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Efficient tests of stock return predictability ☆

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Abstract

Conventional tests of the predictability of stock returns could be invalid, that is reject the null too frequently, when the predictor variable is persistent and its innovations are highly correlated with returns. We develop a pretest to determine whether the conventional t-test leads to invalid inference and an efficient test of predictability that corrects this problem. Although the conventional t-test is invalid for the dividend–price and smoothed earnings–price ratios, our test finds evidence for predictability. We also find evidence for predictability with the short rate and the long-short yield spread, for which the conventional t-test leads to valid inference.

JEL classification: C12; C22; G1

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1. Introduction

Numerous studies in the last two decades have asked whether stock returns can be predicted by financial variables such as the dividend–price ratio, the earnings–price ratio,

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Drawing on the work of Stambaugh (1999), Lewellen (2004) motivates the statistic by interpreting the term $\beta_{ue}(\widehat{\rho}-\rho)$ as the "finite-sample bias" of the OLS estimator. Assuming that $\rho \leqslant 1$, Lewellen tests the predictability of returns using the statistic $Q(\beta_0, 1)$.

3. Inference with a persistent regressor

Fig. 1 is a time-series plot of the log dividend–price ratio for the NYSE/AMEX value-weighted index and the log smoothed earnings–price ratio for the S&P 500 index at quarterly frequency. Following Campbell and Shiller (1988), earnings are smoothed by taking a backwards moving average over ten years. Both valuation ratios are persistent and even appear to be nonstationary, especially toward the end of the sample period. The 95% confidence intervals for ρ are $[0.957, 1.007]$ and $[0.939, 1.000]$ for the dividend–price ratio and the earnings–price ratio, respectively (see Panel A of Table 4).

The persistence of financial variables typically used to predict returns has important implications for inference about predictability. Even if the predictor variable is I(0), first-order asymptotics can be a poor approximation in finite samples when ρ is close to one because of the discontinuity in the asymptotic distribution at $\rho = 1$ (note that $\sigma_x^2 = \sigma_e^2/(1-\rho^2)$ diverges to infinity at $\rho = 1$). Inference based on first-order asymptotics could therefore be invalid due to size distortions. The solution is to base inference on more accurate approximations to the actual (unknown) sampling distribution of test statistics. There are two main approaches that have been used in the literature.

The first approach is the exact finite-sample theory under the assumption of normality (i.e., Assumption 1). This is the approach taken by Evans and Savin (1981, 1984) for

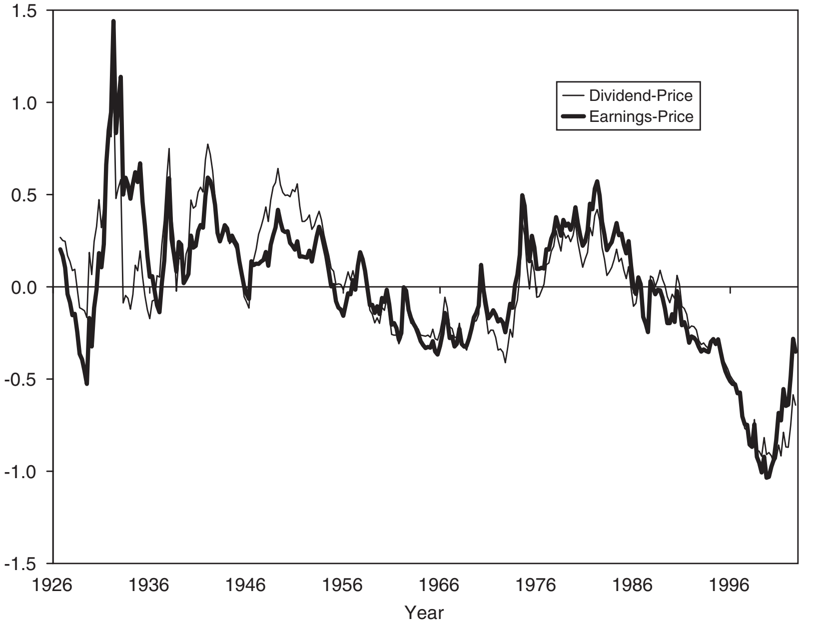


Fig. 1. Time-series plot of the valuation ratios. This figure plots the log dividend–price ratio for the CRSP value-weighted index and the log earnings–price ratio for the S&P 500. Earnings are smoothed by taking a 10-year moving average. The sample period is 1926:4–2002:4.

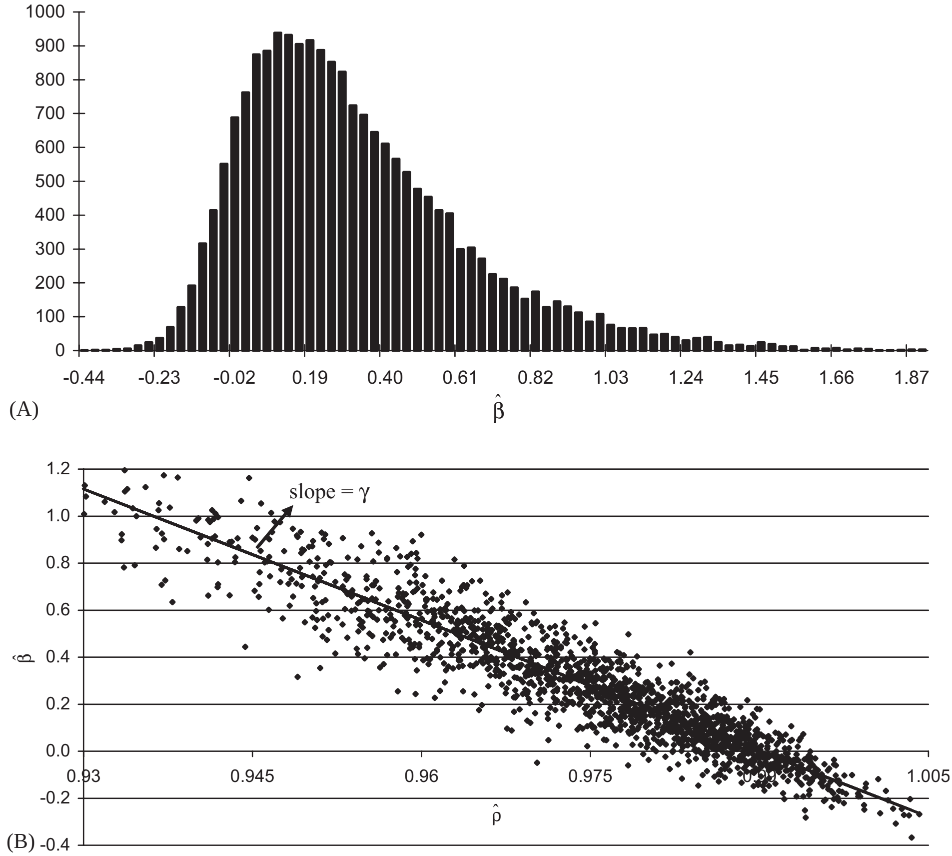


Fig. 1. Sampling distribution of $\hat{\beta}$ and $\hat{\rho}$. The figure shows the distribution of the OLS slope estimates from $r_t = \alpha + \beta x_{t-1} + \varepsilon_t$ and $x_t = \phi + \rho x_{t-1} + \mu_t$. Panel A shows the marginal, or unconditional, distribution of $\hat{\beta}$ and Panel B shows the joint distribution of $\hat{\beta}$ and $\hat{\rho}$. The plots are based on Monte Carlo simulations (20,000 in Panel A and 2,000 in Panel B). The true parameters are $\beta = 0$, $\rho = 0.99$, $\text{cor}(\varepsilon, \mu) = -0.92$, $\sigma_\varepsilon = 0.04$, $\sigma_\mu = 0.002$, and $T = 300$. Panel A: Marginal distribution of $\hat{\beta}$. Panel B: Joint distribution of $\hat{\beta}$ and $\hat{\rho}$.

might still be useful if the autocorrelation is a bit lower, but it would depend on the underlying parameters (the empirical tests later illustrate this point).

The previous paragraph suggests that DY's sample autocorrelation determines whether the conditional or unconditional test is better. Ideally, we could choose between the tests in advance, before looking at the data. From an ex ante perspective, the conditional test has greater power when ρ is close to one, but the opposite is true once ρ drops below some level that depends on the other parameters. (The appendix discusses power in more detail.) However, without prior information about ρ, we can't say ahead of time which test is better. Thus, it makes sense to rely on both tests and to calculate an overall significance level that reflects the probability of rejecting using either test.

Table 4
Estimates of the model parameters

Series	Obs.	Variable	p	δ	DF-GLS	95% CI: ρ	95% CI: c
Panel A: S&P 1880–2002, CRSP 1926–2002							
S&P 500	123	d–p	3	−0.845	−0.855	[0.949, 1.033]	[−6.107, 4.020]
		e–p	1	−0.962	−2.888	[0.768, 0.965]	[−28.262, −4.232]
Annual	77	d–p	1	−0.721	−1.033	[0.903, 1.050]	[−7.343, 3.781]
		e–p	1	−0.957	−2.229	[0.748, 1.000]	[−19.132, −0.027]
Quarterly	305	d–p	1	−0.942	−1.696	[0.957, 1.007]	[−13.081, 2.218]
		e–p	1	−0.986	−2.191	[0.939, 1.000]	[−18.670, 0.145]
Monthly	913	d–p	2	−0.950	−1.657	[0.986, 1.003]	[−12.683, 2.377]
		e–p	1	−0.987	−1.859	[0.984, 1.002]	[−14.797, 1.711]
Panel B: S&P 1880–1994, CRSP 1926–1994							
S&P 500	115	d–p	3	−0.835	−2.002	[0.854, 1.010]	[−16.391, 1.079]
		e–p	1	−0.958	−3.519	[0.663, 0.914]	[−38.471, −9.789]
Annual	69	d–p	1	−0.693	−2.081	[0.745, 1.010]	[−17.341, 0.690]
		e–p	1	−0.959	−2.859	[0.591, 0.940]	[−27.808, −4.074]
Quarterly	273	d–p	1	−0.941	−2.635	[0.910, 0.991]	[−24.579, −2.470]
		e–p	1	−0.988	−2.827	[0.900, 0.986]	[−27.322, −3.844]
Monthly	817	d–p	2	−0.948	−2.551	[0.971, 0.998]	[−23.419, −1.914]
		e–p	2	−0.983	−2.600	[0.970, 0.997]	[−24.105, −2.240]
Panel C: CRSP 1952–2002							
Annual	51	d–p	1	−0.749	−0.462	[0.917, 1.087]	[−4.131, 4.339]
		e–p	1	−0.955	−1.522	[0.773, 1.056]	[−11.354, 2.811]
		r_3	1	0.006	−1.762	[0.725, 1.040]	[−13.756, 1.984]
		y–r_1	1	−0.243	−3.121	[0.363, 0.878]	[−31.870, −6.100]
Quarterly	204	d–p	1	−0.977	−0.392	[0.981, 1.022]	[−3.844, 4.381]
		e–p	1	−0.980	−1.195	[0.958, 1.017]	[−8.478, 3.539]
		r_3	4	−0.095	−1.572	[0.941, 1.013]	[−11.825, 2.669]
		y–r_1	2	−0.100	−2.765	[0.869, 0.983]	[−26.375, −3.347]
Monthly	612	d–p	1	−0.967	−0.275	[0.994, 1.007]	[−3.365, 4.451]
		e–p	1	−0.982	−0.978	[0.989, 1.006]	[−6.950, 3.857]
		r_3	2	−0.071	−1.569	[0.981, 1.004]	[−11.801, 2.676]
		y–r_1	1	−0.066	−4.368	[0.911, 0.968]	[−54.471, −19.335]

This table reports estimates of the parameters for the predictive regression model. Returns are for the annual S&P 500 index and the annual, quarterly, and monthly CRSP value-weighted index. The predictor variables are the log dividend–price ratio (d–p), the log earnings–price ratio (e–p), the three-month T-bill rate (r_3), and the long-short yield spread (y–r_1). p is the estimated autoregressive lag length for the predictor variable, and δ is the estimated correlation between the innovations to returns and the predictor variable. The last two columns are the 95% confidence intervals for the largest autoregressive root (ρ) and the corresponding local-to-unity parameter (c) for each of the predictor variables, computed using the DF-GLS statistic.

much smaller. For these predictor variables, the pretest rejects the null hypothesis, which suggests that the conventional t-test leads to approximately valid inference.

4.3. Testing the predictability of returns

In this section, we construct valid confidence intervals for β through the Bonferroni Q-test to test the predictability of returns. In reporting our confidence interval for β, we scale it by $\widehat{\sigma}_e/\widehat{\sigma}_u$. In other words, we report the confidence interval for $\widetilde{\beta} = (\sigma_e/\sigma_u)\beta$ instead

Table 5
Tests of predictability

Series	Variable	t-stat	$\widehat{\beta}$	90% CI: β		Low CI β
				t-test	Q-test	($\rho = 1$)
Panel A: S&P 1880–2002, CRSP 1926–2002						
S&P 500	d–p	1.967	0.093	[−0.040, 0.136]	[−0.033, 0.114]	−0.017
	e–p	2.762	0.131	[−0.003, 0.189]	**[0.042, 0.224]**	−0.023
Annual	d–p	2.534	0.125	[−0.007, 0.178]	**[0.014, 0.188]**	0.020
	e–p	2.770	0.169	[−0.009, 0.240]	**[0.042, 0.277]**	0.002
Quarterly	d–p	2.060	0.034	[−0.014, 0.052]	[−0.009, 0.044]	−0.010
	e–p	2.908	0.049	[−0.001, 0.068]	**[0.010, 0.066]**	0.002
Monthly	d–p	1.706	0.009	[−0.006, 0.014]	[−0.005, 0.010]	−0.005
	e–p	2.662	0.014	[−0.001, 0.019]	**[0.002, 0.018]**	0.001
Panel B: S&P 1880–1994, CRSP 1926–1994						
S&P 500	d–p	2.233	0.141	[−0.035, 0.217]	[−0.048, 0.183]	−0.081
	e–p	3.321	0.196	**[0.062, 0.272]**	**[0.093, 0.325]**	−0.030
Annual	d–p	2.993	0.212	**[0.025, 0.304]**	**[0.056, 0.332]**	0.011
	e–p	3.409	0.279	**[0.048, 0.380]**	**[0.126, 0.448]**	0.012
Quarterly	d–p	2.304	0.053	[−0.004, 0.083]	[−0.006, 0.076]	−0.027
	e–p	3.506	0.079	**[0.018, 0.107]**	**[0.027, 0.109]**	0.005
Monthly	d–p	1.790	0.013	[−0.004, 0.022]	[−0.007, 0.017]	−0.013
	e–p	3.185	0.022	**[0.002, 0.030]**	**[0.005, 0.028]**	0.000
Panel C: CRSP 1952–2002						
Annual	d–p	2.289	0.124	[−0.023, 0.178]	[−0.007, 0.183]	0.020
	e–p	1.733	0.114	[−0.078, 0.178]	[−0.031, 0.229]	−0.025
	r_3	−1.143	−0.095	[−0.229, 0.045]	[−0.231, 0.042]	—
	y–r_1	1.124	0.136	[−0.087, 0.324]	[−0.075, 0.359]	−0.156
Quarterly	d–p	2.236	0.036	[−0.011, 0.051]	[−0.010, 0.030]	0.005
	e–p	1.777	0.029	[−0.019, 0.044]	[−0.012, 0.042]	−0.003
	r_3	−1.766	−0.042	**[−0.084, −0.004]**	**[−0.084, −0.004]**	−0.086
	y–r_1	1.991	0.090	**[0.009, 0.162]**	**[0.006, 0.158]**	−0.002
Monthly	d–p	2.259	0.012	[−0.004, 0.017]	[−0.004, 0.010]	0.001
	e–p	1.754	0.009	[−0.006, 0.014]	[−0.004, 0.012]	−0.001
	r_3	−2.431	−0.017	**[−0.030, −0.006]**	**[−0.030, −0.006]**	−0.030
	y–r_1	2.963	0.047	**[0.020, 0.072]**	**[0.020, 0.072]**	0.016

This table reports statistics used to infer the predictability of returns. Returns are for the annual S&P 500 index and the annual, quarterly, and monthly CRSP value-weighted index. The predictor variables are the log dividend–price ratio (d–p), the log earnings–price ratio (e–p), the three-month T-bill rate (r_3), and the long-short yield spread (y–r_1). The third and fourth columns report the t-statistic and the point estimate $\widehat{\beta}$ from an OLS regression of returns onto the predictor variable. The next two columns report the 90% Bonferroni confidence intervals for β using the t-test and Q-test, respectively. Confidence intervals that reject the null are in bold. The final column reports the lower bound of the confidence interval for β based on the Q-test at $\rho = 1$.

predictability is sufficiently strong that a relatively inefficient test can also find predictability.

In Panel C, we report the results for the subsample since 1952. In this subsample, we cannot reject the null hypothesis for the valuation ratios (d–p and e–p). For the T-bill rate and the yield spread (r_3 and $y-r_1$), however, we reject the null hypothesis except at annual frequency. For the interest rate variables, the correlation δ is sufficiently small that conventional inference based on the t-test leads to approximately valid inference. This is

Figure 1. Log Dividend Yield

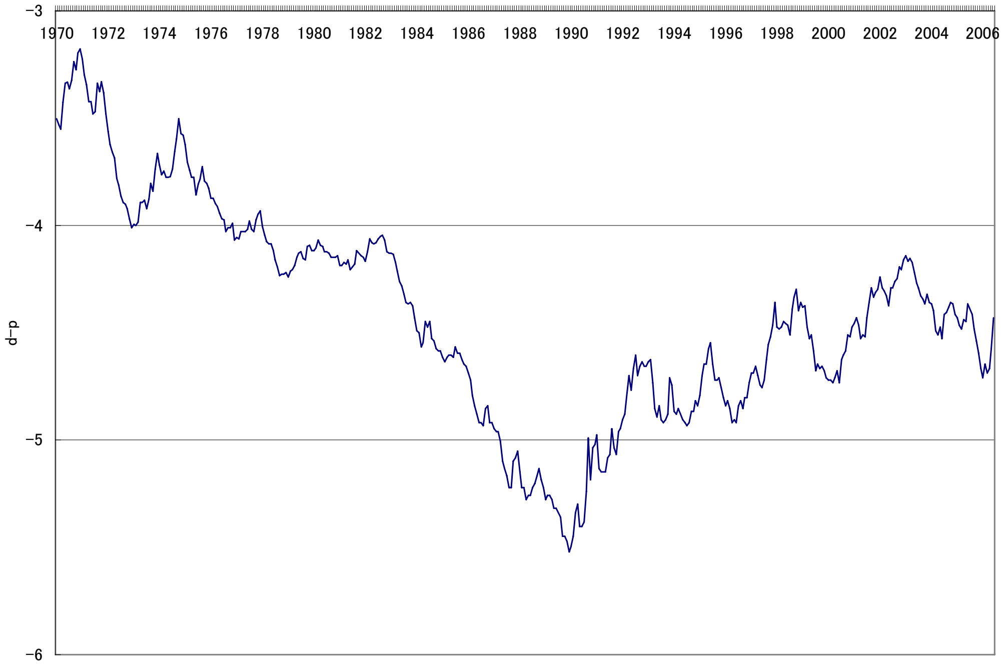
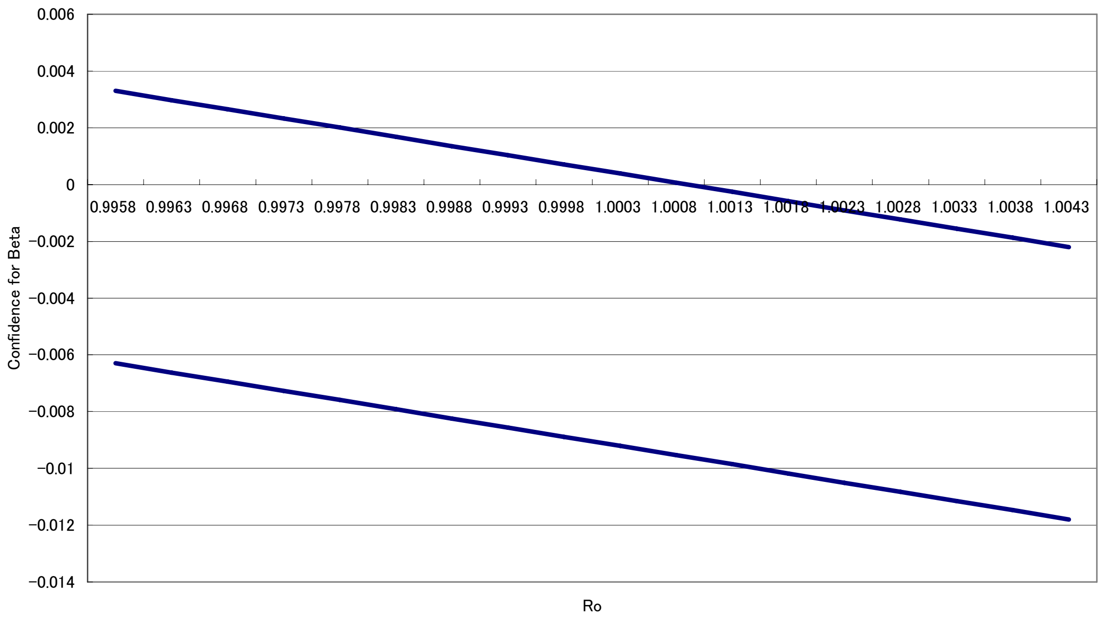


Figure 2. Bonferroni Confidence Intervals for Dividend Yield.

This figure plots the 90% confidence interval for β over the confidence interval for ρ, based on Q test

(1) Monthly data

Full Sample Monthly



Sub Sample Monthly

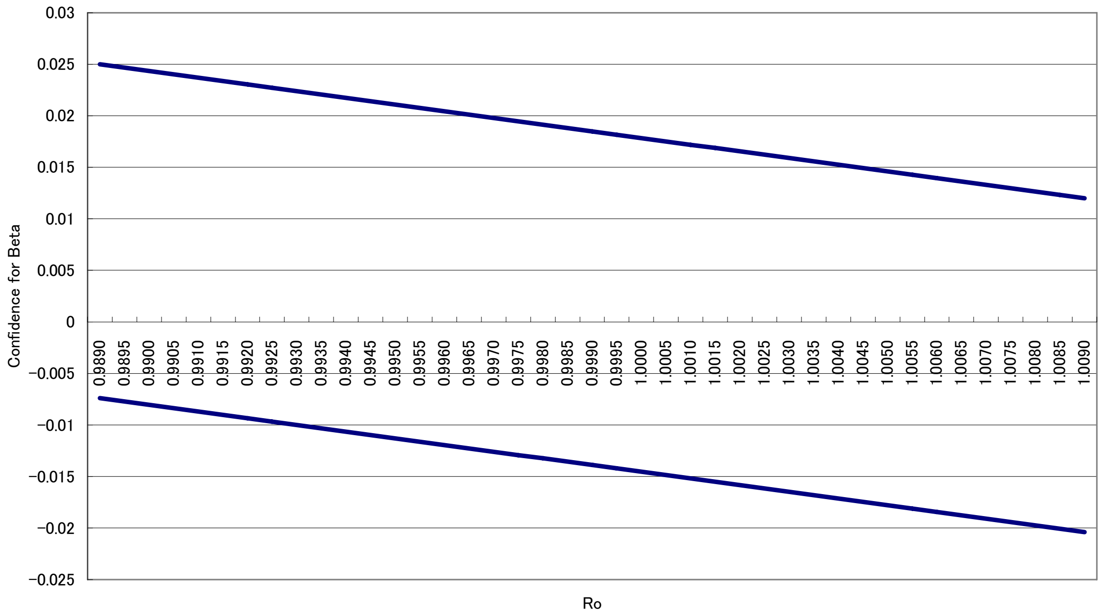


Figure 2 (continued)

(2) Quarterly data