THE CONSUMPTION-WEALTH AND BOOK-TO-MARKET RATIOS IN A DYNAMIC ASSET PRICING CONTEXT*

Belén Nieto and Rosa Rodríguez**

WP-EC 2002-24

Correspondence to: B. Nieto. Universidad de Alicante, Departamento de Economía Financiera, Campus San Vicente del Raspeig, s/n. Alicante, Spain. E-mail: belen.nieto@ua.es

Editor: Instituto Valenciano de Investigaciones Económicas, S.A.

Primera Edición Septiembre 2002

Depósito Legal: V-3615-2002

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* The authors are grateful to Gonzalo Rubio and Fernando Restoy for their comments and suggestions. The financial support from the Ministerio de Ciencia y Tecnología is gratefully acknowledged. Any errors are our own.

** B. Nieto: Universidad de Alicante. R. Rodríguez: Universidad Europea de Madrid.

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A B S T R A C T

We discuss whether stock returns in Spain are predictable using a proxy for the logarithm of the consumption-aggregate wealth ratio, specifically the deviations of the common trend in consumption, labor income, and household asset holdings. The predictability regression used is based on intertemporal asset pricing models, which indicate that the consumption-wealth ratio is a function of the expected returns. The difficulties in this unobservable ratio are solved as in Lettau and Ludvigson (2001). The results show a partial capability of the proxy to forecast returns, but a good behavior of the book-to-market ratio as a predictor. A positive and approximate linear relationship between this financial ratio and the macroeconomic variable can be proved theoretically and supported empirically, thus confirming the predictive power of the book-to-market and, of course, its use as a state variable in asset pricing models.

JEL classification: E44, G12.

Keywords: Stock markets, Predictability, Consumption, Aggregate wealth, Book-to-Market.

R E S U M E N

En este trabajo nos preguntamos si en España los rendimientos financieros se pueden predecir utilizando una proxy del logaritmo del ratio consumo/riqueza, concretamente las desviaciones en la tendencia común existente entre el consumo, la renta laboral y la riqueza financiera de los hogares. Esta relación de predecibilidad está inspirada en los modelos intertemporales de valoración de activos, que indican que este ratio es una función de los rendimientos esperados futuros. Las dificultades inherentes a este ratio, no observable en la práctica, se resuelven como en Lettau and Ludvigson (2001). Los resultados muestran una moderada capacidad del ratio consumo/riqueza en la predicción de rendimientos, sin embargo ponen de manifiesto la sorprendente capacidad del ratio agregado valor contable/valor de mercado. Una aproximada relación lineal y positiva entre este ratio financiero y la variable macroeconómica puede probarse teóricamente y verificarse empíricamente, justificando, de esta forma, el poder de predicción de rendimientos que presenta el ratio valor contable/valor de mercado y, por tanto, su generalizado uso como instrumento en los modelos de valoración.

Clasificación JEL: E44, G12.

Palabras clave: Mercado de valores, Predecibilidad, Consumo, Riqueza, Valor contable/Valor de mercado.

1. INTRODUCTION

Recent empirical evidence seems to suggest that financial asset returns are predictable to some degree. Thirty years ago this would have been taken as a rejection of market efficiency. However, modern financial economics suggests to us that other rational factors may account for such predictability. Thus, time varying expected returns due to changing business conditions could generate predictability. Many articles document the predictability of returns using macroeconomic and past financial information. These include lagged returns (Fama and French, 1988a; Poterba and Summers, 1988), dividend yield (Campbell and Shiller, 1988a; Fama and French, 1988b and 1989; Hodrick, 1992), short term interest rates (Campbell, 1987), spreads of interest rates (Campbell, 1987; Fama and French, 1989; Keim and Stambaugh, 1986), book-to-market ratios (Davis, 1994; Chan, Jegadeesh and Lakonishok, 1995; Kothari, Shanken and Sloan, 1995; Kothari and Shanken, 1997; Pontiff and Schall, 1999; Lewellen, 1999; Nieto, 2001) output variables and inflation (Balvers et al ,1990; Schwert, 1990; Chen, 1991; Rodríguez et al, 2002), among others.

In a recent article, Lettau and Ludvigson (2001a) report additional interesting evidence. They find that aggregate consumption, asset holdings, and labor income share a common long-term trend, but may deviate from one another in the short-run. They use these transitory deviations from the common trend as a new variable to forecast returns. Their results show that, for the US market, this variable captures a large part of the variability in returns, despite the fact that consumption, labor income, and asset holdings individually bear little relationship to future stock returns. One measure of the success of this new variable is the fact that it is used in the most recent literature for traditional asset pricing applications where other methods have enjoyed little success to date (Lettau and Ludvigson, 2001b and 2001c; Hodrick and Zhang, 2001; or Santos and Veronessi, 2001). The reason is easy to understand if we notice that given the connection between predictability in time series and the cross section of stock returns, lagged instruments that are shown to predict market returns are natural conditioning variables for testing asset pricing models in cross section.

Hence, the obvious question is why deviations from the common long-term trend in consumption and wealth should forecast stock returns. This feature arises as an implication of a wide range of investor behavior models, where consumption is a function of aggregate wealth. So, for a wide family of preferences, the log of the consumption-wealth ratio can be written as a function of the expected returns of the market portfolio (see Campbell and Mankiw, 1989, among others). Before we address the empirical exercise of linking the log of consumption-wealth ratio and future returns it is important to emphasize the existing problems concerning this ratio. The most important one is that the aggregate wealth, specifically the human capital component, is unobservable. In this sense, Lettau and Ludvigson (2001a) propose to approximate the aggregate wealth with observable variables: asset holdings and labor income. Furthermore, given that these variables seem to be non-stationary, if we want to work with the deviations from the common trend between them and consumption, we should find a stable cointegrating relation between them. Finally, we need to find consistent estimators for the cointegration parameters.

In this article we estimate this new variable for the Spanish case and study its ability to forecast future returns. The situation as regard the predictability of returns in this market is very similar to that in other markets: the variables used to date are unable to explain returns in a reasonable way (Marhuenda and Gómez, 1997; Peiró, 1990 and Rubio, 1986 and 1988). Unfortunately, our results show that the approximation of the consumption-wealth ratio computed as in Lettau and Ludvigson (2001a) has a limited power in forecasting quarterly returns in the Spanish market for the period considered. However, when we compare the behavior of our proxy with variables traditionally used as instruments, such as the book-to-market ratio, interesting empirical points arise. First of all, we have found that the correlation between this financial ratio and the proxy of the consumption-wealth ratio is extremely high (93%). And for our sample, only the book-to-market variable forecasts returns. These two findings are linked: the high correlation suggests that the financial ratio could contain some information that is in the macroeconomic ratio, making the former a good predictor of returns. This intuition is easy to understand if it is realised that the book value of a firm can be seen by investors as an indicator of future cash flows. In this sense, this variable would play the same role as dividends. Under an accounting principle that relates book values with non distributed earnings, we are able to obtain a theoretical expression that justifies both the forecasting power of the book-to-market variable and the positive correlation between it and the consumption-wealth ratio.

The article is organized as follows. In Section 2 we describe the framework that justifies the relationship between consumption, wealth and future returns. Section 3 presents the empirical test necessary to obtain the cointegrating relation between the variables that approximate the consumption-wealth ratio. Section 4 checks the behaviour of the proxy forecasting returns. Section 5 shows the theoretical expressions that support the empirical findings related with the good behaviour of book-to-market ratio in asset pricing. Finally, Section 6 concludes the work.

2. THE FRAMEWORK

In this section we present the general framework that relates consumption, wealth and expected returns.

Assume a representative agent economy in which all wealth including human capital is tradable. Define W_t as the aggregate total wealth (human capital plus asset holdings) in period t. C_t to be consumption at time t and $R_{m,\, t+1}$ is the net return on wealth from period t to t+1. Then the representative agent´s dynamic budget constraint can be written,

$$W_{t+1} = (1 + R_{m,t+1})(W_t - C_t) \tag{1}$$

indicating that the wealth in the next period will be the wealth does not consume in the present and the return that this wealth has generated. Labor income does not appear explicitly in (1) because of the assumption that the market value of tradable human capital is included in wealth.

Campbell (1993) points out that if the consumption-aggregate wealth ratio is stationary, the budget constraint may be approximate by taking a first order Taylor expansion around the mean of the log of the consumption-wealth ratio. The resulting approximation is

$$\Delta w_{t+1} \approx r_{m,t+1} + K_c + \left(1 - \frac{1}{r_c}\right)(c_t - w_t)\,, \tag{2}$$

where each lower case variable denotes the log of the corresponding variable, $r_c \equiv 1 - \exp(\overline{c} - \overline{w})$ and K_c is a constant that plays no role in what follows. Combining this with the trivial equality $\Delta w_{t+1} = \Delta c_{t+1} - \Delta(c_{t+1} - w_{t+1})$, solving the resulting difference equation forward and taking expectations, we can write the budget constraint in the form

$$c_t - w_t = E_t\left[\sum_{j=1}^{\infty} r^j (r_{m,t+j} - \Delta c_{t+j})\right] + \frac{r\,k}{1-r}, \quad (3)$$

where the operator E_t denotes mathematical expectation conditional on information available at t. Equation (3) says that if the consumption-wealth ratio is high, then the agent must expect high returns on future wealth or low consumption growth rates. It also implies that if the consumption-wealth ratio is not constant it must be able to predict changes in returns or consumption. The consumption-wealth ratio can only change if consumption growth, returns, or both vary in time.

The framework presents the problem that aggregate wealth, and more precisely its human capital component, is unobservable. One cannot therefore use the model to predict returns. To overcome this obstacle we follow Lettau and Ludvigson (2001a). They assume that the nonstationary component of human capital (H_t) can be described by aggregate labor income (Y_t), implying that $h_t=k+y_t+z_t$, where k is a constant an z_t is a mean zero stationary random variable. This assumption may be rationalized by a number of different specifications linking labor income to the stock of human capital. For example that labor income may be described as the annuity value of human wealth, $Y_t=R_{h,t+1}\ H_t$ where R_{ht+1} is the net return of human capital. Also aggregate labor income can be thought of as the dividend on human capital, as in Campbell (1996) and Jagannathan and Wang (1996). In each of these specifications, the log of aggregate labor income captures the nonstationary component of human capital.

Assuming that aggregate wealth is composed of financial wealth, which can be described by asset holdings (A_t), plus human capital,

$$W_t = A_t + H_t \quad (4)$$

Expressed in logarithmic from the aggregate wealth can be approximated as[1]

[1] We need to express the aggregate wealth in terms of the ratio H_{t+1}/A_{t+1} to obtain $w_{t+1} = a_{t+1} + \log(1+\exp(h_{t+1} - a_{t+1}))$. After that, we make a first-order Taylor expansion around the unconditional mean of the ratio $(h-a)$.

$$w_t = w a_t + (1-w) h_t \,, \qquad (5)$$

where w is the average share of asset holdings in total wealth (A/W), and it is assumed that this proportion is constant along the time. With our data we obtain a mean proportion of the total wealth due to the asset holdings of 0.64 and we can not reject the null of it is constant during our period of time.

Lastly, the authors assume that labor income can approximate the human capital component, then, the empirical variable that will forecast future returns is

$$c_t - w a_t - (1-w) y_t \qquad (6)$$

This linear combination of variables must be stationary to forecast returns. In other words c_t, a_t, and y_t should be stationary or must be cointegrated. In this way [$c_t - w a_t - (1-w) y_t$] give us the deviation from the common trend existing between them. Henceforth we will call this *cay*.

3. ESTIMATION OF THE COMMON TREND BETWEEN CONSUMPTION AND WEATLH

3.1. Data

The data used in the estimation of *cay* are quarterly, seasonally adjusted and in 1990 pesetas. The sample period is from March 1982 to December 1999. We detail the construction process and the data sources below.

We have considered the final domestic consumption of households in current prices as the variable that represents aggregate consumption. The Quarterly National Accounts published by the Spanish National Institute of Statistics provides this information.

The asset holding data are comprised by the household and non-financial firms net worth series provided by the Bank of Spain in the Financial Accounts of the Spanish Economy. This variable is available in quarterly frequencies only from 1994. So, for the first 13 years we compute quarterly data from annual data and share out the annual growth in four parts. To do this, we observed the series after 1994 to find common rules within each year that we could apply in the previous quarters. However, the ups and downs of the series in the different quarters do not follow a common rule. For this reason, we have decided to distribute annual growth in four equal parts. Obviously we are aware that this solution generates a smoothing series for the first years.

The third variable represents the aggregate net labor income of agents. This variable is generated with wages and salaries minus taxes at current prices. The Spanish National Institute of Statistics provides both variables. Quarterly data are available for labor salaries but not for taxes, which are annual. Again, we consider two alternatives: first, we share out the annual increment between the four quarters in equal parts and second, we apply the estimated quarterly growth rate of the labor income series. The results are very similar.

All series are deflated by the Consumer Price Index (1990=100) provided by the Spanish National Institute of Statistics.

The first problem we need to address is that, unlike US data, Spanish data are not always positive for the net asset holding (A_t). Negative signs are possible because the series is in net terms, that is, financial assets less financial liabilities without considering real assets. Unfortunately, we do not have real asset data, an important part of the total asset wealth. So, our series presents negative values from March 1982 to the second quarter of 1983. For these first six values of the sample we have no way to apply the approximation proposed by Lettau and Ludvigson (2001a), because it is necessary to consider the variables in logs. As a solution, we propose assigning a value of one to those quarters where we have a negative value, so the log will be zero, and offsetting the effect by subtracting the value fom the salary. In this way, the overall amount of both variables that will approximate the total wealth of the period will be the same. We have also studied the results with only a sub-sample of positive values, that is, from the third quarter of 1983 and the conclusions of the work do not change. A second alternative is to work only with one variable proxy of wealth, without disaggregating it into asset holding and labor income (W=A+Y). In this case, the variable used to predict returns will be deviations from the common trend between consumption and wealth, which we denote as *cw*.

3.2. *Empirical Tests*

This section describes the procedures followed to test for the presence of cointegrating relations among the variables used and the results of that test. The analysis is presented for the log of the variables denoted c_t, a_t, and y_t and the aggregate w_t.

First of all, each individual variable must pass a unit root test. Table 1 presents a Dickey-Fuller test for the presence of unit root in the variables c_t, a_t, e y_t and the aggregate w_t on several autoregressive structures (Augmented Dickey Fuller). The procedure tests the null hypothesis of a unit root against the alternative hypothesis of stationarity around a linear trend. In all cases and for the four series the results are consistent with the unit root hypothesis at 95% level of confidence.

TABLE 1. DICKEY-FULLER TEST FOR UNIT ROOTS

Augmented Dickey- Fuller t-Statistic				Critical Values		
Variables	Lag=0	Lag=1	Lag=2	1 Percent Level	5 Percent Level	10 Percent Level
c_t	-1,428	-1,080	-2,044	-4,09	-3,47	-3,16
a_t	-2,586	-3,358	-3,559	-4,09	-3,47	-3,16
y_t	-2,431	-3,313	-3,715	-4,09	-3,47	-3,16
w_t	-1,173	-1,943	-2,112	-4,09	-3,47	-3,16

This table reports the Dickey-Fuller test for the presence of a unit root in the variables y_t, c_t, a_t and the aggregate w_t among several autoregressive structures (Augmented Dickey Fuller). The model includes a linear trend and a drift. The sample period is 1982:1 to 1999:4.

Next, we consider the test suggested by Johansen (1988, 1991) to estimate the number of cointegrating relationships, if any. The procedure sets a p-dimensional vector autoregressive model (VAR) with k lags, where p is the number of variables between which we are studying the cointegration. In our case p=3. The Johansen procedure provides two tests for cointegration: First, under the null hypothesis that there are exactly r cointegrating relations, the TRACE statistic offer a likelihood ratio test of this null hypothesis against the alternative that there are p cointegrating relations. The second, an “L-MAX” statistic is used to test the hypothesis of r cointegrating relations against the alternative of r+1 cointegrating relations. Both tests depend on the number of lags assumed in the VAR model. Table 2 reports the obtained results under a number of lag assumptions.

TABLE 2. JOHANSEN COINTEGRATION TEST

Variables c_t, a_t and y_t					Variables c_t y w_t				
One lag in VAR model									
H_0 = r	**L-Max**	**5% CV**	**Trace**	**5% CV**	**L-Max**	**5% CV**	**Trace**	**5% CV**	**H_0 = r**
0	27,75*	20,77	45,71*	29,68	14,69*	14,03	25,03*	15,41	0
1	17,72*	14,03	17,96*	15,41	10,34*	3,76	10,34*	3,76	1
2	0,24	3,76	0,24	3,76					
Two lags in VAR model									
H_0 = r	**L-Max**	**5% CV**	**Trace**	**5% CV**	**L-Max**	**5% CV**	**Trace**	**5% CV**	**H_0 = r**
0	30,21*	20,77	50,41*	29,68	13,77	14,03	20,07*	15,41	0
1	18,89*	14,03	20,20*	15,41	6,30*	3,76	6,30*	3,76	1
2	1,31	3,76	1,31	3,76					
Three lags in VAR model									
H_0 = r	**L-Max**	**5% CV**	**Trace**	**5% CV**	**L-Max**	**5% CV**	**Trace**	**5% CV**	**H_0 = r**
0	47,61*	20,77	61,57*	29,68	15,54*	14,03	19,98*	15,41	0
1	12,99	14,03	13,96	15,41	4,44*	3,76	4,44*	3,76	1
2	0,97	3,76	0,97	3,76					
Four lags in VAR model									
H_0 = r	**L-Max**	**5% CV**	**Trace**	**5% CV**	**L-Max**	**5% CV**	**Trace**	**5% CV**	**H_0 = r**
0	77,85*	20,77	88,77*	29,68	16,54*	14,03	17,59*	15,41	0
1	9,68	14,03	10,92	15,41	1,05	3,76	1,05*	3,76	1
2	1,24	3,76	1,24	3,76					2

This table reports the statistics for the Johansen cointegration test. The statistic L-Max tests the hypothesis of r cointegrating relations in front of r+1 relations. The statistic Trace offers a test for the hypothesis of r cointegrating relations in front or the alternative of 3 relations. Both tests depend on the number of lags assumed in the VAR model. (*) means the rejection of the null hypotheses at 5% of significance level.

The critical values obtained using this approach depend on the trend characteristics of the data. We present results allowing for linear trends in data, but assuming that the cointegrating relation has only one constant. Ludvigson and Steindel (1999) give theoretical reasons that enhance this hypothesis. These authors assert that the long term equilibrium relationship between consumption, labor income and financial wealth do not have deterministic trends, although each individual data series may have deterministic trends.

The results, when we observe the consumption, labor income and asset holdings variables indicate in general a rejection of the null hypothesis of zero cointegrating relations in favor of the existence of at least one cointegrating relation. This result is robust to the different specifications of lags considered and robust to the use of the L-max or Trace statistic. If we consider only the consumption and aggregate wealth variables, we can reject the hypothesis of zero cointegrating relations against the one cointegrating relation hypothesis.

We have found that the consumption, labor income and asset holding variables have unit roots. This would imply that the relations that we can establish between them will be non stables unless that they are cointegrated. Thus, there will be some stationary linear relation between them, although individually they are not stationary. This happens when the variables share common trends that allow us to establish long-term stable equilibrium relations. We have checked, with the test in Johansen (1988, 1991), that the variables are cointegrated, are therefore ready to estimate the existing relationship between them and the to obtain the deviation from their common trends (cay_t or cw_t).

To obtain the long term equilibrium relationship we need to estimate the following equations for disaggregate and aggregate wealth respectively:

$$c_t = b_a a_t + b_y y_t + e_t \quad \text{or} \quad c_t = b_w w_t + e_t \qquad (7)$$

We must note that an OLS estimation of equation (7) would not allow a correct analysis of the significance of the estimates, given that the regressors are non exogenous. One way to solve this problem is to obtain the parameters of the cointegrating relationship by the Johansen (1988) technique[2]. The procedure is maximum likelihood estimation with full information[3]. In this case, the equations generating for *cay* and *cw* with the normalized coefficients of cointegration[4] ant the t-statistics in parenthesis are[5]:

$$cay_t = c_t - 2{,}017 - \underset{(3{,}85)}{0{,}026\,a_t} - \underset{(29.49)}{0{,}790\,y_t} \quad \text{and} \quad cw_t = c_t - 4{,}559 - \underset{(3{,}49)}{0{,}470\,w_t}$$

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2 Another way to eliminate the effect that endogenous regressors have on the probability distribution of the OLS estimator is to use dynamic OLS, that is, to estimate the equation by OLS but to insert dynamism by adding as explanatory variables the past and future changes of a_t and y_t (Stock y Watson, 1993). This is the procedure used by Lettau and Ludvigson (2001a).

3 There are other methods of estimating cointegrating relations. Gonzalo (1989) simulates some of them and finds that if the data are generated by an error correction model likelihood methods present a better behavior.

4 The cointegration vector is not the only one. If $(b_1, b_2, b_3 \cdots b_n)$ is a cointegration vector, then for each non null value of λ, $(lb_1, lb_2, lb_3 \cdots lb_n)$ is also a cointegration vector. Tipically one of the variables is used to normalize the vector, fixing the coefficient at one.

5 This method inserts the constant into the cointegrating relation.

4. RETURNS AND FORECASTING VARIABLES

4.1. Data

This section describes the variables used, and analyzes their ability at forecasting returns. The sample period for this study is the same one considered in the estimation of the variables *cay* and *cw*: quarterly data from March 1982 to December 1999. As we know, the use of the estimated regressors underestimates the variances of the parameters. Also, if the sample period of the estimation is the same as the sample period for analysis the problem is increased due to the contemporaneous correlations. With these problems in mind, the conclusions of this part should be viewed with caution.

The sample includes 205 stocks that have been quoted at some time in our sample period. For each individual asset we compute three variables: the return, the book-to-market ratio and the dividend yield. The quarterly asset return is obtained as the ratio of the price at the end of the quarter and the price at the end of the quarter before. We consider the dividends paid during this period and adjust the returns by the splits. To compute the book-to-market ratio in a quarter we use the book value of the share at 31 December of the year before in the numerator and the product of the number of shares and the price at the end of the quarter as the market value. The dividend yield is obtained as the ratio between the sum of all the dividends paid by the company in the last four quarters and the price at the end of the quarter before.

We compute the corresponding aggregate data from the individual data. The market return is approximated by two indices: the average of the stock returns, as the equal-weighted index (*ree*), and a value-weighted index, using the market value of each asset in December of the last year (*rve*). The aggregate book-to-market ratio (*btm*) and the aggregate dividend yield (*dy*) are obtained as the average of the individual asset ratios. We use the quarterly implicit return of the interest rates of one-year Treasury bonds (Pagarés del Tesoro) as a risk free rate (*r*) up to December 1987, and the quarterly one-year T-bill rate after this date. Finally, we use a variable that represents the term structure of interest rates (*dti*) generated as the quarterly 10-year bond return minus the risk free rate. All the variables are in logs and the market return is computed in excess of the risk free rate to eliminate the price effect, because we are using nominal returns.

Table 3 reports the summary statistics for the variables described previously and the ones estimated in the above section that pick up the deviations between consumption and wealth (*cay* and *cw*). We observe that the market returns for both indices and the variables *cay* and *cw* present similar averages, about 2% quarterly, and also similar standard deviations, although *cw* is more variable than *cay*. In relation to the first order autocorrelations, we observe high persistence of all variables that, presumably, forecast returns. We observe that *cay* and *cw* present a low correlation with returns. The correlations between the remaining variables and returns are also low. Perhaps the most relevant point in this table is the high correlation between *cay* or *cw* and the book-to-market ratio or the spread of interest rates, specially the case of *cw* and *btm*, where the correlation is 93%. Given that the consumption wealth ratio is a macroeconomic variable and the book-to-market ratio is a financial variable, it is very interesting to find such high correlation. In this sense, if the former is a business cycle indicator we can think that the latter also contains similar information. And this would justify the use of such a ratio as a state variable in intertemporal models. We will examine these issues in section 5.

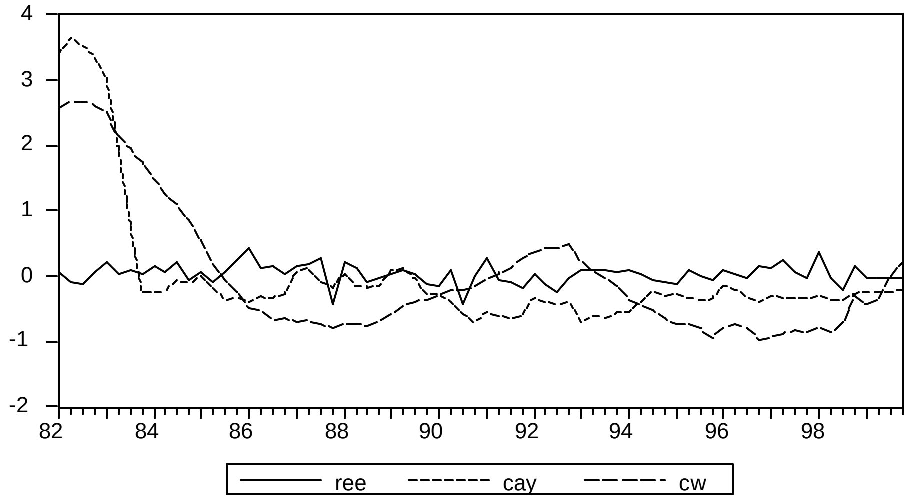
TABLE 3. SUMMARY STATISTICS

	ree	*rve*	*cay*	*cw*	*btm*	*dy*	*dti*
Mean	0.03011	0.0249	0.0185	0.0246	0.2400	-2.8058	0.0043
St. Deviat.	0.1514	0.1286	0.0901	0.1535	0.6849	1.3471	0.0057
Autocorr.	0.039	-0.103	0.969	0.989	0.957	0.177	0.877
Correlation Matrix							
ree	1	0.933	0.018	-0.028	-0.087	0.056	0.048
rve		1	-0.074	-0.094	-0.141	0.106	-0.039
cay			1	0.769	0.644	-0.089	0.785
cw				1	0.925	-0.078	0.581
btm					1	-0.063	0.528
dy						1	-0.162
dti							1

The table shows the summary statistics of the variables from the first row. *ree* is quarterly log excess return on a equal-weighted index of all stocks in the sample, *rve* is the log excess return on a value-weighted index; *cay* represents the deviations in common trend of consumption, asset holdings, and labor income ($c_t - 2.017 - 0.026 a_t - 0.790 y_t$) and *cw* is the estimation of the deviations between consumption and wealth ($c_t - 4.559 - 0.470 w_t$). *btm* is the aggregated book-to-market ratio and *dy* is the aggregated dividend yield. They are computed as the simple average of the corresponding individual measures for all stocks in the sample. *dti* is a yield spread between long and short-term interest rates. The sample period is 1982:1 to 1999:4.

We can anticipate the behaviour of the two proxies of the consumption-wealth ratio by observing figure 1. It plots the standardized trend deviations, *cay* and *cw*, and the standardized excess return on the equal-weighted index. Unfortunately, this figure gives us some insights into the weak capability of the consumption-wealth ratio for predicting returns. It is rare to find episodes during which trend deviations preceded excess returns. Moreover, it seems that the contrary occurs. At some times, returns precede *cay*.

FIGURE 1. RETURNS AND CAY AND CW IN STANDARDIZED UNITS



This figure plots the excess return (solid line) on an equal-weighted index and the variables that proxy the log consumption-wealth ratio (dashed lines), that is, deviations from the common trend in consumption, asset holdings and labor income (*cay*) or consumption and aggregate wealth (*cw*).

4.2. Forecasting regressions

In order to check the extent to which our proxy variables are able to forecast returns, we present the OLS estimation of a regression of the excess equal-weighted index return on the one-quarter lag of the variables described in section 4.1 as potential predictors. The choice of these variables is based on the available empirical evidence[6]. We do not present the results obtained with the return of the value-weighted index because they are very similar. In this exercise, we first analyse the forecasting power of a set of variables that contains *cay*. Secondly, we repeat the estimation with a set of variables that includes *cw*.

[6] See first paragraph of the introduction. Specifically, Nieto (2001) analyzes the forecasting power of these variables for the Spanish market in the same sample period but with monthly data and finds that *btm* has this ability.

Table 4 shows the forecasting regressions with *cay*. The table presents estimates of the parameters of each lagged variable indicated in the first row, the standard t-statistic in parenthesis and the Newey-West corrected t-statistic for generalized serial correlation of the residuals in square brackets. In the last column the adjusted R-square is reported. We can observe that individually none of the variables can explain future returns, although some combinations of them offer us somewhat better results. In general, *btm* is statistically significant when *cay* is considered jointly, and the t-statistic of the latter shows a little improvement when *dti* is included too. In that case, we find the biggest R-square (2.57%).

Given this result, and due to the strong correlation between the variables *cay* and *btm* or *cay* and *dti*, also observed in table 3, we compute orthogonal variables regressing *btm* and *dti* on *cay*. Using the residuals of those regressions instead of the original variables, we eliminate not only the correlation between the two independent variables and *cay* but also the correlation between *btm* and *dti*, avoiding multicolinearity problems in the estimation. The results are,

$$btm_t = 0.1496 + \underset{(7.04)}{4.8962}\, cay_t + rbtmcay_t \qquad R^2 = 40.65$$

$$dti_t = 0.00337 + \underset{(10.62)}{0.0497}\, cay_t + rdticay_t \qquad R^2 = 61.15$$

The analysis of these orthogonal variables jointly with *cay* in predicting returns is shown in table 4B. The predictive power of *btm* is confirmed: using only the residuals of it on *cay* the variable is now able to explain returns better than any combination of the variables in table 4. On the other hand, the partial significance of *cay* in the previous table completely disappears[7].

[7] When we consider the return on value-weighted index we find the same conclusions: the forecasting power is centered on *cay* and *btm* when both these variables are in the regression, and their strong correlation makes the residuals of the latter on the former the sole relevant variable.

TABLE 4. FORECASTING REGRESSIONS WITH CAY

Constant	*ree*	*cay*	*btm*	*dy*	*dti*	R^2
0.0284	0.0389					-1.30
(1.53)	(0.32)					
[1.59]	[0.28]					
0.0297		-0.0047				-1.45
(1.60)		(-0.02)				
[1.49]		[-0.03]				
0.0211			0.0348			1.06
(1.10)			(1.32)			
[1.05]			[1.60]			
0.0269				-0.0010		-1.44
(0.64)				(-0.07)		
[0.64]				[-0.08]		
0.0182					2.6680	-0.43
(0.80)					(0.84)	
[0.80]					[0.76]	
0.0285	0.0389	-0.0058				-2.78
(1.49)	(0.32)	(-0.03)				
[1.51]	[0.28]	[-0.04]				
0.0191	0.0536		0.0359			-0.10
(0.97)	(0.45)		(1.35)			
[1.00]	[0.38]		[1.67]			
0.0248	0.0397			-0.0013		-2.77
(0.58)	(0.33)			(-0.09)		
[0.59]	[0.28]			[-0.11]		
0.0173	0.0340				2.6241	-1.78
(0.75)	(0.28)				(0.82)	
[0.78]	[0.25]				[0.76]	
0.0204		-0.2988	0.0602			1.51
(1.07)		(-1.15)	(1.75)			
[0.98]		[-1.35]	[2.12]			
0.0270		-0.0038		-0.0010		-2.93
(0.63)		(-0.02)		(-0.07)		
[0.61]		[-0.02]		[-0.08]		
0.0058		-0.3594			7.1330	-0.10
(0.23)		(-1.11)			(1.39)	
[0.24]		[-1.05]			[1.34]	
0.0029		-0.3088	0.0634	-0.0061		0.33
(0.07)		(-1.17)	(1.80)	(-0.44)		
[0.05]		[-1.39]	[2.02]	[-0.42]		
-0.0017		-0.6208	0.0579		6.6992	2.57
(-0.07)		(-1.74)	(1.69)		(1.32)	
[-0.06]		[-1.82]	[2.11]		[1.30]	
-0.00849		-0.6158	0.0593	-0.0026	6.5072	1.15
(-0.19)		(-1.71)	(1.68)	(-0.18)	(1.25)	
[-0.16]		[-1.81]	[1.96]	[-0.19]	[1.27]	

Table 4: This Table reports the OLS estimates of the forecasting regressions for the excess return on an equal-weighted index as market return (*ree*) on one lag of the variables of the first row. *cay* represents the deviations from the common trend of consumption, asset holdings, and labor income ($c_t - 2.017 - 0.026 a_t - 0.790 y_t$); *btm* is the aggregated book-to-market ratio; *dy* is the aggregated dividend yield, both are computed as the simple average of the corresponding individual measures for all stocks in the sample; *dti* is a yield spread between long and short-term interest rates. Standard t-statistics are shown in parentheses. The Newey-West corrected t-statistics are reported in square brackets. The last column reports the adjusted R^2, in percent terms. The sample period is 1982:1 to 1999:4.

TABLE 4B. FORECASTING REGRESSIONS WITH CAY

Constant	*cay*	*rbtmcay*	*rdticay*	R^2
0.0294		0.0602		2.93
(1.65)		(1.76)		
[1.57]		[2.14]		
0.0297			7.1329	1.35
(1.66)			(1.40)	
[1.69]			[1.35]	
0.0296	-0.0044	0.0579	6.6992	2.57
(1.62)	(-0.02)	(1.69)	(1.32)	
[1.57]	[-0.02]	[2.11]	[1.30]	

This Table reports the OLS estimates of the forecasting regressions of the excess return on an equal-weighted index as market return (*ree*) on one lag of the variables of the first row. *cay* represents the deviations in common trend of consumption, asset holdings, and labor income ($c_t - 2.017 - 0.026 a_t - 0.790 y_t$); *rbtmcay* are the residuals of the aggregated book-to-market ratio on *cay* ($btm_t - 0.150 - 4.896 cay_t$); *rdticay* are the residuals of the interest rates term structure on *cay* ($dti_t - 0.0034 - 0.050 cay_t$). Standard t-statistics are showed in parentheses. The Newey-West corrected t-statistics are reported in brackets. The last column reports the adjusted R^2, in percent terms. The sample is 1982:1 to 1999:4.

Tables 5 and 5B present the same analysis with *cw* instead of *cay*. The results show that the deviations from the common trend between consumption and aggregate wealth are not individually significant in predicting returns neither. Adding *btm* to the regression makes the two estimates statistically different from zero and the R-square coefficient increases from –1.4% to 19.4%. As before, if we eliminate the correlation between the variables using the residuals of the following regressions,

$$btm_t = 0.1383 + 4.1290\, cw_t + rbtmcw_t \qquad R^2 = 85.44$$
$$(20.44)$$

$$dti_t = 0.00386 + 0.0216\, cw_t + rdticw_t \qquad R^2 = 32.82$$
$$(5.97)$$

the results confirm the evidence obtained with *cay*. The residuals of *btm* on *cw* have a strong predictive impact on future returns, as occurs when we include the two original variables in the regression[8].

[8] The use of the value-weighted index as a measure of returns produces very similar estimates and slightly higher adjusted R-square coefficients.

TABLE 5. FORECASTING REGRESSIONS WITH CW

Constant	*ree*	*cw*	*btm*	*dy*	*dti*	R^2
0.0300		-0.0156				-1.42
(1.62)		(-0.13)				
[1.54]		[-0.16]				
0.0288	0.0385	-0.0146				-2.76
(1.52)	(0.32)	(-0.12)				
[1.57]	[0.27]	[-0.15]				
-0.0107		-1.1742	0.2799			19.44
(-0.57)		(-4.09)	(4.34)			
[-0.51]		[-4.20]	[4.63]			
0.0280		-0.0145		-0.0007		-2.91
(0.65)		(-0.12)		(-0.05)		
[0.63]		[-0.14]		[-0.06]		
0.0134		-0.1104			4.3960	-1.05
(0.57)		(-0.76)			(1.12)	
[0.59]		[-0.78]			[1.05]	
-0.0305		-1.1807	0.2840	-0.0068		18.61
(-0.75)		(-4.09)	(4.36)	(-0.55)		
[-0.66]		[-4.12]	[4.51]	[-0.54]		
-0.0297		-1.2929	0.2830		4.9160	20.61
(-1.29)		(-4.35)	(4.42)		(1.41)	
[-1.26]		[-4.05]	[4.57]		[1.50]	
-0.0389		-1.2915	0.2849	-0.0035	4.7198	19.50
(-0.95)		(-4.32)	(4.39)	(-0.27)	(1.32)	
[-0.91]		[-4.02]	[4.44]	[-0.30]	[1.46]	

This Table reports the OLS estimates of the forecasting regressions of the excess return on an equal-weighted index as market return (*ree*) on one lag of the variables of the first row. *cw* is the estimation of the deviations between consumption and total wealth ($c_t - 4.559 - 0.470\, w_t$); *btm* is the aggregated book-to-market ratio; *dy* is the aggregated dividend yield, both are computed as the simple average of the corresponding individual measures for all stocks in the sample; *dti* is a yield spread between long and short-term interest rates. Standard t-statistics are showed in parentheses. The Newey-West corrected t-statistics are reported in square brackets. The last column shows the adjusted R^2, in percent terms. The sample period is 1982:1 to 1999:4.

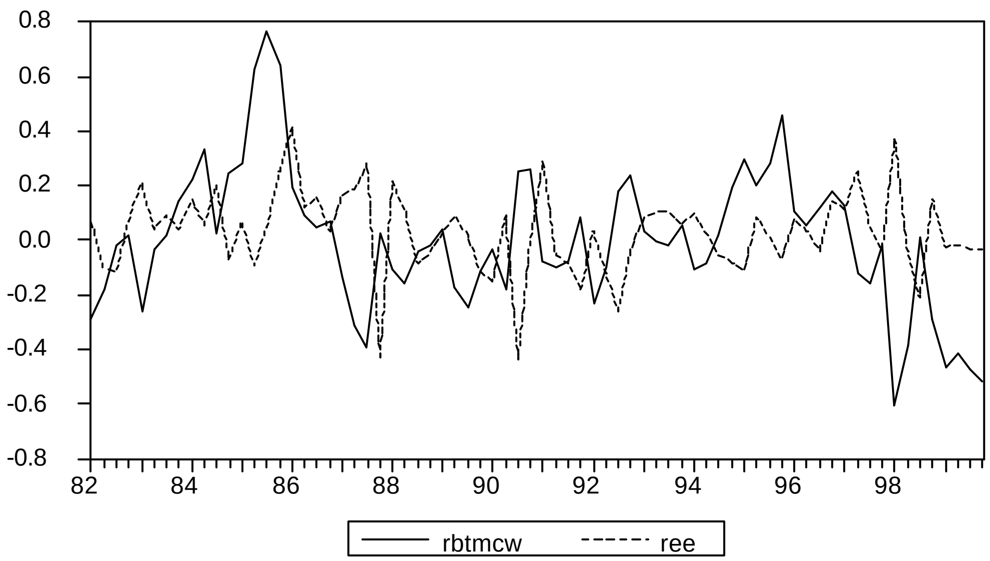
TABLE 5B. FORECASTING REGRESSIONS WITH CW

Constant	*cw*	*rbtmcw*	*rdticw*	R^2
0.0276		0.2799		20.57
(1.71)		(4.37)		
[1.49]		[4.66]		
0.0296			4.3959	0.39
(1.64)			(1.13)	
[1.63]			[1.04]	
0.0279	-0.0184	0.2830	4.9160	20.61
(1.71)	(-0.17)	(4.42)	(1.41)	
[1.56]	[-0.16]	[4.57]	[1.50]	

This Table reports the OLS estimates of the forecasting regressions of the excess return on an equal-weighted index as market return (*ree*) on one lag of the variables of the first row. *cw* is the estimation of the deviations between consumption and total wealth ($c_t - 4.559 - 0.470\, w_t$); *rbtmcw* are the residuals of the aggregated book-to-market ratio on *cw* ($btm_t - 0.138 - 4.129\, cw_t$); *rdticw* are the residuals of the interest rates term structure on *cw* ($dti_t - 0.0039 - 0.022\, cw_t$). Standard t-statistics are shown in parentheses and Newey-West corrected t-statistics are reported in square brackets. The last column reports the adjusted R^2, in percent terms. The sample period is 1982:1 to 1999:4.

So we can conclude this section by asserting that *cay*, *cw*, and *btm* are the variables with some information about future returns, but it is necessary to combine the first two with the third to find that capability[9]. In this sense, we might think that both contain some common information, although *btm* is more volatile. If that extra variability can explain the changes in future returns, the deviations from the common trend between *cw* and *btm* provide the variable with the ability required. Figure 2 shows many episodes in which *rbtmcw* precedes excess returns.

FIGURE 2. RESIDUALS OF BOOK-TO-MARKET ON CW AND EXCESS RETURNS



This figure illustrates the path of the residuals of a regression of *btm* on *cw* (solid line) and the path of the excess returns (dashed line).

4.3. Long horizon forecasts

In this section, we investigate the predictive power of the variables considered above in forecasting consumption and returns with longer horizons. Following equation (3) an increase in the consumption wealth ratio must precede a higher future market return or a smaller future consumption growth.

[9] In fact, the Johansen test shows that *cay* and *btm*, on one side, and *cw* and *btm*, on the other, present significant cointegrating relations in all sample periods.

We start by studying whether the variables that represent the deviations in the common trend of consumption and wealth or the deviations in the common trend of the consumption-wealth ratio and *btm* can forecast consumption growth at different horizons. Table 6 presents the estimation of single equation regressions that have cumulate consumption growth from 1 to 8 quarters ($\Delta c_H = \Delta c_t + ... + \Delta c_{t+h}$, $H = 1,2,...,8$, $h = 1,\ldots,7$)[10] as the dependent variable. For each regression, the table reports the estimated coefficient on the explanatory variable; its standard t-statistic in parenthesis, and its Newey-West corrected t-statistic in square brackets. The last number in each row is the adjusted R-square.

TABLE 6. FORECASTING LONG-HORIZON REGRESSIONS. CONSUMPTION GROWTH.

H	*1*	*2*	*3*	*4*	*8*
cay	-0.0106	-0.0143	-0.0204	-0.0146	0.7141
	(-0.83)	(-0.81)	(-0.72)	(-0.37)	(3.28)
	[-1.40]	[-0.98]	[-0.93]	[-0.38]	[1.98]
	-0.44	-0.50	-0.72	-1.31	13.45
cw	-0.0186	-0.0362	-0.0591	-0.0808	-0.1843
	(-2.59)	(-4.03)	(-4.49)	(-5.03)	(-4.94)
	[-2.98]	[-2.95]	[-3.34]	[-3.47]	[-4.31]
	7.55	18.11	21.95	26.62	27.07
rbtmcay	-0.0061	-0.01299	-0.0209	-0.0027	-0.0434
	(-2.94)	(-5.63)	(-6.46)	(-8.43)	(-8.03)
	[-3.92]	[-5.04]	[-6.43]	[-7.48]	[-7.32]
	9.84	30.73	41.10	51.14	50.21
rbtmcw	-0.0045	-0.0134	-0.0265	-0.0356	-0.094
	(-0.99)	(-2.37)	(-3.46)	(-4.11)	(-5.24)
	[-1.85]	[-3.22]	[-4.27]	[-5.22]	[-5.13]
	-0.04	6.30	13.92	19.19	29.6

This Table reports the OLS estimates of the forecasting regressions of the *H*-period consumption growth on one lag of the variables in the first column. *cay* represents the deviations in common trend of consumption, asset holdings, and labor income ($c_t - 2.017 - 0.026 a_t - 0.790 y_t$); *cw* is the estimation of the deviations between consumption and total wealth ($c_t - 4.559 - 0.470 w_t$); *rbtmcay* are the residuals of the aggregated book-to-market ratio on *cay* ($btm_t - 0.150 - 4.896 cay_t$); *rbtmcw* are the residuals of the aggregated book-to-market ratio on *cw* ($btm_t - 0.138 - 4.129 cw_t$). Standard t-statistics are in parentheses below the estimates. The Newey-West corrected t-statistics are reported in square brackets. The last number is the adjusted R^2, in percent terms. The sample period is 1982:1 to 1999:4.

The results indicate that *cay* does not contain information about consumption growth for the next year and only becomes a significant forecaster at a growth horizon of 2 years. The other three variables are much powerful predictors at any horizon, offering bigger R-square

[10] In the same way, the accumulated returns are computed.

coefficients as the horizon increases. As we might expect from the theoretical relation, at all horizons *cay* and *cw* predict drops in future consumption growth, except the parameter on *cay* at 8-quarter horizon. But moreover, the residuals of *btm* on *cay* or *cw* behave in this way too. Again, this evidence reinforces the use of *btm* as a state variable.

Independently of the ability of the variables to forecast changes in consumption growth, they should forecast future returns. We analyze this issue by considering single and multiple equation regressions and report the results in tables 7 and 8, respectively. In table 8A, *cay* forms part of the set of variables considered while in table 8B *cw* is considered.

Table 7 shows that the excess return on the equal-weighted index contains information about its future temporal behavior at horizons longer than two quarters. The same occurs with the variable that represents the term structure of interest rates. These two cases present the highest R-square coefficients at a two-year horizon (52%). The capability to forecast returns of *cay* and *cw* is negligible at any horizon, and only the former can forecast returns at the longest term, as happened with the consumption growth. The variable *dy* only becomes a significant forecaster at a return horizon of two years, consistent with the existing evidence. Finally, the residuals of *btm* on *cay* or on *cw* are the only variables that can explain the return at the following quarter, consistent with the results of the previous section, and the latter maintains this ability one quarter longer.

Finite sample problems with overlapping data in long-horizon regressions may be avoided by using vector autoregressions (Campbell, 1991; Hodrick, 1992). We now analyze the estimates of a multiple equation regression using a VAR specification. In general terms, the results confirm those obtained individually. Tables 8A and 8B show the results of a set of variables that contain *cay* and *cw* respectively. Each table presents two panels: the first shows the estimates when predicting the next quarter of the equal-weighted index return and the second the parameters of the first equation from a VAR in which the dependent variable is the H-period return. The last column reports the adjusted R-square coefficient. Consistent with the results presented in table 2, the first row of table 8A shows that *rbtmcay* is the only variable that forecasts the next quarter returns. For the remaining rows in the first panel, except *dy*, we can observe a strong temporal persistence: the variables explain their own futures, generating higher R-square coefficients. *cay* is the most auto-correlated variable, which is explained by the lag of *ree*[11] (remember figure 2), of *rbtmcay,* and of *rdticay*. Furthermore, *ree* also forecasts changes in *dy* and *rdticay*. The results of the second panel are consistent with those presented in table 7. Considering all variables jointly we find that

[11] This is also observable with US data. See Lettau and Ludvigson (2001a).

market return forecasts its future at horizons longer than one quarter. The biggest R-square coefficient is obtained at a two-year horizon, where all variables are statistically significant.

TABLE 7. FORECASTING LONG-HORIZON INDIVIDUAL REGRESSIONS. EXCESS RETURNS

H	*1*	*2*	*3*	*4*	*8*
rme	2.6680	3.9585	10.3426	23.1151	106.7615
	(0.84)	(0.86)	(1.70)	(2.98)	(8.41)
	[0.76]	[0.65]	[1.38]	[1.98]	[5.99]
	-0.43	-0.36	2.67	10.35	52.15
cay	-0.0047	0.0237	0.0444	0.2132	10.3747
	(-0.02)	(0.08)	(0.11)	(0.40)	(3.92)
	[-0.03]	[0.06]	[0.11]	[0.47]	[2.15]
	-1.45	-1.44	-1.45	-1.25	18.31
cw	-0.01556	-0.0478	-0.0978	-0.1399	-0.9526
	(-0.13)	(-0.24)	(-0.45)	(-0.50)	(-1.57)
	[-0.16]	[-0.23]	[-0.36]	[-0.39]	[-0.84]
	-1.42	-1.36	-1.17	-1.11	2.23
btm	0.0348	0.0147	-0.0063	-0.0126	-0.1658
	(1.32)	(0.38)	(-0.13)	(-0.21)	(-1.44)
	[1.60]	[0.39]	[-0.12]	[-0.18]	[-0.81]
	1.06	-1.23	-1.44	-1.43	1.64
dy	-0.0010	0.0071	-0.0242	-0.0302	-0.1126
	(-0.07)	(0.36)	(-1.02)	(-1.07)	(-2.63)
	[-0.08]	[0.33]	[-0.69]	[-0.80]	[-2.61]
	-1.44	-1.25	0.06	0.20	8.43
dti	2.6680	3.9585	10.3426	23.1151	106.7615
	(0.84)	(0.86)	(1.70)	(2.98)	(8.41)
	[0.76]	[0.65]	[1.38]	[1.98]	[5.99]
	-0.43	-0.36	2.67	10.35	52.15
rbtmcay	0.0602	0.0217	-0.0156	-0.0387	-0.2419
	(1.77)	(0.43)	(-0.26)	(-0.53)	(-2.16)
	[2.14]	[0.40]	[-0.20]	[-0.40]	[-1.10]
	2.93	-1.17	-1.37	-1.07	5.39
rbtmcw	0.2799	0.1723	0.0933	0.0933	-0.1087
	(4.38)	(1.69)	(0.73)	(0.61)	(-0.44)
	[4.66]	[1.48]	[0.63]	[0.60]	[-0.33]
	20.58	2.57	-0.68	-0.94	-1.27

This Table reports the OLS estimates of the forecasting regressions of the *H*-period excess return on an equal-weighted index (*ree*) on one lag of the variables in the column on the left. *cay* represents the deviations in common trend of consumption, asset holdings, and labor income ($c_t - 2.017 - 0.026 a_t - 0.790 y_t$); *cw* is the estimation of the deviations between consumption and total wealth ($c_t - 4.559 - 0.470 w_t$); *btm* is the aggregated book-to-market ratio; *dy* is the aggregated dividend yield, both are computed as the simple average of the corresponding individual measures for all stocks in the sample; *dti* is a yield spread between long and short-term interest rates; *rbtmcay* are the residuals of the aggregated book-to-market ratio on *cay* ($btm_t - 0.150 - 4.896 cay_t$); *rbtmcw* are the residuals of the aggregated book-to-market ratio on *cw* ($btm_t - 0.138 - 4.129 cw_t$). Standard t-statistics are in parentheses below the estimates. The Newey-West corrected t-statistics are reported in square brackets. The last number is the adjusted R^2, in percent terms. The sample period is 1982:1 to 1999:4.

TABLE 8A. FORECASTING LONG-HORIZON VECTOR AUTOREGRESSIONS WITH CAY.

	Constant	ree_{t-1}	cay_{t-1}	$rbtmcay_{t-1}$	dy_{t-1}	$rdticay_{t-1}$	R^2
ree	-0.0031	0.0613	-0.3147	0.0622	-0.0034	6.2766	0.02
	(-0.07)	(0.50)	(-0.85)	(1.73)	(-0.24)	(1.19)	
cay	0.0004	-0.0296	0.7503	-0.0083	0.0007	2.7241	95.17
	(0.07)	(-2.03)	(18.89)	(-1.93)	(0.39)	(4.33)	
rbtmcay	0.0134	0.0004	0.6315	0.9034	0.0097	-17.4608	82.71
	(0.21)	(0.00)	(2.18)	(17.46)	(0.47)	(-2.30)	
dy	-2.4083	-2.2620	1.1742	0.4217	0.1279	-61.073	10.00
	(-6.41)	(-2.20)	(0.69)	(1.39)	(1.07)	(-1.37)	
rdti	-0.0009	0.0055	-0.0033	0.0006	-0.0003	0.5965	44.06
	(-1.16)	(2.64)	(-0.96)	(0.98)	(-1.05)	(6.59)	
H							
2	0.0181	1.0613	-0.0029	0.0622	-0.0034	6.2766	51.83
	(0.41)	(8.71)	(-0.01)	(1.73)	(-0.24)	(1.19)	
3	-0.0168	1.0898	0.1076	0.0340	-0.0276	16.932	42.17
	(-0.28)	(6.69)	(0.37)	(0.71)	(-1.45)	(2.36)	
4	0.0381	0.9752	0.3199	-0.0035	-0.0220	33.413	34.74
	(0.50)	(4.67)	(0.74)	(-0.06)	(-0.91)	(3.62)	
8	0.1519	0.8158	7.2666	-0.1888	-0.0504	89.2769	66.93
	(1.71)	(3.35)	(4.20)	(-2.71)	(-1.83)	(7.42)	

This Table shows the OLS estimates from vector autoregressions of the excess return on an equal-weighted index (*ree*), the estimated deviations in common trend of consumption, asset holdings, and labor income ($cay_t = c_t - 2.017 - 0.026 a_t - 0.790 y_t$), the residuals of the aggregated book-to-market ratio on *cay* ($rbtmcay_t = btm_t - 0.150 - 4.896 cay_t$), the aggregated dividend yield (*dy*), and the residuals of the interest rates term structure on *cay* ($rdticay_t = dti_t - 0.0034 - 0.050 cay_t$). Standard t-statistics are in parenthesis. The last column reports the adjusted R^2 appear, in percent terms. The sample period is 1982:1 to 1999:4. In the bottom panel, we use the *H*-period accumulated excess return for the prediction in long horizons. Only the results of the first equation of the VAR are shown.

TABLE 8B. FORECASTING LONG-HORIZON VECTOR AUTOREGRESSIONS WITH CW.

	Constant	ree_{t-1}	cw_{t-1}	$rbtmcw_{t-1}$	dy_{t-1}	$rdticw_{t-1}$	R^2
ree	0.0097	0.1206	-0.0078	0.2986	-0.0051	4.3407	19.74
	(0.24)	(1.10)	(-0.07)	(4.53)	(-0.40)	(1.21)	
cw	0.0090	-0.0645	0.9349	-0.0423	0.0037	0.6944	98.62
	(1.77)	(-4.64)	(68.95)	(-5.08)	(2.29)	(1.53)	
rbtmcw	-0.0062	0.0422	0.1977	0.7207	0.0004	-3.3011	47.73
	(-0.11)	(0.28)	(1.34)	(7.98)	(0.02)	(-0.67)	
dy	-2.3997	-2.1757	1.0484	0.8051	0.1342	-35.038	9.71
	(-6.36)	(-2.09)	(1.03)	(1.29)	(1.12)	(-1.04)	
rdti	-0.0011	0.0054	-0.0020	0.0008	-0.0003	0.7428	67.61
	(-1.50)	(2.62)	(-1.00)	(0.63)	(-1.25)	(11.16)	
H							
2	0.0097	1.1206	-0.0078	0.2986	-0.0051	4.3407	61.33
	(0.24)	(10.18)	(-0.07)	(4.53)	(-0.40)	(1.21)	
3	-0.0267	1.1409	0.0069	0.2329	-0.0303	11.380	45.35
	(-0.46)	(7.15)	(0.04)	(2.41)	(-1.64)	(2.07)	
4	0.0288	1.0292	0.0344	0.2106	-0.0257	24.5058	35.84
	(0.38)	(4.92)	(0.15)	(1.66)	(-1.08)	(3.23)	
8	0.1497	0.8923	1.1862	-0.1013	-0.0539	96.6596	64.82
	(1.62)	(3.52)	(2.68)	(-0.65)	(-1.90)	(8.20)	

This Table reports the OLS estimates from vector autoregressions of the excess return on an equal-weighted index (*ree*), the estimation of the deviations between consumption and total wealth ($cw_t = c_t - 4.559 - 0.470 w_t$), the residuals of the aggregated book-to-market ratio on *cw* ($rbtmcw_t = btm_t - 0.138 - 4.129 cw_t$), the aggregated dividend yield (*dy*), and the residuals of the interest rates term structure on *cw* ($rdticw_t = dti_t - 0.0039 - 0.022 cw_t$). Standard t-statistics are in parentheses. In the last column the adjusted R^2 is reported in percent terms. The sample period is 1982:1 to 1999:4. In the bottom panel we use the *H*-period accumulated excess return for the prediction in long horizons. Only the results of the first equation of the VAR are shown.

When we use *cw* instead of *cay* (table 8B), the results are similar. The main differences are that *cw* is still more persistent than *cay* (second row of the first panel), and the predictive power of *rbtmcw* is also presented at two, three, and four-quarter horizons.

Summarizing, the proxies of the consumption-wealth ratio are only able to forecast returns at a two-years horizon, indicating that their trends have information about accumulated future returns but their weak variability cannot explain the strong changes in returns in the sort term. Moreover, their predictive power in the long-term is no bigger than that of other variables such as dividend yield or interest rate term structure. The only variable that is partially relevant in the short-term prediction is *btm*. As this financial ratio has a high correlation with *cw*, it is not surprise that the elimination of this common trend using *rbtmcw* generates an increase in its predictive power showing significant coefficients at horizons from one to four quarters. This variable offers an adjusted R-square of 61% when we use equal-weighted index to compute excess return, and 54% when we use the value-weighted index in the prediction at a six-month horizon. Moreover, *rbtmcw* is also able to forecast consumption growth at a horizon of two quarters or more.

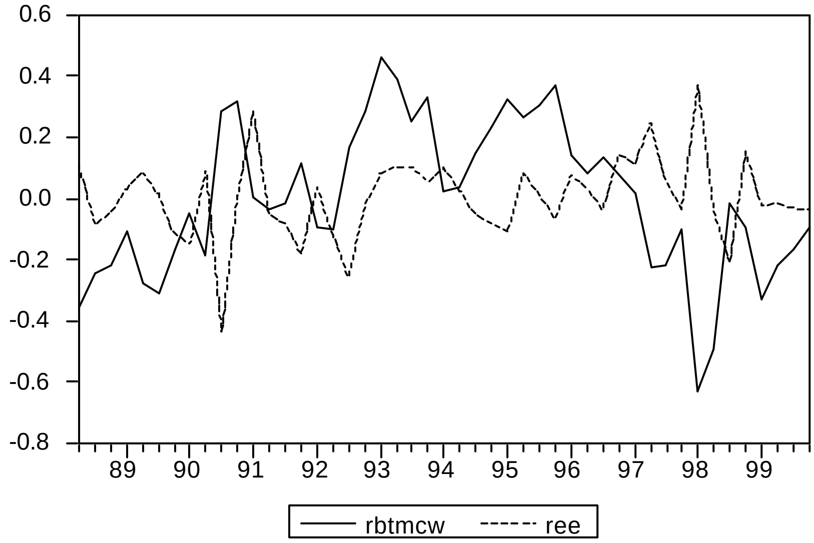
4.4. Robustness

In the above results, we obtain the estimated parameters of the predictive regressions using variables estimated with the total sample. We are concerned about the potential "look-ahead" bias of that result. To examine whether the estimates are robust, we perform out-of-sample forecasts where the parameters used to construct *cay* or *cw* are reestimated at each period, using data available at the time of the forecast. We start with 25 quarters (1982:1-1988:1). With this sample period we estimate the cointegrating relation between consumption and wealth and compute *cay* and *cw*. These variables will be used in the forecast of the return at the next quarter (1988:2). Next, we up-date the series to 1988:2 and recompute *cay* and *cw*, which will be used in the explanation of the market return referred to 1988:3, and so on. The forecasting period thus covers from 1988:2 to 1999:4. In each recursive estimation of *cay* and *cw* we can assert that the variables in their construction present significant cointegrating relations.

If we regress the excess return on the first lag of each reestimated variable which approaches the consumption-wealth ratio, we find negative slopes (-0.45 and –0.50, respectively). This result is consistent with those obtained with the total sample, but *cw* is now a relevant forecaster, explaining 7% of the future changes in the return on the two market indices. Despite the fact that an out-of-sample procedure is likely to induce significant sampling error in the coefficient estimates because of the smaller size of the sample. Adding the *btm* variable to the regressions affects the parameters of *cay* or *cw*: the slope of *cw* is doubled and offers a bigger t-statistic, and the parameter of *btm* is similar to the one obtained with the full sample and is also statistically significant. Between them these two variables explain 19.7% of the future equal-weighted index return and 17.4% of the future value-weighted index return. Again, the results indicate a high correlation between *cw* and *btm* (67% in this case).

When we use *cw* and the residuals of *btm* on *cw* as forecaster variables, the results show that these two variables are relevant considering both standard t-statistics and serial correlation corrected t-statistics. Moreover the R-square coefficient is 13% if we use only the latter. Figure 3 evidences its predictive power.

FIGURE 3. RESIDUALS OF BOOK-TO-MARKET ON UPDATED CW AND EXCESS RETURNS



This figure illustrates the path of the residuals of a regression of *btm* on *cw* (solid line) and the path of the excess returns (dashed line). The parameters used to compute *cw* are reestimated every period.

5. WHY DOES THE BOOK-TO-MARKET RATIO FORECAST RETURNS?

Since the work of Rosenberg, Reid and Lanstein (1985), empirical literature has shown how the stocks of firms with high financial ratios offer higher returns. From arguments such as a sample-specific effect (Black (1993), Mackinlay (1995)), or irrational behavior of investors (DeBondt and Thaler (1987), Lakonishock, Shleifer and Vishny (1994)) to the defense of the use of the book-to-market ratio as a factor in asset pricing models under risk arguments (Fama and French (1993, 1995, 1996, 1998) or characteristic arguments (Daniel and Titman (1997)), a variety of explanations can be found. Researchers have found this evidence of the value effect in different sample periods (Davis, Fama and French (2000), Davis (1994)), and in many different countries (Chan, Hamao and Lakonishock (1991), Capaul, Rowley and Sharpe (1993), Fama and French (1998), Liew and Vassalou (2000)). So, if the financial ratio contains information about stock returns we might assume that it could be used as a state variable.

In this work we have presented empirical evidence that shows how a book-to-market aggregate ratio is able to forecast returns for quarterly Spanish data from 1982 to 1999.

Furthermore, we find that a proxy of consumption-wealth ratio, which theoretically and empirically is an indicator of economic cycles (Lettau and Ludvigson (2001a), Santos and Veronesi (2001)), has very similar movements to the book-to-market ratio. In fact, a combination of the two ratios can explain 20% of future returns. Given these results, new questions arise: do the two variables share common information? Is this why the book-to-market ratio is a good instrument in asset pricing? We will answer these questions affirmatively in the following subsections, but first let us see what intuition says.

Theoretically, dividends forecast returns because they are the cash flows that investors expect for holding stock (Campbell and Shiller, 1988a). The value that the investor places on shares depends on these future cash flows. Let we suppose that the shares belong to a firm that never distributes dividends. The investor knows that he is not going to obtain those flows, but the price of the shares is not zero because the undistributed earnings could mean expectations of future cash flows. As non-distributed earnings today increase the book value of the firm today, an increase in book value is associated with bigger expected future payoffs and with an increase tomorrow in the expected return on the shares[12]. In this way, we can justify a positive and high contemporaneous correlation between consumption and book value: higher expected future wealth produces an increase in the proportion of consumption today. And this statement is the basis for the use of this financial ratio as a macroeconomic variable.

We present theoretical support for the above intuition in the following subsections. The idea relies on an accounting relation between dividends and book values. If we assume that the dividend-price ratio does not work as the theory says, due to non stable corporate dividend policy, a relation between that variable and the book-to-market ratio permits the latter to take over the role of the former. This is the line followed in the works of Ohlson (1995), Feltham and Ohlson (1995), Vuolteenaho (2000) and Cohen, Polk and Vuolteenaho (2001).

5.1. A book-to-market-based model

Next, we develop a book-to-market-based model following Vuolteenaho (2000). Under the assumption that the book-to-market ratio does not behave explosively, and using an accounting principle, we can approximate that ratio as an infinite discounted sum of future

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[12] The book value at time t contains the non-distributed earnings of that period.

stock returns, profitability and dividend-book ratio. In this way, we justify the power of the book-to-market ratio in predicting returns.

From the definition of the stock return,

$$1+R_{t+1}=\frac{P_{t+1}+D_{t+1}}{P_t} \tag{8}$$

taking logs in (8), and using a first-order Taylor expansion around the mean of the dividend-price ratio, we can write the log stock return as

$$r_{t+1}\cong K_d+\Delta d_{t+1}+(d_t-p_t)-r_d(d_{t+1}-p_{t+1}) \tag{9}$$

where K_d is a constant and $r_d=\frac{\overline{P}}{\overline{P}+\overline{D}}$.

On the other hand, we define the return on earnings from t to t+1 as the rate between earnings in this period (X_{t+1}) and the book value of the firm in the previous period (B_t). The corresponding log return on earnings is

$$e_{t+1}=\log\left(1+\frac{X_{t+1}}{B_t}\right). \tag{10}$$

Assuming that the clean-surplus accounting is satisfied, that is, the book value in period t+1 equals the book value of the last period plus earnings less dividends,

$$B_{t+1}-B_t=X_{t+1}-D_{t+1} \tag{11}$$

combining equations (9) and (10), and using a first-order Taylor expansion around the mean of the ratio dividend-book, we can approximate the log return on earnings as a linear function of that ratio.

$$e_{t+1} \cong K_b - r_b(d_{t+1} - b_{t+1}) + \Delta d_{t+1} + (d_t - b_t) \qquad (12)$$

Where K_b is a constant and $r_b = \frac{\bar{B}}{\bar{B}+\bar{D}}$.

Subtracting (9) from (12) yields an equation that relates divergences between the stock and accounting return with changes in book-to-market ratio at one previous moment in the log dividend to book value ratio of this period, and in the dividend-price ratio at the present period:

$$e_{t+1} - r_{t+1} = K_{bd} - (b_t - p_t) - r_b(d_{t+1} - b_{t+1}) + r_d(d_{t+1} - p_{t+1}) \qquad (13)$$

where $K_{bd} = K_b - K_d$.

Equation (13) is a linear difference relation for the log stock price. Solving forward and taking conditional expectations at time t, it is possible to express the book-to-market ratio as an infinite discounted sum of futures stock and accounting returns, thus showing that the book-to-market variable contains information about future expected returns.

$$b_t - p_t = \frac{K_{bd}}{1 - r_d} + E_t\left[\sum_{j=0}^{\infty} r_d^j \left(r_{t+1+j} - e_{t+1+j} - (r_b - r_d)(d_{t+1+j} - b_{t+1+j})\right)\right] \qquad (14)$$

This approximate model for the book-to-market ratio says that it is high when investors expect high future stock returns, low future returns on earnings, or changes in the proportion in which earnings are distributed. If the mean of the ratio between book value and dividends is greater than the mean of the dividend-price ratio, an increase in the book-to-market ratio today is associated with a decrease in the fraction of earnings paid as dividends in the future. But, if the dividend-price ratio is grater than the book-dividend ratio in mean, a high book-to-market ratio today is associated with an increase in the proportion of future earnings that are distributed.

The results in tables 4 and 5 support this theoretical expression. However the book-to-market ratio is not only able to forecast returns, but the strong correlation between it and the variable that approximates the consumption-wealth ratio makes the residuals of the former on the latter the main predictor in our analysis. In that sense, we can assume that these two variables contain some common information given that both of them could forecast returns theoretically. Under this idea, it is reasonable to think that there must be some positive and contemporaneous relation between the book-to-market ratio and the consumption-wealth ratio. The next section shows such a relation.

5.2. The book-to-market ratio and consumption-wealth ratio share common information

Given that the consumption-wealth ratio contains information about the next period stock return, as the budget constraint says in equation (2),

$$r_{t+1} \cong \Delta w_{t+1} - K_c - \left(1 - \frac{1}{r_c}\right)(c_t - w_t)$$

and using the fact that the dividend-price ratio at time t contains information about the stock returns in that period due to the definition of returns in equation (9), there is an expression that relates the consumption-wealth ratio at time t with the dividend-price ratio in the next period.

$$c_t - w_t = \left(\frac{r_c}{1-r_c}\right)\left[K_{cd} - \Delta w_{t+1} + (p_{t+1} - p_t)\right] + \frac{r_c(1-r_d)}{(1-r_c)}(d_{t+1} - p_{t+1}) \qquad (15)$$

Where $K_{cd} = K_c + K_d$.

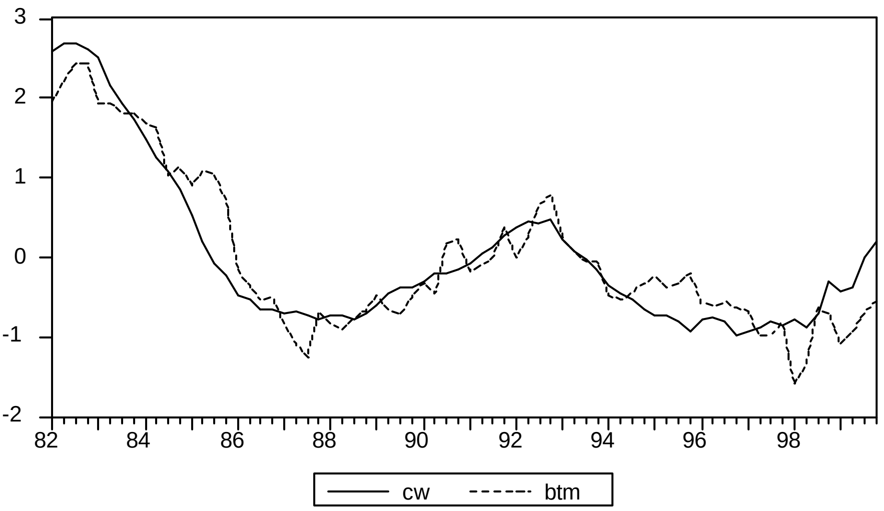
The above equation says that if a representative agent expects an increase in the stock price or a major payout in dividends he will consume more today. In other case, he would expect his wealth in the next period to be higher.

Under the clean-surplus accounting that relates the book-price ratio today and dividend-price ratio in the next period (equation (13)), we can express equation (15) in terms of book-to-market ratio instead of dividend-price ratio.

$$c_t - w_t = \left(\frac{r_c}{1-r_c}\right)\left[K - \Delta w_{t+1} + (p_{t+1} - p_t) + \left(\frac{1-r_d}{r_d}\right)\left(e_{t+1} - r_{t+1} + r_b(d_{t+1} - b_{t+1})\right)\right] + \frac{r_c(1-r_d)}{r_d(1-r_c)}(b_t - p_t) \qquad (16)$$

As we have shown, a positive and contemporaneous relation between the consumption-wealth ratio and the book-to-market ratio is justifiable. Such a relation supports the high correlation between the two ratios observed in our sample (table 3). The two variables that approximate the consumption-wealth ratio in this work present high correlation with the book-to-market ratio (64% in the case of *cay* and 93 % in the case of *cw*). This high correlation between the financial ratio and the second proxy of the consumption-wealth ratio is quite evident from the temporal behavior of both series in Figure 4.

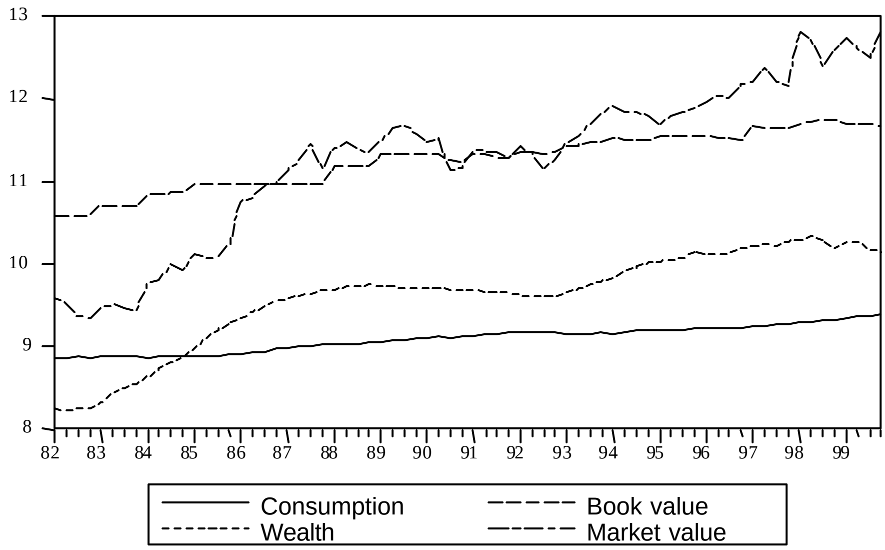
FIGURE 4. CW AND BTM: STANDARDIZED UNITS



This figure plots the *cw* variable (solid line) and the book-to-market variable (dashed line). *cw* represents the deviations from the common trend between consumption and the aggregate wealth.

To some extent it seems reasonable to expect the denominators of the two ratios to be responsible for this common path, given that, by definition, prices take part in both the (financial) wealth and the market value. The numerators and denominators of the two ratios are plotted in Figure 5. In this figure, we find that aggregate wealth shares a common trend with market value, but consumption also shares such a trend with book value. In fact, the correlation between the first two variables (96.5%) is almost as great the correlation between the other two (97.2%). The fact that book value and consumption are highly correlated supports the use of the former as an indicator of the state of the economy. And both the greater variability of book value as compared to consumption and the greater variability of market value as compared to wealth explain the greater volatility of the financial ratio in relation to a smoother consumption-wealth ratio, thus confirming the first variable is able to forecast returns better than the second.

FIGURE 5. CONSUMPTION, BOOK VALUE, WEALTH, AND MARKET VALUE



This figure plots the components of the consumption-wealth ratio and of the book-to-market ratio.

6. CONCLUSION

Given the budget constraint of a representative agent in intertemporal portfolio decision problems, there is a positive relationship between the proportion of wealth that the agent consumes at a given moment and future market returns. This relation is the basis for the theoretical ability of the consumption-wealth ratio to explain both cross sectional variations in returns and over time variation. As this ratio varies the relation between stock returns and consumption growth also varies, generating changes in the risk premium that investors require to hold stock. As a consequence, analysing whether a variable can forecast returns and whether it is a good state variable are not independent issues.

Without forgetting the above assertion, in this article we study whether the approach to the consumption-wealth ratio proposed by Lettau and Ludvigson (2001a) is able to forecast returns in the Spanish stock market, as it does in the US market. By using a manipulation of the budget constraint, the authors obtain an estimation of that variable that allows them to overcome the problem of an unobservable total wealth. They approximate aggregate total wealth by using labor income as a proxy of human capital and asset holdings as a proxy of financial wealth. In this way, they can write total wealth as an approximate weighted sum of these two components and estimate the consumption-wealth ratio as the deviations from the common trend of consumption, asset holdings, and labor income. They find that this new variable forecasts approximately a 10% of quarter returns, at short and long horizons, with statistical significance.

The results for a sample of quarterly Spanish data form 1982 to 1999 used to analyze the predictive power of two variables, *cay* and *cw*, constructed following Lettau and Ludvigson (2001a) unfortunately show a different behavior. Although their paths show a mean reversion process, as happens for returns, their weak volatility in the short term makes them unable to explain changes in (future) returns. Hence, it is necessary to add more variables, such as the dividend yield, the book-to-market aggregate ratio or a structure term of interest rates. In this exercise, the only partially relevant variable is *btm*, in individual regressions. If we combine this variable with *cw* a high proportion of future quarterly returns (20%) can be explained.

A deeper analysis of this finding reveals an extraordinary correlation between *btm* and *cw* in our sample period and our market. For that reason, it is necessary to orthogonalize the two variables to perform the significance analysis of the estimates in the forecasting regressions. Instead of *btm* we use the deviations between its trend and the consumption wealth ratio trend. We find that those deviations are responsible for a high adjustment coefficient. We must be cautious when interpreting these results. It is not difficult to guess that the volatility of *btm* is due to its denominator (market value) and, thus, the ability to forecast returns could arise because of the forced correlation between these two variables as a consequence of their construction process (Berk, 1995). Despite that, and from our point of view, the main conclusion that we want to stress is that the common movement of consumption and book value can give us insights into the correct use of the latter to approximate expectations of future payoffs, thus justifying its use as a state variable in conditional asset pricing models.

Empirical results support the use of this financial ratio along the lines indicated in the present work and lead us to think that it could be justifiable theoretically. If book value is considered as an indicator of expected future cash flows, we can understand that it could play the same role as dividends in asset pricing models and we could obtain a book-to-market-based model along the lines of Campbell and Shiller's dividend-based work. The work of Vuolteenaho (2000) is based on this. Using the clean-surplus accounting relation between book value, earnings, and dividends, the author obtains an expression in which future returns can be forecasted with the book-to-market ratio. Under the same premise, we prove that an approximate positive and linear relation between consumption-wealth ratio and book-to-market ratio exists.

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