Kellogg School of Management
FINC 585-3: Asset Pricing
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Assignment 2

Problem 1.

For this problem, we will be using the dataset `Shiller_ie_Data.xls` available on CANVAS, downloaded from Robert Shiller's website. It has a pre-calculated **PE** ratio and provides both **dividend** and **price level** data for the S&P index. The variable construction can be seen from the Excel formulas generating the scaled data from the raw observations.[1] As indicated, **T-bill** data are available from many sources including FRED.

For this exercise, we take an initial look at predictive return regressions, where macro-finance variables are used to forecast the future equity premium. The task is to gauge whether there is (statistically significant) evidence of predictability in the S&P equity-index returns minus the risk-free rate (use 3-month T-bill rates – available from FRED at the St. Louis Fed).

In formal notation, $\mathbf{r^e(t+1) = r(t+1) - i(t)}$, where $r(t+1)$ is the monthly continuously compounded nominal return on the S&P index from the end of month t to end of month $t+1$, and $i(t)$ is the 3-month T-bill rate at the end of month t.

As predictors, we will choose the PE-ratio (price/earnings ratio), the DP-ratio (dividend/price ratio), and the relative interest rate (current 3-month T-bill rate minus the average 3-month T-bill rate over the prior last 12 month). This is labeled **RREL**.

The relevant predictive OLS regression take the form:

$$r^e(t+1) = a + b'X(t) + u(t), \qquad t = 0, 1, \ldots, T$$

where t refers to the (end of) month for the observation.

a) Run the regression above with only the PE-ratio as the explanatory (X) variable. Use the sample period from January 1963 - December 2022. Obtain OLS standard errors, assuming no heteroskedasticity or autocorrelation in the innovations, and assess the significance of the relevant regression coefficient and compute the R^2 statistic.

b) Repeat the exercise from a), but with only the DP-ratio as the explanatory variable.

c) Repeat the exercise from a), but with only the RREL as the explanatory variable.

d) Repeat the exercise from a), but use both the PE-ratio and the RREL as regressors.

e) Now, assess the significance of the regression coefficient(s) in the above regressions using heteroscedasticity robust standard errors (White standard errors).

[1] For more information on the dataset, check the 'Data Description.html' also available on CANVAS.

f) Repeat e) with heteroscedasticity and autocorrelation consistent (Newey-West) st. errors.

g) Does the change of method for computing standard errors make any difference to the size of the estimated standard errors? Does it change your conclusions?

Solution.

The results are presented in Tables 1 and 2. The first table presents the results for the regressions for the Value Weighted Index, while the second table presents the results for the Equal Weighted Index. The numbers in parenthesis correspond to the t-statistics using homoskedastic standard errors. The numbers in brackets, using White heteroskedastic std. errors. Finally, the numbers in curly brackets show the t-statistics using the Newey-West standard errors. As we can see, there is not much predictability in the returns when it comes to these factors. Both the Price-to-Earnings and the Dividend-to-Price ratios are not statistically significant in columns (a), (b) and (d) in both tables. The Relative Interest Rate (RREL) is significant at 5% under all std. errors but the R^2 it is able to generate is really low (usually around 0.9%).

Comparing the t-statistics from the tables we also conclude that the method to estimate the standard errors increases as we add more robustness (Homoskedastic → White → HAC). However, for every variable in our model, this change in the standard errors is not enought to change the significance of the coefficients. □

Table 1: Testing for Returns Predictability (Value Weighted)

	Dependent variable: vwretd			
	(a)	(b)	(c)	(d)
Constant	0.003	0.003	0.005***	0.005
	(1.063)	(0.631)	(3.317)	(1.424)
	[0.959]	[0.591]	[3.323]	[1.268]
	{0.892}	{0.583}	{3.206}	{1.110}
P/E	0.000			0.000
	(0.752)			(0.307)
	[0.624]			[0.250]
	{0.570}			{0.211}
D/P		0.093		
		(0.666)		
		[0.604]		
		{0.622}		
RREL			-4.619**	-4.512**
			(-2.470)	(-2.370)
			[-2.376]	[-2.316]
			{-2.311}	{-2.193}
Observations	719	719	719	719
R^2	0.001	0.001	0.008	0.009
Adjusted R^2	-0.001	-0.001	0.007	0.006
Residual Std. Error	0.043 (df=717)	0.043 (df=717)	0.043 (df=717)	0.043 (df=716)
F Statistic	0.565 (df=1; 717)	0.443 (df=1; 717)	6.100** (df=1; 717)	3.093** (df=2; 716)
Note:				*p<0.1; **p<0.05; ***p<0.01
				Stars w.r.t homoskedastic std. errors
				( ): Homoskedastic t-stat; [ ]: White t-stat; { }: HAC t-stat

Table 2: Testing for Returns Predictability (Equal Weighted)

	Dependent variable: ewretd			
	(a)	(b)	(c)	(d)
Constant	0.004	0.001	0.008***	0.005
	(1.036)	(0.286)	(4.201)	(1.395)
	[0.814]	[0.277]	[4.208]	[1.083]
	{0.805}	{0.302}	{4.469}	{0.994}
P/E	0.000			0.000
	(1.315)			(0.863)
	[0.916]			[0.593]
	{0.925}			{0.546}
D/P		0.224		
		(1.397)		
		[1.290]		
		{1.420}		
RREL			-5.518**	-5.171**
			(-2.566)	(-2.363)
			[-2.405]	[-2.239]
			{-2.522}	{-2.147}
Observations	719	719	719	719
R^2	0.002	0.003	0.009	0.010
Adjusted R^2	0.001	0.001	0.008	0.007
Residual Std. Error	0.050 (df=717)	0.050 (df=717)	0.050 (df=717)	0.050 (df=716)
F Statistic	1.730 (df=1; 717)	1.951 (df=1; 717)	6.583** (df=1; 717)	3.663** (df=2; 716)

Note: *p<0.1; **p<0.05; ***p<0.01
Stars w.r.t homoskedastic std. errors
( ): Homoskedastic t-stat; [ ]: White t-stat; { }: HAC t-stat