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Dividend Growth & Return Predictibility

A Dynamic Approach

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Executive Summary

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Dividend yields are a determinant of asset prices, but changes in dividend growth impact both dividend yields and discount rates. As a result, dividend growth is typically treated as a known constant in most of the literature.

In this paper, we develop a dynamic approach to forecasting dividend growth using Bayesian filtering techniques, which improves markedly on standard linear methods. The resulting growth-adjusted dividend yield improves out-of-sample return predictions by several orders of magnitude. These results show that dynamic cash flow modeling can significantly improve the performance of expected return models.

1. Introduction

1. Introduction

Cash flow forecasts should play an important role in value investing and, in turn, in asset management. But while there is a large amount of research on how cash flow ratios may be used as predictors of expected returns, the forecasting of cash flows themselves and how changes in cash flow forecasts impacts expected returns has been largely ignored.

This literature includes Fama and French (1988); Campbell and Shiller (1988b); Cochrane (1992, 2011); Lettau and Ludvigson (2001); Lewellen (2004); Campbell and Yogo (2006); Ang and Liu (2007); Campbell and Thompson (2008); Welch and Goyal (2007); Lettau and Van Nieuwerburgh (2008); Chen and Zhao (2009); Chen (2009); Binsbergen et al. (2010); Maio and Santa-Clara (2015); Bollerslev et al. (2015). Koijen and Van Nieuwerburgh (2011) provides a review of recent work of this area.

In this paper, we propose a dynamic cash flow forecasting model, provide evidence that future dividend growth is predicted by current dividend yields, and highlight the importance of taking expected dividend growth into account when modeling expected returns. Our approach provides an effective way to capture new information and regime shifts in the forecast of dividend growth, thus yielding better out-of-sample return prediction results.

The asset pricing identity that links dividend yields to dividend growth and discount rates is a fundamental arguments for using the log dividend-price ratio to forecast equity returns. With no variation in the forecast of future dividend growth, ant variation in the dividend-price ratio is solely due to changes in expectations of future returns Cochrane (2008). However, if expected dividend growth changes over time, it should be taken into account in the fluctuations of the valuation multiple.

We propose a predictive regression of future dividend growth on current dividend yield, and extend it with the addition of a dynamic estimation-error correction structure using Kalman filtering techniques. A Markov Chain Monte Carlo estimator using Gibbs sampling (see Gelfand and Smith (1990); Robert (Robert)) generates the posterior distribution by iteratively simulating from two simpler distribution: latent components from the Kalman filter and a Bayesian regression. Both of these distributions are well understood and tractable, and combining them forms an estimation procedure that is manageable given the numerical complexity of the model.

Our cash flow model generates dynamic forecasts of dividend growth rates for both the portfolio level and individual firms, and exhibits greater accuracy and robustness to regime shifts than static techniques, e.g. OLS regressions, used in previous studies such as Ang (2012) and Zhu et al. (2015).

Next, we propose an dividend growth-adjusted dividend yield metric that takes into account changes in forecasts of

1. Introduction

dividend growth. This adjusted variable allows controlling for shocks to dividend growth when estimating expected returns using dividend yields, following Ang (2012).

Using the dividend growth-adjusted measure of the dividend yield in combination with our dynamic dividend growth forecasts improves the out-of-sample power of expected returns prediction by several orders of magnitude, increasing the R^2 from 4.8% to 18.6%

These results have implications not only for the corporate finance literature on cash flow forecasting but also for the asset pricing literature.

The rest of this paper is organized as follows: section 2 briefly reviews the role of cash flow forecasting in the asset pricing literature; section 3 details the approach taken to modeling cash flows and expected return; section 4 describes the market data used to test the model; section 5 reports our cash flow and return forecasting results. Section 6 concludes.

2. Related Literature

2. Related Literature

2.1 Asset pricing papers tend to ignore cash flows

The asset pricing literature tends to overlook the role of dividend growth. Thus, Fama and French (1988) and Hodrick (1992) focus on long-horizon expected (excess) returns but do not try to predict dividend growth as a function of contemporary dividend yields.

Campbell and Shiller (1989) use vector auto-regression (VAR) tests of the dividend discount model, but do not develope a dividend growth forecasting equation. In Campbell and Ammer (1993), cash flows do not appear at all in VAR tests even though realised cash flows are observable. Instead, the authors specify a stochastic process for returns and indirectly infer news about dividend growth from the VAR as a remainder term.

2.2 Research using cash flows is static in nature

Academic research focusing on cash flow forecasting is relatively rare in comparison with the number of papers looking at expected returns. Papers looking at dividends and dividend growth typically adopt static approaches, i.e. frequentist statistical inference, implemented at the portfolio level and do not aim to capture any the regime shift or structural change in the data.

Bansal and Yaron (2004) forecast dividend growth as a persistent unobservable component that is common to consumption growth, whereas Lettau and Ludvigson (2005) predict dividend growth from a stationary linear combination of consumption, dividends, and labor income. Binsbergen et al. (2010) use an AR(1) process to model expected dividend growth, and Kelly and Pruitt (2013) use equity portfolio dividend yields to forecast returns *and* dividend growth for the market portfolio.

In most papers expected dividend growth is considered to be a known process or a constant and not related to dividend yields, and even the papers recognise that dividend growth is not an independent and identically distributed process do not attempt to relate it to dividend yields.

Ang (2012) is one of the few papers exploring how dividend growth might be predictable as a function of dividend yields, using the log-linear dividend yield model of Campbell and Shiller (1988a) for single-periods and weighted long-horizon regressions, following Cochrane (1992).

Zhu et al. (2015) considers univariate regressions and a multivariate regression conditioning on 11 fundamental and macroeconomic predictors including the dividend yield. Introducing additional predictors improves the in-sample explanatory power of the model but also increase out-of-sample overfitting. Still, both of these use static regression models at the portfolio level, ignoring regime shifts in financial markets.

Thus, current research does not integrate dynamic approaches to modeling cash flows

2. Related Literature

and fails to link changes in return forecasts with changes and improvements in cash flow forecasts.

Despite the theoretical link between cash flow forecasts and expected returns, it is possible that cash flows have long been ignored in the literature because of the poor results afforded by static models of future cash flows.

3. Dividend Growth & Return Modeling

3. Dividend Growth & Return Modeling

Most quantitative applications in cash flow forecasting or asset pricing adopt a frequentist statistical inference: the approacch consists of estimating unknown parameters over a specified 'look-back' period and using these estimates to derive expected values.

The *ad hoc* length of the 'look-back' period and loss of observations as the window shifts forward can be expected to make this approach less robust than Bayesian dynamic models, which offer a more consistent formulation of the problem: each time a new cash flow period passes, model parameters are updated by combining prior (*ex ante*) beliefs about future cash flow paths and the corresponding risk (uncertainty) with new information and without information loss.

Inherited from signal processing techniques the in-sample and out-of-sample performance of Bayesian dynamic methods is typically superior to static models, as we show in the rest of this paper: a linear combination of dividend growth forecasts estimated dynamically integrates new information about variations in dividend growth forecasts, and is, *in fine*, better able to forecast equity returns, at both portfolio and individual firm levels.

In what follows, we propose a framework for estimating the relative power of dynamic dividend forecasting compared to the static approaches. We first describe a pricing equation expressing asset prices as a function of dividend growth and which serves as the basis for testing the out-of-sample predictive power of dynamical models relative to static ones.

3.1 Pricing Equation

We follow Campbell and Shiller (1988a) and consider the price-dividend ratio P_t/D_t, which is the present value of future expected dividends discounted back by the market's total expected return:

$$\frac{P_t}{D_t} = E_t\left[\sum_{i=1}^{\infty} \exp\left(\sum_{j=1}^{i}(-r_{t+j} + g_{t+j})\right)\right]. \tag{3.1}$$

where, P_t is the asset price and D_t is the dividend at time t, r_t and g_t are the log return and dividend growth rates at time t, respectively and *exp* and E_t are the exponential operator and conditional expectation at time t, respectively.

In Equation (3.1), the price-dividend ratio is highly non-linear but still following Campbell and Shiller (1988a), we know that closed-form expressions and linear approximation of (3.1) can be obtained that yield a time-series model.

Taking the standard definition of realized total returns,

$$1 + R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t},$$

multiplying both numerator and denominator on the right-hand side by the price at $t+1$, taking logs on both sides, then summing and subtracting the log of dividend growth from t to $t+1$, yields the

3. Dividend Growth & Return Modeling

following identity:

$$r_{t+1} = \log\left(1 + \frac{D_{t+1}}{P_t + 1}\right)$$
$$+(p_{t+1} - d_{t+1}) - (p_t - d_t) + \Delta d_{t+1},$$

where small letters denote logs of the variables represented by capital letters.

Taking a first-order Taylor-expansion of the log return definition, Campbell and Shiller (1988a) obtain the approximation:

$$r_{t+1} \approx k + \rho(p_{t+1} - d_{t+1}) - (p_t - d_t) + g_{t+1}, \tag{3.2}$$

where $p_t - d_t$ is the log price-dividend ratio, $g_{t+1} = \Delta d_{t+1}$ is one-period dividend growth, and k is a linearization coefficient given by:

$$k = -\log(\rho) - (1-\rho)\log(1/\rho - 1)$$
$$\text{with } \rho = 1/\left(1 + \exp\left(\overline{p-d}\right)\right),$$

and $\overline{p-d}$ denotes the historical average of log price-dividend ratio up to time t.

Assuming equation (3.2) holds exactly and rewriting it with $p_t - d_t$ on the left-hand side, we have a recursive equation upon which we can take conditional expectations to derive a log-linear equivalent specification to equation (3.1):

$$p_t - d_t = \frac{k}{1-\rho} + \tag{3.3}$$
$$\mathrm{E}\left[\sum_{j=0}^{\infty} \rho^j(-r_{t+j+1} + g_{t+j+1})\right].$$

Multiplying each side by -1 yields an approximate log-linear identity for the dividend yield:

$$dy_t = d_t - p_t = -\frac{k}{1-\rho} + \tag{3.4}$$
$$\mathrm{E}_t\left[\sum_{j=0}^{\infty} \rho^j(-g_{t+j+1} + r_{t+j+1})\right], \tag{3.5}$$

where dy_t is the log dividend yield at time t.

The relationship between the log dividend yields, expected dividend growth and conditional expected returns is evident from equation (3.5). Intuitively, a low current log dividend yield dy_t implies that either future dividend growth rates are high, or future discount rates are low, or both.

Thus if we regress future dividend growth rates on current log dividend yields dy_t, we expect to see negative coefficients; and if we regress future returns on current log dividend yields dy_t, we expect to see positive coefficients.

This relationship provide us with a benchmark for evaluating the improved predictive power of the dynamic dividend growth model that we describe next.

3.2 Dividend Growth Model

Say that dividend growth is a latent (unobservable) process resulting from the complex interaction of technology, the business cycle, financial leverage and management decisions. In other words, it is unknown *ex ante* and time-varying.

3. Dividend Growth & Return Modeling

The dividend growth rate forecast is written:

$$g_{t+1} = \alpha + \beta_t dy_t + \varepsilon_t \qquad (3.6)$$

where dy_t is the log dividend yield, and g_{t+1} is the one-year ahead dividend growth rate.

Estimating regression (3.6) using ordinary least squares (OLS) regression, raises at least three issues:

1. The look-back period used to get the best coefficient estimate is set arbitrarily. As the rolling window shifts forward, information is lost, which may lead to abrupt changes in the coefficient estimates;
2. The dividend yield on the RHS is an endogenous and stochastic regressor, causing OLS coefficient estimates to be biased (see Stambaugh (1999));
3. OLS estimates do not take estimation errors into account to improve new parameter estimates.

A state-space dynamic linear model addresses these issues:

1. We use the prior updating methodology common to all Kalman filtering techniques Kalman (1960) to integrate new data as and when it arrives without having to drop historical information abruptly.
2. Endogeneity is addressed by the iterative nature of the Bayesian framework.
3. Estimation-error correction is introduced by recursively calculating the conditional distribution of the quantities of interest and taking into account how much ant new observation differs from the previous estimate.

3.2.1 Kalman filter

The dynamic linear model consist of the following two equations:

$$x_t = f_t x_{t-1} + \omega_t \qquad \text{(state equation)}, \qquad (3.7)$$

$$g_t = h'_t x_t + \upsilon_t \qquad \text{(observation equation)}, \qquad (3.8)$$

where x_t is the unobservable state of the system (i.e. the true dividend growth rate stochastic process) at time t, f_t is the evolution function, g_t is the observed cash flow growth rate at time t, and h'_t is a vector of explanatory variables.

ω_t and υ_t are two independent white noise sequences with zero mean and unknown variances, W and V respectively. Matrix W is usually diagonal which translates to independent random walks for the regression coefficients.

To obtain a forecast mean and variance of dividend growth, g_t, we need to solve the posterior distribution of unknown parameters $\Lambda = (f_t, V, W)$, which can be expanded with the state variables for numerical tractability.

3.2.2 Estimation and sampling

The Markov Chain Monte Carlo (MCMC) analysis of dynamic models is accomplished by decomposing the sampling scheme into iteratively sampling the states, conditional on the fixed parameters and then sampling

3. Dividend Growth & Return Modeling

the fixed parameters, conditional on the states.

In this vein, we use a Bayesian Gibbs sampling algorithm to produce the joint posterior distribution by iteratively sampling from two simple distributions.

The first distribution includes the state variables, which estimates the underlying unobserved components.

The second one contains the observations and control variables, and is estimated by linear regression. The resulting posterior distribution $p\left(x_{1:t}, \Lambda | g_{1:t}, \text{prior}\right)$ is sampled from the two simple distributions as mentioned above.

The first part is the most challenging, as the state variables in the first distribution represents the entire path of the unobserved cash flows for any new information, conditional on the control variables, the latent variable and the parameters.

To solve this issue, we use the Forward Filtering Backwards Sampling (FFBS) (Frühwirth-Schnatter (1994); Carter and Kohn (1994)) method which incorporates the use of the Kalman filter. FFBS provides an efficient way to sample a path of state variables conditioning on available information. More details of the procedure is presented in Appendix.

Finally, we use diffuse priors for the parameters, and adopt an exact treatment given by Koopman and Durbin (2003) to eliminate any large rounding errors, as also detailed in Appendix. Our Gibbs sampler uses $2,000$ runs for the initial burn-in, followed by $5,000$ iterations to simulate the posterior distribution.

Next, we describe the model of expected returns that links our dividend growth forecast with the pricing equation describe above.

3.3 Expected Return Model

To relate the one-period dividend growth forecast thus obtained to expected returns, we make the simplifying assumption that the average of all one-period forecasts of g until time t can be used as the expected dividend growth from t to ∞ in pricing equation (3.5). In other words, the expected value of a random variable is assumed to be the long-run average value of repetitions of the experiment it represents. Hence, we write:

$$\mathrm{E}[g_{t+j+1}] = \bar{g}_{t+1} \tag{3.9}$$

Using equation (3.9) in equation (3.5), we get:

$$dy_t = -\frac{k}{1-\rho} + \mathrm{E}_t\left[\sum_{j=0}^{\infty} \rho^j (r_{t+j+1})\right] \tag{3.10}$$

$$-\sum_{j=0}^{\infty} \rho^j \bar{g}_{t+1}, \tag{3.11}$$

3. Dividend Growth & Return Modeling

which can be further simplified and re-arranged to:

$$\sum_{j=0}^{\infty} \rho^j \mathrm{E}_t \left[(r_{t+j+1}) \right] = dy_t + \tag{3.12}$$

$$\frac{\overline{g}_{t+1}}{1-\rho} + \frac{k}{1-\rho}. \tag{3.13}$$

Equation (3.12) indicates that conditional expected returns are a function of the current log dividend yield and the mean of the dividend growth forecasts up to time $t+1$.

From equation (3.5), we know that future returns are positively correlated with current log dividend yield (dy_t) and negatively correlated with future log dividend growth. If future dividend growth is constant (as well as the estimate of the unconditional mean of the log price-dividend ratio), then equation (3.12) only depends on the current dividend yield, and expected returns can be estimated by a recursion of future returns on the current log dividend yields alone, or, following Fama and French (1988) and Cochrane (2008):

$$r_{t+1} = \alpha_{dy} + \beta_{dy} dy_t + \varepsilon_{t+1} \tag{3.14}$$

If however, future dividend growth changes over time, current log dividend yield is not a sufficient predictor of future returns.

Consequently, we create a 'growth adjusted' dividend yield by adding the dividend growth term in (3.12) to the log dividend yield in (3.14), that is:

$$dy_t^{adj} = dy_t + \frac{\overline{g}_{t+1}}{1-\rho}. \tag{3.15}$$

The dividend-growth-adjusted expected return model is written:

$$r_{t+1} = \alpha_{adj} + \beta_{adj} dy_t^{adj} + \varepsilon_{t+1}. \tag{3.16}$$

For a given level of expected returns, when expected cash flow growth increases (decreases), current prices go up (down), and the dividend yield decreases (increases). hence, with the growth-adjusted dividend yield as the return predictor, any change in the current log dividend yield is partially offset by a change in future dividend growth, making dy_t^{adj} less sensitive to fluctuations in dividend growth forecasts. As a result, adding $\frac{\overline{g}_{t+1}}{1-\rho}$ to dy_t controls for the impact of fluctuations in expected dividend growth on expected returns, making any net changes in dividend yield more directly related to changes in expected returns.

Next, we describe the data we use to test the predictive power of our model.

4. Data

4. Data

Our empirical analysis are based on annual S&P 500 index and its constituents. Annual data is retrieved from Datastream for the 1962-2016 period.

Following standard practice, annual dividends D_t are summed over the past twelve months to remove seasonality in the dividend series. The log dividend yield is given by:

$$dy_t = \log\left(\frac{D_t}{P_t}\right). \qquad (4.1)$$

The continuously compounded dividend growth rates g_t is computed as:

$$g_t = \log\left(\frac{D_t}{D_{t-1}}\right), \qquad (4.2)$$

which produces a time-series of annual log dividend growth.

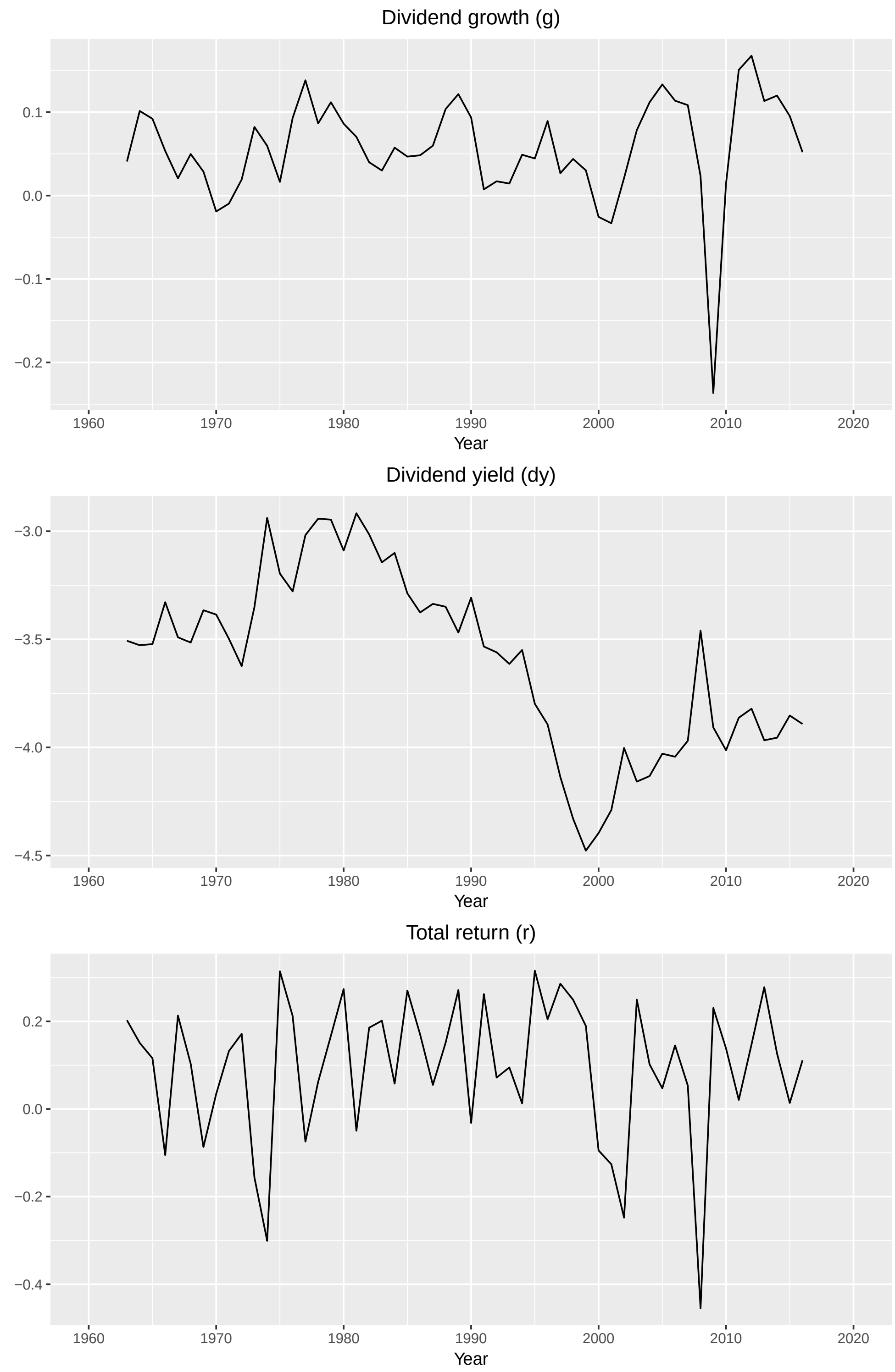
Figure 1 plots the annual time series of value-weighted portfolio dividend growth, dividend yield, and total returns (including capital gains and dividend income). Significant losses and increased volatility at the time of the economic downturns are clearly visible: the dividend yield (dy) exhibits a continuous decline from the 1980s, followed by an increase after the burst of the tech bubble in 2000, reaching a new peak in 2008 around the advent of the global financial crisis and the stock market crash. Conversely, dividend growth (g) does not exhibit a strong trend over time but declines sharply during the recent global financial crisis period 2008-2009. Total returns (r) follow the known business cycle, with sharp drops in bad times such as 1974, 2001 and 2008. Casual observation of figure 1 suggests that total returns are negatively related to dividend yields and positively related to dividend growth, as proposed in equation (3.5).

Descriptive statistics are reported in table 1. We note that log dividend yield is the most volatile variable of interest, total returns have almost zero autocorrelation, log dividend yield are highly autocorrelated (0.901), while dividend growth is weakly autocorrelated (0.435) at the 1% significance level.

Next, we report our dividend and return forecasts compared with static models, followed by a comparison of the the return forecasts afforded by different dividend growth models.

4. Data

Figure 1: S&P500 log returns, dividend yields and growth, 1962-2016



4. Data

Table 1: Descriptive statistics, S&P500, 1962-2016

	Mean	Std	Min	Max	AR1
Dividend growth (g)	0.057	0.061	-0.237	0.168	0.435
Dividend yield (dy)	-3.601	0.413	-4.478	-2.917	0.901
Total return (r)	0.095	0.16	-0.455	0.316	0.007

Source: CRSP

5. Results

5. Results

In this section, we report the forecasting results for our dynamic linear dividend growth model (DLM) compared to OLS regression (Reg) and moving average (MA) models at the portfolio and firm level, using a 10, 20 an 30 year rolling window in section 5.1. We then examine whether our dynamic dividend-growth-adjusted model of expected returns can improve the estmation of expected return recursion in section 5.2.

5.1 Dividend growth forecasts

We only report coefficients estimates in this section but the algorithm is able to produces the posterior distribution of all parameters and latent variables of the model described in (3.7) and (3.8).

5.1.1 Coefficient estimates and volatility

Figure 2 shows the coefficients estimates for the DLM and Reg models on both full sample and sample excluding the sharp decline of dividend growth in 2009. The DLM model consistently produces negative coefficients, while the signs of coefficients estimated by Reg models vary frequently over time. The coefficients generated by regression with 30 years look-back period (Reg-30) on sample excluding the sharp decline of dividend growth in 2009 are even all positive, as shown in right panel of Figure 2.

According to equation (3.5), future growth rates and log dividend yields are negatively related i.e. the "true" value of the coefficient should be negative. This suggests that OLS estimates are severely biased, as they produce both positive and negative signs across time. Only coefficients estimated by the DLM model are in line respect this relation, meaning they are likely to be closer to the true coefficient values. Test statistics of the OLS model reported in appendix confirm that it is the OLS parameter estimates that are severly biased, confirming the inadequacy of static models when estimating future dividend growth.

DLM coefficient estimates are also less volatile than those estimated by OLS, in both the full sample and sample excluding the sharp decline of dividend growth in 2009. DLM estimates become stable as time passes and more 'learning' takes place. When a shock occurs in 2009, the DLM model self-corrects by taking into account its latest forecasting error.

Coefficient estimates for the OLS regressions move more erratically because they are more influenced by new data. The length of the look-back period also makes estimates based on shorter windows more volatile. The 2009 spike shows that OLS estimates are very sensitive to extreme values.

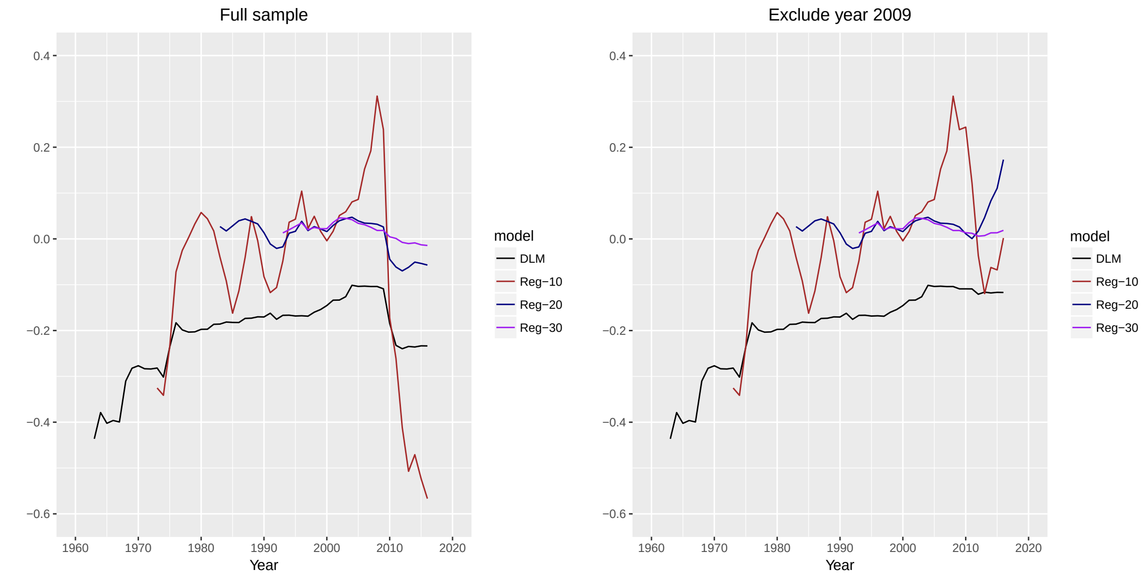
5.1.2 Root-mean squared error

The better forecasting power of the DLM is confirmed by looking at the root-mean squared errors (RMSE) of the different models. The RMSE is used to compare estimation errors and prediction errors of different models and is written:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}},$$

5. Results

Figure 2: Coefficient Estimation



where $\hat{y}_t$ is the *estimated* value of observation y_t when computed in-of-sample, and is the *predicted* value for observation y_t when the calculations are performed out-of-sample. Model M_1 is always preferred over model M_2 if, out-of-sample, $RMSE(M_1) < RMSE(M_2)$.

In-sample, the DLM model perform much better than OLS models using any rolling window length as shown in Table 2. It is not a surprise considering that DLM models are built to implement prediction-error corrections. Still, we note that precision is greater by several orders of magnitude.

Table 3 shows the out-of-sample performance of the DLM, OLS and moving average (MA) models. Using both the full sample, the DLM model still generates the lowest RMSE, 0.054, while the best OLS and MA models, Reg-30 and MA-10, have an RMSE of 0.083 and 0.067 respectively. The same hold when excluding the 2009 shock. These results indicate that the DLM is always preferable to OLS or MA models for the purpose of forecasting dividend growth.

Figure 3 plots the out-of-sample RMSE across calendar year for DLM, regression and moving average models using a value-weighted portfolio. Although the results from all models show spikes in 2009, the magnitude of the RMSE for the DLM model is significantly lower. The overall distribution of the RMSE for the DLM is also less volatile than for OLS and MA models. The DLM is more robust to the business cycle.

Finally, figure 4 and 5 illustrate firms level RMSE distribution over time, for DLM and OLS models, respectively. Similar superiority of the DLM is found at the firm level. A more detailed time series of descriptive statistics is presented in Appendix.

5. Results

Figure 3: Portfolio level RMSE by Year

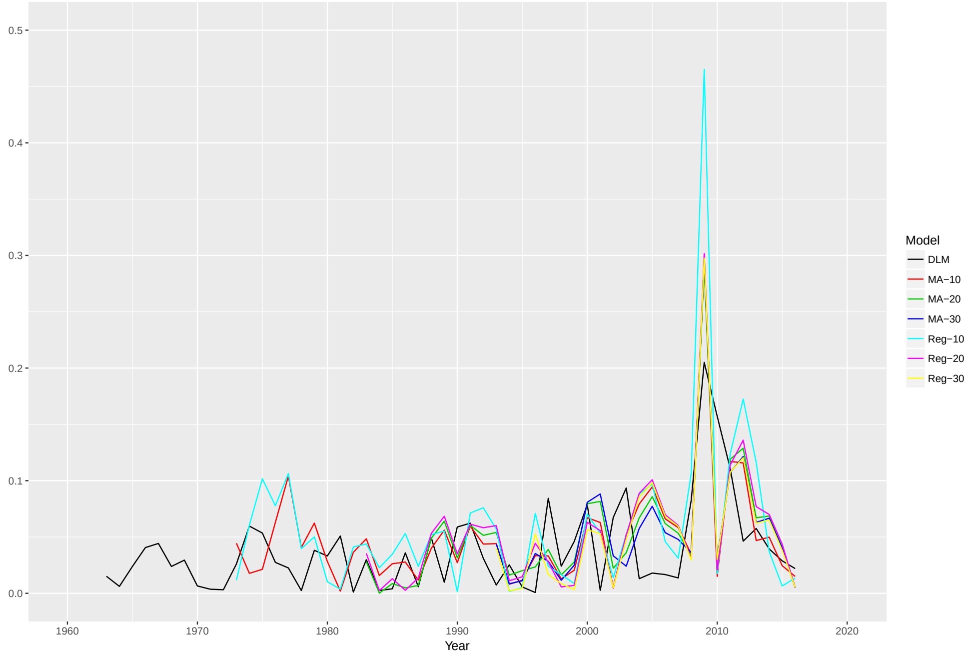
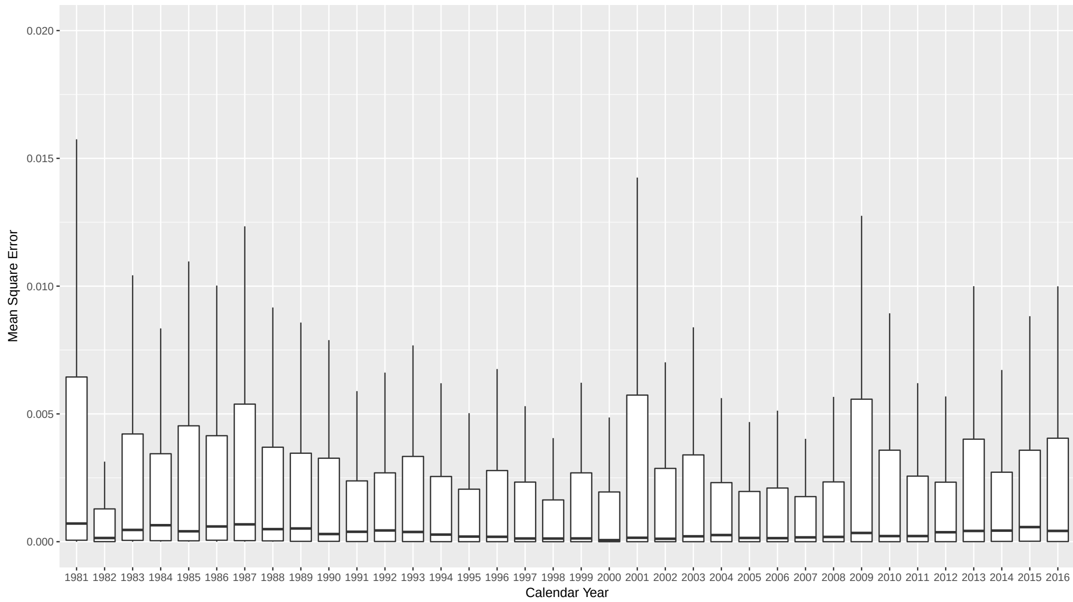


Figure 4: Firms Level RMSE by DLM



5. Results

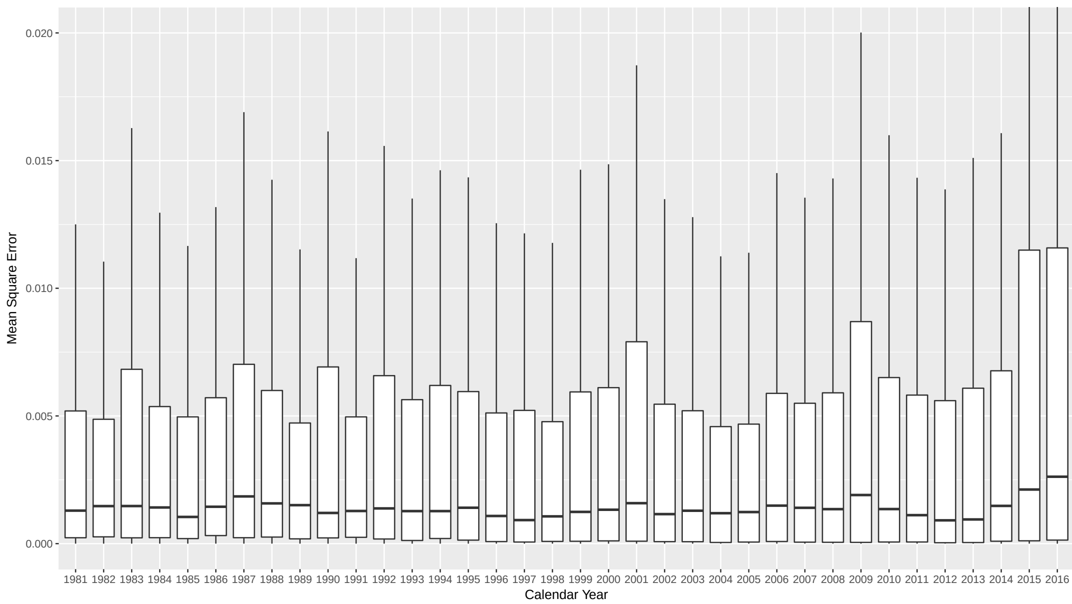
Table 2: In-sample RMSE

	DLM	Reg-10	Reg-20	Reg-30
Full Sample	6.909e-08	0.042	0.05	0.05
Exclude Yr2009	5.175e-07	0.037	0.041	0.042

Table 3: Out-of-sample RMSE

	DLM	Reg-10	Reg-20	Reg-30	MA-10	MA-20	MA-30
Full Sample	0.054	0.094	0.076	0.083	0.067	0.073	0.082
Exclude Yr2009	0.042	0.058	0.053	0.056	0.048	0.052	0.054

Figure 5: Firms Level RMSE by OLS regression



Next, we compare return forecasts implied by the dividend yield and growth-adjusted dividend yield.

5.2 Return forecasts

Having established the superiority of the DLM for the purpose of forecasting dividend growth, we consider whether the dividend-growth-adjusted dividend yield performs better than the unadjusted version as a predictor of returns, and whether modeling dividend growth as a latent process to be estimated by a Kalman filter thus improves the predictability of returns.

Following equation (3.12), $\overline{g}_{t+1}$ is computed using 10-year moving averaged of the dividend growth forecasts up to time $t+1$ (which roughly corresponds with a full business cycle).

5. Results

Figure 6: Adjusted (by DLM model) vs. Unadjusted Log Dividend Yield

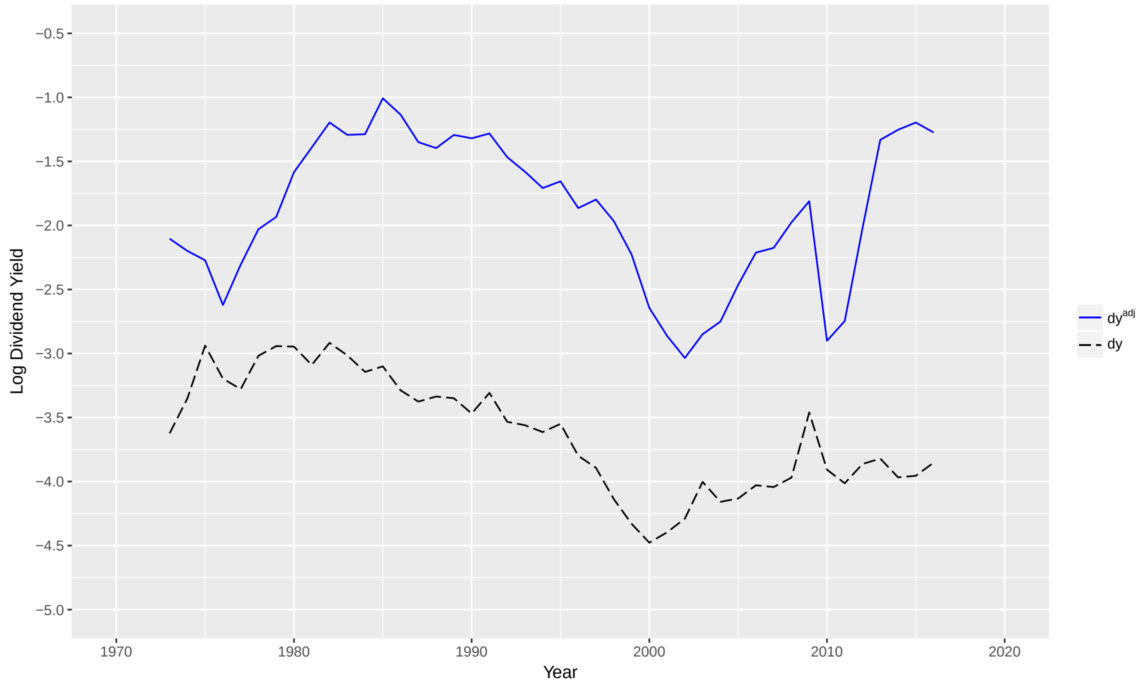


Figure 6 shows that the adjusted (DLM version) and unadjusted log dividend yield are highly correlated but that the dividend-growth-adjusted version is more volatile. The coefficient of correlation between dy_t^{adj} and dy_t is 0.54, whereas the standard deviations of dy_t^{adj} and dy_t are 0.58 and 0.45, respectively.

dy_t^{adj} is more volatile than dy_t for two reasons:

1. Expected returns are positively correlated with future dividend growth;
2. The current log dividend yield is positively correlated with expected returns but negatively correlated with future dividend growth, hence, shocks to future dividend growth accompanied by shocks to expected returns have opposite effects which dampens the change in the dividend yield. Adding the dividend growth adjustment $\frac{\bar{g}_{t+1}}{1-\rho}$ to dy_t offsets this effect.

Figure 7 plots the 10-year moving average of predicted dividend growth $\bar{g}_{t+1}$. We note that following pessimistic dividend growth prospects of the 1970s, over the last 40 years, $\bar{g}_{t+1}$ oscillated between 0.02 and 0.08.

Table 4 reports the return prediction results using the dividend-growth-adjusted (DLM version) and the unadjusted log dividend yield.

The slope estimate of the regression with dy_t^{adj} from DLM model (β_{adj}^{DLM}=0.105) is very close to that of the dy_t (β_{unadj}=0.133). This fact, together with the result that dy_t^{adj}

5. Results

Figure 7: Dividend Growth Forecasts, 10-year moving average of $\bar{g}_{t+1}$

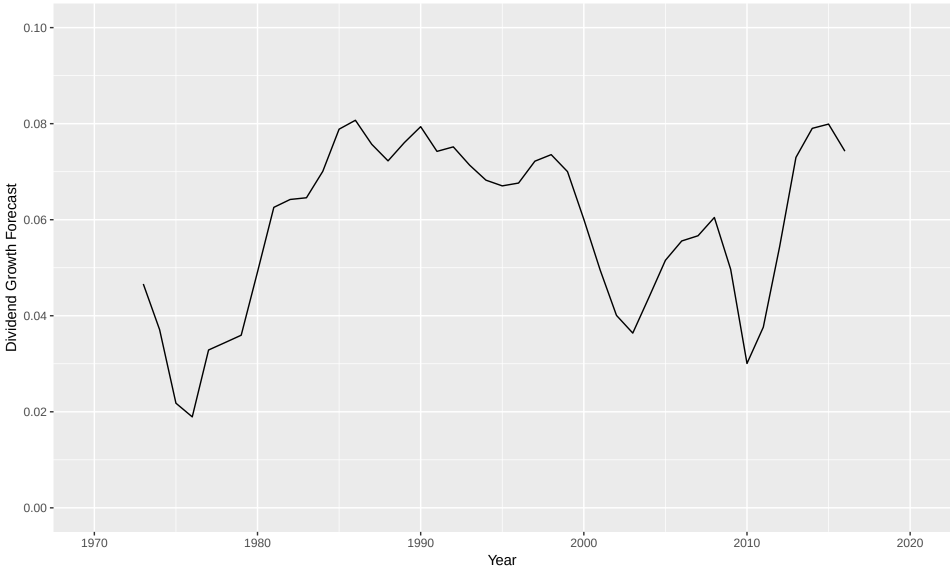


Table 4: Return Predictability

	Slope	t-stat	R^2_{IS}	R^2_{OOS}
Adjusted	0.105	2.224	0.121	0.186
Unadjusted	0.133	2.034	0.098	0.048

is more volatile than dy_t, indicates that estimates of future returns based on the growth-adjusted log dividend yield vary more than those linked to the unadjusted version, and the former version successfully isolate the fluctuation due to variation in expected returns. Hence, this increase in variability of return prediction is the reason underlying the superior performance of the adjusted log dividend yield.

The last column of Table 4 shows the out-of-sample performance of these forecasts, using an out-of-sample R^2 statistic that can be compared with the in-sample R^2statistic. This is as defined by Campbell and Thompson (2008):

$$R^2_{OOS} = 1 - \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r}_t)^2},$$

where $\hat{r}_t$ is the fitted value from a predictive regression estimated through period $t-1$, and $\bar{r}_t$ is the historical average return estimated through period $t-1$.

The growth-adjusted log dividend yield outperforms the unadjusted version as a predictor of expected returns both in-sample and out-of-sample. The dividend-growth-adjusted log dividend yield is able to explain 12.1% of the variation in returns whereas unadjusted version explains 9.8%.

In terms of statistical significance, the t-statistic for regression on adjusted log

5. Results

dividend yield equals 2.224, compared to a t-statistic of 2.034 for the unadjusted metric.

These results illustrate the benefits of isolating variations in the dividend yield caused by fluctuations in expected returns from those resulting from changes in dividend growth expectations.

The difference in the out-of-sample performance of the two candidate variables is notable. The adjusted log dividend yield delivers a positive and larger out-of-sample R^2 of 18.6%, as opposed to the unadjusted version which much smaller R^2 of 4.8%. Additionally, the correlation between log dividend yield dy_t and the adjustment $\frac{\bar{g}_{t+1}}{1-\rho}$ is is low at -0.27.

Finally, table 5 reports the in-sample and out-of-sample R^2 of return prediction results using dividend-growth-adjusted dividend yield with the static benchmark models used above i.e. OLS regression and moving average models. Using the growth-adjusted dividend yield with OLS and MA models with 10 and 20 years rolling window delivers a negative out-of-sample R^2, meaning that these predictions underperform the historical average return, or the simplest model. The OLS and MA model with a 30 years rolling window do generate a positive out-of-sample R^2 of 4.0% and 4.8%, but these are significantly lower than that of our DLM. This provides evidence of the synergistic effect between dy_t and $\frac{\bar{g}_{t+1}}{1-\rho}$ in the dynamic model.

This last results also illustrates why cash flow data is seldom used in the asset pricing literature since any adjustement for this synergy betweem dividend growth and dividend yields is lost with static models.

5. Results

Table 5: In-sample and Out-of-sample R^2 using dy^{adj} from regression and moving average models models

	MA-10	MA-20	MA-30	Reg-10	Reg-20	Reg-30
In-sample	0.111	0.089	-0.002	0.103	0.221	0.032
Out-of-sample	-0.152	-0.218	0.040	-0.053	-0.262	0.048

6. Conclusion

6. Conclusion

This paper shows that better cash flow forecasts using dynamic models is material to improving models of expected returns, especially insofar as changes in expected cash flows have multiple effects on expected returns. We separate the component of the dividend yield that varies with expected returns from the one that varies with expected dividend growth by removing dividend growth from the dividend-price ratio. The resulting variable leads to superior return forecasts than those obtained using the unadjusted dividend-price ratio. These results indicate that forecasting dividend growth matters when predicting stock returns and provide important evidence for return predictability.

By allowing for more accurate inference than the procedures traditionally employed in the literature, forecasting cash flows using dynamic linear modeling provides new evidence on the return and cash flow predictability inherent in the data. Specifically, we find that the dynamic relation between current log dividend yield and future dividend growth is significant, while predicted future dividend growth strongly predicts future returns. These finding stands in sharp contrast to the view expressed by a number of studies in the literature that cash flows are largely unpredictable.

Future applications of the state-space model of expected dividends described in this paper include exploiting its ability to predict cash flow volatility as well as its expected value and to relate estimates of the conditional dividend volatility to market discount rates.

It is also worth noting that the proposed dynamic cash flow model is not limited to dividend growth rates and dividend yields of public markets. It is a generalized cash flow forecasting method, which can be applied to other elements of cash flow statement and to private firms, in particular those firms that provide investors with long-term cash flows such as real estate or infrastructure.

A. Estimation Procedure

A. Estimation Procedure

A.1 Exact Initial Kalman Filter

Considering the following dynamic linear model:

$$x(t) = f_t x(t-1) + \upsilon(t)(\text{state equation}), \quad (A.1)$$

$$y(t) = g_t x(t) + \omega(t)(\text{observation equation}), \quad (A.2)$$

with the assumption of initial state $x(0) \sim N(a_0, P_0)$. In most practical applications, at least some of the elements of a_0 and P_0 are unknown. A general model for the initial state $x(0)$ is:

$$x(0) = a + A\boldsymbol{\delta} + R_0\eta_0, \quad \eta \sim N(0, Q_0), \quad (A.3)$$

where a is known, $\boldsymbol{\delta}$ is a vector of unknown quantities, the matrices A and R_0 are selection matrices, that is, they consist of columns of the identity matrix I_m; they are defined so that $A'R_0 = 0$. The matrix Q_0 is assumed to be positive definite and known.

The vector $\boldsymbol{\delta}$ is treated as a random variable and we assume that

$$\boldsymbol{\delta} \sim N(0, \kappa I_q), \quad (A.4)$$

where $\kappa \rightarrow \infty$. Considering the Kalman filter with initial conditions $a_0 = E[x(0)] = a$ and $P_0 = Var[x(0)]$ where

$$P_0 = \kappa P_\infty + P_*, \quad (A.5)$$

Here $P_\infty = AA'$ and $P^* = R_0 Q_0 R$. A simple approximate technique is to replace κ in (A.5) by an arbitrary large number and then use the standard Kalman filter, which was employed by Harvey and Phillips (1979). While the device can be useful for approximate exploratory work, it is not recommended for general use since it can lead to large rounding errors. To resolve this issue, we adopt an exact treatment given by Koopman and Durbin (2003).

Analogously to the decomposition of the initial matrix P_0 in (A.5), Koopman and Durbin (2003) shows that the mean square error matrix P_t has the decomposition

$$P_t = \kappa P_{\infty,t} + P_{*,t} + O(\kappa^{-1}), \quad t = 2, \dots, n, \quad (A.6)$$

where $P_{\infty,t}$ and $P_{*,t}$ do not depend on $\boldsymbol{\kappa}$. It will be shown that $P_{\infty,t} = 0$ for $t > d$, where d is a positive integer which in normal circumstances is small relative to sample size n. The consequence is that the standard Kalman filter applies without change for $t = d+1, \dots, n$ with $P_t = P_{*,t}$.

The decomposition (A.6) leads to the similar decompositions

$$F_t = \kappa F_{\infty,t} + F_{*,t} + O(\kappa^{-1}), \quad (A.7)$$

$$M_t = \kappa M_{\infty,t} + M_{*,t} + O(\kappa^{-1}), \quad (A.8)$$

and, since $F_t = g_t P_t g_t{}' + H_t$ and $M_t = P_t g_t{}'$, we have

$$F_{\infty,t} = g_t P_{\infty,t} g_t{}', \quad F_{*,t} = g_t P_{*,t} g_t{}' + H_t,$$
$$M_{\infty,t} = P_{\infty,t} g_t{}', \quad M_{*,t} = P_{*,t} g_t{}', \quad (A.9)$$

for $t = 1, \dots, d$. The Kalman filter derived as $\kappa \rightarrow \infty$ is called the exact initial Kalman filter. The derivation of the exact initial Kalman filter is based on the expansion for $F_t^{-1} = [\kappa F_{\infty,t} + F_{*,t} + O(\kappa^{-1})]^{-1}$ as a power

A. Estimation Procedure

series in κ^{-1}, that is

$$F_t^{-1} = F_t^{(0)} + \kappa^{-1} F_t^{(1)} + \kappa^{-2} F_t^{(2)} + O(\kappa^{-3}), \quad \text{(A.10)}$$

for large κ. Since $I_p = F_t F_t^{-1}$ we have

$$I_p = (\kappa F_{\infty,t} + F_{*,t} + \kappa^{-1} F_{a,t} + \kappa^{-2} F_{b,t} + \ldots) \times (F_t^{(0)} + \kappa^{-1} F_t^{(1)} + \kappa^{-2} F_t^{(2)} + \ldots).$$

On equating coefficients of κ^j for $j = 0, 1, 2, \ldots$ we obtain

$$\begin{aligned} F_{\infty,t} F_t^{(0)} &= 0, \\ F_{*,t} F_t^{(0)} + F_{\infty,t} F_t^{(1)} &= I_p, \\ F_{a,t} F_t^{(0)} + F_{*,t} F_t^{(1)} + F_{\infty,t} F_t^{(2)} &= 0, \quad \text{etc.} \end{aligned} \quad \text{(A.11)}$$

To solve equation (A.11) when $F_{\infty,t}$ is nonsingular, we have

$$F_t^{(0)} = 0, \quad F_t^{(1)} = F_{\infty,t}^{-1}, \quad \text{(A.12)}$$

$$F_t^{(2)} = -F_{\infty,t}^{-1} F_{*,t} F_{\infty,t}^{-1}. \quad \text{(A.13)}$$

The matrices $K_t = f_t M_t F_t^{-1}$ and $L_t = f_t - K_t g_t$ depend on the inverse matrix F_t^{-1} so they also can be expressed as power series in κ^1. We have

$$K_t = f_t[\kappa M_{\infty,t} + M_{*,t} + O(\kappa^{-1})](\kappa^{-1} F_t^{(1)} + \kappa^{-2} F_t^{(2)} + \ldots),$$

so

$$K_t = K_t^{(0)} + \kappa^{-1} K_t(1) + O(\kappa^{-2}), \quad \text{(A.14)}$$

$$L_t = L_t^{(0)} + \kappa^{-1} L_t^{(1)} + O(\kappa^{-2}), \quad \text{(A.15)}$$

where

$$K_t^{(0)} = f_t M_{\infty,t} F_t^{(1)}, \quad \text{(A.16)}$$

$$L_t(0) = f_t - K_t(0) g_t, \quad \text{(A.17)}$$

$$K_t^{(1)} = f_t M_{*,t} F_t^{(1)} + f_t M_{\infty,t} F_t^{(2)}, \quad \text{(A.18)}$$

$$L_t(1) = -K_t(1) g_t. \quad \text{(A.19)}$$

(A.20)

Consequently, on letting $\kappa \to \infty$, the updates for $P_{\infty,t+1}$ and $P_{*,t+1}$ are given by

$$\begin{aligned} P_{\infty,t+1} &= f_t P_{\infty,t} L_t^{(0)\prime}, \\ P_{*,t+1} &= f_t P_{\infty,t} L_t^{(1)\prime} + f_t P_{*,t} L_t^{(0)\prime} + R_t Q_t R_t', \end{aligned} \quad \text{(A.21)}$$

for $t = 1, \ldots, n$. The matrix P_{t+1} also depends on terms in κ^{-1}, κ^2, etc. But these terms will not be multiplied by κ or higher powers of κ within the Kalman filter recursions. Thus the updating equations for P_{t+1} do not need to take account of these terms.

This establishes that for nondegenerate models there is a value d of t such that $P_{\infty,t} \neq 0$ for $t \leq d$ and $P_{\infty,t} = 0$ for $t > d$. Thus when $t > d$ we have $P_t = P_{*,t} + O(\kappa^{-1})$ so on letting $\kappa \to \infty$ we can use the standard Kalman filter starting with $a_{d+1} = a_{d+1}^{(0)}$ and $P_{d+1} = P_{*,d+1}$.

A.2 Bayesian Gibbs sampling algorithm

A.2.1 Unknown Parameters of Concern

In a classical framework, one typically starts by estimating the unknown parameters by maximum likelihood. Suppose that we have n random vectors, $Y_1, \ldots, Y_n$, whose distribution depends on unknown variance parameter $\psi = (\sigma^2, \omega^2)$. We will denote the joint density of the observations for a particular value of the parameter, by $p(y_1, \ldots, y_n; \psi)$. The likelihood function is defined to be the probability density of the observed data read as a function of ψ, i.e., denoting the likelihood by L, we can write $L(\psi) = \text{const.} * p(y_1, \ldots, y_n; \psi)$. For a state space model, it is convenient to write the

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joint density of the observations in the form

$$p(y_1, \ldots, y_n; \psi) = \prod_{t=1}^{n} p(y_t | y_{1:(t-1)}; \psi),$$

where $p(y_1, \ldots, y_n; \psi)$ is the conditional density of y_t given the data up to time $t-1$, assuming that ψ is the value of the unknown parameter. Knowing that the terms occurring the right hand side of the probability density with mean a_t and variance Q_t, the loglikelihood can be writen as

$$l(\psi) = -\frac{1}{2}\sum_{t=1}^{n} log|Q_t|$$

$$-\frac{1}{2}\sum_{t=1}^{n}(y_t - a_t)' Q_t^{-1}(y_t - f_t),$$

where the a_t and the Q_t depend implicitly on ψ. To obtain the MLE of unknown paratmeter ψ, the loglikelihood is numerically maximized:

$$\hat{\psi} = argmaxl(\psi).$$

Since the unknown parameter ψ occurrs in the definition of the state space models of interest, we minimize the compound function obtained in two steps by building the state space models first, and then evaluating its negative loglikelihood, as a function of the matrices defining it. A suggestive graphical representation is as follows:

$$\psi \Rightarrow \text{state space models} \Rightarrow l(\psi).$$

A.2.2 Distribution from State Variables

The state variables for the unobserved equity payout of any new infrastructure project are simulated conditioning on latent variables, the parameters and the control inputs. Specifically, we need to sample from the distribution of states $x(1), \ldots, x(T)$ conditioning on the parameters and observed data. The FFBS method is used, which provides an efficient way to sample a path of state variables defined by the state space model as mentioned before.

The setup described above enables us to use the Kalman filter to compute the filtered distribution of $x(1), \ldots, x(T)$. The Kalman filter generates the distribution of $x(t)$ conditioning on $Y(t)$, for any time t. However, $x(t)$ have to be sampled conditioning on the entire time series $Y(1), \ldots, Y(T)$. This is archieved by the backward smoother, which effectively runs a Kalman filter backwards, beginning at time T. The conditional distribution of the state vector is given by:

$$p\left[x(1)\ldots x(T)|Y^T\right] = \tag{A.22}$$

$$p\left[x(T)|Y^T\right]\prod_{t=1}^{T-1} p\left[x(t)|Y^t, x(t+1)\right], \tag{A.23}$$

where $Y^t = (Y(1), \ldots, Y(t))$ consists of the observations up to time t.

Let's define $\hat{x}_{t|i} = E[x(t)|Y^i]$ and $V_{t|i} = Var[x(t)|Y^i]$ as mean and variance of $x(t)$ conditional on the observations up to

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time i. Note that all conditional distributions are assumed normal and hence fully characterized by their means and variances (Kalman (1960); Anderson and Moore (1979)) for simplicity. When implementing the methods, covariance matrix will be considered if relevant and the variables will be transformed if distributions are not normal.

In the forward filtering step, for $t = 1, ..., T$, we calculate $\hat{x}(t|t)$ and $V(t|t)$ by iterating on the forward filter, through a predicting and an updating part. The predicting part contains the two equations:

$$\hat{x}_{t|t-1} = f_t \hat{x}_{t-1|t-1}, \tag{A.24}$$

and

$$V_{t|t-1} = V_{t-1|t-1} + \sigma^2. \tag{A.25}$$

For the updating part, as long as $x(t)$ remains unobserved, we update

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K\left[Y(t) - g_t \hat{x}_{t|t-1}\right], \tag{A.26}$$

and

$$V_{t|t} = V_{t|t-1}\left(1 - g_t K\right), \tag{A.27}$$

where the Kalman gain K is given by

$$K = \frac{g_t V_{t|t-1}}{1 + g_t^2 V_{t|t-1}}. \tag{A.28}$$

To estimate the unobserved or missing equity payout, we need to force $\gamma_c = 0$ if there is no information available. We then obtain $\hat{x}_{t|t} = \hat{x}_{t|t-1}$ and $V_{t|t} = Vt|t-1$. For observed equity payouts, $\hat{x}_{t|t} = x_{obs}(t)$ and $s_{t|t} = 0$.

In the backward sampling part, $x(T)$ is started to be simulated from the normal distribution with mean $\hat{x}_{T|T}$ and variance $V_{T|T}$, as described before. For $t = T-1, ..., 1$, we simulate $x(t)$ from the conditional distribution $p\left[x(t)|Y^t, x(t+1)\right]$, derived from a filtering problem where the sample of $x(t+1)$ provides an additional observation of $v(t)$. The derivation is similar to the updating part mentioned above.

A.2.3 Distribution for Observations

The distributions of observations $Y(1), ..., Y(t)$ are sampled conditioning on the unknown states $x(t)$ and parameters. This distribution is proportional to its likelihood function and the properties of posterior distribution of linear regressions can be used here.

A.3 Firm Level RMSE Distribution

The following two tables show the descriptive statistics of the firm level out-of-sample RMSE across calendar year for DLM and regression models, using a value-weighted portfolio. The median, standard deviation and maximum of RMSE for DLM model is lower than those for regression model in most calendar years.

B. Statistical Appendix

B. Statistical Appendix

To further study the coefficient estimate of OLS regression and validate the model assumptions, we run it on the full S&P 500 data and investigate the regression diagnostic tests. Table 6 presents the diagnostic test statistics and corresponding p-values.

The results of Breusch-Pagan test shows that there is no heteroskedasticity, meaning the assumption of homoskedasticity is satisfied. However, the p-value of t-test is 0.857, indicating the coefficient estimate is not significant.

The Shapiro test statistic rejects the normal assumption of residual and the Box-Ljung test statistic shows the evidence of significant residual autocorrelation.

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Table 6: Diagnostic tests for OLS regression model, S&P500, 1962-2016

	T test	Breusch-Pagan test	Shapiro test	Box-Ljung test
Test statistic	-0.181	0.067	0.859	34.72
P-value	0.857	0.796	0.000	0.000

Table 7: Descriptive statistics of RMSE for the DLM model, S&P500 constituents, 1981-2016

Year	Mean	Median	Std	Min	Max
1981	0.034	0.001	0.009	0	0.074
1982	0.004	0	0.014	0	0.12
1983	0.014	0	0.017	0	0.133
1984	0.009	0.001	0.024	0	0.2
1985	0.012	0	0.014	0	0.112
1986	0.017	0.001	0.02	0	0.183
1987	0.01	0.001	0.015	0	0.149
1988	0.011	0	0.021	0	0.215
1989	0.009	0.001	0.013	0	0.095
1990	0.008	0	0.019	0	0.204
1991	0.009	0	0.032	0	0.336
1992	0.015	0	0.024	0	0.182
1993	0.008	0	0.026	0	0.256
1994	0.005	0	0.013	0	0.157
1995	0.006	0	0.028	0	0.337
1996	0.006	0	0.02	0	0.249
1997	0.005	0	0.022	0	0.215
1998	0.005	0	0.015	0	0.143
1999	0.007	0	0.021	0	0.171
2000	0.008	0	0.02	0	0.268
2001	0.025	0	0.026	0	0.326
2002	0.005	0	0.017	0	0.196
2003	0.009	0	0.025	0	0.219
2004	0.008	0	0.016	0	0.15
2005	0.009	0	0.011	0	0.116
2006	0.005	0	0.015	0	0.144
2007	0.018	0	0.018	0	0.196
2008	0.006	0	0.021	0	0.188
2009	0.013	0	0.028	0	0.283
2010	0.01	0	0.026	0	0.34
2011	0.006	0	0.018	0	0.189
2012	0.008	0	0.017	0	0.187
2013	0.008	0	0.023	0	0.238
2014	0.009	0	0.022	0	0.237
2015	0.009	0.001	0.032	0	0.297
2016	0.009	0	0.028	0	0.295

B. Statistical Appendix

Table 8: Descriptive statistics of RMSE for the regression model, S&P500 constituents, 1981-2016

Year	Mean	Median	Std	Min	Max
1981	0.005	0.001	0.166	0	1.714
1982	0.006	0.001	0.03	0	0.42
1983	0.007	0.001	0.062	0	0.632
1984	0.008	0.001	0.03	0	0.313
1985	0.006	0.001	0.046	0	0.48
1986	0.008	0.001	0.087	0	0.974
1987	0.007	0.002	0.034	0	0.378
1988	0.008	0.002	0.043	0	0.363
1989	0.006	0.002	0.065	0	0.968
1990	0.008	0.001	0.037	0	0.48
1991	0.011	0.001	0.045	0	0.601
1992	0.01	0.001	0.115	0	1.723
1993	0.009	0.001	0.032	0	0.422
1994	0.006	0.001	0.015	0	0.106
1995	0.009	0.001	0.022	0	0.253
1996	0.006	0.001	0.02	0	0.169
1997	0.008	0.001	0.016	0	0.146
1998	0.006	0.001	0.019	0	0.246
1999	0.009	0.001	0.025	0	0.359
2000	0.008	0.001	0.028	0	0.268
2001	0.01	0.002	0.17	0	2.907
2002	0.007	0.001	0.018	0	0.209
2003	0.008	0.001	0.038	0	0.566
2004	0.006	0.001	0.035	0	0.4
2005	0.005	0.001	0.105	0	2.052
2006	0.006	0.001	0.025	0	0.43
2007	0.007	0.001	0.247	0	4.856
2008	0.008	0.001	0.019	0	0.193
2009	0.011	0.002	0.039	0	0.389
2010	0.008	0.001	0.041	0	0.48
2011	0.007	0.001	0.024	0	0.401
2012	0.007	0.001	0.038	0	0.48
2013	0.008	0.001	0.033	0	0.48
2014	0.009	0.001	0.04	0	0.576
2015	0.014	0.002	0.027	0	0.233
2016	0.012	0.003	0.036	0	0.54

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About EDHEC Infrastructure Institute-Singapore

About EDHEC Infrastructure Institute-Singapore

EDHEC*infra* addresses the profound knowledge gap faced by infrastructure investors by collecting and standardising private investment and cash-flow data and running state-of-the-art asset pricing and risk models to create the performance benchmarks that are needed for asset allocation, prudential regulation, and the design of new infrastructure investment solutions.

Origins

In 2012, EDHEC-Risk Institute created a thematic research program on infrastructure investment and established two Research Chairs dedicated to long-term investment in infrastructure equity and debt, respectively, with the active support of the private sector.

Since then, infrastructure investment research at EDHEC has led to more than 20 academic publications and as many trade press articles, a book on infrastructure asset valuation, more than 30 industry and academic presentations, more than 200 mentions in the press, and the creation of an executive course on infrastructure investment and benchmarking.

A testament to the quality of its contributions to this debate, EDHEC*infra*'s research team has been regularly invited to contribute to high-level fora on the subject, including G20 meetings.

Likewise, active contributions were made to the regulatory debate, in particular directly supporting the adaptation of the Solvency-II framework to long-term investments in infrastructure.

This work has contributed to growing the limited stock of investment knowledge in the infrastructure space.

A Profound Knowledge Gap

Institutional investors have set their sights on private investment in infrastructure equity and debt as a potential avenue toward better diversification, improved liability-hedging, and reduced drawdown risk.

Capturing these benefits, however, requires answering some difficult questions:

1. **Risk-adjusted performance measures** are needed to inform strategic asset allocation decisions and monitor performance;
2. **Duration- and inflation-hedging properties** are required to understand the liability-friendliness of infrastructure assets;
3. **Extreme risk measures** are in demand from prudential regulators, among others.

Today none of these metrics is documented in a robust manner, if at all, for investors in privately held infrastructure equity or debt. This has left investors frustrated by an apparent lack of adequate investment solutions in infrastructure. At the same time, policy-makers have begun calling for a widespread effort to channel long-term savings into capital projects that could support long-term growth.

To fill this knowledge gap, EDHEC has launched a new research platform, EDHEC*infra*, to collect, standardise, and produce investment performance data for infrastructure equity and debt investors.

Mission Statement

Our objective is the creation of a global repository of financial knowledge and investment benchmarks about infrastructure equity and debt investment, with a focus on delivering useful applied research in finance for investors in infrastructure.

We aim to deliver the best available estimates of financial performance and risks of reference portfolios of privately held infrastructure investments and to provide

About EDHEC Infrastructure Institute-Singapore

investors with valuable insights about their strategic asset allocation choices in infrastructure, as well as to support the adequate calibration of the relevant prudential frameworks.

We are developing unparalleled access to the financial data of infrastructure projects and firms, especially private data that is either unavailable to market participants or cumbersome and difficult to collect and aggregate.

We also bring advanced asset pricing and risk-measurement technology designed to answer investors' information needs about long-term investment in privately held infrastructure, from asset allocation to prudential regulation and performance attribution and monitoring.

What We Do

The EDHEC*infra* team is focused on three key tasks:

1. **Data collection and analysis**: we collect, clean, and analyse the private infrastructure investment data of the project's data contributors as well as from other sources, and input it into EDHEC*infra*'s unique database of infrastructure equity and debt investments and cash flows. We also develop data collection and reporting standards that can be used to make data collection more efficient and more transparently reported. This database already covers 15 years of data and hundreds of investments and, as such, is already the largest dedicated database of infrastructure investment information available.

2. **Cash- flow and discount-rate models**: Using this extensive and growing database, we implement and continue to develop the technology developed at EDHEC-Risk Institute to model the cash flow and discount-rate dynamics of private infrastructure equity and debt investments and derive a series of risk and performance measures that can actually help answer the questions that matter for investors.

3. **Building reference portfolios of infrastructure investments**: Using the performance results from our asset pricing and risk models, we can report the portfolio-level performance of groups of infrastructure equity or debt investments using categorisations (e.g., greenfield vs. brownfield) that are most relevant for investment decisions.

Partners of EDHEC*infra*

Monetary Authority of Singapore

In October 2015, Deputy Prime Minister of Singapore Tharman Shanmugaratnam announced officially at the World Bank Infrastructure Summit that EDHEC would work in Singapore to create "usable benchmarks for infrastructure investors."

The Monetary Authority of Singapore is supporting the work of the EDHEC Singapore Infrastructure Investment Institute (EDHEC*infra*) with a five-year research development grant.

Sponsored Research Chairs

Since 2012, private-sector sponsors have been supporting research on infrastructure investment at EDHEC with several Research Chairs that are now under the EDHEC Infrastructure Investment Institute:

About EDHEC Infrastructure Institute-Singapore

1. The EDHEC/NATIXIS Research Chair on the Investment and Governance Characteristics of Infrastructure Debt Instruments, 2012-2015
2. The EDHEC/Meridiam/Campbell-Lutyens Research Chair on Infrastructure Equity Investment Management and Benchmarking, 2013-2016
3. The EDHEC/NATIXIS Research Chair on Infrastructure Debt Benchmarking, 2015-2018
4. The EDHEC / Long-Term Infrastructure Investor Association Research Chair on Infrastructure Equity Benchmarking, 2016-2019
5. The EDHEC/Global Infrastructure Hub Survey of Infrastructure Investors' Perceptions and Expectations, 2016

Partner Organisations

As well as our Research Chair Sponsors, numerous organisations have already recognised the value of this project and have joined or are committed to joining the data collection effort. They include:

- The Global Infrastructure Hub;
- The European Investment Bank;
- The World Bank Group;
- The European Bank for Reconstruction and Development;
- The members of the Long-Term Infrastructure Investor Association;
- Over 20 other North American, European, and Australasian investors and infrastructure managers.

EDHEC*infra* is also :

- A member of the Advisory Council of the World Bank's Global Infrastructure Facility
- An honorary member of the Long-term Infrastructure Investor Association

EDHEC Infrastructure Institute Publications

EDHEC Infrastructure Institute Publications

EDHEC Publications

- Blanc-Brude, F., A. Chreng, M. Hasan, Q. Wang, and T. Whittaker. "Private Infrastructure Equity Indices: Benchmarking European Private Infrastructure Equity 2000-2016" (June 2017).
- Blanc-Brude, F., A. Chreng, M. Hasan, Q. Wang, and T. Whittaker. "Private Infrastructure Debt Indices: Benchmarking European Private Infrastructure Debt 2000-2016" (June 2017).
- Blanc-Brude, F., G. Chen, and T. Whittaker. "Towards Better Infrastructure Investment Products: A Survey of Investors' Perceptions and Expectations from Investing in Infrastructure" (July 2016).
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EDHEC Infrastructure Institute Publications

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Books

EDHEC Infrastructure Institute Publications

- Blanc-Brude, F., and M. Hasan. *Valuation and Financial Performance of Privately-Held Infrastructure Investments*. London: PEI Media, 2015.

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