Expected returns and expected dividend growth: time to rethink an established empirical literature

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This article examines various state-space and VAR model specifications to investigate the contributions of expected returns and expected dividend growth to movements in the price-dividend ratio. We show that both models involve serious inference problems that need to be dealt with carefully. We propose procedures that offer more reliable inference results, and the corrected inferences indicate that the aggregate data of dividends and returns alone do not provide strong enough evidence to support the notion that the expected returns dominate the stock price variation. However, we show that an alternative measure of cash flows termed the net payout by Larrain and Yogo (2008) appears to lend strong support to the notion that the expected cash flow explains a large fraction of the firm value variation. This finding remains robust in both state-space and VAR decompositions with the corrected inference.

Keywords: stock price decomposition; state-space model; weak identification

JEL Classification: G12; C32; C58

I. Introduction

An important inquiry in finance over the last three decades has been the extent to which expected returns and expected cash flows contribute to movements in the price-dividend ratio. The vector autoregression (VAR) decomposition methodology has been employed, using both the traditional definition of dividends as well as a broader measure (termed net payout), and have found that expected returns contribute to most of the movement in the price-dividend ratio when traditional dividends are employed, while expected net payout contributes to most of the movement in the price-net payout ratio when this broader definition of dividends is employed. When a state-space methodology is employed, the results also have expected returns as being the primary contributor to movements in the price-dividend ratio when dividends are used as the cash flow measure.

This article makes an important contribution by illustrating that the earlier empirical work in this area is subject to severe inference problems which make their findings unreliable. This article revisits this subject by focusing on the important inference problems that have plagued the extant literature. In particular when we apply proper inference measures we find that the aggregate returns and dividends data cannot provide sufficient statistical evidence to support the notion that it is expected returns that explains the majority of the fluctuation in the...
Expected returns and expected dividend growth

price-dividend ratio when dividends are used as the cash flow measure. This is true whether we use the VAR decomposition approach or the state-space modelling approach. This work also extends Ma and Wohar (2013) in a number of dimensions by exploring different model specifications of the state-space model and by using additional measures of the cash flows. In particular, we find that when we employ the broader measure of dividends (net payout) and employ proper inference measures, we find that expected net payout growth contributes most to movements in the price-net payout ratio and expected returns contribute nothing.

The objective we set out in this article is challenged by the fact that neither expected cash flows nor expected discount rates are observable. Two primary approaches have been proposed to capture these unobserved expectations of future variables: VAR and the state-space model. Remarkably, applications of the two approaches using dividends as the cash measure have reached the same conclusion: almost all aggregate stock price variations are driven by discount rate news and almost none by cash flow news. Notable papers among the large body of literature that adopts the VAR methodology include Campbell and Shiller (1988a, 1988b), Campbell (1991), Shiller and Beltratti (1992), Cochrane (1992), and Campbell and Ammer (1993). Examples of work that apply the state-space methodology are Balke and Wohar (2002) and Binsbergen and Koijen (2010).

As a preview of our work, we first estimate the state space model of dividend growth and price-dividend as in Binsbergen and Koijen (2010). Although the point estimates indicate that the expected return is very persistent and explains the bulk of the price-dividend variations, such estimated state space model are plagued by a small expectation shock relative to the corresponding realized shock in the return process. The small signal-to-noise ratio of the state-space model implies weak identification (in the sense of Nelson and Startz (2007)) and that the standard inference tends to underestimate the uncertainty of the contribution estimate. The corrected inference based on Ma and Nelson (2012) suggests that the contribution of expected returns to movements in the price-dividend ratio is statistically insignificant. This finding is consistent with the intuition that when the predictable component of returns is small the uncertainty of its contribution is large. We show that a stylized VAR decomposition equipped with nonparametric bootstrapped inferences yields a similar result.

To bring to bear more information to this central issue in asset pricing, we consider an alternative measure of the cash flows. Recently, Larraín and Yogo (2008) construct a broader measure of the cash flows termed the net payout that is the sum of dividends, interest, equity repurchases net of issuance, and debt repurchase net of issuance, and they find that the ratio of net payout to asset value is primarily explained by the expected future cash flows growth. We extend our methodology to their unique data set and show that the finding that the expected cash flows dominate the firm value variations remains robust in both of the estimated state-space model and VAR decomposition with corrected inference.

Finally, one important contribution of our article is to present a framework and method to deal with the problem of weak identification in state-space models which results in seemingly significant test statistic while actually the parameters are being estimated with little precision. We show how one might determine whether a particular process is weakly identified and then present methods which yield proper inferences. These are important as the state-space methodology has become more and more prevalent in the literature.

II. The State-Space Model of Stock Price Decomposition

Campbell and Shiller (1988a, b) derive the following well-known log-linear approximation for the log return:

\[ r_{t+1} \approx \kappa + \Delta d_{t+1} + \rho \cdot pd_{t+1} - pd_t \quad (1) \]

where \( \Delta d_{t+1} \) is the log dividend growth, \( pd_{t+1} \) the log price-dividend ratio, and the two constants \( \rho \) and \( \kappa \) depend on the steady-state log price-dividend ratio. Forward iteration gives rise to the result that today’s price-dividend ratio is the sum of expectations of (discounted) future dividends growth and future returns:

\[ pd_t = \frac{\kappa}{1 - \rho} + E_t \sum_{j=0}^{\infty} \rho^j (\Delta d_{t+1+j} - r_{t+1+j}) \quad (2) \]

In order to study which of the two components (future dividends growth and future returns) on the right-hand side of Equation 2 is more responsible for the price-dividend variations on the left-hand side, one has to have an estimate the expectations of future dividend growth and future returns. One standard approach in the literature is to rely on the VAR model to extract these unobserved expectations (see, for example, Campbell and Shiller (1988a)). Another line of research such as by Balke and Wohar (2002), and Binsbergen and Koijen (2010) instead

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1 Balke and Wohar (2002) find the more general result that the factor with the largest degree of persistence is the factor that contributes most to movements in the price-dividend ratio.

2 The methodology in this section draws heavily from Ma and Wohar (2014).
employed the state-space approach to directly model and estimate the expectation processes. An alternative to the VAR model, the state-space approach attempts to model expectations directly as latent factors. One other notable advantage of the state-space approach is its ability to capture potentially long-lasting serial correlations that a VAR model with finite number of lags cannot do, because the state-space model usually implies moving averaging terms in its reduced form.

**Model estimation and the variance decomposition**

In principle, we can decompose dividend growth and returns into two components: the expected values and any difference between the expectations and the actual values:

\[
\Delta d_{t+1} = g_t + e_{t+1}^d
\]

(3)

\[
r_{t+1} = \mu_t + e_{t+1}^r
\]

(4)

where \( g_t = E_t[\Delta d_{t+1}] \) is the conditional expectation of the dividend growth and \( e_{t+1}^d \) is the difference between the expected value and the actual one, i.e. the so-called news shock; likewise, \( \mu_t = E_t[r_{t+1}] \) denotes the expected value of returns and and \( e_{t+1}^r \) is the news shocks. The news shocks are assumed to be i.i.d, respectively. However, the expectations may contain important dynamics and thus are modelled as stationary AR processes:

\[
\phi_g(L) \cdot (g_t - c_g) = e_t^g
\]

(5)

\[
\phi_{\mu}(L) \cdot (\mu_t - c_\mu) = e_t^\mu
\]

(6)

where \( \phi_g(L) \) and \( \phi_{\mu}(L) \) are lag polynomials with \( p \) lags. The expectations shocks \( e_t^g \) and \( e_t^\mu \) are assumed to i.i.d.

To facilitate calculations of the components in Equation 2, vectorize the state variables to obtain the companion form of (5) and (6):

\[
Z_t^g = A_g \cdot Z_{t-1}^g + V_t^g
\]

(7)

\[
Z_t^\mu = A_\mu \cdot Z_{t-1}^\mu + V_t^\mu
\]

(8)

where \( Z_t^g = (g_t - c_g, \ldots, g_{t-p+1} - c_g)' \), \( Z_t^\mu = (\mu_t - c_\mu, \ldots, \mu_{t-p+1} - c_\mu)' \), \( V_t^g = (e_t^g, \ldots, 0)' \), \( V_t^\mu = (e_t^\mu, \ldots, 0)' \); \( A_g \) and \( A_\mu \) are the corresponding loading matrix. It is then easy to derive:

\[
E_t \sum_{j=0}^{\infty} \rho^j (\Delta d_{t+1+j}) = e_t^r \cdot (I - \rho \cdot A_g)^{-1} \cdot Z_t^g + \frac{c_g}{1-\rho}
\]

(9)

where \( e_t^r \) is a column vector that has 1 as its first element and zero elsewhere.

Substituting in (9) and (10), we rewrite Equation 2 as:

\[
pd_t = \frac{\kappa}{1-\rho} + \frac{c_g - c_\mu}{1-\rho} + e_t^r \cdot (I - \rho \cdot A_g)^{-1} \cdot Z_t^g
\]

(11)

As Cochrane (2008b) pointed out, the identity (2) implies a restriction that all shocks in Equations 3-6 have to satisfy. Such restriction in our general context is given below:

\[
e_t^r = e_t^d + e_t^c \cdot \left( (I - \rho \cdot A_g)^{-1} \cdot \rho V_{t+1}^g \right)
\]

(12)

One practical implication of the above restriction is that one only needs to select two observed variables out of the three, namely, dividend growth, returns and price-dividend ratio, to estimate the model and the rest of the model can be backed out. To be comparable, we first follow Binsbergen and Koijen (2010) to choose the pair \( \Delta d_{t+1} \) and \( pd_{t+1} \) with one lag to estimate the model. The resulting state-space model consists of the following measurement equation:

\[
\begin{bmatrix}
\Delta d_{t+1} \\
pd_{t+1}
\end{bmatrix} =
\begin{bmatrix}
c_g \\
A
\end{bmatrix} +
\begin{bmatrix}
0 & 1 & 0 & 0 \\
B_2 & 0 & -B_1 & 0
\end{bmatrix}
\begin{bmatrix}
g_{t+1} - c_g \\
g_t - c_g \\
\mu_{t+1} - c_\mu \\
e_{t+1}^d
\end{bmatrix}
\]

(13)

The transition equation that describes the dynamic evolution of the state variables is:

\[
\begin{bmatrix}
g_{t+1} - c_g \\
g_t - c_g \\
\mu_{t+1} - c_\mu \\
e_{t+1}^d
\end{bmatrix} =
\begin{bmatrix}
\phi_{g,1} & 0 & 0 & 0 \\
1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}
\begin{bmatrix}
g_{t+1} - c_g \\
g_t - c_g \\
\mu_{t+1} - c_\mu \\
e_{t+1}^d
\end{bmatrix}
+
\begin{bmatrix}
\phi_{e,1}^g \\
e_{t+1}^c \\
0 \\
e_{t+1}^d
\end{bmatrix}
\]

(14)
where the constants implied by one lag are:
\[ A = \frac{1}{\rho^2} + \frac{1}{\sigma^2 g} \], \[ B_1 = \frac{1}{\rho g} \], \[ B_2 = \frac{1}{\sigma^2 g} \].

To make the model general, we allow for possible correlations between shocks (see Morley et al. (2003)). However, Cochrane (2008b) and Rytchkov (2008) show that one correlation in this particular model is not identifiable. Since Binsbergen and Koijen (2010) choose to restrict \( \sigma_{dg} = 0 \), we follow the same strategy to make our results comparable. Finally, the variance–covariance matrix of three shocks is given by
\[
\begin{bmatrix}
\sigma^2_d & \sigma^2_{dg} & \sigma^2_{g} \\
\sigma_{dg} & \sigma_{dg} & \sigma_{gg} \\
\sigma_{dg} & \sigma_{dg} & \sigma^2_{g}
\end{bmatrix}.
\]

We retrieve the CRSP market indices of NYSE/AMEX/NASDAQ stocks as the market portfolio and follow Hansen et al. (2008) aggregation procedure to construct the annual equity return and dividend growth series for the period 1946–2011. Using this data we estimate the above state-space model using the maximum likelihood estimation by following the procedure in Kim and Nelson (1999). Table 1 reports the estimation results.\(^4\)

We note that most of the estimations results in Table 1 are similar to Binsbergen and Koijen (2010).\(^5\) What is of particular importance is the very persistent process for the expected return: the AR(1) parameter estimate is not only large (\( \phi_{\mu,1} = 0.9233 \)) but its SE appears quite small, giving rise to a very tight 95% confidence interval [0.8361, 1.0105]. On the other hand, the expected dividend growth is far less persistent. We also conduct a test again the null hypothesis \( \phi_{\mu,1} = \phi_{g,1} \), and the LR test statistic clearly rejects the null of equal persistence.\(^6\)

We employ the approach of Cochrane (2008a) to decompose the price-dividend variation into two covariance components: the covariance of the price-dividend ratio with future dividend growth and future returns:
\[
Var(pd_t) = Cov \left( \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}, pd_t \right) + Cov \left( -\sum_{j=0}^{\infty} \rho^j r_{t+1+j}, pd_t \right)
\]
\[ (15) \]

These two covariance terms reflect the ability of the price-dividend ratio to predict future returns and future dividend growth. With the specification of one lag in our model, we further obtain:
\[
\begin{align*}
\text{Cov} \left( \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}, pd_t \right) &= \left[ \frac{Var(g_t)}{(1 - \rho \phi_{g,1})^2} \right] \\
&= \left[ \frac{Cov(g_t, \mu_t)}{(1 - \rho \phi_{g,1})^2} \right] \\
&= \left[ \frac{Cov(g_t, \mu_t)}{(1 - \rho \phi_{g,1})^2} \right] \\
\end{align*}
\]
\[ (16) \]

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\(^3\) Hansen, Heaton and Li’s data sources and procedures to compute return and dividend series are available on Nan Li’s website: http://www.bsg.edu.sg/staff/bizm. Note that this way of backing out and aggregating dividends is different from the way in Ma and Wohar (2013) that backs out the annual dividends directly from the annual returns as in Cochrane (2011).

\(^4\) We also estimate the model using quarterly data and obtain similar results. These results are available upon request.

\(^5\) We focus on the estimation of the cash-reinvestment dividends model since the market-reinvestment dividends model yields similar variance decomposition of the price-dividend variation.

\(^6\) We also estimate most of our models using the longer sample period starting from the year 1927. Except for some notable differences of some correlation estimates, the major result that the returns contribution dominates remains the same. These results are available upon request.
\[
\text{Cov}\left( -\sum_{j=0}^{\infty} \rho^j r_{t+1+j}, pd_t \right) = \frac{\text{Var}(\mu_t)}{(1-\rho \phi_{\mu,1})^2} \frac{\text{Cov}(g_t, \mu_t)}{(1-\rho \phi_{g,1})(1-\rho \phi_{\mu,1})}
\]

(17)

The above results highlight the fact that the relative size of the two contributions in (15) depends critically on the persistence of the expectations processes through their loadings \(\frac{1}{1-\rho \phi_{\mu,1}}\) and \(\frac{1}{1-\rho \phi_{g,1}}\), besides the variances and covariances. It is also important to notice that a rise of the persistence parameters \(\phi_{g,1}\) and \(\phi_{\mu,1}\) increases both the contributions loadings and the variances themselves. The impact of the increasing persistence on such decomposition will become extremely pronounced given the non-linear feature of the loading functions. A similar feature is explored in the long-run risk literature (see Ma (2013)). Therefore, the much persistent expected return process tends to imply a very large contribution to the stock price variations. In particular, we present the variance decomposition results based on the above state-space model in Table 2. Since a rise in the price-dividend ratio typically predicts a decline in future returns, we report the negative of that covariance as a normalization to facilitate comparison. The results reveal that most of the price-dividend variation seems to come from its comovement with the expected future returns.

We plot the filtered estimates of the expected dividend growth in Fig. 1, together with the actual dividend growth series. It is interesting that since the estimation results end up revealing a very small amount of noise relative to the signal, the expected dividend growth turns out to be almost identical to the actual dividend growth series. When we plot the difference between these two series, essentially the estimated news shock \(\hat{\epsilon}_t\), in Fig. 2, the difference becomes visible. The small difference between these two series is consistent with a very small amount of noise relative to the signal, or the large signal-to-noise ratio \(\sigma_{\epsilon}/\sigma_d = 21.2698\), as reported in Table 1. When we plot the filtered estimates of the expected return together with the actual return series in Fig. 3, however, the picture is quite different. In particular, the expected return is very persistent, and there is a substantial difference between the two. This pattern, interestingly, reflects the other extreme, that is, a small signal-to-noise ratio \(\sigma_{\epsilon}/\sigma_r = 0.1022\), as again reported in Table 1. We present the historical decompositions of the price-dividend ratio in Fig. 4. The price-dividend ratio appears to be primarily explained by the expected return contribution, which is consistent with the overall variance decomposition in Table 2. The primary reason that the expected return tracks the price-dividend movements so well is its high persistence.

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**Table 2. State-space decomposition of price-dividend ratio (Model 1: dividend growth and log price-dividend, one lag)**

<table>
<thead>
<tr>
<th>Covariance decomposition of price-dividend ratio (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Covariance of dividend and price-dividend</td>
</tr>
<tr>
<td>Negative of covariance of returns and price-dividend</td>
</tr>
</tbody>
</table>

*Notes: Annual data from the period 1946 to 2011 is used. The identification condition is \(\rho_{\delta t} = 0\). By construction contributions add up to 100%.*
Weak identification and corrected inference

One important feature about the above state-space model based on the rational expectation concept is that the time series dynamics of the actual series and its expectation can be drastically different as long as the signal-to-noise ratio is small. This was pointed out as early as in Nelson and Schwert (1977). However, under this circumstance, the small signal-to-noise ratio raises a serious issue about the statistical uncertainty around the parameter estimates, in particular the persistence parameter. Intuitively, small signal indicates a large amount of uncertainty around the parameter estimates. However, Nelson and Startz (2007) show that the standard inference is often misleading and unreliable under this condition that they named the zero-information-limit-condition or ZILC. Recall that in Table 1 the large persistence estimate of the expected return is accompanied by a very small SE. This is counter-intuitive and needs to be corrected.

We first show explicitly that the ZILC holds in this context. The state-space representation for return process implies a reduced-form ARMA process:

\[
(1 - \phi_{\mu,1}L) \cdot (r_{t+1} - c_\mu) = \varepsilon_{t+1}^r - \phi_{\mu,1} \cdot \varepsilon_t^r + \varepsilon_t^\mu
\]

(18)

Granger and Newbold’s (1986) theorem implies an ARMA(1,1) representation:

\[
(1 - \phi_{\mu,1}L) \cdot (r_{t+1} - c_\mu) = (1 - \theta L) \cdot u_{t+1}
\]

(19)

Assuming uncorrelated shocks, the mappings between the parameters in the ARMA and state-space models are done by computing and equating the variance and auto-covariance \((\gamma_0, \gamma_1)\) of the right-hand sides of Equations 18 and 19:

\[
\gamma_0 : (1 + \phi_{\mu,1}^2) \sigma_r^2 + \sigma_{\mu}^2 = (1 + \theta^2) \sigma_u^2
\]

(20)

\[
\gamma_1 : \phi_{\mu,1} \sigma_r^2 = \theta \sigma_u^2
\]

(21)

The unique MA parameter \(\theta\) that implies invertibility is given by:

\[
\theta = \begin{cases} 
\frac{[1 + (\phi_{\mu,1} - 1) \sigma_r^2 - \sqrt{(1 - \phi_{\mu,1})^2 \sigma_r^2 + 2 (1 + \phi_{\mu,1}) \sigma_{\mu}^2}]}{2 \phi_{\mu,1}}, & \text{for } \phi_{\mu,1} \neq 0 \\
0, & \text{for } \phi_{\mu,1} = 0
\end{cases}
\]

(22)

where the signal-to-noise ratio is denoted by \(S = \sigma_\mu / \sigma_r\). When the signal-to-noise ratio becomes arbitrarily small, the AR and MA roots become arbitrarily close to each other, resulting in a near root cancellation of the ARMA process:

\[
\lim_{S \to 0} \left( \phi_{\mu,1} - \theta \right) = 0
\]

(23)

As Nelson and Startz (2007) show, the ARMA model with near root cancellation is subject to ZILC and under this circumstance the estimated SE for either AR or MA estimate will appear too small, leading to a large size
distortion of the standard \( t \)-test. Even worse, the persistence estimate often tends to be upward biased in this situation, reflecting the ‘pile-up’ issue. We implement a simple Monte Carlo simulation to give readers some idea about the size distortion of a standard \( t \)-test of the persistence estimate \( \hat{\phi}_{\mu,1} \) when the return process is weakly identified. In this experiment, we generate data from the estimated state-space model using the values of parameter estimates in Table 1, except for the persistence parameters for both expected dividend growth and expected returns that we specify at a low level, i.e. \( \phi_{\mu,1} = \phi_{g,1} = 0.1 \) as the null hypothesis. For each simulated set of data, we estimate the model and calculate the \( t \)-statistic of the persistence estimate. We find that the standard \( t \)-test for the return persistence parameter \( \phi_{\mu,1} \) is indeed oversized and rejects the null about 42% of the time using the 5% critical value. Furthermore, we plot \( \hat{\phi}_{\mu,1} \) and its estimated SE in Fig. 5. There is clearly a negative correlation between the estimated SE and the absolute size of the persistence estimate on both ends of the graph. This pattern is in particular troublesome as it suggests that when the persistence parameter is estimated to be high, it is very likely the time that its estimated SE is too small.

Ma and Nelson (2012) propose a valid testing strategy in the presence of a small signal-to-noise ratio based on a linear approximation to the exact test of Fieller (1954) for a ratio of regression coefficients, and they show that such test is also in the LM principle of Breusch and Pagan (1980) since the test is evaluated under the null. They find that this test has much improved finite sample performance compared with the standard \( t \)-test when the model is weakly identified. Furthermore, they also evaluate the power performance of this test under the alternative and find that this test has a good power to detect a departure from the null in the DGP.

The valid testing strategy for \( \phi_{\mu,1} \) involves two steps. First, estimate the following reduced-form VARMA for the dividend growth and price-dividend under the null \( \phi_{\mu,1} = \phi_0 \):

\[
(1 - \phi_{g,1}L) \Delta d_{t+1} = (1 - \phi_{g,1}L)(1 - \phi_{\mu,1}L) [\Delta d_{t+1}]
\]

where the shocks \( [u_{1t+1} ~ u_{2t+1}]' \) are allowed to be correlated. In the second step, compute the \( t \)-statistic for the null \( \lambda = 0 \) in the following regression:

\[
(1 - \phi_{g,1}L)pd_{t+1} = \tau \cdot \sum_{i=1}^{\infty} \phi_0^{i-1} \tilde{u}_{2t+1-i} + \lambda \cdot \sum_{i=2}^{\infty} (i-1) \cdot \phi_0^{i-2} \tilde{u}_{2t+1-i}
\]

where \( \tilde{u}_{2t+1-i} \) are the residuals from estimating the system in the first step.

---

Fig. 5. State-space model 1: scatter plot of the expected returns persistence estimates and their estimated SEs in the Monte Carlo simulation.
Equation 25 is obtained by taking a first-order Taylor expansion of the second equation of (24) around the null $\phi_{\mu,1} = \phi_0$. Here, $\tau = \phi_{\mu,1} - \theta_2$, $\lambda = \tau \cdot (\phi_{\mu,1} - \phi_0)$, $\hat{\phi}_{g,1}$ and $\tilde{\alpha}_{2t+1}$ are the restricted estimates under the null from the first step. The reduced-form test statistic for the null $\phi_{\mu,1} = \phi_0$ is a standard $t$-statistic for testing the null $\lambda = 0$. We use the same simulated data in the above Monte Carlo experiment to compute the reduced-form test statistic for $\phi_{\mu,1}$ and find that the reduced form test rejects the null of low persistence, i.e. $\phi_{\mu,1} = 0.1$ about 18% of the time at the 5% level, which, although not perfect, is much better than that of the standard $t$-test which rejects the null about 42% of the time. Furthermore, Ma (2013) finds that this test has good power in detecting a departure from the null in the bivariate VARMA model even when the model is weakly identified.

However, we would like to emphasize that the weak identification does not condemn all state-space models. Specifically, a particular process of the state-space model becomes weakly identified only when the signal-to-noise ratio of that process is small. For processes that have large signal-to-noise ratio, the issue of weak identification is not a practical concern, and the standard inference likely remains valid. For example, in our estimated Model 1, the dividend growth process has a signal-to-noise ratio as large as $\sigma_{\mu}/\sigma_d = 21.2698$ (see Table 1). Therefore, the standard $t$-test for the persistence estimate of the expected dividend growth should function just fine. In our simulation experiment, the standard $t$-test for the persistence parameter of the expected dividend growth $\phi_{g,1}$ rejects the null only about 14% of the time using the 5% critical value, which is indeed about as good as the reduced-form test.

Numerically inverting the above reduced-form test statistic, we obtain the 95% confidence interval for the persistence parameter $\phi_{\mu,1}$ in Fig. 6. The reduced-form test indicates a much wider confidence interval than that of the standard test. This casts a serious doubt on the large contribution of the expected returns to the price-dividend variation, given that such decomposition critically depends on the large persistence estimate.

### III. Robustness of the State-Space Model: Alternative Specifications

Although in theory any combination of the two variables out of $\Delta d_{t+1}, p d_{t+1}, r_{t+1}$ should produce identical results up to the Campbell–Shiller approximation errors, different state-space models may implicitly impose different non-linear restrictions and thus produce different decomposition results. In this section, we explore alternative combinations of the variables and present the resulting variance decomposition.

**The combination of returns and price-dividend ratio**

In this model, we use returns along with the price-dividend ratio. The state-space model consists of the measurement equation:

\[
\begin{align*}
\begin{bmatrix}
\Delta d_{t+1} \\
p d_{t+1} \\
r_{t+1}
\end{bmatrix} &=
\begin{bmatrix}
\Phi & \Sigma & \Gamma \\
\Pi & \Delta & \Psi \\
\Theta & \Phi & \Xi
\end{bmatrix}
\begin{bmatrix}
\Delta d_{t} \\
p d_{t} \\
r_{t}
\end{bmatrix}

\end{align*}
\]
And the transition equation:

\[
\begin{bmatrix}
\mu_{t+1} - c_\mu \\
\mu_t - c_\mu \\
g_{t+1} - c_g \\
\epsilon_{r_t+1}^f
\end{bmatrix} =
\begin{bmatrix}
\phi_{\mu,1} & 0 & 0 & 0 \\
1 & 0 & 0 & 0 \\
0 & 0 & \phi_{g,1} & 0 \\
0 & 0 & 0 & \epsilon_{r_t+1}^f
\end{bmatrix}

\begin{bmatrix}
\mu_{t+1} - c_\mu \\
\mu_t - c_\mu \\
g_{t+1} - c_g \\
\epsilon_{r_t+1}^f
\end{bmatrix}
\]

(26)

where the constants are given by \( A = \frac{\sigma_\mu}{\rho} + \frac{c_g - c_\mu}{\rho} \), \( B_1 = \frac{1}{1-\rho_{gd}} \), \( B_2 = \frac{1}{1-\rho_{eg}} \), and the variance–covariance matrix of the three shocks is \( \begin{bmatrix}
\sigma_r^2 & \sigma_{rg} & \sigma_{rg} \\
\sigma_{rg} & \sigma_g^2 & \sigma_{rg} \\
\sigma_{rg} & \sigma_{rg} & \sigma_g^2
\end{bmatrix} \).

To impose the same identification restriction \( \rho_{gd} = 0 \), we use the nonlinear relationship (12) with one lag specification:

\[
\epsilon_{r_t+1} = \epsilon_{r_{t+1}}^f + \rho \cdot \left(1 - \rho \phi_{g,1}\right)^{-1} \epsilon_{r_{t+1}}^g - \rho \cdot \left(1 - \rho \phi_{g,1}\right)^{-1} \epsilon_{r_{t+1}}^g - \rho
\]

(28)

\[
\sigma_{dg} = \sigma_{rg} - \rho \cdot \left(1 - \rho \phi_{g,1}\right)^{-1} \sigma_g^2 + \rho
\]

(29)

**Table 3.** State-space estimation result (Model 2: returns and log price-dividend, one lag)

<table>
<thead>
<tr>
<th>Parameter estimates</th>
<th>( c_g )</th>
<th>0.0586 (0.0113)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \phi_{\mu,1} )</td>
<td>0.3080 (0.1174)</td>
<td></td>
</tr>
<tr>
<td>( c_\mu )</td>
<td>0.0900 (0.0138)</td>
<td></td>
</tr>
<tr>
<td>( \phi_{g,1} )</td>
<td>0.9346 (0.0413)</td>
<td></td>
</tr>
<tr>
<td>( \sigma_r )</td>
<td>0.1598 (0.0140)</td>
<td></td>
</tr>
<tr>
<td>( \sigma_g )</td>
<td>0.0143 (0.0067)</td>
<td></td>
</tr>
<tr>
<td>( \rho_{gd} )</td>
<td>0.8473 (0.0610)</td>
<td></td>
</tr>
<tr>
<td>( \rho_{eg} )</td>
<td>0.2342 (0.1429)</td>
<td></td>
</tr>
<tr>
<td>Log-likelihood value</td>
<td>115.0644</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** Annual data from the period 1946 to 2011 is used; numbers in parenthesis are SEs. The identification condition is \( \rho_{dg} = 0 \). \( c_g \) is the average dividend growth rate; \( \phi_{g,1} \) is the AR(1) parameter in the expected dividend growth process; \( c_\mu \) is the average return; \( \phi_{\mu,1} \) is the AR(1) parameter in the expected return process; \( \sigma_r \) is the size of the news shock to the realized dividend growth in Equation 3; \( \sigma_g \) is the size of the news shock to the realized return in Equation 4; \( \rho_{gd} \) is the size of the shock to the expected dividend growth in Equation 5; \( \rho_{eg} \) is the size of the shock to the expected return in Equation 6; \( \rho_{dg} \) is the correlation between the news shock to realized return and the shock to the expected returns; \( \rho_{eg} \) is the correlation between the shock to the expected return and the shock to the expected dividend growth.

**Table 4.** State-space variance decomposition (Model 2: returns and log price-dividend, one lag)

<table>
<thead>
<tr>
<th>Variance decomposition of price-dividend ratio (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Covariance of dividend and price-dividend</td>
</tr>
<tr>
<td>Negative of covariance of returns and price-dividend</td>
</tr>
</tbody>
</table>

**Notes:** Annual data from the period 1946 to 2011 is used. The identification condition is \( \rho_{dg} = 0 \). By construction all contributions add up to 100%.

The combination of dividend growth and returns

Using the combination of dividend growth and returns, we set up the state-space model that consists of the measurement equation:

\[
\begin{bmatrix}
\Delta d_{t+1} \\
\rho d_{t+1}
\end{bmatrix} =
\begin{bmatrix}
c_g \\
c_\mu
\end{bmatrix} +
\begin{bmatrix}
1 & 0 & 1 & 0 \\
0 & 1 & 1 & B_1 
\end{bmatrix}

\begin{bmatrix}
\mu_{t+1} - c_\mu \\
\mu_t - c_\mu \\
g_{t+1} - c_g \\
\epsilon_{r_{t+1}}^f
\end{bmatrix}
\]

\[
\begin{bmatrix}
\mu_{t+1} - c_\mu \\
\mu_t - c_\mu \\
g_{t+1} - c_g \\
\epsilon_{r_{t+1}}^f
\end{bmatrix}
\]

(30)
where the constants are given by $B = \frac{1}{1 - \phi_{g,1}}$, and the variance–covariance matrix of three shocks is $\begin{bmatrix} \sigma_{\mu}^2 & \sigma_{\mu g} & \sigma_{g}^2 \\ \sigma_{\mu g} & \sigma_{g}^2 & \sigma_{g}^2 \\ \sigma_{g}^2 & \sigma_{g}^2 & \sigma_{g}^2 \end{bmatrix}$. We again impose the same identification restriction $\sigma_{dg} = 0$.

Table 5 reports the estimation results of this model. The most interesting result is that now the persistence parameter for the expected returns becomes less persistent ($\phi_{\mu,1} = 0.8530$). Furthermore, although the expected returns remain primarily responsible for the price-dividend variation (see Table 6), its contribution becomes much smaller compared with the first two models.

### IV. VAR Decompositions

The VAR model return decomposition has been widely adopted in the literature to study the contributions of cash flow news and discount rate news to stock price variations. In this section, we aim to offer some formal statistical inference in the VAR return decomposition.

This body of work typically chooses the predictive variables (for example, the price-dividend ratio) in the VAR framework to estimate expectations of future market fundamentals. Using the Campbell and Shiller’s (1988a, 1988b) log linear return approximation, this work decomposes asset prices into the expectations of future returns and future dividend growth.

There are a number of limitations and pitfalls in such VAR decompositions. For example, the finding in the extant literature that expected returns dominate dividend growth in explaining movements in the price-dividend ratio, is sensitive to the time period (Chen, 2009), and to the choice of predictive variables (Goyal and Welch, 2008; Chen and Zhao, 2009).

Table 5. State-space estimation result (Model 3: dividend growth and returns, one lag)

<table>
<thead>
<tr>
<th>Parameter estimates</th>
<th>( \hat{\phi}_{\mu,1} )</th>
<th>0.1779</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \hat{\phi}_{g,1} )</td>
<td>0.2678 (0.1185)</td>
<td></td>
</tr>
<tr>
<td>( \hat{\sigma}_{\mu} )</td>
<td>0.8530 (0.0610)</td>
<td></td>
</tr>
<tr>
<td>( \hat{\sigma}_{g} )</td>
<td>0.0630 (0.0055)</td>
<td></td>
</tr>
<tr>
<td>( \hat{\rho}_{dg} )</td>
<td>-0.9583 (0.5869)</td>
<td></td>
</tr>
<tr>
<td>( \hat{\rho}_{ag} )</td>
<td>0.2850 (0.1362)</td>
<td></td>
</tr>
<tr>
<td>Log-likelihood value</td>
<td>116.4949</td>
<td></td>
</tr>
<tr>
<td>Implied parameters</td>
<td>( \hat{\sigma}_{\mu} )</td>
<td>0.1551 (0.0135)</td>
</tr>
<tr>
<td>( \hat{\rho}_{dg} )</td>
<td>0.9633 (0.5838)</td>
<td></td>
</tr>
<tr>
<td>( \hat{\rho}_{ag} )</td>
<td>-0.8472 (0.0580)</td>
<td></td>
</tr>
<tr>
<td>( \hat{\rho}_{g} )</td>
<td>0.2678 (0.1185)</td>
<td></td>
</tr>
<tr>
<td>( \hat{\kappa} )</td>
<td>0.1342</td>
<td></td>
</tr>
<tr>
<td>( \hat{\rho} )</td>
<td>0.9701</td>
<td></td>
</tr>
<tr>
<td>ZILC parameters</td>
<td>( \hat{\sigma}<em>{\mu}/\hat{\sigma}</em>{g} )</td>
<td>0.1779</td>
</tr>
<tr>
<td>( \hat{\sigma}<em>{\mu}/\hat{\sigma}</em>{dg} )</td>
<td>96.9542</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Annual data from the period 1946 to 2011 is used; numbers in parenthesis are SEs. The identification condition is \( \rho_{dg} = 0 \). \( \hat{\phi}_{g,1} \) is the average dividend growth rate; \( \hat{\phi}_{\mu,1} \) is the AR(1) parameter in the expected dividend growth process; \( \hat{\sigma}_{\mu} \) is the average return; \( \hat{\phi}_{\mu,1} \) is the AR(1) parameter in the expected return process; \( \hat{\sigma}_{g} \) is the size of the shock to the realized dividend growth in Equation 3; \( \hat{\sigma}_{g} \) is the size of the news shock to the realized dividend growth in Equation 4; \( \hat{\sigma}_{g} \) is the size of the shock to the expected dividend growth in Equation 5; \( \hat{\sigma}_{g} \) is the size of the shock to the expected return in Equation 6; \( \hat{\rho}_{dg} \) is the correlation between the news shock to realized dividend growth and the shock to the expected return; \( \hat{\rho}_{ag} \) is the correlation between the shock to the expected return and the shock to the expected dividend growth.

Table 6. State-space variance decomposition (Model 3: dividend growth and returns, one lag)

| Variance decomposition of price-dividend ratio (%) | 26.71 |
| Covariance of dividend and price-dividend | 73.29 |

Notes: Annual data from the period 1946 to 2011 is used. The identification condition is \( \rho_{dg} = 0 \). By construction all contributions add to 100%.

In this article, we focus on the formal statistical inference of the contributions in the VAR decomposition. Specifically we construct the inference using a nonparametric bootstrap procedure. We work with the following stylized VAR specification:

$$
\begin{bmatrix}
\hat{r}_{t+1} \\
\hat{X}_{t+1}
\end{bmatrix}
= F \cdot 
\begin{bmatrix}
\hat{r}_{t} \\
\hat{X}_{t}
\end{bmatrix} + V_{t+1}
$$
Table 7. VAR variance decomposition (four lags)

<table>
<thead>
<tr>
<th>Variance decomposition of price-dividend ratio (%)</th>
<th>95% Critical values (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Covariance of dividend and price-dividend</td>
<td>9.80 7.19 196.56</td>
</tr>
<tr>
<td>Negative of covariance of returns and price-dividend</td>
<td>90.20 96.56 92.81</td>
</tr>
</tbody>
</table>

Notes: Annual data from 1 the period 946 to 2011 is used; the contributions are normalized to sum up to 100%. Note that for covariance contributions the critical values are two-sided, i.e., the left one is 2.5% percentile and the right one is 97.5% percentile.

where $X_{t+1}$ is a vector containing variables that predict returns. In this work, the only predictive variable is the price-dividend ratio; $\hat{F}$ is the companion matrix that allows for a general $VAR(p)$ specification. Given the parameter estimates, we can compute first compute the contribution of the expected returns to the price-dividend variations. Then the contribution of the expected dividend growth can be backed out using the Campbell–Shiller return identity. The contribution of the expected returns is given by:

$$E_t \sum_{j=0}^{\infty} \rho^j r_{t+1+j} = \epsilon_t' \cdot \hat{F} \cdot (I - \rho \hat{F})^{-1} \cdot Z_t$$  \hspace{1cm} (33)

where $Z_t = [r_t \hspace{0.5cm} X_t]'$ and $\epsilon_t$ is the selection vector.

We apply this method to our annual data from the period 1946 to 2011. We present the price-dividend decomposition in Table 7 using four lags. As typical in this literature, the VAR decomposition reveals that most of the stock price variations are primarily explained by the expected returns. In particular, the decomposition shows that about 90% of the price-dividend variation comes from its comovement with the expected returns.

To investigate the statistical significance of these contributions, we offer an inference based on the nonparametric bootstrapping procedure. In our bootstrapping exercise, we use the coefficients estimates from the above estimated VAR but set all coefficients in the return forecasting equation to zeros. In doing this, we assume no return forecastability as the null hypothesis and also the benchmark case to study the empirical distributions of relevant metrics. We implement the nonparametric bootstrapping with replacement. For each set of bootstrapped data, we estimate the VAR, compute and record the price-dividend decomposition results. We do 5000 replications. The 95% upper percentile of the empirical cumulative distribution of the expected return contribution is 92.81%, which is larger than the point estimate (see Table 7). As a result, the large contribution of the expected returns is barely significant at 5% level.

To offer more details about the empirical distributions of these bootstrapped returns and dividends contributions and explain how we calculate the bootstrapped critical values, we plot the histograms of the two covariance contributions in Figs 7 and 8. Since the distributions in this case are two-sided, the 95% critical values are two-sided, one representing the 2.5% percentile on the left and one 97.5% percentile on the right. Notice that the point estimate of the return contribution is smaller than the right-side critical value in Fig. 7 and as a result the null cannot be rejected. Furthermore, Fig. 8 tells the other side of the same story. The data is generated under the joint null of 0% return contribution and 100% dividend contribution. The point estimate of the dividend growth contribution is 9.80% and is small, but it is still well above the left side critical value, and thus, we cannot reject the joint null hypothesis.

Notes: The graph is based on 5000 replications; the scale of y-axis is made the same as that of Fig. 8 to facilitate comparison; the rightmost (leftmost) bar counts the percentage of those contributions greater (less) than 200% (~200%).
V. Larrain and Yogo’s Alternative Measure of Cash Flows

In a very important study, Larrain and Yogo (2008) point out the shortcomings of using the dividends and dividend-yield in the stock price decomposition. They construct a broader measure of cash flows, namely, the net payout that includes dividends, interest, equity repurchase net of issuance and debt repurchase net of issuance. Using the VAR decomposition, they show that the expected future cash flows turn out to contribute most to the variation of the net payout yield, the ratio of net payout to asset value. In this section, we estimate both the state-space and VAR model to decompose the variation of the net payout ratio and offer further statistical inference of these contributions estimates using the proposed methodology so far.\(^{10}\)

The state-space variance decomposition

Larrain and Yogo (2008) show that the present value relationship as laid out by (1) through (2) holds for the net payout \(\Delta d\), asset returns \(r\) and the ratio of asset values to net payout \(pd\). We select the observed variables \(\Delta d_{t-1}, pd_{t}\) and setting lag \(p = 1\) to estimate the state-space model as set up by (13) and (14). The identification restriction is \(\sigma_{d0} = 0\).\(^{11}\) The state-space estimation results and the variance decomposition results are reported in Tables 9 and 10, respectively.

We find that the expected net payout growth is more persistent than the expected returns. But the persistence of the expected net payout growth is nowhere near that of the expected returns when using the price-dividend data (see Section II). Furthermore, our state-space model reports consistent results with Larrain and Yogo (2008) that when measuring cash flows using this broader term the expected cash flows seem to contribute most to the asset valuation fluctuations: the covariance contribution of the expected net payout growth is 100.52% (see Table 10). This is opposite to what one would find using the price-dividend and dividends data.

Certainly the small signal-to-noise ratio is a concern. We apply the Ma–Nelson procedure and the valid inference for \(\phi_{c,1}\), the confidence interval for the persistence estimate of the expected net payout growth, turns out to have two disjoint intervals: \([-0.99, -0.09]\)U\([0.36, 0.99]\), of which the second interval appears to be consistent with the notion of the predictable cash flows growth. In order to sharpen the inference, we further restrict the dynamics of the expected return process. When we restrict the AR parameter of the expected returns process to be zero, the valid inference of Ma–Nelson procedure produces a much tighter confidence

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\(^{9}\) This data set is available on Robert Shiller’s website: http://www.econ.yale.edu/~shiller/data.htm

\(^{10}\) We thank Yogo for generously providing their data set.

\(^{11}\) We find that the model fails to converge for the identification restriction \(\sigma_{d0} = 0\).
The VAR decomposition

Table 9. State-space estimation result (Model 1: net payout growth and log asset-payout ratio, one lag)

<table>
<thead>
<tr>
<th>Parameter estimates</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c_p$</td>
<td>0.0655</td>
</tr>
<tr>
<td>$\phi_{e,1}$</td>
<td>0.7784</td>
</tr>
<tr>
<td>$c_p$</td>
<td>0.0794</td>
</tr>
<tr>
<td>$\phi_{e,1}$</td>
<td>-0.3392</td>
</tr>
<tr>
<td>$\sigma_d$</td>
<td>0.3497</td>
</tr>
<tr>
<td>$\sigma_p$</td>
<td>0.0454</td>
</tr>
<tr>
<td>$\sigma_g$</td>
<td>0.0889</td>
</tr>
<tr>
<td>$\rho_{d/p}$</td>
<td>0.3433</td>
</tr>
<tr>
<td>$\rho_{d/g}$</td>
<td>-0.9287</td>
</tr>
<tr>
<td>Log-likelihood value</td>
<td>25.3069</td>
</tr>
</tbody>
</table>

Table 10. State-space variance decomposition (Model 1: net payout growth and log asset-payout ratio, one lag)

<table>
<thead>
<tr>
<th>Variance decomposition of price-dividend ratio (%)</th>
<th>95% Critical values (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Covariance of dividend and price-dividend</td>
<td>85.92, −57.50, 48.98</td>
</tr>
<tr>
<td>Negative of covariance of returns and price-dividend</td>
<td>14.08, 51.02, 157.50</td>
</tr>
</tbody>
</table>

Table 11. VAR variance decomposition (four lags)

Notes: Annual data from the period 1927 to 2004 in Larrain and Yogo (2008) is used. The identification condition is $\rho_{gg} = 0$.

The VAR decomposition

We also apply the same bootstrap procedure as in Section IV to Larrain and Yogo’s data set to provide a VAR decomposition result. First of all, we do not attempt to employ all three data and estimate the over-identified model as in Larrain and Yogo (2008). Instead, we first estimate the VAR using the returns and the asset payout ratio, and then we estimate another VAR model consisting of the payout growth and the asset payout ratio. We find that our results are robust in both models and therefore we report the decomposition results along with their bootstrapped confidence intervals for the VAR model that consists of payout growth and the asset payout ratio in Table 11. VAR decomposition gives rise to a similar result of the state-space decomposition: the net payout growth seems to explain a large fraction of the payout yield variation. To investigate the statistical significance of this result, we resort to the bootstrap procedure.

Notice here since now the cash flows contribution becomes large, we want to test the null hypothesis of zero contribution by the cash flows. Therefore, in our bootstrapping, we use the coefficients estimates from the above estimated VAR but set all coefficients in the net payout growth forecasting equation to zeros. In doing this we assume no payout forecastability as the null hypothesis and also the benchmark case. The bootstrapped critical values are reported in Table 11. Based on the 5% critical values, the contribution of the expected payout growth to the asset payout ratio is not only large (85.92%) but also statistically significant. The point estimate exceeds the 5% critical value by a large margin.

To offer more details about the empirical distributions of these bootstrapped returns and net payout contributions, we plot the histograms of the two covariance contributions in Figs 9 and 10. Notice that the point estimate of the net payout growth contribution is much larger than the right-side critical value in Fig. 9 and as a result the null is strongly rejected. Furthermore, Fig. 10 tells the other side of the same story. The data is generated under the joint null of 0% net payout growth contribution and 100% returns contribution. The point estimate of the returns contribution is 14.08% and is well below the left-side critical value, and thus, we again strongly reject the joint null hypothesis.
In summary, the VAR decomposition results with bootstrapped confidence intervals provide strong evidence in support of the finding by Larrain and Yogo that the cash flows, when measured in a broader term, can contribute most to the firm value variations.

VI. Conclusion

The extant literature examining the factors that contribute to movements in the aggregate price-dividend ratio have yielded, to some, a puzzling result employing the standard definition of dividends. Employing both VAR decomposition methodology as well as state-space modelling methods, the empirical results of the extant literature find that it is expected returns that contribute most to movements in the price dividend ratio rather than expected dividend growth (which might be expected from finance theory). When a broader definition of dividends (net payout) is employed, one finds that it is the broader measure of cash flows that contributes most to movements in the price-net payout ratio. Nonetheless, it remains puzzling why expected returns so strongly contribute to movements in the price dividend ratio.

This article contributes to the existing literature by illustrating that the earlier empirical work in this area is subject to severe inference problems which make their findings unreliable. This article revisits this subject by focusing on the important inference problems that have plagued the extant literature. We show that estimated state-space model is plagued by a small expectation shock relative to the corresponding realized shock in the return process. The small signal-to-noise ratio of the state-space model implies weak identification and that the standard inference tends to underestimate the uncertainty of the contribution estimate. When we adjust for proper inference, we find that the aggregate returns and dividends data cannot provide sufficient statistical evidence to support the notion that it is expected returns that explain the majority of the fluctuation in the price-dividend ratio. We show that a stylized VAR decomposition equipped with nonparametric bootstrapped inferences yields a similar result. However, the broader measure of dividends (termed net payout) does hold up to scrutiny and is found to significantly contribute to movements in the price-net payout ratio.

References


