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Estimating earnings trend using unobserved components framework

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ABSTRACT

Regressions for predicting long-term stock returns often use moving averages of earnings as the earnings trend. We show that the earnings trend can be directly estimated using unobserved components models. The estimated trends improve the fit of predictive regressions.

1. Introduction

Empirical studies by Campbell and Shiller (1998, 2001) show that valuation ratios can be used for predicting long-term real stock returns. In particular, they use the price-smoothed earnings ratio computed by assuming a ten-year moving average of real earnings as earnings 'trend,' i.e., the component that captures long-term future earnings.[1] Computing a multi-year moving average reduces the effect of cyclical fluctuations on corporate earnings. Averaging past earnings in valuation analysis is a common approach first recommended by Graham and Dodd (1934), but it may not be the best way to model the earnings trend. This paper relaxes the assumption of the moving average trend by letting the data speak. We directly estimate the earnings trend using unobserved components models. Our models use both the real earnings data and long-term real stock returns data. The unobserved components framework also allows us to compare the performance of different statistical assumptions by using the Schwarz Information Criterion.

The theoretically and statistically appealing motivation for estimating the earnings trend is derived from the Beveridge and Nelson (1981) decomposition of a time series into its trend and cycle components. The trend can be interpreted as a long-term conditional forecast of the time series. Morley (2002) and Morley et al. (2003) show that the Beveridge–Nelson decomposition can be usefully cast into an unobserved components framework which allows the trend and the cycle shocks to be correlated. Further studies by Ord et al. (1997) and Anderson et al. (2006) show that the perfect correlation between the shocks, as in the Beveridge–Nelson decomposition, can be modeled as a single source shock. Laubach (2001) argues in a different context of estimating NAIRUs that bivariate modeling can also help to reduce the uncertainty around the estimated unobserved components.

This paper uses the above developments in the unobserved components modeling to estimate the earnings trend under three different assumptions about correlation of shocks. The results indicate a fairly volatile earnings trend in all three cases. The fit of the long-run stock returns predictive regression is higher in all the cases relative to the moving average trend. However, the 90% confidence intervals of the estimated trends tend to include the moving average trend.

2. Unobserved components model and estimates

The following unobserved components model is used for estimating the earnings trend.[2] The first measurement equation uses log real earnings, e_t, to be decomposed into two unobserved components: its permanent (or stochastic trend) part p_t and the cyclical part c_t.

$$e_t = p_t + c_t. \quad (1)$$

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[1] Many other empirical studies also use the smoothed price–earnings ratio for predicting stock returns. These studies are not mentioned due to space considerations.

[2] Harvey (1989) provides a comprehensive treatment of unobserved components models.

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The permanent part is assumed to follow a random walk with a constant drift μ in Eq. (2). The cyclical part c_t is assumed to follow an autoregressive process in Eq. (3). Following Morley (2002) and Morley et al. (2003), we use an autoregressive process of order two.

$$p_t = \mu + p_{t-1} + \varepsilon_t \tag{2}$$

$$\phi(L)c_t = \omega_t \tag{3}$$

The second measurement equation, Eq. (4), is the future stock returns equation. The stock return over the next 10 years, r_{t+1}^{10}, depends on a constant, the valuation ratio shown by log real stock price (s_t) minus the permanent part of log real earnings (p_t) and a serially correlated unobserved component f_{t+1} to account for other omitted factors. The f_{t+1} component is assumed to take a moving average form based on comparison of SICs (not reported) in Eq. (5). We use ten lags in the moving average process.

$$r_{t+1}^{10} = \alpha + \beta(s_t - p_t) + f_{t+1} \tag{4}$$

$$f_{t+1} = \theta(L)\nu_{t+1} \tag{5}$$

We use three specifications of the correlations between the three shocks ε_t, ω_t and ν_{t+1}. In the first specification, they are assumed to be uncorrelated as in Clark (1987) and Harvey (2008). In the second and third specifications, following Anderson et al. (2006), which uses the Beveridge–Nelson result of perfectly negative correlation of the shocks, ε_t and ω_t are assumed to be perfectly correlated and modeled as a single source shock using $\omega_t = \gamma\varepsilon_t$. The shock ε_t is assumed to be uncorrelated to ν_{t+1} in the second specification and we allow for that correlation to be estimated in the third specification.

We use annual average data ranging from 1871 to 2007 obtained from Robert Shiller's web site. The ten-year stock return is computed from 1871 to 1997 where the 1997 stock return denotes the stock return from 1997 to 2007. Therefore, based on data availability, we are able to estimate the earnings trend from 1871 to 1996. We estimate the parameters of the model using maximum likelihood and then use the Kalman filter to obtain the estimates of the trend. The standard errors of the estimated trends are computed using Hamilton's (1986) procedure and are based on 1000 Monte Carlo replications.

The results are reported in Table 1, and the estimated trends are shown in Fig. 1. Panel A of Table 1 shows that the valuation ratio based on the ten-year moving average of earnings predicts future long-term stock returns with a fit of 19%. The upper-left panel of Fig. 1 shows the moving average trend. Panel B of Table 1 shows the parameter estimates from the bivariate unobserved components model with uncorrelated shocks. The estimate of μ shows that real earning grew at an average annual rate of 1.4%. The standard deviations of all shocks are moderate and fairly precisely estimated. The estimated earnings trend is shown in the upper-right of Fig. 1 along with its 90% confidence interval and the moving average trend. One can observe that although the estimated earnings trend appears to be fairly different from the moving average trend, the 90% confidence interval does include the moving average trend almost all of the time. The regression of the long-term future stock returns on the estimated earnings trend has a fit of about 29%, which is 10% higher than fit obtained using the moving average trend.

Panel C of Table 1 reports the parameter estimates using a single source of shock between the trend and cycle of real earnings but uncorrelated with shocks to future real stock returns ν_{t+1}. The estimates are largely similar to those in Panel B, although the point estimate of the standard deviation of the shock to the earnings trend is higher, implying a more volatile trend. The lower-left panel of Fig. 1 shows the estimated trend, which appears to be more volatile than the trend in the uncorrelated case. The fit of the stock returns regression on the valuation ratio based on the estimated trend is still about 29%.

Panel D of Table 1 reports the parameter estimates using a single source of shock between the trend and cycle of real earnings and correlated with shocks to future real stock returns ν_{t+1}. The estimates are largely similar to those in Panel C. The point estimate of the standard deviation of the shock to earnings trend is higher than that reported in Panel B, implying a more volatile trend. The correlation between the trend shock and the future stock returns shock is estimated to be −0.23, low but precisely estimated. The lower-right panel of Fig. 1 shows the estimated trend which appears to be more volatile than the trend in the uncorrelated case. The fit of the stock returns regression on the valuation ratio based on the estimated trend is marginally lower at about 28% but still higher than the 19% fit reported in Panel A. This model also shows the lowest SIC of the three unobserved components models, implying that it provides the best description for the data.

The $(s_t - p_t)$ term in Eq. (4) can be viewed (up to a constant) as a deviation of the aggregate stock prices from the earnings trend, or as a proxy for stock market mispricing. Brown and Cliff (2005) find that stock market valuation errors are positively correlated with investor sentiment. We examined the relation between our mispricing proxy and the investor sentiment index from Baker and Wurgler (2006). The sentiment index is estimated as the first principal component of the closed-end fund discount, equity share in new security issues, and lagged NYSE turnover. The coefficient of the sentiment index in a linear regression for the 1934–1996 period using the trend estimates from the three unobserved components models was positive and significant at the 10% level.[3]

Table 1
Model parameter estimates.

A. The 10-year moving average regression					
α	β			R^2	
1.987 (0.35)	−0.671 (0.13)			0.186	
B. The UC model with uncorrelated shocks					
μ	σ_ε	σ_ν	σ_ω	R^2	SIC
0.014 (0.01)	0.056 (0.02)	0.137 (0.01)	0.123 (0.01)	0.288	−1.158
C. The UC model with single shock for earnings and uncorrelated with stock returns					
μ	σ_ε	σ_ν		R^2	SIC
0.014 (0.01)	0.065 (0.02)	0.141 (0.01)		0.287	−1.189
D. The UC model with single shock for earnings and correlated with stock returns					
μ	σ_ε	σ_ν	$\rho_{\varepsilon\nu}$	R^2	SIC
0.014 (0.01)	0.067 (0.02)	0.135 (0.01)	−0.227 (0.09)	0.284	−1.193

Note: standard errors are shown in parentheses. The R^2s are computed by regressing the 10-year future stock returns on a constant and the difference of log real stock price and estimated trend from the given model. The SICs represent Schwarz Information Criterion and are computed for the bivariate UC models only.

3. Conclusion

The main contribution of this paper is to show that the earnings trend can be estimated by using a bivariate unobserved components framework under different assumptions about correlations of the shocks. All three estimated trends show a better fit of the regression equation using the price–earnings ratio to predict long-term stock returns than the traditional specification using the moving average earnings trend. The drawback of the estimated trends is that their 90% confidence interval almost always includes the moving average trend. However, this drawback will become less of an issue with availability of more data, making the unobserved components models an asymptotically attractive choice.

[3] These results are not tabulated to save space, but are available upon request.

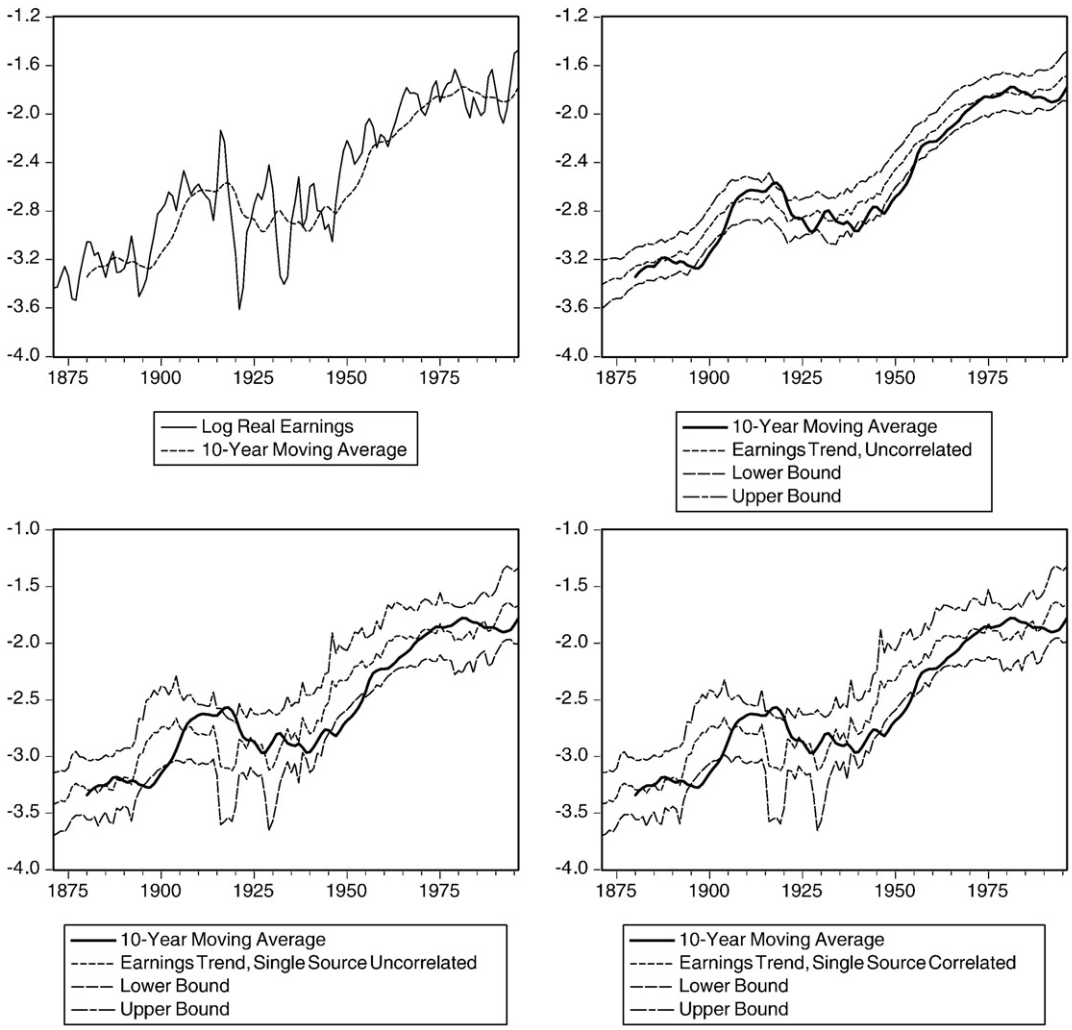

Fig. 1. Estimates of earnings trends. Note: the upper-left panel shows the logarithm of real earnings data and its 10-year moving average. The upper-right panel shows the estimated log real earnings trend and its 90 percent confidence interval when the shocks are uncorrelated with each other. The lower-left panel shows the estimated log real earnings trend and its 90 percent confidence interval when the permanent shocks to real earnings are perfectly correlated to its transitory shocks but uncorrelated to future stock returns shock. The lower-right panel shows the estimated log real earnings trend and its 90 percent confidence interval when the permanent shocks to real earnings are perfectly correlated to its transitory shocks and correlated to future stock return stock. The standard errors of the trends are based on 1000 Monte Carlo replications.

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