1} = \mu_{t+1} - \delta_0$ and $\tilde{g}_{t+1} = g_{t+1} - \gamma_0$.

It is straightforward to show that the log-linearized present value model of Campbell and Shiller (1988) leads to the following relationship among the log price-dividend ratio (pd_t), expected return (μ_t) and expected dividend growth (g_t):

$$pd_{t+1} = \overline{pd} - B_1\tilde{\mu}_{t+1} + B_2\tilde{g}_{t+1} \tag{5}$$

where $\overline{pd} = -\ln(\exp(\delta_0 - \gamma_0) - 1)$ is the mean of the log price-dividend ratio; $B_1 = \frac{1}{1-\rho\delta_1}$, $B_2 = \frac{1}{1-\rho\gamma_1}$, and $\rho = \frac{\exp(pd)}{1+\exp(pd)}$. Note that by multiplying both sides of equation (5) by $(1-\delta_1 L)$, where L is the lag operator, we have:

$$pd_{t+1} = (1-\delta_1)\overline{pd} + B_2(\gamma_1 - \delta_1)g_t + \delta_1 pd_t - B_1\varepsilon^{\mu}_{t+1} + B_2\varepsilon^{g}_{t+1}. \tag{6}$$

In order to estimate the model that consists of equations (1)–(5), we construct a state-space model. We employ equations (4) and (6) to form a measurement equation. Equation (2) is used as a transition equation. Hence, a state-space model we estimate is given below:

Transition equation:

$$\begin{bmatrix} \widetilde{g}_t \\ \varepsilon^D_{t+1} \\ \varepsilon^g_{t+1} \\ \varepsilon^\mu_{t+1} \end{bmatrix} = \begin{bmatrix} \gamma_1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \widetilde{g}_{t-1} \\ \varepsilon^D_t \\ \varepsilon^g_t \\ \varepsilon^\mu_t \end{bmatrix} + \begin{bmatrix} 0 \\ \varepsilon^D_{t+1} \\ \varepsilon^g_{t+1} \\ \varepsilon^\mu_{t+1} \end{bmatrix} \tag{7}$$

$(X_{t+1} = F \cdot X_t + \varepsilon^X_{t+1},\ \varepsilon^X_{t+1} \sim i.i.d.\, N(0,Q))$, where $Q = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & \sigma^2_D & \sigma_{gD} & \sigma_{\mu D} \\ 0 & \sigma_{gD} & \sigma^2_g & \sigma_{\mu g} \\ 0 & \sigma_{\mu D} & \sigma_{\mu g} & \sigma^2_\mu \end{bmatrix}$.

Measurement equation:

$$\begin{bmatrix} \Delta d_{t+1} \\ pd_{t+1} \end{bmatrix} = \begin{bmatrix} \gamma_0 \\ (1-\delta_1)\overline{pd}_{t+1} \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & \delta_1 \end{bmatrix} \begin{bmatrix} \Delta d_t \\ pd_t \end{bmatrix}$$

$$+ \begin{bmatrix} 1 & 1 & 0 & 0 \\ B_2(\gamma_1 - \delta_1) & 0 & B_2 & -B_1 \end{bmatrix} \begin{bmatrix} \widetilde{g}_t \\ \varepsilon^D_{t+1} \\ \varepsilon^g_{t+1} \\ \varepsilon^\mu_{t+1} \end{bmatrix} \tag{8}$$

$(Y_{t+1} = M_0 + M_1 \cdot Y_t + M_2 \cdot X_{t+1})$

Finally, the variance-covariance matrix for innovations in (1), (2), and (4) can be written as

$$var\left(\begin{bmatrix} \varepsilon^D_{t+1} \\ \varepsilon^g_{t+1} \\ \varepsilon^\mu_{t+1} \end{bmatrix} \right) = \begin{bmatrix} \sigma^2_D & \sigma_{gD} & \sigma_{\mu D} \\ \sigma_{gD} & \sigma^2_g & \sigma_{\mu g} \\ \sigma_{\mu D} & \sigma_{\mu g} & \sigma^2_\mu \end{bmatrix} \tag{9}$$

Since we identify three innovations from two observables in the measurement equations, we need to impose a restriction on the variance-covariance matrix in (9). Following Binsbergen and Koijen (2010) and Rytchkov (2008), the identification restriction imposed in this study is $\sigma_{gD} = 0$, that is $\rho_{gD} = 0$.[4]

3. EMPIRICAL RESULTS

3.1. DATA

The data for the Korean stock market is taken from the Korean Statistical Information Service (KOSIS).[5] They provide the dividend yields and the market

[4]Rytchkov (2008) used various values for ρ_{gD} and showed that the results are not sensitive.

[5]The website address of KOSIS is http://www.kosis.kr/.

index for the Korea stock exchange, which is known as the KOSPI index. Since the with-dividend return or the without-dividend index are not provided in the KOSIS, we construct the dividend data (D_t) for the KOSPI from the product of dividend yield and price (e.g. $D_t = \frac{D_t}{P_t} \times P_t$). Then, we log-transpose price and dividend and construct the log price-dividend ratio, stock returns and the growth rates of dividends. We analyze the annual price and dividend to accord with Binsbergen and Koijen (2010) and to avoid the seasonal effect of dividend payments.[6] We have access to annual dividend yields data from 1976 through the KOSIS, but figures for the years 1978 and 1979 seem to have some problem because the amount recorded is zero. As a result, our data points are 31, from 1980 to 2010. Although this seems to be small, we are able to obtain estimates and to make inferences regarding the Korean stock market.[7][8]

Table 1: Summary Statistics

	Number of observations	Mean	Standard deviation	Autocorrelation
r_t	31	0.1233	0.3396	-0.0119
Δd_t	31	0.0150	0.2245	-0.1062
pd_t	31	3.8110	0.6919	0.6671

Note: r_t denotes stock returns, Δd_t denotes dividend growth rates, and pd_t denotes the price-dividend ratio. All data are annual ones. Autocorrelation reports the correlation between x_t and x_{t-1} for $x_t = r_t, \Delta d_t$, or pd_t.

Table 1 shows summary statistics for stock returns (r_t), dividend growth rates

[6] The construction of dividends in this study is comparable to the cash-reinvested dividends in Binsbergen and Koijen (2010). Although Binsbergen and Koijen (2010) also examined the market-reinvested dividends, we did not analyze the market-reinvested dividends for the following reasons. First, we need to estimate more parameters for the market-reinvested dividends case, whereas the number of observations is limited. Second, stock returns are not influenced by the choice of dividends type according to Binsbergen and Koijen (2010).

[7] We have also examined other datasets to see whether we can have a longer sample size. However, we have found that the monthly dividend yields data of the KOSIS start from only 1993, and those of the Datastream start from only 1987. As a result, we use the annual data of the KOSIS.

[8] In case of the well known stock return predictability results in Fama and French (1988), the number of observations for annual predictive regressions varied from 30 to 60. Also, Burmeister and Wall (1982) applied the Kalman filtering approach to the German hyper-inflation period while fixing the sample size at 40. The robust results and limited sample sizes in these studies suggest that our results might not be entirely due to the small sample.

Table 2: Estimation Results of the State-space Model

Parameter		Point estimate	T-statistic
Estimates by MLE			
mean parameters	A_0	4.1784	(15.6665)***
	γ_0	0.0163	(0.4606)
persistency parameters	γ_1	-0.1430	(-0.7716)
	δ_1	0.7791	(9.7092)***
volatility parameters	σ_D	0.0308	(0.6822)
	σ_g	0.2179	(7.7521)***
	σ_μ	0.0672	(2.5194)**
correlation parameters	$\rho_{\mu g}$	0.3532	(1.9397)*
	$\rho_{\mu D}$	-0.9356	(-13.6141)***
	ρ_{gD}	0	
Implied parameters by the present-value model			
mean of μ_t	δ_0	0.0315	(0.8774)
linearization parameter	ρ	0.9849	

Note: The model, described in Section 2, is estimated by MLE, and the data is the market index for the Korea stock exchange between 1980 and 2010. The superscripts '*', '**', and '***' denote the significance level at the 10%, 5%, and 1% level, respectively.

(Δd_t), and the price-dividend ratio (pd_t). The average annual stock return in the Korean stock market is around 12%, while the average annual growth rate of dividends is 1.5%. The first lag autocorrelation in Table 1 shows that the price-dividend ratio is more persistent than stock returns or dividend growth rates in Korea, which is quite common in other countries such as the US.

3.2. ESTIMATION RESULTS

Table 2 presents the estimation results for the Korean market under the Binsbergen and Koijen model described in the previous section. Interesting points emerge from the table. First, the expected return for the Korean market is persistent, but less persistent with the measure of 0.77 than 0.932 for the US market in Binsbergen and Koijen (2010).[9] The persistence coefficient (δ_1) is significant in terms of t-statistics, and the formal likelihood ratio test for $\delta_1 = 0$ will be pre-

[9] Our results can be compared with the case of cash-reinvested dividends in Table II of Binsbergen and Koijen (2010).

sented in the next sub-section. Unlike the persistence coefficient for the expected stock returns, however, the persistence of expected dividend growth (γ_1) is not significant, although it suggests a slightly negative autocorrelation.

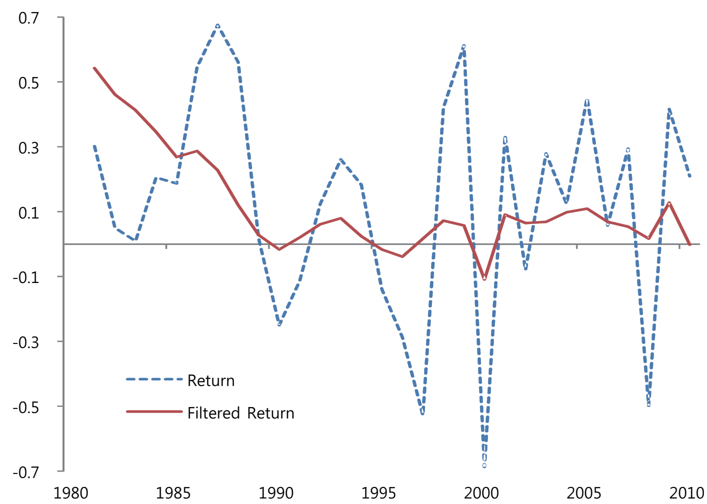
Second, the correlation between innovations of expected return and expected dividend growth, $\rho_{\mu g}$, is 0.35 in the Korean market, similar to the figure of 0.417 for the US market. The estimates are positive and significantly different from zero at the 10% level, and this result is consistent with findings in the literature. Lettau and Ludvigson (2005) and Menzly, Santos, and Veronesi (2004) find that the price-dividend ratio contains information about expected returns and expected dividend growth rates and that both types of information offset each other partly under the price-dividend ratio. Both studies further argue that the two canceling components contained in the price-dividend ratio is a reason for the low predictive power of the price-dividend ratio. Similarly to the US case in Lettau and Ludvigson (2005), the positive value for $\rho_{\mu g}$ might be a reason for the no-stock-return predictability by the price-dividend ratio in Korea, which is reported in Kim and Kim (2004) and Kim and Park (2009).

Third, the estimated expected returns and expected dividend growth rates are plotted along with realized returns and dividend growth rates in Figures 1 and 2. Interestingly, the estimated expected stock returns are negative in 1995 and 1996, which is immediately before the outbreak of Asian crisis. The estimated expected stock returns are also negative in 2000 which is around the time when the internet bubble burst in the US stock market. Figures 1 and 2 imply that both expected stock returns and dividend growth rates do not seem constant but to vary over time. This conjecture will be tested also formally in the next sub-section.

3.3. HYPOTHESIS TESTS

The estimation results in the previous section have revealed interesting and important points regarding expected stock returns and expected dividend growth rates. More specifically, expected returns appear to vary over time, while expected dividend growth rates do not. Also, expected stock returns seem to contain a persistent component, whereas expected dividend growth rates do not. In this sub-section, we conduct formal hypothesis tests regarding these issues. Since the maximum likelihood approach is taken for the estimation, we conduct the likelihood ratio test similarly to Binsbergen and Koijen (2010). The likelihood ratio test statistics, which is asymptotically chi-square-distributed, can be written as follows:

$$LR = 2(\Omega_1 - \Omega_0)$$



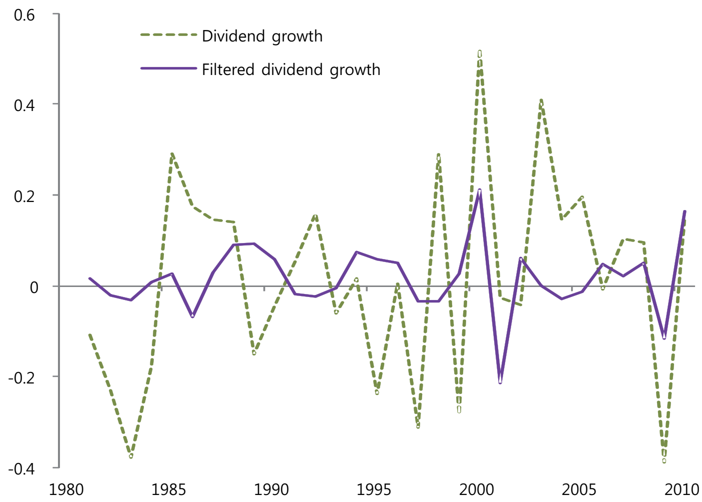
Note: The dotted line is the plot of actual stock returns while the solid line is the plot of expected stock returns estimated by the state-space model.

Figure 1: Estimated expected stock returns and actual stock returns

where Ω_1 is the log-likelihood under the unconstrained model and Ω_0 is the log-likelihood under the null hypothesis.

In order to test whether the persistence coefficient of expected returns (δ_1) is equal to zero, the null hypothesis considered is $H_0 : \delta_1 = 0$ and the LR has χ_1^2-distribution. Symmetrically, the likelihood ratio test to examine the null hypothesis of $\gamma_1 = 0$ is performed also to check whether the persistence coefficient of expected dividend growth (γ_1) is equal to zero. The test results are shown in the first two rows of Table 3. Consistently with the estimation results, the null hypothesis of $\delta_1 = 0$ can be rejected at the 5% level, whereas the null hypothesis of $\gamma_1 = 0$ cannot be rejected. These results imply that expected stock returns have a persistent component but expected dividend growth rates do not in the Korean stock market.

We also consider the null hypothesis of $H_0 : \delta_1 = \sigma_\mu = \sigma_{\mu g} = \sigma_{\mu D} = 0$ to check whether stock returns are predictable. This null hypothesis implies that stock returns are unpredictable and all variations in the price-dividend ratio stem from changes in expected dividend growth rates. According to the test result presented in the third row of Table 3, the null hypothesis can be rejected at the 1% level, which suggests that stock returns are predictable. The use of the state-



Note: The dotted line is the plot of actual dividend growth rates while the solid line is the plot of expected dividend growth rates estimated by the state-space model.

Figure 2: Estimated expected dividend growth rates and actual dividend growth rates

space model has provided formal test results for the stock return predictability, which could be impossible from predictive regressions with the price-dividend ratio as in the results of Hjalmarsson (2010).[10] Unlike the result for expected stock returns, however, the null hypothesis of $\gamma_1 = \sigma_g = \sigma_{\mu g} = 0$ cannot be rejected, which implies that the dividend growth rates are unpredictable.

3.4. VARIANCE DECOMPOSITIONS

Variance decompositions for the price-dividend ratio and unexpected stock returns are conducted in this sub-section. From equation (5), the variance decomposition of the price-dividend ratio can be expressed as follows:

$$\mathrm{var}(pd_t) = B_1^2 \mathrm{var}(\mu_t) + B_2^2 \mathrm{var}(g_t) - 2B_1 B_2 \mathrm{cov}(\mu_t, g_t) \tag{10}$$

The first term in equation (10) indicates the contribution of expected stock returns to the variation in the price-dividend ratio, whereas the second term rep-

[10] Hjalmarsson (2010) demonstrates that stock returns have a predictable component but cannot be predicted by the price-dividend ratio for most countries.

Table 3: Hypothesis Tests

Hypothesis	LR test statistics
$H_0 : \delta_1 = 0$	6.0035**
$H_0 : \gamma_1 = 0$	0.5981
$H_0 : \delta_1 = \sigma_\mu = \sigma_{\mu g} = \sigma_{\mu D} = 0$	16.9219***
$H_0 : \gamma_1 = \sigma_g = \sigma_{\mu g} = 0$	3.5335

Note: The likelihood ratio test statistics for $H_0 : \delta_1 = 0$ or $H_0 : \gamma_1 = 0$ has χ^2_1-distribution. The likelihood ratio test statistics for $H_0 : \delta_1 = \sigma_\mu = \sigma_{\mu g} = \sigma_{\mu D} = 0$ has χ^2_4-distribution, while the test statistics for $H_0 : \gamma_1 = \sigma_g = \sigma_{\mu g} = 0$ has χ^2_3-distribution. The superscripts '*', '**', and '***' denote the significance level at the 10%, 5%, and 1% level, respectively.

resents the contribution of the expected dividend growth rate. The last term measures the covariance between these two components. We normalize all terms on the right-hand side of equation (10) by $\text{var}(pd_t)$ such that the sum of all terms on the right-hand side becomes 100%. Table 3 reports the results of the variance decomposition of the price-dividend ratio. Similarly to findings in the literature, most of the variation in the price-dividend ratio results from the variation in expected returns in the Korean market. This result is also consistent with those in Table 3 in the sense that variations in the price-dividend ratio are related more closely with expected stock returns. However, the variation in the expected dividend growth rates can explain merely 17-18% of the variation in the price-dividend ratio. Hence, the ratio of the variation in the expected stock returns to the variation in the expected dividend growth is approximately 6, and the offsetting covariance term is around 16%.

We can also consider the variance decomposition of unexpected stock returns, which can be expressed as follows:

$$r_{t+1} - \mu_t = -\rho B_1 \varepsilon^{\mu}_{t+1} + \rho B_2 \varepsilon^{g}_{t+1} + \varepsilon^{D}_{t+1} \tag{11}$$

Like Binsbergen and Koijen (2010), we can group the last two terms together, such that the variation in unexpected stock returns can be decomposed to the variation of the expected stock returns, the variation of the dividend growth rate, and the covariance between the two. The results are shown in the lower panel of Table 3. The results under our model are quite similar to those in Binsbergen and Koijen (2010). We also assess the correlation in innovations between the expected stock returns and unexpected stock returns ($\text{Corr}(\varepsilon^{\mu}_t, \varepsilon^{R}_t)$). This corre-

Table 4: Variance Decomposition

Expected Returns (A)	Dividend Growth (B)	Covariance	(A)/(B)	Corr($\varepsilon_t^{\mu}, \varepsilon_t^{R}$)
Price-Dividend Ratio				
98.97	17.39	-16.36	5.69	
Unexpected Stock Returns				
84.41	37.95	-22.36	2.22	-0.80

Note: In the upper panel, 'Expected returns (A)' indicates the contribution of variance of expected returns on the variance of the price-dividend ratio, while 'Dividend growth (B)' reflects the contribution of variance of expected dividend growth rates on the variance of the price-dividend ratio. 'Covariance' denotes the covariance between estimated expected returns and estimated dividend growth rates. In the lower panel, 'Expected returns (A)' indicates the contribution of variance of shock to expected returns on the variance of shock to the unexpected stock returns, while 'Dividend growth (B)' reflects the contribution of variance of shocks to dividend growth rates on the variance of shock to the unexpected stock returns. 'Covariance' denotes the covariance between shock to expected returns and shocks to dividend growth rates.

lation performs an important role in the formation of a prior and in explaining the expected returns in the work of Pastor and Stambaugh (2009). Consistent with their argument, the correlation is estimated to be highly negative (-0.80).

3.5. PREDICTABILITY

We address whether the estimated expected stock returns and expected dividend growth rates can be utilized in forecasting future stock returns and dividend growth rates, respectively. We examine this issue by comparing the forecasting performance of the current model with that from an OLS regression having the lagged price-dividend ratio as a regressor. Due to the limited sample size, this issue is examined by conducting an in-sample analysis rather than an out-of-sample analysis. Hence the measure comparing the forecast performance is the in-sample R^2, the one employed in the study of Binsbergen and Koijen (2010). Hence, it can be expressed as $R^2 = 1 - \frac{\widehat{var}(r_{t+1} - \hat{\mu}_t)}{\widehat{var}(r_{t+1})}$ for returns and $R^2 = 1 - \frac{\widehat{var}(\Delta d_{t+1} - \hat{g}_t)}{\widehat{var}(\Delta d_{t+1})}$ for the dividend growth rate.

Table 5 compares this R^2 from the state-space model and R^2 from the predictive regression. The dependent variable in the predictive regression is either

Table 5: In-Sample Predictability

	Stock Returns	Dividend Growth Rates
Predictive regression	17.1	9.7
State-space model	14.9	10.1

Note: This table compares in-sample R-square values from the predictive regression with the lagged price-dividend ratio and from the state-space model. The forecast horizon is one year.

stock returns or dividend growth rates. The forecast horizon is one year considering our limited sample size. For stock returns, the state-space model hardly improves the goodness of fit, as compared with the predictive regression. In fact, the R^2 from the state-space model is comparable to that from the predictive regression (17.1% vs. 14.9%), which is similar to Binsbergen and Koijen (2010) reporting that the R^2 from both approaches are almost equal. This result is not surprising if we recall the hypothesis test result for $H_0 : \gamma_1 = \sigma_g = \sigma_{\mu g} = 0$. The hypothesis is not rejected in Table 3, which suggests that variations in expected dividend growth make little contribution in explaining variations in the price-dividend. In other words, movements in the price-dividend ratio are closely related with changes in expected stock returns in the Korean market. As a result, the simple OLS regression with the lagged price-dividend ratio appears to perform better than the state-space model. Unlike the result from the stock return side, the state-space model makes slightly better prediction for one-year-ahead dividend growth rate than the predictive regression (10.1% vs. 9.7%). However, this difference does not appear significant.

4. CONCLUSIONS

We have applied the state-space approach to the Korean stock market. The results that we have obtained are quite different from those for the US market reported in previous studies. First, estimated expected stock returns vary over time and contain persistent and predictable component, while estimated expected dividend growth rates do not. Also, we are not able to reject the null hypothesis that expected dividend growth rates are constant over time. Second, the variance decomposition analysis states that variations in expected stock returns play a more crucial role in understanding the variations of the price-dividend ratio than expected dividend growth rates do. Expected stock returns and expected dividend growth rates cancel each other partly similarly to the finding by Lettau and Ludvigson (2005). Third, shocks to expected stock returns are relatively more important to explain unexpected shocks to stock returns than shocks to expected dividend growth or unexpected dividend growth. We also find that the correlation in innovations between the expected stock returns and unexpected stock returns is significantly negative, which is consistent with Pastor and Stambaugh (2009). Finally, the state-space approach does not perform better than the predictive regression approach in terms of forecasting ability for future stock returns or future dividend growth rates. This poor forecasting ability might be due to limited sample size in this study. Hence, we leave this issue for future research when more observations have accumulated.

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