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Predicting the U.S. bear stock market using the consumption-wealth ratio

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Abstract

This paper examines the predictive ability of the consumption-wealth ratio for the U.S. bear stock market using quarterly data on the S&P500 index. By evaluating the in-sample and out-of-sample performance with, respectively, the Pseudo-R^2 and the quadratic probability score, it is found that the consumption-wealth ratio is a useful leading indicator in predicting bear markets.

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1. Introduction

Motivated by the idea that macroeconomic variables may affect future consumption and investment opportunities, numerous studies have examined the predictability of stock returns using macroeconomic variables and provided evidence supporting it; for a recent study, see Rapach, Wohar, and Rangvid (2005). As stock returns may behave differently in bull and bear markets (e.g., Kim and Zumwalt, 1979; Gordon and St-Amour, 2000; Cunado, Gil-Alana, and de Gracia, 2010), predicting the bear market is thus helpful for market participants because such a prediction is important not only for managing market risk but also for market timing. However, most of the related studies focused only on defining and identifying bear and bull markets (e.g., Maheu and McCurdy, 2000; Pagan and Sossounov, 2003). Until recently, Chen (2009) investigated the predictive ability of macroeconomic variables (e.g., yield spreads, inflation rates, money stocks, aggregate output, unemployment rates) and found that the yield spread and the inflation rate do contain useful information for predicting the U.S. bear stock market.

In this paper, we extend the work of Lettau and Ludvigson (2001) by examining the performance of the consumption-wealth ratio for predicting the U.S. bear stock market, rather than stock returns. Since Lettau and Ludvigson (2001) established a model in which the consumption-wealth ratio can be represented as a function of future expected returns on the market portfolio (as well as returns on human capital and changes in log consumption), many empirical studies have found the usefulness of this variable in predicting stock returns. For example, Li (2005) found that it is a practically useful predictor for the U.S. stock returns; see also Guo (2006) and Della Corte, Sarno, and Valente (2010). Gao and Huang (2008) also found that it can explain the cross sectional stock returns in the U.K. and Japan. As a high consumption-wealth ratio will correspond to high future stock returns and hence reduce the probability of the bear market, all of the studies, however, examined only the performance of the consumption-wealth ratio for predicting stock returns. It is thus of interest to see if the consumption-wealth ratio can also serve as a good leading indicator for predicting the U.S. bear market.

To examine the predictive ability of the consumption-wealth ratio, we consider a probit model with the dependent variable indicating the bear markets, identified using quarterly data on the S&P 500 index and the nonparametric Bry-Boschan method considered in Candelon, Piplack, and Straetmans (2008). Based on the Pseudo-R^2 (as a measure of the in-sample fit) and Diebold and Rudebusch's (1989) quadratic probability score (QPS, as a measure of the out-of-sample performance), our empirical study reveals that as compared to the yield spread and the inflation rate, the consumption-wealth ratio is a better leading indicator for predicting U.S. bear stock market, even when the consumption-wealth ratio is constructed using recursive estimation rather than full-sample estimation.

This paper proceeds as follows. In Section 2., we introduce the consumption-wealth ratio constructed by Lettau and Ludvigson (2001) and related econometric techniques employed in our empirical study. The empirical results are then presented in Section 3.. Section 4. concludes the paper.

2. Consumption-Wealth Ratio and Methodology

Let C_t, W_t, and R_t be, respectively, consumption, aggregate wealth, and return (on aggregate wealth) at time t. Then the intertemporal budget constraint of a representative agent can be expressed as

$$W_{t+1} = (1 + R_{t+1})(W_t - C_t).$$

Under suitable conditions, Campbell and Mankiw (1989) derive an approximation of the intertemporal budget constraint above and obtain

$$c_t - w_t = \mathbb{E}_t\left[\sum_{s=1}^{\infty} \rho^s \big(r_{t+s} - \Delta c_{t+s}\big)\right], \tag{1}$$

where $c_t = \ln C_t$, $w_t = \ln W_t$, $r_t = \ln(1 + R_t)$, $\mathbb{E}_t$ is the conditional expectation operator with information available at time t, Δ is the first difference operator, and ρ is the stead-state ratio of new investment to wealth.

As $W_t = A_t + H_t$ with asset wealth A_t and human capital H_t, W_t is unobservable because H_t is unobservable. To overcome this problem, Lettau and Ludvigson (2001) derive, under the assumption that H_t can be well-described by labor income Y_t (i.e., $h_t = \delta + y_t + \nu_t$, where $h_t = \ln H_t$, $y_t = \ln Y_t$, δ is a constant, and ν_t is a stationary random variable with mean zero), that equation (1) can be further approximated as

$$c_t - \omega a_t - (1-\omega) y_t = \mathbb{E}_t\left[\sum_{s=1}^{\infty} \rho^s \big(\omega r_{a,t+s} + (1-\omega) r_{h,t+s} - \Delta c_{t+s}\big)\right] + (1-\omega)\nu_t, \tag{2}$$

where $a_t = \ln A_t$, $r_{a,t}$ is the return on asset wealth, $r_{h,t}$ is the return on human capital, and ω is the share of asset wealth in aggregate wealth. Under the requirement of stationarity for the random variables on the light-hand side of equation (2), c_t, a_t, and y_t are cointegrated with a cointegrating vector $[1 \;\; -\omega \;\; -(1-\omega)]'$. Therefore, the consumption-wealth ratio variable can be constructed as $cay_t = c_t - \hat{\beta}_a a_t - \hat{\beta}_y y_t$ with the estimated cointegrating vector $[1 \;\; -\hat{\beta}_a \;\; -\hat{\beta}_y]'$ obtained from the dynamic least squares (DLS) method of Stock and Watson (1993); see Lettau and Ludvigson (2001, pp. 822-823) for more detail.

To identify bear (bull) markets in which market prices decrease (increase) generally (see also Candelon et al., 2008, p. 1024, for discussion of this definition), we adopt the nonparametric Bry-Boschan approach. Let p_t be the log market price at time t. Then a trough (peak) occurs at time t when $p_t < (>)\, p_{t\pm i}$, $i = 1, \ldots, \ell$, where ℓ is a window size. Given the identified troughs and peaks, the peak-to-trough (trough-to-peak) periods are then identified as the bear (bull) markets with $D_t = 1$ ($D_t = 0$).

As the dependent variable D_t is a binary variable, we consider the probit specification (Probit-CAY):

$$\mathbb{P}(D_{t+\kappa} = 1) = \Phi(\gamma_o + \gamma_1 cay_t), \tag{3}$$

where κ is the forecast horizon, Φ is the standard normal distribution function, and γ_o and γ_1 are unknown parameters for which the maximum likelihood (ML) estimators $\hat{\gamma}_{o,T}$ and $\hat{\gamma}_{1,T}$ can be obtained by maximizing the log likelihood function: $\ln \mathcal{L}(\gamma_o, \gamma_1) = \sum_{t=1}^{T-\kappa}[D_{t+\kappa} \ln \Phi(\gamma_o + \gamma_1 cay_t) + (1 - D_{t+\kappa}) \ln(1 - \Phi(\gamma_o + \gamma_1 cay_t))]$, where T is the sample size.

As in Chen (2009), we compute the following Pseudo-R^2 proposed by Estrella (1998) to measure the in-sample performance of the probit model above.

$$\text{Pseudo-}R^2 = 1 - \left(\frac{\ln \mathcal{L}(\hat{\gamma}_{o,T}, \hat{\gamma}_{1,T})}{\ln \mathcal{L}(\tilde{\gamma}_{o,T}, 0)}\right)^{(-2/(T-\kappa))\ln \mathcal{L}(\tilde{\gamma}_{o,T},0)},$$

where $\tilde{\gamma}_{o,T}$ is a constrained maximum likelihood estimator under the restriction $\gamma_1 = 0$. Note that Pseudo-$R^2 \in [0, 1]$ and the higher Pseudo-R^2 the better the model fits the data. To evaluate the out-of-sample performance, we also compute the QPS proposed by Diebold and Rudebusch (1989). Let $\hat{\gamma}_{o,j}$ and $\hat{\gamma}_{1,j}$ be the recursive maximum likelihood estimators using first j observations. Then we have the (out-of-sample) probability forecasts $\widehat{\mathbb{P}}(D_{j+\kappa} = 1) = \Phi(\hat{\gamma}_{o,j} + \hat{\gamma}_{1,j} cay_j)$, $j = R, R+1, \ldots, T-\kappa$ and the QPS can be computed as

$$\text{QPS} = \frac{1}{T - \kappa - R + 1} \sum_{j=R}^{T-\kappa} 2\left[\widehat{\mathbb{P}}(D_{j+\kappa} = 1) - D_{j+\kappa}\right]^2.$$

Note that QPS $\in [0, 2]$ and a lower QPS indicates a better out-of-sample performance.

3. Empirical Results

In our empirical study, we employ quarterly data from 1953:Q3-2008:Q4 to examine the predictive ability of the Probit-CAY model for six different forecast horizons: $\kappa = 1, 2, 3, 4, 6, 8$. The data on cay_t are obtained from Lettau's website and the (quarter-end) closing prices of the S&P500 index (transformed from monthly data downloaded from the website of Yahoo!Finance) are used to identify the bear markets. As pointed out in Candelon et al. (2008, p. 1024) that the Bry-Boschan-approach-based turning points change only marginally with window size, we thus follow Candelon et al. (2008) and Chen (2009) and consider $\ell = 2$ (i.e., two quarters or six months) in identifying the bear markets.

For comparison, we also consider two macroeconomic variables: the inflation rate (the change of log personal-consumption-expenditure prices, denoted as inf_t) and the yield spread (the difference between the 10-year Treasury constant maturity rate and the 3-month Treasury bill rate, denoted as ysd_t). The data used to construct

Table I: In-sample predictability: ML estimates and Estrella's (1998) Pseudo-R^2.

	$\kappa = 1$	$\kappa = 2$	$\kappa = 3$	$\kappa = 4$	$\kappa = 6$	$\kappa = 8$
Probit-CAY						
cay_t	-17.75^{***}	-21.32^{***}	-22.37^{***}	-23.38^{***}	-24.95^{***}	-23.08^{***}
Pseudo-R^2	0.04	0.05	0.06	0.06	0.07	0.06
Probit-INF						
inf_t	13.04	9.90	-4.11	-11.71	-15.38	-20.12
Pseudo-R^2	0.00	0.00	0.00	0.00	0.01	0.01
Probit-YSD						
ysd_t	1.90	1.64	1.81	2.49^{**}	2.01	2.66^{**}
Pseudo-R^2	0.01	0.01	0.01	0.02	0.01	0.02
Probit-Joint						
cay_t	-16.67^{***}	-20.67^{***}	-22.61^{***}	-24.16^{***}	-26.31^{***}	-24.66^{***}
inf_t	2.20	-1.15	-18.57	-31.72^{**}	-33.74^{**}	-39.84^{**}
ysd_t	1.35	1.05	1.64	2.65^{**}	2.28^{*}	3.18^{**}
Pseudo-R^2	0.04	0.06	0.07	0.09	0.10	0.10

Note: *, **, and *** indicate significantly different from zero at the 10%, 5%, and 1% levels, respectively. 0.00 indicates the value less than 0.01.

these two variables are obtained from the Board of Governors of the Federal Reserve System and the corresponding probit models (i.e., the model (3) with cay_t replaced by either inf_t or ysd_t) are denoted as Probit-INF and Probit-YSD, respectively. Given these three variables, it is of interest to see if a model with these three variables jointly can improve the prediction performance. Therefore, we also consider the probit specification (Probit-Joint): $\mathbb{P}(D_{t+\kappa} = 1) = \Phi(\gamma_o + \gamma_1 cay_t + \gamma_2 inf_t + \gamma_3 ysd_t)$ for which the unknown parameters γ_o, γ_1, γ_2, and γ_3 can be estimated using maximum likelihood estimation and the in-sample and out-of-sample performance can also be evaluated using Pseudo-R^2 and QPS, respectively.

The ML estimates and Pseudo-R^2 for the four probit models are reported in Table I. As shown in equation (2), a higher value of cay_t may imply higher future asset returns so that the probability of the bear market in the future should reduce. It is thus expected that the parameter value of cay_t in the Probit-CAY model is negative. As expected, the ML estimates for cay_t are all negative, regardless of the forecast horizon κ. Moreover, all of these estimates are significantly different from zero at the 1% level. By contrast, all of the ML estimates for inf_t are insignificant at any conventional significance levels and the ML estimates for ysd_t are only significantly positive for longer forecast horizons ($\kappa = 4, 8$). We also observe from Pseudo-R^2 that the Probit-CAY model is better than the Probit-INF and Probit-YSD models. On the other hand, these three models tend to have better performance for longer forecast horizons and the pattern of Pseudo-R^2 for the Probit-CAY model is hump-shaped.

Table II: Out-of sample predictability: Diebold and Rudebusch's (1989) QPS.

	$\kappa = 1$	$\kappa = 2$	$\kappa = 3$	$\kappa = 4$	$\kappa = 6$	$\kappa = 8$
Probit-CAY	0.459	0.459	0.458	0.452	0.463	0.484
Probit-INF	0.475	0.492	0.502	0.499	0.503	0.489
Probit-YSD	0.472	0.490	0.490	0.485	0.498	0.509
Probit-Joint	0.472	0.498	0.497	0.485	0.503	0.507
Probit-CAY-R	0.467	0.473	0.475	0.470	0.452	0.466

Note: QPS $\in [0, 2]$ and a lower QPS indicates a better out-of-sample performance.

As for the Probit-Joint model, the results do not change substantially. The ML estimates for cay_t remain strongly significant for all κ, yet the ML estimates for inf_t and ysd_t get significant only for $\kappa = 4, 6, 8$. Compared the in-sample performance of Probit-Joint with that of Probit-CAY, we can see that the Probit-Joint model does not necessarily outperform the Probit-CAY model for short forecast horizons ($\kappa = 1, 2, 3$), yet the former does outperform the Probit-CAY model when κ gets larger so that the ML estimates of inf_t and ysd_t become significant. This suggests that as far as longer-forecast-horizon prediction is concerned, these three macro-variables may be employed jointly to improve the in-sample performance of predictability.

It is well known that a model with a good in-sample performance does not necessarily have a good out-of-sample performance. To examine the out-of-sample performance, we compute Diebold and Rudebusch's (1989) QPS with $R = 45$ (i.e., the first recursive ML estimates are obtained using data from 1953:Q3-1964:Q3) and present the results in Table II. Clearly, the QPS of Probit-CAY is lower than those of Probit-INF and Probit-YSD, regardless of the forecast horizon. It follows that the Probit-CAY model enjoys advantage in out-of-sample prediction. As for the Probit-Joint model, although it is found that this model can have a better in-sample performance for longer forecast horizons, it does not outperform the Probit-CAY model in terms of out-of-sample predictability.

To assess if the better out-of-sample performance of the Probit-CAY model is due to the "look-ahead" bias (see the discussions in Brennan and Xia, 2005 and Lettau and Ludvigson, 2005), we also consider the Probit-CAY-R model in which cay_t are estimated recursively by using only the data available at the time of prediction and using the DLS method with the lead/lag lengths ranging from 1 to 6. As the results with different lengths are qualitatively similar, we only report the results with length 6 in Table II; the other results are available from the authors upon request. Clearly, the Probit-CAY-R model still dominates the Probit-INF, Probit-YSD, and Probit-Joint models. More interesting, the Probit-CAY-R model may even outperform the Probit-CAY model when $\kappa = 6$ and $\kappa = 8$.

4. Conclusion

In this paper, we examine the ability of the consumption-wealth ratio to predict the U.S. bear stock market. By using quarterly data on the S&P500 index, both the in-sample and out-of-sample measures indicate that the consumption-wealth ratio does contain information about future U.S. bear markets so that it can serve as a useful leading indicator in predicting U.S. bear markets. As the focus of our empirical study is only on the U.S. stock market, it is of interest to see if this variable can also be a good leading indicator for other stock markets. This may be an interesting direction for future research.

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