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The Economic Value of Predictability in Portfolio Management

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Abstract

This paper evaluates the evidence on return predictability from an economic perspective: it asks whether investors would have been able and willing to exploit dividend-price signals in order to allocate capital efficiently. We use a simple model that incorporates a time varying investment opportunity set into a mean-variance portfolio maximization framework, and derive the optimal capital allocation weights for: (*i*) a naive strategy based on average realized returns; and (*ii*) a class of strategies that condition on dividend-price signals. While our data supports in-sample evidence of return predictability, the out-of-sample returns of the naive strategy are higher than those of all conditional portfolio specifications based on a certainty equivalent metric and portfolio turnover. The degree of underperformance is most dramatic in the last three decades: an investor who had used dividend-price ratios as signals for capital allocation in the period 1990-2012 would have consistently generated lower returns than by following a naive strategy. These results suggest that dividend-price predictability offers no economic value to investors.

Keywords: Equity Premium; Stock Returns; Dividend Yield; Out-of-Sample Prediction; Portfolio Choice.
JEL Codes: G11; G14; G17.

1 Introduction

Are stock returns predictable? If so, do dividend-price signals really add economic value to an investor who needs to make capital allocation choices? This paper accomplishes two goals. First, we survey the literature on equity predictability and provide an update on empirical evidence by using sample data until 2012; the presence of Post-Crisis information allows us to investigate the statistical robustness of previous results. Second, we study the economic value of dividend-price predictability by considering the optimal portfolio choice decision of an agent who uses dividend-price ratios to model conditional expected returns. If predictability can indeed be exploited in real time, information encoded in predictive state variables is of considerable interest to practitioners who can develop market-timing portfolio strategies to enhance profits.

The capital allocation model we adopt is based on the work of Brandt and Santa-Clara (2006), and accommodates a time varying investment opportunity set. The economic

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intuition is simple: the optimal fraction of the portfolio that is allocated to the risky asset is increasing in expected returns, so that portfolio choice is sensitive to the information content of predictors such as dividend yields. We compare the out-of-sample performance of portfolios based on this conditioning information to that of benchmark «naive» portfolios that allocate capital based on a moving average of realized returns. If dividend yields actually predict returns in a way that is economically valuable for an investor, a strategy based on dividend-yield signals should be preferable to one that relies on the assumption that returns are *i.i.d*. We follow De Miguel *et al.* (2009) and use three metrics to gauge economic value: Sharpe ratios of realized returns, certainty equivalents, and portfolio turnover.

The results can be summarized as follows. First, we confirm the results of previous studies by finding evidence of return predictability in the 1947-1990 sample. Both the economic and statistical significance of the slope coefficients are increasing in maturity, and as are high as 60% for holding period horizons of 5 years. Dividend growth predictability, on the other hand, is almost non-existent. These results, which are robust in terms of the choice of the predictor (dividend-price ratios or yields), confirm the widespread notion that time variation in dividend-price ratios captures time variation in expected returns. We also find, however, that these results are highly sample specific: when the sample is extended to the period 1926-2012, the level of return predictability is cut by half. Second, we assess the economic value of predictability for an investor who makes real-time capital allocation decisions based on dividend-price signals. We find that some signals generate marginal value to investors when evaluated on the basis of Sharpe ratios. From a certainty equivalent and portfolio turnover perspective, however, the naive portfolio always beats the more sophisticated conditional specifications. We present a simple performance attribution graphic diagnostic that shows that treating ratios as trading signals outperformed naive strategies only during the 50s and 70s/80s. An investor who had used dividend ratios as signals for capital allocation would have consistently underperformed a naive strategy from the early 90s until today.

The rest of the paper is organized as follows. After a survey of related literature in Section 2, Section 3 describes the portfolio model and the metrics of economic value-added we adopt. Next, Section 4 presents the data and the empirical results. Section 5 concludes the paper.

2 Related Literature

This paper is related to two streams of the asset pricing literature: predictability and optimal portfolio choice.

The question of equity predictability plays a central role in the theory of finance for at least two reasons. First, it is traditionally linked to tests of the Efficient Market Hypothesis (EMH). Second, it is of great significance for both portfolio managers and market regulators. The first who conjectured that asset prices follow a random walk was a French mathematician, Louis Bachelier, in his 1900 PhD thesis, «The Theory of Speculation». Paul Samuelson later discovered Bachelier's work, and Bachelier's dissertation, along with some initial empirical studies, were published in 1964 in an anthology edited by Paul Cootner. Some of these empirical works showed evidence that professional investors were generally unable to outperform a simple passive benchmark. The efficient market hypothesis (EMH) emerged as a prominent theory and, in 1970, Fama published a review of both the theory and the evidence of the EMH (Fama, 1970). His article carefully proposed three different forms of financial market efficiency: weak, semi-strong and strong. Following this influential article, a vast empirical literature has focused on whether asset prices follow a random walk.

In the mid-1980s, however, an increasingly large number of empirical works were finding that, in contrast to the random walk view, stock returns are predictable by financial ratios and in particular by the dividend yield and the price-earning ratio (Fama and French, 1989). Was the paradigm of market efficiency dead? Indeed, the initial economic interpretation of the strong evidence of predictability was that these tests were rejecting the efficient market hypothesis. Fama (1991), however, suggested that, far from rejecting the main paradigm, the evidence was simply rejecting the assumption that expected returns are constant: time-variation in expected returns can be consistent with market efficiency. Indeed, over the past thirty years, several asset pricing theories have proposed alternative explanations for the time variation in conditional expected returns. The most influential streams of this literature include: (*i*) habit models in which the effective level of risk aversion is time-varying and countercyclical (see Campbell and Cochrane, 1999); (*ii*) long-run risk models in which small but persistent shocks to consumption growth are priced (see Bansal and Yaron, 2004); (*iii*) rare disaster models (see Gabaix, 2009); (*iv*) heterogeneous beliefs models (see Detemple and Murthy (1994), and Buraschi and Jiltsov(2006)). In all these models, time-varying expected returns are an equilibrium outcome and predictability is consistent with market efficiency.

The result obtained by Fama and French (1988) that dividend yields predict future stock returns has given impetus to a vast literature on predictability. Today, the emerging consensus is that: «Despite these difficulties, the evidence for 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» (Campbell, 2000, p. 1523). Indeed, several financial variables have been proposed as candidate state variables that help predict future stock returns. These include the dividend-price ratios (Rozeff, 1984; Campbell and Shiller, 1988a; Fama and French, 1988; Hodrick, 1992); earning-price ratio (Campbell and Shiller, 1988b; Campbell and Shiller, 1998); book-to-market ratio (Kothari and Shanken,1997; Pontiff and Schall, 1998); dividend-payout ratio (Lamont, 1998); term and default spreads on bonds (Campbell, 1987; Fama and French, 1989); short-term interest rates (Campbell, 1987; Hodrick, 1992; Ang and Bekaert, 2007); equity share in total new equity and debt issues (Baker and Wurgler, 2000); consumption-wealth ratio (Lettau and Ludvigson, 2001). Evidence of predictability is also present in the cross-section: Fama and French (1992) found evidence that firms sorted by book-to-market ratio and size are also predictable. While at the beginning most of the effort was spent on equity returns, more recent studies show evidence of predictability in other asset classes as well.

At the same time, several scholars have suggested that the evidence on the predictability of stock returns based on in-sample regressions may be spurious. In the context of dividend ratios, for example, Goetzmann and Jorion (1993) and Ang and Bekaert (2007) have criticized the conclusions based on these specifications and several scholars have highlighted the low in-sample power of many of these tests (see also Nelson and Kim, 1993; and Valkanov, 2003). Goyal and Welch (2008) use data up to 2006 to study the predictive variables proposed by the empirical literature. They find that the evidence is sample specific and some of the statistical significance depends on using data up to the 1973-1975 Oil Shock period. Their results motivate the importance to study the economic value of predictability in the context of optimal portfolio formation. Estimation error and spurious predictive results could negatively affect the out-of-sample portfolio performance of an investor seeking to use these models for market timing. The contribution of this paper is to provide rigorous empirical evidence on this issue.

We also draw from a second stream of the asset pricing literature that studies optimal portfolio choice when the investment opportunity set is time varying. In principle, return predictability can be exploited in the construction of optimal portfolios. In practice, computing optimal dynamic portfolios that consistently exploit the return predictability is no easy task. The reason is that closed-form solutions are available only for rather special cases. Most approaches proposed in the literature use different types of numerical methods. Brennan *et al.* (1997), Barberis (2000), and Lynch (2001) use discrete-state approximations to numerically solve for the optimal portfolio choice problem of a long horizon investor when returns are predictable. Campbell and Viceira (1999), Campbell and Viceira (2001), and Campbell and Viceira (2002) use analytical approximations in the neighborhoods of known exact solutions in the context of an infinite horizons portfolio choice problem. Unfortunately, the numerical complexity of these methods is such that most practitioners have eventually gone back to use either the simple and well-known Markovitz allocation or naive portfolios. Recently, Brandt and Santa-Clara (2006) have proposed a methodology that allows to exploit predictability in a time-consistent manner within the context of portfolio optimization. Their idea is an adaptation of the conditionally managed portfolios described in Hansen and Richard (1987): given a state variable that is presumed to forecast returns, they form a portfolio that invests in a set of primitive assets for an amount that is proportional to the level of the conditioning variable. The procedure consists in choosing portfolio weights as simple linear functions of the predictive variables. Thus, the optimal portfolio solution is a simple maximization of the agent's utility function with respect to the parameters of this linear function. This approach allows us to address the economic question that we want to investigate: does return predictability add value to portfolio selection or, rather, do estimation and misspecification errors reduce the out-of-sample performance relative to naive portfolios? In judging predictability based on the economic value that accrues to investors, we follow a relatively young but flourishing strand of literature. De Miguel *et al.* (2009) study the out-of-sample performance of the sample-based mean-variance model relative to a naive equally-weighted portfolio. The authors find that the naive portfolio outperforms the mean-variance model and all its extensions aimed at reducing estimation error. The interpretation of these results is that, in the samples that are available, the costs associated with estimation error outweigh the benefits from efficient allocation. In this paper, we incorporate a time varying opportunity set into the portfolio choice problem and apply the approach of De Miguel *et al.* (2009) to study the economic value of dividend-price ratios for capital allocation strategies. In recent work, Della Corte *et al.* (2008) and Thornton and Valente (2012) use a similar framework in the context of fixed income markets to assess the economic value of bond return predictability.

3 Dividend yields and portfolio management

3.1 Capital allocation models

This section describes the reference model for capital allocation. Since the Markowitz model is inconsistent with time-varying expected returns, we use a one-asset version of the single-period conditional portfolio problem studied by Brandt and Santa-Clara (2006). In a nutshell, this approach reduces the optimal solution of a dynamic strategy problem to a static choice of managed portfolios by assuming that the portfolio weights are proportional to the level of the conditioning variable. This highly stylized model can be thought of as describing the problem of an investment manager who seeks to maximize next-period returns while exploiting predictability signals at the same time.

Let $R_{t+1} = (P_{t+1} + D_{t+1})/P_t$ denote the total return on the market asset between t and $t + 1$, and let x_t denote the portfolio weight of the risky asset. The investor chooses the optimal portfolio weight by solving a standard quadratic maximization problem:

$$\max_{x_t} E_t\left[x_t R_{t+1} - \frac{\gamma}{2} x_t^2 R_{t+1}^2\right], \tag{1}$$

where γ is a risk aversion parameter; by formulating the problem in terms of total returns, we are implicitly assuming that the remainder of the portfolio's value is held as cash with zero return. The Markowitz paradigm is a special case of (1): returns are assumed to be *i.i.d.*, so that conditional expectations can be replaced with their unconditional counterparts and the problem can be solved easily by looking at first order conditions. The complication arises when returns are not *i.i.d.*, the case we consider. We follow Brandt and Santa-Clara (2006) and assume that portfolio weights are proportional to the state variable capturing time variation in expected returns:

$$x_t = \theta Z_t.$$

By substituting the parametric assumption above into x_t and introducing the notation $\tilde{R}_{t+1} = Z_t R_{t+1}$, the maximization problem can be re-written as:

$$\max_{x_t} E_t\left[\theta \tilde{R}_{t+1} - \frac{\gamma}{2} \theta^2 \tilde{R}_{t+1}^2\right].$$

As Brandt and Santa-Clara (2006) highlight, $\tilde{R}_{t+1}$ can be interpreted as the return on a managed portfolio, which invests in the market asset an amount that is proportional to the value of the state variable. Since the same θ maximizes the conditional expected utility at all dates t, it also maximizes the unconditional expected utility:

$$\max_{x_t} E\left[\theta\tilde{R}_{t+1} - \frac{\gamma}{2}\theta^2\tilde{R}^2_{t+1}\right],$$

thus reducing the dynamic strategy problem to a simply static problem. The solution to this maximization problem follows easily from the FOC:

$$\theta = \frac{1}{\gamma}E[\tilde{R}^2_{t+1}]^{-1}E[\tilde{R}_{t+1}]. \tag{2}$$

Since our aim is to study the economic value-added of predictability to investors, we follow De Miguel *et al.* (2009) and estimate (2) recursively over rolling windows of fixed size in order to avoid look-ahead biases. Fixing the size of the rolling window to M, the portfolio weight at time t, $x_t = \theta Z_t$, is obtained by estimating θ via the sample counterpart of (2):

$$\hat{\theta}_{t,Z} = \frac{1}{\gamma}\left[\sum_{s=0}^{M}\tilde{R}^2_{t-s}\right]^{-1}\left[\sum_{s=0}^{M}\tilde{R}_{t-s}\right], \tag{3}$$

so that the time t weight based on signal Z is given by $\hat{x}_{t,Z} = \hat{\theta}_{t,Z}Z_t$. We consider two investment strategies. The first strategy, which acts as a benchmark, is a «naive» strategy that selects the exposure to the market based on observed realized excess returns; this case can be seen as a degenerate managed portfolio with $Z = 1$. The second strategy uses dividend-price ratios as signals. We consider three signals: the dividend-price ratio (DP_t), the earnings-price ratio (EP_t), and the (inverse of the) cyclically-adjusted price-earnings ratio ($1/CAPE_t$). We set the risk aversion parameter to 3; this choice ensures that, in our sample, the portfolio share invested in the market is always between 0 and 1, so that the strategies we consider are self-financing.

How exactly do these capital allocation strategies relate to the classic regressions of realized returns on dividend-price ratios? Consider the expression (2); treating the denominator as a constant of proportionality, and expanding the numerator $E[\tilde{R}_{t+1}] = E[Z_tR_{t+1}]$, we obtain:

$$\begin{aligned}\theta &\propto E[Z_tR_{t+1}]\\ &\propto Cov[R_{t+1}, Z_t] + E[R_{t+1}]E[Z_t]\\ &\propto const. + bVar[Z_t]\end{aligned}$$

where $b = Cov\,[R_{t+1}, Z_t]/Var[Z_t]$ is the slope coefficient of a projection of realized returns on dividend-price ratios. This expression highlights that θ is an affine transformation of the slope coefficient from traditional predictability regressions: consistent with the intuition, the higher the economic significance of predictability in the sample (b), the more sensitive is the optimal market allocation to time variation in the dividend-price ratio (θ).

3.2 Performance evaluation

This section describes the metrics employed to evaluate the economic value of capital allocation strategies. The out-of-sample returns of the capital allocation strategies are defined as realized market returns scaled by the lagged weight, plus uninvested cash:

$$R_{t+1,Z} = \hat{x}_{t,Z} R_{t+1} + (1 - \hat{x}_{t,Z}),$$

Let $\hat{\mu}_Z$ and $\hat{\sigma}_Z$ denote the sample mean and standard deviation of out-of-sample returns $R_{t+1,Z}$:

$$\hat{\mu}_Z = \frac{1}{T-M} \sum_{s=M+1}^{T} R_{s,Z}$$

$$\hat{\sigma}_Z = \sqrt{\frac{1}{T-M} \sum_{s=M+1}^{T} \left(R_{s,Z} - \frac{1}{T-M} \sum_{s=M+1}^{T} R_{s,Z} \right)^2}$$

We follow De Miguel *et al.* (2009) and use three metrics to measure the economic value of our capital allocation strategies. First, we construct Sharpe ratios of realized out-of-sample returns:

$$\hat{S}R_Z = \frac{\hat{\mu}_Z}{\hat{\sigma}_Z}.$$

Next, we compute the certainty equivalent:

$$\hat{C}E_Z = \hat{\mu}_Z - \frac{\gamma}{2} \hat{\sigma}_Z^2.$$

Finally, we construct a turnover metric:

$$\hat{T}O_Z = \frac{1}{T-M} \sum_{s=M+1}^{T} \left| \hat{x}_{s+1,Z} - \hat{x}_{s+,Z} \right|$$

where $\hat{x}_{s+,Z}$ is the market weight before rebalancing at time $s + 1$[1].

4 Empirical results

4.1 Data

All price, dividend, and earnings data refer to the S&P 500 index and are taken from Robert Shiller's website. Given the long span of the sample (1871-2012), we use real (CPI-deflated) variables to ensure that results are not due to inflation effects. Since index dividends and earnings tend to feature high seasonality at monthly and quarterly

[1] The wealth W of the investor grows according to $W_{t+1} = W_t R_{t+1,Z}$. Before rebalancing, the time $t + 1$ market weight is given by $x_{t+} = \frac{W_t x_t R_{t+1}}{W_{t+1}} = x_t \frac{R_{t+1}}{R_{t+1,Z}}$.

frequency, we work with annual (end of year) data. Dividends (earnings) are 12-month moving sums of dividends paid on (earnings generated by) the S&P 500 index; this aggregation procedure implicitly assumes that interim dividends are kept as cash rather than being re-invested in an interest bearing account or in the S&P 500.

4.2 Learning from dividend yields

In order to gain intuition about the economic interpretation of classical predictive regressions, we first review the decomposition of Campbell and Shiller (1988b). Let lower-case letters indicate log-variables, so that $r_{t+1} = \log(R_{t+1})$, and define the (log) dividend-price ratio as $dp_t \equiv d_t - p_t$. Campbell and Shiller (1988b) show that returns can be written as:

$$r_{t+1} = \alpha + \Delta d_{t+1} - \psi dp_{t+1} + dp_t \tag{4}$$

where $\alpha \equiv \log(1+\exp(-dp^*)) + \psi dp^*$, $\psi \equiv \frac{\exp(-dp^*)}{1+\exp(-dp^*)}$ and dp^* is the long-run average of dp_t. Equation (4) is a differential equation which can be solved either forward or backward; iterating forward and imposing a transversality condition (no bubbles) we obtain:

$$dp_t - dp^* = E_t \sum_{s=1}^{\infty} \psi^{s-1}[(r_{t+s} - r^*) - (\Delta d_{t+s} - d^*)].$$

This equation has been studied in a variety of contexts. Two implication emerge. First, if log returns r_t and dividend growth Δd_t are stationary, then log dividend yields $dp_t - dp^* > 0$ are stationary. Second, deviations of the dividend yield from its long run mean dp_t imply that either future returns r_{t+s} or dividend growth Δd_{t+s} will exceed their long run mean. Using annual data for the sample period 1927-2004, Cochrane (2008, p. 1538) argues that since dividend yields only weakly predict future dividend growth at the aggregate level, time variation in dividend yields should mechanically help to explain the time-variation in conditional expected returns.

We review the empirical evidence on the informational content of dividend-price ratios by running two classic predictive regressions:

$$\begin{aligned} R_{t+h} &= a + b(D_t/P_t) + \varepsilon_{t+1} \pm \\ D_{t+h}/D_t &= a + b(D_t/P_t) + \varepsilon_{t+1} \end{aligned}$$

We consider horizons h from 1 to 5 years. Since Goyal and Welch (2003) find that dividend-price ratios (D_t/P_t) and dividend yields (D_t/P_{t-1}) contain different information, and that the empirical evidence in favour of predictability is strongest for the sample up until the 1990s, we report results for both predictors and two samples: 1947-1990 and 1926-2011. Tables 1 and 2 contain the results, for dividend price ratios and yields, respectively.

Table 1: DP ratio predictability. The table reports the output of regressions of cum-dividend returns (left panel) or dividend growth (right panel) on a constant and on dividend-price ratios. Horizons (h) range from 1 to 5 years. T-statistics, reported below the point estimates, use Newey and West (1987) HAC-consistent standard errors (h lags). The top (bottom) panel reports the results for the 1947-1990 (1926-2011) sample

DP RATIO		Returns			Dividend growth		
1947-1990	h	a	b	R^2	a	b	R^2
	1	0.84	5.80	16.67%	0.99	0.79	2.17%
		11.21	3.51		18.06	0.55	
	2	0.69	11.62	30.41%	0.97	1.87	3.66%
		4.79	3.44		10.45	0.79	
	3	0.63	14.97	37.93%	0.96	2.56	4.58%
		3.58	3.94		8.33	0.97	
	4	0.46	21.16	48.53%	0.96	2.59	4.88%
		2.28	5.42		7.27	0.97	
	5	0.17	30.09	60.65%	0.95	3.30	6.54%
		0.67	6.15		5.99	1.07	
1926-2011	h	a	b	R^2	a	b	R^2
	1	1.00	2.15	3.54%	1.10	−1.94	9.35%
		18.51	1.61		29.14	−1.92	
	2	0.95	5.29	9.17%	1.12	−2.17	4.64%
		10.68	2.62		18.56	−1.33	
	3	0.96	6.93	11.02%	1.13	−1.86	2.45%
		7.53	2.63		14.93	−0.94	
	4	0.90	10.41	16.34%	1.13	−1.67	1.70%
		5.33	3.06		15.32	−0.88	
	5	0.90	12.35	17.66%	1.14	−1.47	1.28%
		4.25	2.76		15.05	−0.78	

Table 2: DP yield predictability. The table reports the output of regressions of cum-dividend returns (left panel) or dividend growth (right panel) on a constant and on dividend-price yields. Horizons (h) range from 1 to 5 years. T-statistics, reported below the point estimates, use Newey and West (1987) HAC-consistent standard errors (h lags). The top (bottom) panel reports the results for the 1947-1990 (1926-2011) sample

DP YELD		Returns			Dividend growth		
1947-1990	h	a	b	R^2	a	b	R^2
	1	0.89	4.48	12.22%	0.97	1.32	7.40%
		11.29	2.75		18.54	1.00	
	2	0.87	7.16	14.41%	0.96	1.97	5.05%
		7.83	3.02		11.92	1.02	
	3	0.76	11.61	28.62%	0.97	2.11	3.89%
		5.49	4.23		10.05	1.06	
	4	10.52	19.03	48.87%	0.96	2.54	5.83%
		2.85	5.77		8.38	1.22	
	5	0.29	26.49	59.26%	0.93	3.50	9.25%
		1.30	6.93		6.84	1.46	
1926-2011	h	a	b	R^2	a	b	R^2
	1	0.97	2.73	4.88%	1.01	0.13	0.03%
		18.59	2.29		32.82	0.14	
	2	0.97	4.85	6.59%	1.03	0.15	0.02%
		10.72	2.47		20.20	0.11	
	3	0.94	7.28	10.41%	1.03	0.42	0.11%
		7.24	2.68		15.45	0.26	
	4	0.90	10.16	13.08%	1.05	0.51	0.13%
		4.99	2.71		12.89	0.28	
	5	0.91	11.82	13.51%	1.08	0.01	0.00%
		3.85	2.30		12.81	0.01	

When we use dividend-price ratios as predicting variable, we find strong evidence that returns can be forecasted in the 1947-1990 sample period. At a one year horizon, the t-statistics of the slope coefficient is 3.51 (we use Newey and West (1987) corrected HAC consistent standard errors) and the R^2 is equal to 16%. As we increase the holding period horizon, the degree of predictability increases and at an horizon of five years, the t-statistic is 6.15 with an R^2 equal to 60%. At the same time, the nature of this predictability is clearly not related to the predictability of dividend growth. Indeed, at any horizon, the slope coefficient of a regression of future dividend growth onto current dividend-price ratio is not statistically different from zero. It is interesting to observe, however, that the result is substantially weakened as we extend the sample period to include both the period before WWII and the more recent period after 1990 until 2011. In the extended sample period, while the slope coefficient is generally significant, the predictability is lost for the holding period horizon of 1 year. Moreover, the R^2 is substantially reduced: it is equal to 9% at a two year holding period horizon and reaches 17% at a five year horizon. Interestingly, the slope coefficients of future dividend growth predictive regressions switch sign and turn negative. A negative slope coefficient is consistent with economic theory: a drop in prices, thus an increase in the dividend-price ratio, should forecast a drop in future dividends.

When we consider dividend yields as the forecasting factor, the previous results are confirmed. In general, we find that the dividend yield is a slightly weaker predictor. In the 1947-1990 sample period the slope coefficient is strongly significant and the R^2 ranges between 12% and 59%. The statistical significance is extremely strong for holding period returns of 5 years. Also the statistical significance of dividend yields is substantially weakened in the extended sample 1926-2011: the highest R^2, at the 5 years horizon, does not exceed 13%. Interestingly, predictive regressions for future dividend growth produce slope coefficients which are positive (thus with the wrong sign), but the null hypothesis of no significance is never rejected. In the extended sample period, the failure of dividend yields to forecast future fundamentals is very noticeable with R^2 never exceeding 1% at any holding period. This evidence reinforces the argument that time variation in the dividend-price ratio captures time variation in the price of risk rather than the dynamics of fundamentals.

The somewhat lack of robustness of predictive regression across sub-samples has induced scholars to explore the out-of-sample performance of predictors. Goyal and Welch (2008) run out-of-sample regressions in which expected future returns at time $t + 1$ are based only on information available at time t. They find that in some subsamples a naive forecast obtained from the sample mean of returns up to time t can do better than a predictive regression that uses dividend-price ratio as a conditioning variable. Cochrane (2008) argues, however, that «Out-of-sample R^2 is not a test; it is not a statistic that somehow gives us better power to distinguish alternatives than conventional full-sample hypothesis tests». Indeed, the lower out-of-sample performance of the dividend-price ratio cannot be used as a test of the null hypothesis that returns are *i.i.d.* As the return decomposition 4 shows, the null hypothesis of *i.i.d.* returns has additional implications that need to be jointly tested. Cochrane (2008) argues that, among these other hypotheses, the most important to rule out return predictability is a large predictability of future dividend-growth and a small «long-run» return predictability. Thus, on the basis of the results pesented in Tables 1 and 2, one can hardly argue against Cochrane's conclusion that «there is in fact less than a 5% chance that our data or something more extreme is generated by a coherent world with unpredictable returns».

The out-of-sample results reported by Goyal and Welch (2008) serve, however, as a clear warning on the practical use of dividend-price ratios in portfolio management. The forecasting variable is persistent and dividends are known to be the outcome of corporate decisions that tend to smooth dividend distributions. These results raise an important question: if expected returns are time-varying and dividend yields are an important state variable, what is the economic value of predictability in the context of optimal portfolio choice? We address this question in the next section.

4.3 The economic value of dividend yields

We consider four alternative strategies to construct the optimal portfolios. The first portfolio is a benchmark naive portfolio that does not use conditioning information to predict future returns. In this case the market allocation is based on a simple average of realized returns (NAIVE); the other three portfolios use cash-flow ratio signals as conditioning information. The first signal is the dividend-price ratio (DP), the second signal is the earning-price ratio (EP), and the third is (inverse of) the cyclically adjusted price-to-earnings ratio (1/CAPE). Optimal portfolio weights are estimated recursively via rolling windows of M annual observations, with M being either 30, 60, or 90 years. In all cases, the information used to construct a portfolio is strictly based on data available up to that moment, thus ruling out any potential look-ahead bias.

Table 3 summarizes the sample statistics of 1-year out-of-sample portfolio returns of the four capital allocation strategies. Using a rolling window of 30 years and holding the portfolio for 1 year, we find that the average real return is 2.26% for the 1/CAPE portfolio, followed by the DP and EP portfolios with average real returns equal to 2.21% and 2.08%, respectively. Interestingly, however, all the three portfolios produce lower mean returns than the NAIVE portfolio. The result is even sharper when using median returns. While the NAIVE portfolio produces a median real return of 2.77%, the DP portfolio produces a median real return of 1.90%. Some interesting results emerge also from higher order moments. The standard deviation of the the NAIVE portfolio is clearly higher than the three portfolios based on conditioning information. This is especially true for $M = 60$ and 90. This suggests that while conditioning information is of limited use to forecast the first moment of expected returns, it seems to be valuable to reduce the dispersion of the distribution of expected returns. This effect is quite striking when we look at the «skewness» and «minimum» returns. At horizons of $M = 60$ and 90, the skewness of the NAIVE portfolio is highly negative, while the skewness of the portfolios based on conditioning information is positive for $M = 60$, and close to zero for $M = 90$. The economic impact of the negative skewness is evident when we look at the minimum returns, which are –11.62% for the NAIVE portfolio at $M = 60$, versus minimum returns of –7.24% for the DP portfolio. The result is confirmed when we consider $M = 90$. These findings motivate the need to compare the four portfolios on the basis of economic value metrics.

Table 3: Portfolio return statistics. The Table contains the sample statistics of 1-year out-of-sample portfolio returns of four capital allocation strategies. The first column contains the results for a naive strategy that chooses the market allocation based on a simple average of realized returns; the second, third and fourth column use cash-flow ratio signals as conditioning information. Optimal portfolio weights are estimated recursively via rolling windows of M annual observations; the top, medium, and bottom panel report results for windows of size 30, 60, and 90 years, respectively

		NAIVE	DP	EP	1 / CAPE
M = 30	Mean	2.35%	2.21%	2.08%	2.26%
	Median	2.77%	1.90%	1.74%	1.79%
	Stdev	5.74%	5.22%	5.53%	5.49%
	Skew	−0.24	0.22	−0.67	0.39
	Kurtosis	2.70	3.89	6.40	4.84
	Min	−11.66%	−12.88%	−23.79%	−13.98%
	Max	15.62%	19.07%	16.74%	21.45%
	Nobs	111	111	111	101
M = 60	Mean	2.55%	2.18%	2.33%	2.13%
	Median	3.42%	1.74%	1.79%	1.84%
	Stdev	5.51%	4.47%	4.64%	3.75%
	Skew	−0.24	0.87	0.22	0.13
	Kurtosis	2.93	5.27	3.05	3.02
	Min	−11.62%	−7.24%	−9.15%	−7.30%
	Max	15.60%	19.95%	15.44%	12.05%
	Nobs	81	81	81	71
M = 90	Mean	1.91%	1.29%	1.55%	1.66%
	Median	3.08%	1.45%	1.85%	1.49%
	Stdev	4.92%	2.90%	3.88%	3.74%
	Skew	−0.73	−0.14	−0.02	−0.02
	Kurtosis	3.03	3.16	4.31	3.50
	Min	−11.53%	−6.56%	−9.95%	−8.14%
	Max	10.36%	8.48%	13.12%	11.35%
	Nobs	51	51	51	41

Table 4: Economic value. The Table contains economic value statistics of 1-year out-of-sample portfolio returns of four capital allocation strategies. The statistics include: Sharpe ratio (SR), certainty equivalent (CE), and portfolio turnover (TO). The first column contains the results for a naive strategy that chooses the market allocation based on a simple average of realized returns; the second, third and fourth column use cash-flow ratio signals as conditioning information. Optimal portfolio weights are estimated recursively via rolling windows of M annual observations; the top, medium, and bottom panel report results for windows of size 30, 60, and 90 years, respectively

		NAIVE	DP	EP	1 / CAPE
M = 30	SR	0.41	0.42	0.38	0.41
	CE	1.85%	1.80%	1.62%	1.81%
	TO	3.50%	7.47%	8.11%	7.08%
M = 60	SR	0.46	0.49	0.50	0.57
	CE	2.10%	1.89%	2.01%	1.91%
	TO	3.40%	6.08%	7.19%	5.24%
M = 90	SR	0.39	0.45	0.40	0.44
	CE	1.55%	1.17%	1.33%	1.45%
	TO	3.13%	4.39%	5.77%	5.32%

Table 4 summarizes economic value statistics of the 1-year out-of-sample returns of the four portfolios. We consider three statistics: (*i*) Sharpe ratio (SR); (*ii*) certainty equivalent (CE); and (*iii*) portfolio turnover (TO). Using rolling windows of $M = 30$, we find that

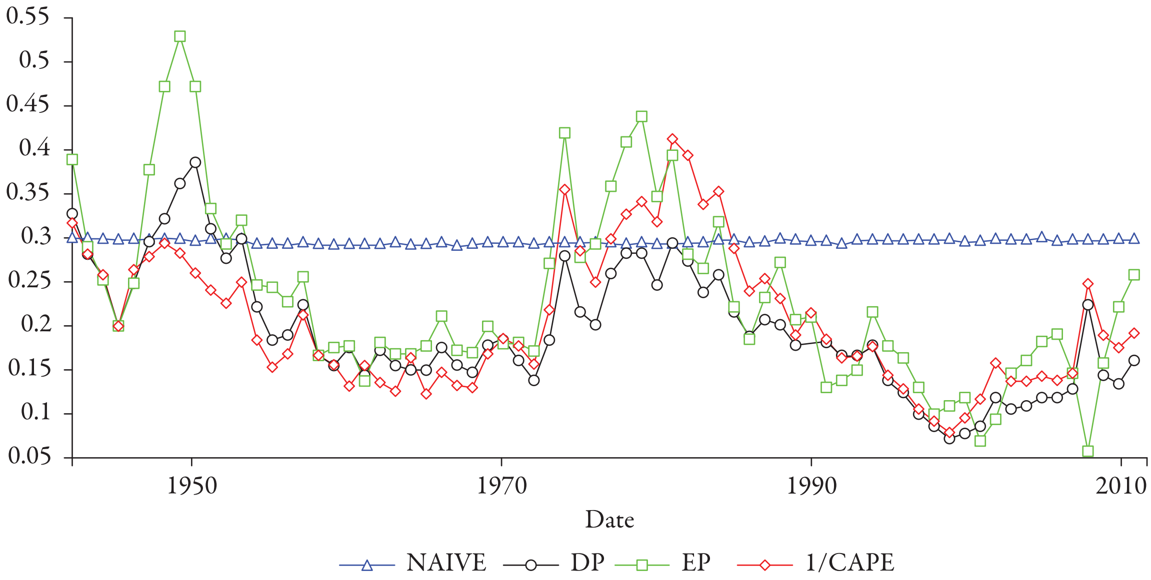

Figure 1: Market weights. The Figure plots the estimated market allocation weights $\hat{x}_{t,Z}$ for four capital allocation strategies: a naive strategy that chooses the market allocation based on a simple average of realized returns and three strategies that use cash-flow ratio signals as conditioning information. Optimal portfolio weights are estimated recursively via rolling windows of 60 annual observations.

the Sharpe ratio of the NAIVE portfolio is roughly equivalent to that of the three dynamic portfolios. For $M = 60$ and 90, however, the Sharpe ratios of the dynamic portfolios are generally larger than the NAIVE one. For $M = 90$, in particular, the Sharpe ratio of the DP portfolio is 0.45 versus 0.39 for the NAIVE portfolio. When we compare the four strategies based on their certainty equivalent (thus accounting for the agent's risk aversion), we find that the NAIVE strategy has the largest CE value. We also find that the NAIVE strategy has also another important property: it implies the lowest portfolio turnover.

The dynamics of portfolio weights is summarized by Figure 1. We find that while the NAIVE strategy, by construction, implies a portfolio weight which is very persistent, the allocation to the risky asset implied by the use of conditioning variable is highly time-varying. We also find that, in general, the signals provided by DP, PE, and 1/CAPE ratios are indeed quite similar. Some noticeable exceptions emerge. At the end of the 2007-2008 crisis, the EP ratio was suggesting a sharp reduction in exposure to risky assets. The signal coming from the DP and 1/CAPE ratios, on the other hand, was suggesting an aggressive increase in exposure to the equity market. Aside from this noticeable case, however, the three signals feature a strong positive correlation, with the EP ratio implying the most aggressive dynamic reallocation. Interesting examples are at the end of WWI and at the end of the second Oil Shock, when the PE ratio implied a bullish exposure to equity markets; in both cases, the optimal allocation to risky assets was far greater than what was implied by the DP ratio.

Figure 2 shows the difference in cumulative performance of the four strategies. As of 2012, the NAIVE portfolio would have produced larger gains than the three dynamic portfolios. The EP portfolio trails the NAIVE portfolio closely and, for an extended

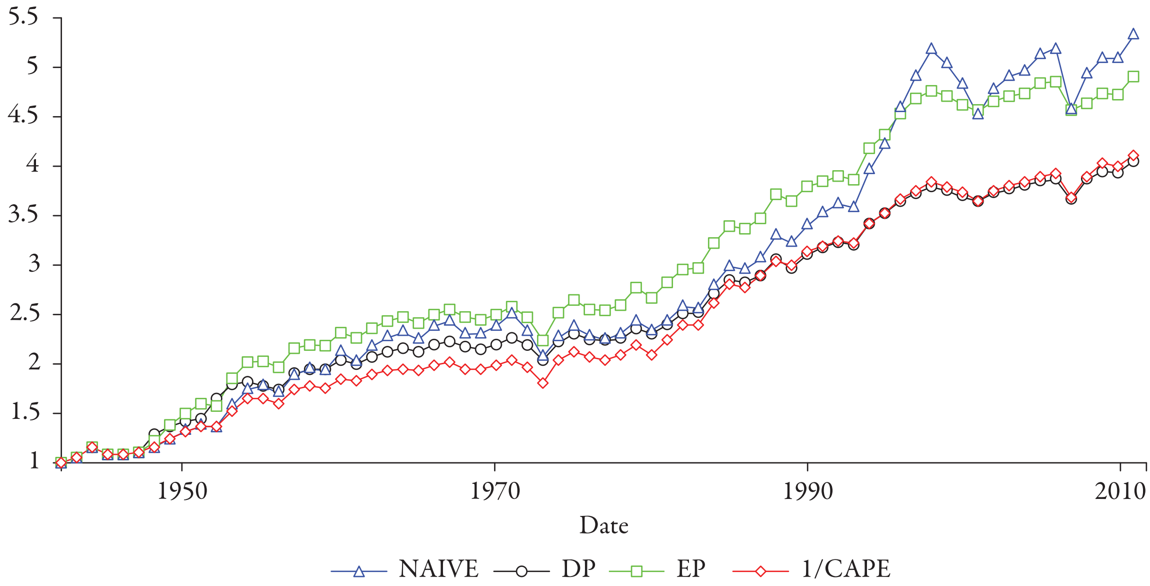

Figure 2: Cumulative returns. The Figure plots the cumulative returns of four capital allocation strategies: a naive strategy that chooses the market allocation based on a simple average of realized returns, and three strategies that use cash-flow ratio signals as conditioning information. Optimal portfolio weights are estimated recursively via rolling windows of 60 annual observations.

period (up until 1997) produces the largest cumulative returns. Once the compounding effect is taken into account, the difference in the final value of a 1 dollar invested in the 20s is quite striking. While the real value of the initial investment increased about 4 times using the DP and 1/CAPE strategy, the NAIVE strategy produced an increase in real terms of 5.3 times the initial capital invested.

In order to investigate in greater detail the relative performance of the three dynamic strategies, we multiply the difference in market allocation of conditional strategies relative to the naive portfolio by the market return: $(x_{t,Z} - x_{t,\text{NAIVE}})R_{t+1}$; positive values of this quantity indicate that the conditional strategy has allocated more (less) capital to the market in bullish (bearish) markets. Figure 3 plots $(x_{t,Z} - x_{t,\text{NAIVE}})R_{t+1}$ for $M = 60$. We find that dynamic strategies have outperformed the NAIVE strategy in only two periods: immediately after WWII, between 1948 and 1952, and in the 1970s during the two Oil Shocks; in the rest of the sample, the NAIVE strategy has produced higher returns.

These results suggest that while a consensus has emerged in finance that the dividend-price ratio is a powerful predictive variable which helps to explain the time-variation in expected excess returns, a real time portfolio strategy based on dividend-price ratio would have not outperformed a strategy based on the assumption that market returns are *i.i.d.*

5 Conclusion

The empirical literature of the past thirty years has built a strong body of evidence in support of the notion that equity returns are predictable; advances on the theoretical front, on the other hand, have provided equilibrium foundations to justify the idea

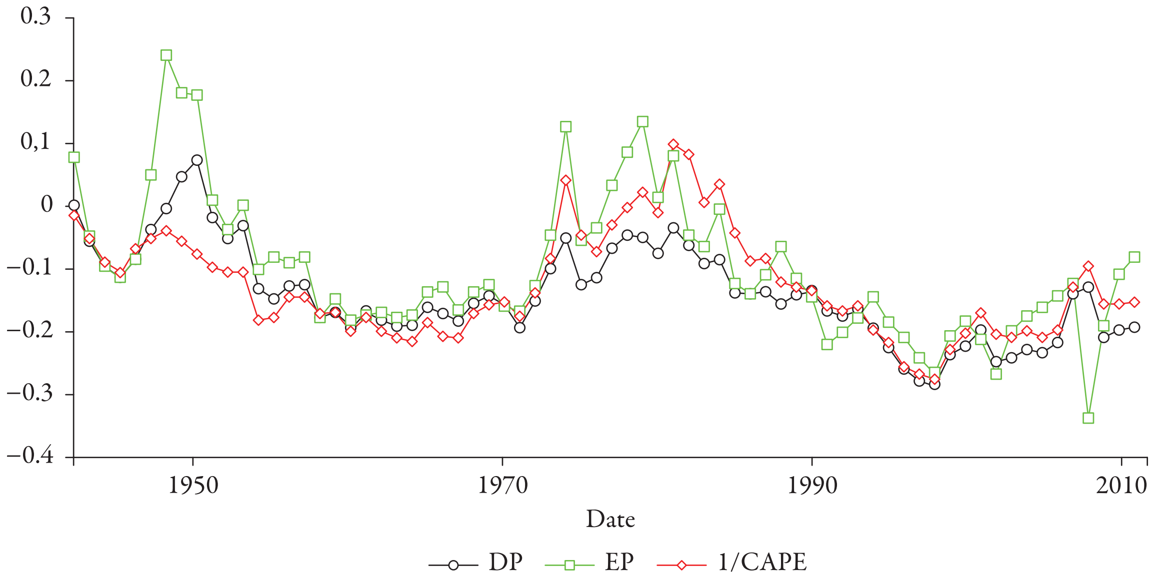

Figure 3: Performance attribution. Each line plots the spread between the market allocation weights of a conditional and a naive strategy times the market return one period later: $(\hat{x}_{t,Z} - \hat{x}_{t,NAIVE}) R_{t+1}$. Values above zero indicate that the conditional strategy has outperformed the naive strategy in a given period. The naive strategy chooses the market allocation based on a simple average of realized returns, while the conditional strategies use cash-flow ratio signals as conditioning information. Optimal portfolio weights are estimated recursively via rolling windows of 60 annual observations.

that returns are not *i.i.d.* Recent studies, however, have cast doubts on these findings on statistical grounds: subsample analysis shows great variation in the level of predictability, and the out-of-sample forecast power of dividend-price ratios is disappointing.

This paper tackles the issue of predictability from a capital allocation perspective: we ask whether a portfolio manager would have been able and willing to exploit dividend-price ratios to enhance performance. We find that the answer to this question is, alas, «no». A sophisticated investor who had consistently relied on dividend-price signals over the past century would now find himself lagging behind the naive investor. When examined in the light of the economic value of out-of-sample returns, in-sample predictability is a mirage that can be traced back to 50s and 70s/90s.

The results are based on the assumption of a 1-year investment horizon. This assumption might bias the rejection of the null of predictability in two ways. First, we know from in-sample regressions that predictability is strongest for long horizons, so that an increase in the holding period returns of the investor might increase the economic value of dividend-price signals for portfolio performance. Second, by assuming a myopic horizon, we are ignoring the impact that hedging demand may have on optimal weights. We however believe that our model, while highly stylized, is effective in describing the real-world problem of active portfolio managers whose performance is evaluated over short horizons: for this class of investors, strategies based on dividend-price ratios are likely to prove disappointing.

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References

Ang A. and Bekaert G. (2007) 'Stock Return Predictability: Is it There?', *Review of Financial Studies*, 20(3), pp. 651-707.

Baker M. and Wurgler J. (2000) 'The Equity Share in New Issues and Aggregate Stock Returns', *Journal of Finance*, 55(5), pp. 2219-2257.

Bansal R. and Yaron A. (2004) 'Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles', *Journal of Finance*, 59(4), pp. 1481-1509.

Barberis N.C. (2000) 'Investing for the Long Run when Returns are Predictable', *Journal of Finance*, 55, pp. 225-264.

Brandt M.W. and Santa-Clara P. (2006) 'Dynamic Portfolio Selection by Augmenting the Asset Space', *Journal of Finance*, 61(5), pp. 2187-2217.

Brennan M.J., Schwartz E.S., Lagnado R. (1997) 'Strategic Asset Allocation', *Journal of Economic Dynamics and Control*, 21, pp. 1377-1403.

Buraschi A. and Jiltsov A. (2006) 'Model Uncertainty and Option Markets with Heterogeneous Beliefs', *Journal of Finance*, 61(6), pp. 2841-2897.

Campbell J.Y. (1987) 'Stock Returns and the Term Structure', *Journal of Financial Economics*, 18(2), pp. 373-399.

Campbell J.Y. (2000) 'Asset Pricing at the Millennium', *Journal of Finance*, 55, pp. 1515-1567.

Campbell J.Y. and Cochrane J.H. (1999) 'By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior', *Journal of Political Economy*, 107(2), pp. 205-251.

Campbell J.Y. and Shiller R.J. (1988a) 'Stock Prices, Earnings, and Expected Dividends', *Journal of Finance*, 43(3), pp. 661-676.

Campbell J.Y. and ShillerR.J. (1988b) 'The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors', *Review of Financial Studies*, 1(3), pp. 1455-1508.

Campbell J.Y. and Shiller R.J. (1998) 'Valuation Ratios and the Long-Run Stock Market Outlook', *Journal of Portfolio Management*, 24(2), pp. 11-26.

Campbell J.Y. and Viceira L.M. (1999) 'Consumption and Portfolio Decisions when Expected Returns Are Rime Varying', *Quarterly Journal of Economics*, 114, pp. 433-495.

Campbell J.Y. and Viceira L.M. (2001) 'Who Should Buy Long-Term Bonds?', *American Economic Review*, 91, pp. 99-127.

Campbell, J.Y. and Viceira, L.M. (2002). *Strategic Asset Allocation: Portfolio Choice for Long-term Investors*. Oxford University Press: Oxford.

Cochrane J.H. (2008) 'The Dog That Did Not Bark: A Defense of Return Predictability', *Review of Financial Studies*, 21(4), pp. 1533-1575.

Della Corte P., Sarno L., Thornton D.L. (2008) 'The Expectation Hypothesis of the Term Structure of Very Short-Term Rates: Statistical Tests and Economic Value', *Journal of Financial Economics*, 89(1), pp. 158-174.

Detemple J. and Murthy. S. (1994) 'Intertemporal Asset Pricing with Heterogeneous Beliefs', *Journal of Economic Theory*, 62, pp. 294-320.

Fama E.F. (1970) 'Efficient Capital Markets: A Review of Theory and Empirical Work', *Journal of Finance*, 25 (2), pp. 383-417.

Fama E.F. (1991) 'Efficient Markets: II', *Journal of Finance*, 46(5), pp. 1575-1618.
Fama E.F. and French K.R. (1988) 'Dividend Yields and Expected Stock Returns', *Journal of Financial Economics*, 22(1), pp. 3-25.
Fama E.F. and French K. R. (1989) 'Business Conditions and Expected Returns on Stocks and Bonds', *Journal of Financial Economics*, 25(1), pp. 23-49.
Fama E.F. and French K.R. (1992) 'The Cross-Section of Expected Stock Returns', *Journal of Finance*, 47, pp. 427-465.
Gabaix X. (2009) 'Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro Finance', *The Quarterly Journal of Economics*, 127(2), pp. 645-700.
Goetzmann W.N. and Jorion P. (1993) 'Testing the Predictive Power of Dividend Yields', *Journal of Finance*, 48(2), pp. 663-679.
Goyal A. and Welch I. (2003) 'Predicting the Equity Premium with Dividend Ratios', *Management Science*, 49(5), pp. 639-654.
Goyal A. and Welch I. (2008) 'A Comprehensive Look at the Empirical Performance of Equity Premium Prediction', *Review of Financial Studies*, 21(4), pp. 257-286.
Hansen L.P. and Richard S.F. (1987) 'The Role of Conditioning Information in Deducing Testable Restrictions Implied by Dynamic Asset Pricing Models', *Econometrica*, 55, pp. 587-613.
Hodrick R.J. (1992) 'Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement', *Review of Financial Studies*, 5(3), pp. 257-286.
Kothari S. and Shanken J. (1997) 'Book-to-Market, Dividend Yield, and Expected Market Returns: A Time-Series Analysis', *Journal of Financial Economics*, 44(2), pp. 169-203.
Lamont O. (1998) 'Earnings and Expected Returns', *Journal of Finance*, 53(5), pp. 1563-1587.
Lettau M. and Ludvigson S. (2001) 'Consumption, Aggregate Wealth, and Expected Stock Returns', *Journal of Finance*, 56(3), pp. 815-849.
Lynch A.W. (2001) 'Portfolio Choice and Equity Characteristics: Characterizing the Hedging Demands Induced by Return Predictability', *Journal of Financial Economics*, 62, pp. 67-130.
DeMiguel V., Garlappi L., Uppal R. (2009) 'Optimal Versus Naive Diversification: How Inefficient is the 1/N Portfolio Strategy?', *Review of Financial Studies*, 22(5), pp. 1915-1953.
Nelson C.R. and Kim M.J. (1993) 'Predictable Stock Returns: The Role of Small Sample Bias', *Journal of Finance*, 48(2), pp. 641-661.
Newey W.K. and West K.D. (1987) 'A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix', *Econometrica*, 55(3), pp. 703-708.
Pontiff J. and Schall L.D. (1998), 'Book-to-Market Ratios as Predictors of Market Returns', *Journal of Financial Economics*, 49(2), pp. 141-160.
Rapach D. E. and Wohar M.E. (2006) 'In-Sample vs. Out-of-Sample Tests of Stock Return Predictability in the Context of Data Mining', *Journal of Empirical Finance*, 13(2), pp. 231-247.
Rozeff M.S. (1984) 'Dividend Yields Are Equity Risk Premiums', *Journal of Portfolio Management*, 11(1), pp. 68-75.
Samuelson P. (1965) 'Proof That Properly Anticipated Prices Fluctuate Randomly', *Industrial Management Review*, 6, pp. 41-49.
Thornton D.L. and Valente G. (2012) 'Out-of-Sample Predictions of Bond Excess Returns and Forward Rates: An Asset Allocation Perspective', *Review of Financial Studies*, 25(10), pp. 3141-3168.
Valkanov R. (2003) 'Long-Horizon Regressions: Theoretical Results and Applications', *Journal of Financial Economics*, 68(2), pp. 201-232.