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Modifications on Book-Valued Ratios

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ABSTRACT

Purpose:
In this paper we try to explain US stock market variations and cash flow fundamentals by employing three different book-valued based ratios. First, we explore the explanatory capacity of the simple book-market ratio on time-varying expected returns, and procced on altering its construction so as to enhance its performance. We then run the extra mile by constructing two new ratios, the book-dividends and book-earnings ratios based on the long-run equilibrium relationships between book, dividends and earnings. Our analysis includes evidence of predictability on dividend and earnings growth rates on the S&P 500 for the most recent sample period 1926-2018. We also investigate the ratios' forecastability by sub-sampling.

Design/methodology/approach:
We commence our analysis with the conventional book-market (bm) ratio and by failing to reject the hypothesis of a unit root, we propose the modified book-market (mbm) ratio, whose construction is based on the long-run equilibrium relationship between book (b) and market (m) values. We proceed on associating book values to dividends and earnings series and fix the book-earnings (be) and the dividend-book (db) ratios. We similarly modify be and db, and examine their forecasting performance on returns, dividend and earnings growth.

Findings:
In-sample evidence suggests that an investor who employs mbm can improve its forecasts by 37% and 41% in the 7- and 10-year return horizon, while the modified dividend-book (mdb) proves even more beneficial by explaining 53% and 59% in similar return horizons. Our modified book-earnings (mbe) has a very good in-sample fit to the earnings growth data unlike the rest of the predictors. With respect to the out-of-sample performance, mbm manages to surpass the simplistic forecast benchmark only at the 10-year horizon by 15% while mdb attains an impressive R^2_{oos} of 47% and 71% at the 7- and 10-year return horizon.

Research limitations/implications:
Further research is required so as to solve the earnings puzzle in terms of forecasting along with the necessity to understand the economical sources behind non-stationarity in valuation ratios.

Originality/value:
We believe that our paper may prove enlightening to investors focused on portfolio allocation and asset pricing and scholars interested in return forecasting, capital budgeting and risk identification.

1. Introduction

The empirical literature on stock return predictability includes a large number of financial variables with the capacity to predict future stock returns. To name but a few, the dividend-price ratio (Fama and French, 2002; Cochrane, 2008), the price-earnings ratio (Lamont, 1998; Campbell and Shiller, 2001), the book-market ratio (Kothari and Shanken, 1997; Pontiff and Schall, 1998), the dividend-earnings ratio (Lamont, 1998), the term and default spreads on bonds (Welch and Goyal, 2008), as well as the consumption-wealth ratio (Lettau and Ludvigson, 2001) are only some

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indicative examples of the most renowned variables with evident forecastability. Despite the econometric limitations related to either overlapping observations or the lack of exogenous regressors in the predictive regression models (Nelson and Kim, 1993; Stambaugh, 1999), Campbell (2000, pg. 1523) comments that "***the evidence of predictability survives at reasonable if not overwhelming levels of statistical significance. Most financial economists appear to have accepted that aggregate returns do contain an important predictable component***".

Since the focus of the present study is the book-market (bm) ratio, evidence that relate return predictability with bm is originated in the studies of Fama and French (1992, 1993) who find that bm can explain variations in cross-sectional data. Later studies of Davis (1994) and Chan et al. (1995) follow, reconfirming the forecastability of bm, while Kothari et al. (1995) and Loughran (1996) argue that both the significance and the magnitude of the ratio's predictive capacity may depend on data mining and various biases in the database employed. Cochrane (1999) supports that it is the prices rather than the book values that determine any forecastability of the ratio; low price-book values today are a signal of high average returns tomorrow, thus regardless whether we study individual stocks or sort them into portfolios, book values alone express minor predictive ability. On the other hand, strong evidence of the ability of bm to forecast returns on time-series data is primarily reported by Kothari and Shanken (1997) and Pontiff and Schall (1998). Kothari and Shanken (1997) compare the predictive capacity of the dividend yield to bm and conclude that the latter is a stronger predictor in their full sample. Also, Pontiff and Schall (1998) support that bm predicts market returns and attribute this capacity to the fact that book values proxy for expected cash flows. Their main rationale is that provided that cash flow is constant, then an increase in the discount rate leads to a decrease in the market value and consequently, an increase in bm ratio. This may explain the positive relation between future returns and present bm ratios. In their study they construct two bm ratios, based on either S&P or DJIA book values, and find that the S&P bm ratio is by far a better forecaster of market returns, even when they sub-sample. Finally, they relate this forecastability to the capacity of book value to forecast cash flows by retrieving cointegration relations between earnings and book values of the two indexes.

There are two critical issues that characterize forecasting superiority of the indicated valuation ratios; persistency and stationarity. With regards to the first issue, the more persistent the variables, the stronger the forecasts we receive particularly when we extend the forecasting horizon (see the discussion in Campbell and Viceira, 2002; Campbell and Yogo, 2006; Chen, 2009). The stationarity concern on the other hand, is a more complex issue. Traditionally, valuation ratios with predictive capacity have been treated as stationary processes in adherence to standard economic principles. The basis of this assumption though is rather fragile since it lies on the argument that both the data and the horizons, we examine are infinite. However, in practice this argument does not hold since data and horizons are well specified in all studies. Consequently, in an attempt to be more "pragmatic", we can sideline the stationarity issue and examine the presence of long-run equilibrium relations among the pairs of series on which valuation ratios such as the dividend and earnings yields, and book-market are constructed. In fact, the existence of cointegration vectors in the aforementioned ratios is no news to empirical finance. Froot and Obstfeld (1991) fail to reject the null hypothesis of a unit root between dividends-prices, dividends-earnings and price-earnings. Also, Pontiff and Schall (1998) retrieve evidence of a cointegration vector between earnings and book values and try to find the source of predictability in S&P and DJIA data. Research efforts expand on tri-variate vectors as well, with the most indicative examples the cay and cdy variables by Lettau and Ludvigson (2001, 2005) and the dpe by Garrett and Priestley (2012). More specifically, evidence is presented that the long-run relations between consumption (c), asset wealth (a) and income (y) on the one hand, and instead of asset wealth, dividends (d) on the other, can provide substantial forecasts on US returns and dividend growth. Similar findings are reported by Garrett and Priestley (2012) who construct a strong predictor based on the cointegration among dividends (d), prices (p) and earnings (e). More recently, Polimenis and Neokosmidis (2016, 2019) focus on the forecasting behavior of the dividend yield and conclude that by fixing its modified version, (which essentially stands as the stationary trend deviation between dividends and prices) they can provide significant improvements in return forecasting patterns.

Motivated by these findings, the present study attempts to (a) construct a stationary modified book-market (mbm) ratio, (b) explore the cointegration relation of book values to dividends and earnings and (c) examine the predictive ability of these book-valued ratios compared to their modified counterparts. More specifically, we report that we cannot statistically reject the hypothesis of a unit root in bm and proceed on forming its modified counterpart based on the long-run equilibrium relationship between logged book and market values. Our efforts focus on de-noising the simple bm ratio with the hope of tackling with some of its forecasting inabilities. We also isolate dividend, earnings and book values and test for cointegration relations. We find that similarly to bm, there are two cointegration vectors in book values and earnings [b e] and in dividends and book values [d b] and form their modified versions as well. Our simple book-valued ratios, namely bm, be and db are all tested for their forecastability alongside with their modified versions on high quality S&P 500 annual return, dividends and earnings growth data.

The main findings are that (a) the modified bm (mbm) has a better return in-sample fit over the traditional bm, (b) the modified db (mdb) provides substantial forecasting improvements compared to the rest book-valued ratios, explaining 59% of total return variations in-sample, and (c) our book-earnings (be) ratio is able to reveal better the forecasting patterns in earnings growth. Regarding the out-of-sample (oos) outcomes (a) our mbm is able to surpass the simplistic forecast benchmark at the longest horizon in contrast to bm, (b) both be and mbe do not generalize well thus further research is needed to comprehend this extra complexity in earnings-ratios composition and (c) an investor who employs our mdb is able to enhance his forecasts by 47% and 71% at the 7- and 10-year return horizon.

The main contribution of the present study is to re-evaluate the predictive capacity of the simple book-market ratio on S&P 500 data and extend the analysis by revealing its forecastability, if any, in dividend and earnings growth. By slightly altering the conventional composition of bm through employing a stationary trend deviation between logged

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book and market values, we manage to improve the ratio's forecasting benefits. Additionally, by fixing ratios (both simple and modified) based on the long-run equilibrium relations between logged dividend and earnings to book values, we present new evidence of enhanced predictability in the empirical literature. We believe that our paper may prove enlightening to investors focused on portfolio allocation and asset pricing and scholars interested in return forecasting, capital budgeting and risk identification.

The rest of the paper is organized as follows. In the next subsection, we discuss the necessity to study the non-stationarity of the simple ratios and form their modified versions. Section 2 presents the data and stresses on the methodology followed to estimate the stationary trend deviation between book and market (or dividends, or earnings) values. In section 3 in-sample and out-of-sample predictability findings ate discussed. Section 4 includes the concluding remarks.

1.1 Non-stationary book-valued ratios

The vast majority of the studies in the field consider valuation ratios similar to this paper stationary and base this assumption on the infinity of the samples and the forecasting horizons. In reality though, both the size of the samples and the horizons we examine (either in the short or the long run) are well-specified, let alone when statistical tools are used, they cannot reject the hypothesis of the existence of a unit root (see the discussion in Lamont, 1998; Goyal and Welch, 2003; Lettau and Ludvigson, 2001, 2005 among others). Consequently, non-stationarity and persistency are strong traits of the series that comprise dividend and earnings yields, and as we will show later book-market ratio as well.

Table 1a: Correlation matrix and descriptive statistics.

	r_t	re_t	rr_t	rf_t	bm_t	mbm_t	Mean	Std	AR (1)
r_t	1						0.09	0.19	0.06
re_t	0.99	1					0.06	0.19	0.06
rr_t	0.98	0.99	1				0.06	0.19	0.02
rf_t	0.07	-0.09	-0.03	1			0.03	0.03	0.90
bm_t	-0.16	-0.17	-0.20	0.15	1		-0.71	0.52	0.91
mbm_t	-0.16	-0.22	-0.23	0.42	0.66	1	0.33	0.35	0.83

Note: We present the descriptive statistics for annual nominal ($\mathbf{r_t}$), excess ($\mathbf{re_t}$) and real returns ($\mathbf{rr_t}$), risk-free rates ($\mathbf{rf_t}$), book-market ($\mathbf{bm_t}$) and the modified book-market ($\mathbf{mbm_t}$). The table shows the correlation matrix among the series, as well as the mean, standard deviation and the autocorrelation coefficient based on AR (1) fitted model. Data is annual from 1926-2018.

Table 1b: Correlation matrix and descriptive statistics.

	r_t	re_t	rr_t	rf_t	be_t	mbe_t	db_t	mdb_t	Mean	Std	AR (1)
r_t	1								0.09	0.19	0.06
re_t	0.99	1							0.06	0.19	0.06
rr_t	0.98	0.99	1						0.06	0.19	0.02
rf_t	0.07	-0.09	-0.03	1					0.03	0.03	0.90
be_t	-0.20	-0.19	-0.17	-0.08	1				2.03	0.36	0.62
mbe_t	-0.20	-0.20	-0.18	0.04	0.90	1			2.22	0.31	0.55
db_t	-0.03	0.01	0.00	-0.21	0.35	-0.08	1		-7.37	1.76	1.00
mdb_t	0.05	-0.01	-0.01	0.37	0.15	0.18	0.13	1	-2.47	0.29	0.87

Note: We present the descriptive statistics for annual nominal ($\boldsymbol{r_t}$), excess ($\boldsymbol{re_t}$) and real returns ($\boldsymbol{rr_t}$), risk-free rates ($\boldsymbol{rf_t}$), book-earnings ($\boldsymbol{be_t}$) , the modified book-earnings ($\boldsymbol{mbe_t}$), dividend-book ($\boldsymbol{db_t}$) and the modified dividend-book ($\boldsymbol{mdb_t}$) ratios. The table shows the correlation matrix among the series, as well as the mean, standard deviation and the autocorrelation coefficient based on AR (1) fitted model. Data is annual from 1926-2018.

As shown in descriptive statistics in Table 1a, the book-market ratio has an autocorrelation coefficient $\varphi=0.91$ implying that unit root tests may not have enough power to tackle with such high φ values. Following the same line of thought, we fix two new variables by associating the logged 12-month summed up earnings series (e) with log book values (b) on one hand, and the logged 12-month summed dividends (d) with log book values (b) on the other[1]. As in the case of book-market (bm), the book-earnings (be) and the dividend-book (db) are also highly persistent with autocorrelation coefficients that reach the values of 0.62 and 1.00 respectively as depicted in Table 1b. As it is commonly accepted, true persistence in finite samples tends to be highly underestimated by typical estimation methods. In this study, we mainly use two ways in rejecting stationarity; we firstly use a straightforward ADF test, and we secondly impose a restriction on the cointegration vector [b_t m_t] (also for [b_t e_t], and [d_t b_t]) as summarized in Panel B of Tables 2a, 2b and 2c.Moreover, in the Appendix we cite more robust econometric evidence against the stationarity issue of not only the conventional bm but also of our newly formed be and db.

We proceed our analysis by presenting evidence of long-run equilibrium relationships among three pairs of series, namely (b-m), (b-e) and (d-b) based on the Johansen technique (1991). By imposing a strict restriction on the cointegration vectors [b m], [b e] and [d b], we reject the hypothesis in all three vectors that the logged values of

[1] See section 2.1 of the present study for more details on the ratios' construction.

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each pair are linked with long run equilibrium relations of the form b-m (b-e and d-b respectively). Tables 2a, 2b and 2c present the results.

Table 2a: Cointegration test for the [$\boldsymbol{b_t}$ $\boldsymbol{m_t}$] vector and the null hypothesis of [1 -1].

Panel A	#Coint. Vector	Trace test stat.	5% critical value	
	0	29.79*	0	20.26
	≤1	8.38	≤1	9.16
Panel B	H_0: [1 -1]	χ^2-stat.		
		5.14*		

Note: In Panel A we apply the Johansen testing process, assuming no deterministic trend on the cointegration relationship. The pair [$\boldsymbol{b_t}$ $\boldsymbol{m_t}$] tests for a cointegration relationship between the book (b) and the market values (m). Panel B presents the results for the restriction test that [1 -1] spans the cointegration space among (b, m). (*) and (**) denote the 5% and 1% rejection level respectively. Data are overlapping annual for the period 1926-2018.

Table 2b: Cointegration test for the [$\boldsymbol{b_t}$ $\boldsymbol{e_t}$] vector and the null hypothesis of [1 -1].

Panel A	#Coint. Vector	Trace test stat.	5% critical value	
	0	20.55*	0	15.49
	≤1	0.01	≤1	3.84
Panel B	H_0: [1 -1]	χ^2-stat.		
		4.62*		

Note: In Panel A we apply the Johansen testing process, assuming trending series and no trend on the cointegration relationship. The pair [$\boldsymbol{b_t}$ $\boldsymbol{e_t}$] tests for a cointegration relationship between the book (b) and the 12-month summed-up earnings (e). Panel B presents the results for the restriction test that [1 -1] spans the cointegration space among (b, e). (*) and (**) denote the 5% and 1% rejection level respectively. Data are overlapping annual for the period 1926-2018.

Table 2c: Cointegration test for the [$\boldsymbol{d_t}$ $\boldsymbol{b_t}$] vector and the null hypothesis of [1 -1].

Panel A	#Coint. Vector	Trace test stat.	5% critical value	
	0	23.47*	0	20.26
	≤1	8.93*	≤1	9.16
Panel B	H_0: [1 -1]	χ^2-stat.		
		8.89*		

Note: In Panel A we apply the Johansen testing process, assuming no deterministic trend on the cointegration relationship. The pair [$\boldsymbol{d_t}$ $\boldsymbol{b_t}$] tests for a cointegration relationship between the 12-month summed-up dividends (d) and the book values (b). Panel B presents the results for the restriction test that [1 -1] spans the cointegration space among (d, b). (*) and (**) denote the 5% and 1% rejection level respectively. Data are overlapping annual for the period 1926-2018.

More recent evidence suggests that we should treat dividends and earnings-related ratios as non-stationary because they do include trends (therefore, contradicting the so far established notion that stock prices and corporate fundamentals are highly associated). The entire concept of the dependence relations between corporate dividend and earnings on the one hand, and earnings and stock prices on the other, is now overturn since the data itself is arbitrary and not as linked to asset prices as econometricians traditionally have expected. This perception is further strengthened by statistics, such as the ADF test which cannot reject the presence of a unit root, indicating that the entire finance society should re-consider the non-stationary dynamics of ratios related to these series.

Consequently, the next logical step is to sideline the stationarity concern and proceed in searching for cointegration relationships among the valuation series. We begin by assuming a deterministic long run equilibrium relationship between book (b) and market (m) values, that is a cointegration vector that follows the form:

$$\mathrm{b_t} = \alpha + \beta \mathrm{m_t} \tag{1}$$

We similarly treat book (b) and 12-month summed-up earnings (e), and the 12-month summed-up dividends (d) and book (b) values. By then allowing the data to unfold the true cointegration vector of the form [1 -β] in eq. (1), we fix our modified book-market ratio (mbm) as the stationary cointegration errors of this long-run equilibrium which is expressed as:

$$\mathrm{mbm_t} = \mathrm{b_t} - \beta \mathrm{m_t} \tag{2}$$

The β coefficient in eq. (2) stands as the unique population parameter that harmonizes the relation between book and market values via revealing the stationary trend deviations between them. It essentially manages to express the drift differential between the two series, and if it receives a value lower to unit then it must express the lower growth rate of book values against market values. We believe that the modified book-market (mbm) is a more reliable forecaster compared to the non-stationary bm which includes a small noise trend. Since mbm is highly persistent with an AR (1) coefficient at φ=0.83 (as reported in Table 1a) then its predictive capacity must surpass the short-term horizons and extend in the long-run.

Similarly, the long run relation between b and e, and d and b are studied and we define the modified book-earnings and dividend-book ratios as the stationary cointegration errors of the following long-run equilibriums:

$$\mathrm{mbe_t} = \mathrm{b_t} - \gamma \mathrm{e_\tau}$$

(3)

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$$\mathrm{mdb_t = d_t - \delta b_t}$$
(4)

The rationale remains unaltered since if mbe and mdb show short-horizon forecastability then with autocorrelation coefficients at 0.62 and 1.00 (as reported in Table 1b), they retain the persistency trait strong enough to predict returns both in the short and (perhaps the most interesting) long-run.

Based on annual data, we present evidence that an investor who uses the modified book-market ratio (mbm) can enhance his forecasting in-sample by 32%, 37% and 41% at 5-, 7- and 10-year horizons (medium, medium-to-long, long horizons) against the equivalent values of 16%, 23% and 31% of the traditional book-market (bm) ratio. Furthermore, our modified dividend-book ratio (mdb) is able to predict 38%, 53% and 59% of returns in-sample in similar horizons and provides an astonishing R^2 of 47% and 71% at the 7- and 10-year horizons ahead out-of-sample. The classical bm but also be and db may reveal some predictive capacity, but only in-sample and of lesser magnitude compared to their proposed modified counterparts.

2. Empirical Methodology

This study exploits high quality return data for the S&P 500 index, with and without dividends, as available by CRSP since 1926. Our full sample[2] spans the most recent 93-year period including values from January 1926 to December 2018. We also proceed on examining the ratios' forecastability on the pre and post-1965 sub periods. Nominal data have primarily been used[3] since forecasting in long horizons is highly dependable on whether we use real or nominal returns and dividend growth equivalently (see the discussion in Engsted and Pedersen, 2010).

2.1 Construction of the conventional book-market ratio

The book-market ratio (bm) is essentially the ratio of book to market values and is given by the formula:

$$\mathrm{bm_t = b_t - m_t = log(B_t/M_t)}$$
(5)

The ratio's computation for the months January and February includes the division of book value at the end of two years ago by the price at the end of the current month, while from March to December book value is divided at the end of the previous year by the price at the end of the current month. The data set is similar to other studies that investigate the ratio's ability to forecast returns (see for instance, Goyal and Welch, 2008; Pontiff and Schall, 1998; Kothari and Shanken, 1997).

In an attempt to surpass the observed seasonality in dividend and earnings series when a monthly frequency is used (see for example Chen, 2009), we prefer the annual horizon in fixing the book-earnings and the dividend-book ratios. Firstly, the cointegration is recovered from all series on a monthly frequency and secondly, we modify them accordingly and sample them on an annual horizon so as to match the rest of our econometric analysis. While working on earnings series is straightforward[4], extracting dividends is a more complex issue. There are two key points we need to consider; first, whether the re-investment assumption will be taken into consideration[5] and second, if a simpler and more representative approach on forming the dividend series will be used so as to capture more accurately decision making when it comes to dividend setting schemes in enterprises. In this paper we follow the second approach and extract dividends from monthly gross returns (R_t) where $R_t = \frac{P_t + D_{(t)}}{P_{t-1}}$, and monthly returns due to price gain alone (that is excluding dividends, X_t) where $X_t = \frac{P_t}{P_{t-1}}$. Therefore, dividends at month t follow the form of:

$$\mathrm{D_{(t)} = (\frac{R_{(t)}}{X_{(t)}} - 1) * P_t} \quad (6)$$

Regarding the notation, $D_{(t)}$ is the monthly dividend for month t, while D_t is the ending at month t annual dividend. So, at the annual frequency the annualized dividend computation is given by the formula $D_t = \sum_{i=0}^{11} D(t-i)$. Having calculated annual dividends, the computation of dividend-book ratio is given by:

$$\mathrm{db_t = d_t - b_t = log(D_t/B_t)} \quad (7)$$

Similarly, the book-earnings ratio is estimated as:

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[2] We retrieve our data set from Goyal's database, available at http://www.hec.unil.ch/agoyal.

[3] We have also examined excess and real return predictability with no significant differences in the outcomes.

[4] Earnings data is retrieved by http://www.econ.yale.edu/~shiller/data.htm.

[5] In fact, Chen (2009) argues that reinvested dividends absorb much of the market's volatility for the year, and they may thus tangle with true cash availability to the shareholders.

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$$be_t = b_t - e_t = \log(B_t/E_t)$$
(8)

2.2 The modified book-valued ratios

In this sub-section we describe the econometric methodology followed so as to construct our modified book-market ratio (mbm). Similar steps are followed so as to modify book-earnings (be) and dividend-book (db) ratios.

In order to test for cointegration we base our analysis on the Johansen approach (1995a) which basically examines the number of eigenvalues that are statistically different than zero. The implementation of the approach involves several steps which we describe below.

First, we need to consider a two-dimensional vector $v_t = [b_t\ m_t]'$ and assume that a cointegrating vector c is present. Thus, $c'v_{t-1}$ represents the error in the data set and quantifies at t-1 the extent at which the series deviate from the stationary mean. By examining error correction, we can check the tendency of the cointegrated series to return back to a common stochastic trend. As a result, this trend deviation from equilibrium in the long-run between book and market values (book and earnings, dividends and book values equivalently) helps us derive the modified bm (mbm) which follows the form of eq. (2). The same applies for the modified be (mbe) and the modified db (mdb) of eq. (3) and (4) respectively.

The disequilibrium that mbm contains is corrected by the book and market values at a rate that a vector of their own adjustment speed α captures. Consequently, a multiplicative error-correction term $\boldsymbol{ac'v_{t-1}}$ is formed which we need to consider to a simple VAR model so as to jointly interpret book and market change (Δb and Δm) and generate a VEC(w) model of the form:

$$\Delta v_t = \sum_{i=1}^{w} B_i \Delta v_{(t-i)} + a(c'v_{t-1} + d_0) + d_1 + u_{(t)} \tag{9}$$

As usual we assume at first that all tested vectors follow the form of eq. (9), in other words we examine for deterministic cointegration relationships. However, in the cases of both $[b_t\ m_t]$ and $[d_t\ b_t]$ the data leads to assuming that there is no deterministic trend and no intercept in the data. Thus, in these case eq. (9) is transformed to the following:

$$\Delta v_t = \sum_{i=1}^{w} B_i \Delta v_{(t-i)} + ac'v_{t-1} + u_{(t)}$$
(10)

The next steps include the estimation of either model 9 or 10 in a VAR in levels after assuming a maximum order of 12 lags (since cointegration is tested on series with monthly frequency) and determine the most appropriate lag length for each vector. By employing the Hannan-Quinn (HQ) criterion[6] we conclude that 1 lag should be used for VAR and thus, zero lag for VECM in the case of $[b_t\ m_t]$. As indicated by trace statistics included in Table 2a log book and market values are cointegrated following the form of:

$$mbm_t = b_t - 0.781672m_t \tag{11}$$

Additionally, we pose extra restrictions to show that the vector [1 -1] in each pair does not span the cointegration space. Panel B of Table 2a clearly shows through χ^2 that bm strongly behaves in a non-stationary manner and perhaps unit root tests cannot capture this behavior effectively since we are dealing with highly persistent variables.

The approach followed for the modified book-earnings (mbe) and modified dividend-book (mdb) is similar; consequently, for the vectors [b e] and [d b] we find that there is a long-run equilibrium relationship[7] in each pair that follow the form equivalently:

$$mbe_t = b_t - 0.904375e_t$$
(12)

$$mdb_t = d_t + 0.210458b_t$$
(13)

We primarily focus on the Johansen test since it deals with some of the weaknesses in the Engle-Granger approach. More specifically, there are two main benefits the first of which is that we avoid the two-step procedure that the Engle-Granger technique entails (see more details in the Appendix) and second, we can pose restrictions (like the ones we report in Panels B of Tables 2a, 2b and 2c) to eliminate all doubts on cointegrated series.

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[6] There is valid reason to base the lag length selection on the HQ criterion (see the discussion in Harris and Sollis, 2003).

[7] Findings on each vector can be found in Tables 2b and 2c.

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3. Results

3.1 In-sample predictability

This section includes the primary univariate forecasting regressions based on the conventional book-market ratio (bm) and its modified counterpart (mbm). We have also enriched our analysis with book-earnings (be) and dividend-book (db) ratios and their respective modified counterparts (mbe and mdb). We use annual S&P 500 data so as to form continuously compounded returns for 3, 5, 7 and 10-year horizons (*h* = *3*, *5*, *7*, *10*) for the period 1926-2018. Our forecasting regressions follow the classical form:

$$\mathrm{r_t(h) = \alpha\ + cx_t + u_t(h)} \tag{14}$$

where r_t stands as the log nominal returns at time t and horizon h each time, and x_t is one of the studied predictors each time. We form similar regressions when the left-hand variable is either dividend or earnings growth[8]. Standard errors are GMM corrected based on the Hansen-Hodrick formula.

Table 3*a*: In-sample predictability of nominal returns.

		b	t(b)	R^2			b	t(b)	R^2
$r_t(3)$	bm_t	0.22	2.36	0.11	$r_t(5)$	bm_t	0.32	3.03	0.16
	mbm_t	0.43	2.60	0.22		mbm_t	0.64	3.05	0.32
	be_t	0.11	0.63	0.01		be_t	0.21	1.02	0.03
	mbe_t	0.18	0.76	0.03		mbe_t	0.32	1.08	0.06
	db_t	-0.00	-0.07	0.00		db_t	-0.01	-0.12	0.00
	mdb_t	0.60	4.06	0.29		mdb_t	0.84	5.31	0.38
$r_t(7)$	bm_t	0.39	4.05	0.23	$r_t(10)$	bm_t	0.57	6.59	0.31
	mbm_t	0.71	4.60	0.37		mbm_t	0.90	7.26	0.41
	be_t	0.14	0.86	0.02		be_t	0.17	0.82	0.01
	mbe_t	0.23	0.89	0.03		mbe_t	0.22	0.71	0.02
	db_t	0.01	0.11	0.00		db_t	0.04	0.36	0.01
	mdb_t	1.02	7.32	0.53		mdb_t	1.29	13.52	0.59

Note: Standard errors are GMM corrected. Data is annual spanning the period 1926-2018.

Table 3a presents evidence on the full sample univariate outcomes for all ratios. As it is well understood in empirical literature, forecasting in longer horizons is the mechanical effect of short-horizon same direction forecastability in combination with a highly persistent forecaster (see the discussion in Campbell and Viceira, 2002; Campbell and Yogo, 2006; Cochrane, 2008). Consequently, a highly persistent predictor leads to increased slope coefficients in longer horizons. Our findings confirm these mechanics since both our slope coefficients and R^2s increase impressively as we extend the forecasting horizon. All ratios are able to predict returns in all horizons except book-earnings (be), while the modified ratios perform even better in all the three criteria set, namely slope, t-statistics and R^2.

More specifically, bm can predict returns in all horizons but the modified bm is able to produce better results reaching an R^2 of 37% at h=7 while bm can explain only 23% at the same horizon. Apart from a more enhanced performance over the classical bm, mbm manages to even surpass itself as we increase the horizon. The case is similar for both be and db, with the observed superiority of the modified ratios over return forecasting. For instance, at the 10-year horizon ahead, db can explain 1% of total return variations while mdb reaches the value of 59%. Results for b are of extremely low magnitude, contradicting Pontiff and Schall's findings (1998) who employ a similar ratio; even mbe seems unable to capture any predictive component in returns.

By directly comparing mbm with mdb, we observe that both the slope and the explanatory power (R^2) of mbm is of lesser magnitude since mdb has already reached Cochrane's theoretical limit of 1 in the medium-to-long and the longest horizons while mbm even at h=10 reaches the value of 0.90 (see the discussion in Cochrane, 2011). Moreover, while mbm produces an R^2 of 37% and 41% the 7- and 10-year horizons, mdb is already at 53% and 59%. In other words, the performance of mbm in the longest *h* is already surpassed by mdb in the medium *h*. In an attempt to help understand the evidence, we have isolated these findings in Table 3b.

Table 3b: In-sample predictability of nominal returns for bm and mbm vs. db and mdb.

		b	t(b)	R^2			b	t(b)	R^2
$r_t(3)$	bm_t	0.22	2.36	0.11	$r_t(5)$	bm_t	0.32	3.03	0.16
	mbm_t	0.43	2.60	0.22		mbm_t	0.64	3.05	0.32
	db_t	-0.00	-0.07	0.00		db_t	-0.01	-0.12	0.00
	mdb_t	0.60	4.06	0.29		mdb_t	0.84	5.31	0.38

[8] The main results presented in the paper are on nominal values, even though we have examined the performance of our forecasters in both real and excess values.

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$r_t(7)$	bm_t	0.39	4.05	0.23	$r_t(10)$	bm_t	0.57	6.59	0.31
	mbm_t	0.71	4.60	0.37		mbm_t	0.90	7.26	0.41
	db_t	0.01	0.11	0.00		db_t	0.04	0.36	0.01
	mdb_t	1.02	7.32	0.53		mdb_t	1.29	13.52	0.59

Note: Standard errors are GMM corrected. Data is annual spanning the period 1926-2018.

Therefore, an investor who employs mbm can interpret from 22% to 41% of future return variation for a 3-year to a 10-year horizon. However, the classical bm can explain from 11% to 31% in similar horizons. An even more powerful finding is that by employing mdb, an investor can achieve even better forecasting benefits from 29% to 59% in similar horizons, while the simple db ratio seems uncapable to predict returns. Figure 1 illustrates the direct comparison of mbm to mdb in all horizons by plotting R^2 values for all horizons. The clear dominance of mdb is clearly evident regardless the horizon.

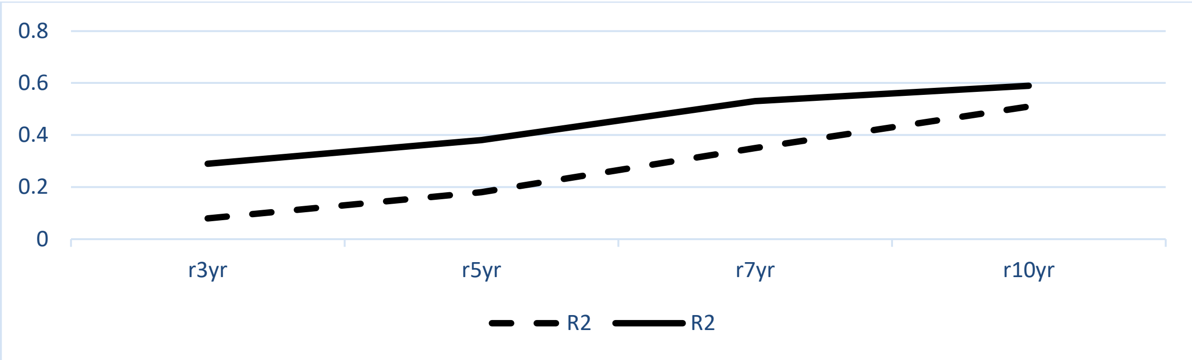

Figure 1: In-sample forecasting in horizons for annual nominal returns.

Note: The figure shows the evolution of $\boldsymbol{R^2}$ as we extend the horizon of our forecasts for the conventional bm and its modified counterpart versus dividend-book and the modified dividend-book ratios. Data is annual spanning the period 1926-2018.

In an attempt to interpret the forecasting benefits derived by high persistency in the predictors, we observe that the high AR (1) coefficient of the modified bm at φ=0.83 must be because bm includes a small, impeded unit root. Yet, the simple bm is even more persistent (at φ=0.91) but this higher persistency does not relate to predictive capacity[9]. We believe that the extra forecastability of the modified over the simple ratios is attributed to this lower persistency which determines the true forecasting horizon.

Additionally, we have examined the ratios' ability to predict excess and real returns and concluded that the findings are not precisely equivalent to the nominal ones, even though the modified ratios retain their upgraded performance. We attribute this to the forecasting ability of the ratios (both conventional and modified) over the risk-free component included in total equity return on the one hand, and inflation growth included in real returns on the other[10].

Table 4: In-sample predictability of dividend and earnings growth.

		b	t(b)	R^2			b	t(b)	R^2
$\Delta d_t(3)$	bm_t	0.08	1.45	0.03	$\Delta d_t(5)$	bm_t	0.13	1.50	0.05
	mbm_t	0.25	2.17	0.14		mbm_t	0.40	1.96	0.24
	be_t	0.10	3.24	0.02		be_t	0.26	2.63	0.10
	mbe_t	0.19	2.06	0.07		mbe_t	0.42	2.73	0.20
	db_t	-0.03	-1.04	0.04		db_t	-0.04	-1.17	0.06
	mdb_t	0.11	1.00	0.02		mdb_t	0.17	1.05	0.03
$\Delta d_t(7)$	bm_t	0.14	1.32	0.05	$\Delta d_t(10)$	bm_t	0.16	1.25	0.07
	mbm_t	0.42	2.38	0.24		mbm_t	0.42	2.02	0.23
	be_t	0.23	3.11	0.07		be_t	0.19	1.83	0.05
	mbe_t	0.40	3.62	0.16		mbe_t	0.32	1.75	0.10
	db_t	-0.05	-1.07	0.07		db_t	-0.04	-0.76	0.05
	mdb_t	0.15	1.07	0.02		mdb_t	0.18	1.04	0.03
$\Delta e_t(3)$	bm_t	0.09	1.42	0.01	$\Delta e_t(5)$	bm_t	0.16	1.73	0.03
	mbm_t	0.24	1.21	0.04		mbm_t	0.43	1.28	0.10
	be_t	0.64	5.29	0.25		be_t	0.78	5.44	0.35
	mbe_t	0.81	7.76	0.31		mbe_t	1.03	5.87	0.46
	db_t	-0.02	-0.65	0.01		db_t	-0.04	-1.13	0.02
	mdb_t	0.05	0.27	0.00		mdb_t	0.11	0.55	0.00
$\Delta e_t(7)$	bm_t	0.15	1.44	0.04	$\Delta e_t(10)$	bm_t	0.14	1.26	0.03

[9] The concept is similar for db (φ=1.00) and mdb (φ=0.87), as well as be (φ=0.62) and mbe (φ=0.55).

[10] Findings are available upon request.

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	mbm_t	0.41	1.46	0.13		mbm_t	0.30	1.05	0.07
	be_t	0.62	6.37	0.30		be_t	0.63	3.59	0.27
	mbe_t	0.84	7.63	0.41		mbe_t	0.77	3.77	0.32
	db_t	-0.04	-0.93	0.03		db_t	-0.03	-0.55	0.01
	mdb_t	0.12	0.77	0.01		mdb_t	0.07	0.36	0.00

Note: Standard errors are GMM corrected. Data is annual spanning the period 1926-2018.

Dividend growth variations are less identifiable by the ratios employed in this study. As evident in Table 4, bm and better yet mbm are ςσαable to capture some predictive components at the medium and longest horizons, providing a maximum R^2 of 24% but still outcomes are limited compared to return forecasting. Our findings find great similarity to other studies that have employed various valuation ratios to predict dividend growth (see for example Ang and Bekaert, 2007; Cochrane, 2008; Chen, 2009). Possible explanations of this limited evidence may be that (a) dividends stand as a poor measure of true-relevant cash-flows since they are susceptible to manipulation, smoothing, censoring and even changes in firms' corporate financial policy (see argumentation in Chiang, 2008; Chen et al. 2009), (b) the positive correlation between expected dividend growth and expected returns may act as a deterrent to the forecasters' ability.

Furthermore, predicting earnings growth remains a challenge by all the forecasters employed except book-earnings (be) that performs astonishingly well despite its weak performance in returns and dividend growth forecasting. In fact, it manages to explain 46% of earnings growth variations at the medium horizon and produces a slope coefficient above 1, even though its capability slightly reduces in the longest *h*. These findings arouse interest for further research since no pivotal conclusions can be drawn on whether earnings growth is predictable after all.

Finally, we further examine the performance of the ratios in two sub-samples, that is the pre and post-1965 periods, so as to test their dynamics and compare outcomes to a more recent environment, including the recent economic turbulences from 2008 and onwards.

3.2 Evidence on sub-sampling

We proceed on examining our entire sample into two different but economically significant sub-periods, namely the pre and post-1965 periods, running similar in-sample forecasting regressions so as to further examine the ratios' forecastability. A similar approach is followed in Pontiff and Schall (1998) who support that there are structural differences in both sub-periods; the ability of bm to predict returns scatters away after 1960s and attribute such behavior in the data's very nature not being representative enough of the equities market as a whole.

Table 5: Sub-sampling: In-sample predictability of nominal returns for the pre-1965 sub-period.

		b	t(b)	R^2			b	t(b)	R^2
$r_t(3)$	bm_t	0.95	4.99	0.55	$r_t(5)$	bm_t	1.16	9.23	0.60
	mbm_t	1.23	6.52	0.67		mbm_t	1.54	13.80	0.78
	be_t	0.30	1.09	0.07		be_t	0.33	0.81	0.06
	mbe_t	0.38	1.33	0.10		mbe_t	0.46	1.08	0.10
	db_t	-0.07	-0.77	0.01		db_t	-0.21	-1.33	0.05
	mdb_t	1.19	3.30	0.46		mdb_t	1.46	4.93	0.50
$r_t(7)$	bm_t	1.01	8.90	0.47					
	mbm_t	1.32	6.05	0.63					
	be_t	0.09	0.32	0.01					
	mbe_t	0.19	0.68	0.02					
	db_t	-0.32	-1.62	0.08					
	mdb_t	1.46	5.38	0.53					

Note: Standard errors are GMM corrected. Data is annual.

Table 6: Sub-sampling: In-sample predictability of nominal returns for the post-1965 sub-period.

		b	t(b)	R^2			b	t(b)	R^2
$r_t(3)$	bm_t	0.11	1.21	0.05	$r_t(5)$	bm_t	0.21	1.97	0.12
	mbm_t	0.19	1.45	0.07		mbm_t	0.37	3.77	0.17
	be_t	-0.03	-0.16	0.00		be_t	0.16	0.62	0.02
	mbe_t	-0.04	-0.16	0.00		mbe_t	0.21	0.81	0.03
	db_t	0.05	0.81	0.03		db_t	0.09	0.83	0.05
	mdb_t	0.40	12.73	0.25		mdb_t	0.63	9.53	0.38
$r_t(7)$	bm_t	0.33	2.75	0.24	$r_t(10)$	bm_t	0.53	6.76	0.42
	mbm_t	0.59	6.97	0.34		mbm_t	0.87	11.85	0.52
	be_t	0.24	0.84	0.04		be_t	0.37	1.53	0.07

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mbe_t	0.32	1.23	0.05	mbe_t	0.44	2.26	0.07
db_t	0.12	0.80	0.07	db_t	0.26	1.74	0.20
mdb_t	0.89	11.62	0.60	mdb_t	1.18	16.03	0.77

Note: Standard errors are GMM corrected. Data is annual.

As shown in Table 5, we confirm the findings of Pontiff and Schall (1998). The conventional bm provides early on at h=5 an R^2 of 60%. The modified ratio though remains clearly superior regardless the horizon and manages to explain up to 78% at the 5-year return horizon. Also, mdb attains a maximum R^2 of 53% at the longest horizon, unlike the simple db whose performance is limited throughout all horizons.

Table 6 on the other hand, summarizes the outcomes for the post-1965 sample. There are mainly two critical observations to make; first, results are of lesser magnitude compared to the pre-1965 sample. This also finds reference to the findings by Pontiff and Schall (1998) who argue that the ratio's ability to predict returns is mainly related to the forecastability of book value to predict future cash flows. Second, the superiority of mbm still holds being in a position to explain 34% and 52% at the 7- and 10-year (medium-to-long and long) horizons ahead variations of the market, while the classical bm provides R^2s of 24% and 42% equivalently[11]. An interesting finding though is the predictive capacity of mdb which seems to perform better not only against its conventional counterpart but also against all other predictors, managing to attain an R^2 of 77% at the longest horizon.

One possible explanation regarding the forecastability of bm is that book values is a good proxy for future cash flows. The product of dividing a cash flow proxy by a current market price is a variable which is strongly correlated with future returns. This discount rate proxy affects firms' market capitalization which may fluctuate over time, regardless of rational or irrational factors. Consistent with this rationale, Pontiff and Schall (1998) construct a bm based on DJIA data and a bm based on S&P data and find that the latter is a better predictor of market returns, while also the S&P book-value is superior in predicting market cash flows. The relation between book values and cash flows may need further examination so as to help us comprehend the predictive capacity of the book-valued ratios to a greater extent.

3.3 Out-of-sample performance

As usual in return predictability studies apart form in-sample forecasts, econometricians evaluate the predictors' out-of-sample (oos) performance as well, that is the ability of the forecasting model to generalize on an independent test data set. We follow a straightforward concept by assuming that $L(y, \hat{v}(x)) = (y - \hat{v}(x))^2$ is the loss from a prediction $\hat{v}(x)$ for a target return y and a forecaster x on a training set. Our goal is the minimization of the so-called out-of-sample (or generalization error) which represents the expected loss over an independent sample. There is respectively an in-sample (or training) error which stands as the average loss within the training sample, but this is totally different to the generalization error. There is a key relationship between the two kinds of errors; the greater the in-sample error, then the less overfit the model is to the data set, and thus the greater it generalizes. If for instance, we consider Fama and French's (2002) preposition and allow for occasional breaks to the levels or the slope of a stationary process then we will receive increased slope coefficients and R^2s in-sample but low oos R^2s. That is mainly due to the weakening power of unit root tests to identify stationary processes with breaks in comparison to the non-stationary ones (as argued first in Perron, 1989). After careful consideration of these effects, we suggest a modified technique (as first shown in Polimenis and Neokosmidis, 2016) which provides significant oos predictive gains.

We proceed on evaluating the forecasting capability of the conventional and our modified ratios out-of-sample (oos) on nominal returns. We use the well-established Campbell and Thompson (2008) technique who estimate an R^2_{oos} statistic by comparing the out-of-sample performance of a selected predictor with return forecastability against a simple forecast benchmark that is based on the simple average of past returns as a forecast. The proposed out-of-sample coefficient of determination is computed via the formula:

$$\mathrm{R}^2_{\mathrm{oos}} = 1 - \left[\sum_t (\mathrm{r_t(h)} - \hat{\mathrm{r}}_t(\mathrm{h}))^2 / \sum_t (\mathrm{r_t(h)} - \bar{\mathrm{r}}_t(\mathrm{h}))^2\right] \qquad (15)$$

where $\hat{r}_t(h)$ stands as the h-years out predicted return using information at time t based on a predictive regression, while $\bar{r}_t(h)$ is the historical average h-year return. We include forecasts at h=5, 7, 10-year horizons on returns. The first step is to divide the sample into an estimation and an evaluation period. In our case the first 15-year period (1926-1941) is considered the minimal estimation period since the quantity of the data must be enough to increase reliability of OLS estimators. The rest of the sample (till 2018) constitutes the evaluation period for which enough data is also needed to ensure reliability of out-of-sample estimates (see the discussion in Goyal and Welch, 2008; Campbell and Thompson, 2008).

In order to estimate the modified versions of the simple ratios it is critical to firstly calculate the true population coefficient β in eq. (1) (and similarly γ in eq. (2) and δ in eq. (4). This could manifest as a re-estimation of the cointegration coefficients between b and m (b and e, and d and b equivalently) on a recursive basis, which implies using data up to a specific point t in time. We need to consider though that this approach carries great sampling errors and eliminates the modified ratios' forecastability. We believe that this happens because forecasting regressions

[11] We have also sub-sampled excess and real returns at similar horizons with no significant changes in the outcomes.

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are run against a proxy mbm_{rec} (mbe_{rec} and mdb_{rec} respectively) instead of the true population coefficient β (or γ or δ).

In an attempt to moderate the aforementioned effect, we proceed on estimating both the recursive but also the full sample oos forecasting performance of the examined ratios (simple and modified) following the concept of Polimenis and Neokosmidis (2016, 2019). We mainly report though the oos R^2s produced by the suggested approach (that is when the cointegrating coefficients are calculated on the entire sample) since the predictive benefits are more robust. However as discussed in Lettau and Ludvigson (2001, 2005) and Polimenis and Neokosmidis (2016, 2019) there is a look-ahead concern when we estimate mbm_{full} (mbe_{full} and mdb_{full} $respectively$)[12]. When we perform analysis in sub-samples, we do not use all available information in estimating parameters thus, we do not "see" the entire predictive capacity as measured with in-sample tests. Yet, the most appropriate approach when modifying simple ratios is to employ the full sample since enough data is needed to ensure reliability of the cointegrating coefficients (see also the case of the cay and cdy variables by Lettau and Ludvigson, 2001, 2005 and the case of the dpe variable by Garrett and Priestley, 2012).

Table 7: Out-of-sample (oos) forecasting.

Returns	$r_t(3)$	$r_t(5)$	$r_t(7)$	$r_t(10)$
bm_t	-1.163	-1.025	-0.427	-0.136
mbm_t	-0.799	-0.656	-0.114	0.156
be_t	-0.190	-0.075	-0.044	-0.089
mbe_t	-0.156	-0.037	-0.010	-0.034
db_t	-0.188	-0.717	-1.310	-1.609
mdb_t	-0.160	0.078	0.473	0.710

Note: We present OOS forecasts for the conventional and modified book-valued ratios. Data is annual for the period 1926-2018.

As mentioned earlier, Table 7 summarizes the results of out-of-sample estimations on nominal returns by all included forecasters based on the full-sample approach. The findings show that (a) the modified ratios provide out-of-sample (oos) improvements against the conventional ones as horizon is extended, (b) mbm proves superior even oos against bm, and (c) the modified db ratio surpasses all ratios included in this study, managing to attain an R^2_{oos} of 71% for *h=10.*

An investor who has seen enough of the entire sample to infer to the cointegration beta with relative confidence will enhance his forecastability for the 7- and 10-year returns by an astonishing R^2_{oos} of 47% and 71% by employing mdb. Unlike mdb though, it is only at the longest horizon that even mbm is able to generate substantial predictability at 15,3% while results are poor for all the other horizons. To illustrate the oos superiority of mdb against mbm, we plot the R^2_{oos} of the two ratios throughout all forecasting horizons in Figure 2.

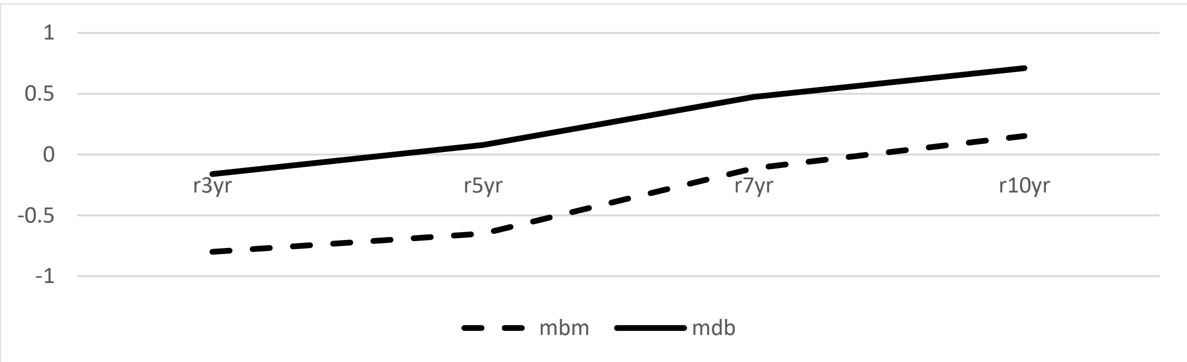

Figure 2: Out-of-sample (oos) forecasting in horizons for annual nominal returns.
Note: The figure shows the evolution of R^2 as we extend the horizon of our forecasts for the modified bm and the modified dividend-book ratios. Data is annual spanning the period 1926-2018.

Additionally, it is evident that all conventional ratios cannot generalize well oos regardless the examined horizon which is in line with existing findings in empirical literature. The issue in most studies is that even though predictability evidence is retrieved in-sample by several valuation ratios (some may be more powerful forecasters than others, but still there is enough predictive ability observed throughout finance literature), it remains trickier to identify models and ratios with similar forecastability out-of-sample (see for instance, Goyal and Welch, 2008; Lettau and Ludvigson, 2005; Cochrane, 2008). Consequently, all the negative R^2_{oos} we retrieve not only by the conventional ratios but also by be and its modified counterpart, confirm previous research and can be mainly interpreted as the inability of these ratios to outperform the simplistic forecast benchmark in all forecasting horizons[13].

[12] This concern addresses the issue of the econometrician seeing enough of the historical data to explore the utter forecasting ability of the modified ratios to his advantage.
[13] We have also run similar forecasts on excess and real returns without any critical change in the outcomes.

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4. Conclusion

This paper examines the forecasting ability of the conventional book-market ratio on S&P 500 high quality annual data covering the period 1926-2018. Our primary focus lies on (a) testing the forecasting performance of book-market (bm) ratio and modify it accordingly based on the long-run equilibrium relationship between book and market values; (b) constructing two new ratios mixing dividend and earnings series with book values and (c) proposing that the modified ratios which basically stand as the stationary trend deviations of the simple ratios, manage to provide substantial forecasting improvements.

The main findings of our study are the following. First, we retrieve long-run equilibrium relationships not only among book and market values, but also between book and earnings, and dividends and book values. Second, the modified book-market (mbm) has a more enhanced nominal return in-sample fit over the conventional bm while third, the modified dividends-book (mdb) ratio performs even better in-sample, managing to explain 59% of total return variations for h=10. Fourth, the book-earnings (be) ratio may not have as strong in-sample fit as the rest but yet, bears fruitful evidence in earnings growth forecasting when both bm and db present poor results. Also, sub-sampling allows us to test the predictive capacity of the examined ratios in a more recent environment; we conclude that bm is a more capable predictor in the pre-1965 sample reconfirming findings of previous studies.

Regarding the ratios' out-of-sample (oos) performance, the modified bm manages to surpass the simplistic forecast benchmark at the longest horizon while bm still struggles throughout all forecasting horizons. The impressive finding is observed at the case of db that attains an astonishing R_{oos}^2 of 47% and 71% at 7- and 10-year returns ahead. However, book-earnings along with its modified counterpart do not generalize well on an independent sample thus further research is required so as to comprehend this extra complexity of the modified approach for earnings.

Overall, we provide valid evidence that the simple bm ratio has impressive forecastability that should not be overlooked by either the dividend or earnings yields. By associating book values to dividends and earnings we manage to increase predictive benefits and provide fresh evidence on one of the strongest indexes in the market. We strongly believe that our work could prove beneficial to investors, portfolio and risk managers, financial analysts, as well as scholars and other researchers on the field. We particularly address one of the most crucial questions in empirical finance of what makes returns predictable and we are confident that we can help practitioners face most of the constant challenges related to these issues. Further research is required so as to solve the earnings puzzle in terms of forecasting along with the necessity to understand the economical sources behind non-stationarity in valuation ratios.

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Appendix

As described in the main text we follow several steps before retrieving evidence of long-run equilibrium relationships and constructing the modified version of the simple ratios. The most important reason why instead of employing the Engle-Granger (EG) method, we focus on the Johansen technique (1988, 1995a) is because the latter manages to eliminate two limitations of the first. In particular, EG approach includes two steps; the 1st regression automatically transfers errors in the residuals to the 2nd regression which tests for unit roots. Also, the estimated (but not observe) residuals require different tables of critical values for standard unit root tests.
Since the analysis of our methodology on the main text focuses on the [b m] vector, here we describe the similar steps we follow for the [b e] and [d b]. The notation we follow assumes $w_t = [b_t\ e_t]'$ and $z_t = [d_t\ b_t]'$ as the vectors of logged book (b) and earnings (e), and log dividends (d) and book (b) values. In order to test for stationarity of the conventional be and db ratios we impose a restriction c=[1 -β]=[1 -1] on the Johansen estimated vectors. In order to specify the most appropriate lag length in each vector, we commence by calculating a VAR model in levels with the highest initial order autoregressive coefficients. We assume a maximum order of 12 lags and conclude based on HQ criterion that we should use 8 lags for VAR (thus, 7 lags for VECM) for vector w_t and 4 lags for VAR (thus, 3 lags for VECM) for z_t.

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Table A1: VECM results between book and market values.

	α	c_t
Δb_t	-0.007024	0.004366
	(0.00327)	(0.00114)
		R^2
		0.004140
Δm_t	0.008470	0.004740
	(0.00461)	(0.00161)
		R^2
		0.003029

Note: The table presents the outcomes from the VECM estimation between the book (b) and market (m) values using the multivariate Johansen procedure. Data is annual for the period 1926-2018. (*) and (**) denote significance at the 5% and 1% rejection level respectively.

Table A2: VECM results between dividends and earnings.

	α	Δw(t-1)	Δw(t-2)	Δw(t-3)	Δw(t-4)	Δw(t-5)	Δw(t-6)	Δw(t-7)	c_t
Δd_t	-0.009319	-0.029438	-0.019585	0.044036	-0.029255	-0.015114	0.043723	0.007376	0.003922
	(0.00370)	(0.03025)	(0.02855)	(0.02781)	(0.02755)	(0.02665)	(0.02645)	(0.02643)	(0.00106)
		-0.040473	0.046129	0.029443	0.022368	0.014940	0.009276	*-0.119241*	R^2
		(0.02324)	(0.02194)	(0.02137)	(0.02117)	(0.02048)	(0.02032)	(0.02031)	0.236592
Δe_t	0.010145	0.049170	-0.321973	0.229817	-0.014454	0.637651	-0.480253	-0.019521	0.001445
	(0.00284)	(0.03750)	(0.04543)	(0.04673)	(0.04655)	(0.04623)	(0.04999)	(0.4300)	(0.00082)
		0.680651	0.110571	0.080940	-0.107729	0.025429	0.150439	*-0.243612*	R^2
		(0.02881)	(0.03491)	(0.03591)	(0.03577)	(0.03552)	(0.03841)	(0.03305)	0.643549

Note: The table presents the outcomes from the VECM estimation between the 12-month summed-up dividends (d) and 12-month summed-up earnings (e) using the multivariate Johansen procedure. Data is annual for the period 1926-2018. (*) and (**) denote significance at the 5% and 1% rejection level respectively.

Table A3: VECM results between dividends and book values.

	α	Δw(t-1)	Δw(t-2)	Δw(t-3)	c_t
Δd_t	-0.006728	0.126819	0.104528	0.367696	-0.000405
	(0.00225)	(0.02820)	(0.02830)	(0.02823)	(0.00067)
		-0.027963	0.023962	-0.014085	R^2
		(0.04951)	(0.04967)	(0.04957)	0.205155
Δb_t	0.000124	-0.011495	-0.000788	0.026777	0.004438
	(0.00394)	(0.01725)	(0.01726)	(0.01724)	(0.00117)
		-0.046642	-0.006349	-0.014974	R^2
		(0.03028)	(0.03030)	(0.03027)	0.002797

Note: The table presents the outcomes from the VECM estimation between the 12-month summed-up dividends (d) and book values (b) using the multivariate Johansen procedure. Data is annual for the period 1926-2018. (*) and (**) denote significance at the 5% and 1% rejection level respectively.

Even though we first test for a cointegration relationship that contains only a constant and has linear trends (also known as deterministic cointegration), we retrieve evidence that there is a long-run equilibrium relationship of this sort only in the vector w_t, while in the case of z_t there is no deterministic trend (similar is the case for [b m]).
Similarly, to Panel B of Table 2a, the respective Panels in Tables 2b and 2c show the results of examining the restriction that the vector [1 -1] spans the cointegration space based on the Johansen technique on [b e] and [d b] which is also rejected at 5% critical level. This constitutes an even more robust indication that bm and its by-products (our be and db) behave in a non-stationary manner and thus, deal with the lower power of unit root tests against highly persistent alternatives.

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