DIVIDENDS, TOTAL CASH FLOW TO SHAREHOLDERS, AND PREDICTIVE RETURN REGRESSIONS

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Abstract—This paper provides new evidence on the predictive power of dividend yields for U.S. aggregate stock returns. Following Miller and Modigliani, we construct a measure of the dividend yield that includes all cash flows to shareholders. We show that this alternative *cash-flow yield* has strong and stable predictive power for returns, and appears robust to a battery of tests that have been proposed in recent critiques of the predictability literature.

I. Introduction

THERE is a large body of research that claims to find evidence that the dividend yield predicts stock returns. More recently however an increasing body of research has cast doubt on the earlier evidence of predictability, attributing it to data mining or other statistical problems.[1] This paper suggests that the clear weaknesses of the dividend yield as a predictor may be due to mismeasurement. Miller and Modigliani (1961) showed that stock market value depends on investor valuation of all cash flows from firms, not just the dividend component. Because the propensity to pay dividends may vary due to (for example) taxation changes, dividends alone may at times be a poor proxy for true cash flow. In this paper we use a new *cash-flow yield* that includes both dividend and nondividend cash flows to shareholders and investigate its predictive power for aggregate stock returns.

In redefining dividends in this way, our work is related to a number of papers that have investigated nondividend cash flows in other contexts. Most studies (for example, Fama & French, 2001; Grullon & Michaely, 2002; Liang & Sharpe, 1999) have focused on the growing importance of repurchases. For the representative investor, however, cash- or bond-financed acquisitions and new issues play an identical role in transferring cash from firms to shareholders (or vice versa in the case of new issues), and both have at times been quantitatively as important as dividends and repurchases. A number of authors (Bagwell & Shoven, 1989; Ackert & Smith, 1993; Mehra, 1998; Allen & Michaely, 2002) have noted the importance of treating all such nondividend cash flows as being equivalent to dividends; but the implications for measures of total cash flow have received distinctly less attention in econometric research.[2]

We use a new data set (Wright, 2004) for the U.S. nonfinancial corporate sector to construct an annual series for total corporate cash flow to shareholders since the start of the twentieth century. We then compare the resulting cash-flow yield with standard yield measures, both from this data set and from the more commonly used S&P 500 series. We show that, in contrast to conventional yield measures, the cash-flow yield has strong and stable predictive power for returns at a range of horizons, and is robust to a battery of tests that have been proposed in recent critiques of the predictability literature.[3]

II. Data

A. Data Sources and Construction

All data used in this paper come from a new annual data set, described in full in Wright (2004), which relates to the total nonfinancial U.S. corporate sector (rather than the more commonly used subset of quoted companies) over the sample 1900–2002, using data from the Federal Reserve's Flow of Funds Tables, from the Bureau of Economic Analysis (1977) where they exist, and from such historical sources as are available in earlier periods.

The core series[4] used in this paper are:

- *Real market value of equities* (V_t): From 1945 to 2002 the nominal value of this series is taken directly from the Federal Reserve's Flow of Funds Accounts, for the market value of equities outstanding for the nonfinancial corporate sector (table B102, line 34). It includes an adjustment that nets out intercorporate cross-holdings (Federal Reserve, 2000). Before 1945, Wright (2004) describes the construction of this series using a combination of two proxies derived from S&P 500 and Cowles's (1938) data on returns and dividend yields, in conjunction with the dividend and new-issue data described below.
- *Real dividends* (D_t): From 1946 onward, the nominal value of this series equals nonfarm, nonfinancial dividends from Flow of Funds Table F102, line 3; and

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[1] On predictability, see, for example, Fama and French (1988), Jegadeesh (1990), Campbell and Shiller (1988, 1998), Pesaran and Timmerman (1995), or the survey in Campbell, Lo, and MacKinlay (1997). For revisionist critiques see, for example, Goetzmann and Jorion (1993), Nelson and Kim (1993), Kirby (1997), Bossaerts and Hillion (1999), Foster, Smith, and Whaley (1997), Stambaugh (1999), Goyal and Welch (2003, 2004), and Ang and Bekaert (2004).

[2] A point stressed in Allen and Michaely's (2002) recent comprehensive review article. The only exceptions of which we are aware are Ackert and Smith (1993) and Mehra (1998).

[3] In concurrent research, Boudoukh et al. (2004) provide similar results to our own on predictability, using a yield measure for quoted companies, adjusted for repurchases. They also show that their measure of the payout yield helps to explain the cross section of expected returns.

[4] All three series are deflated by the consumer price index [also taken from Wright's (2004) database] to derive real values.

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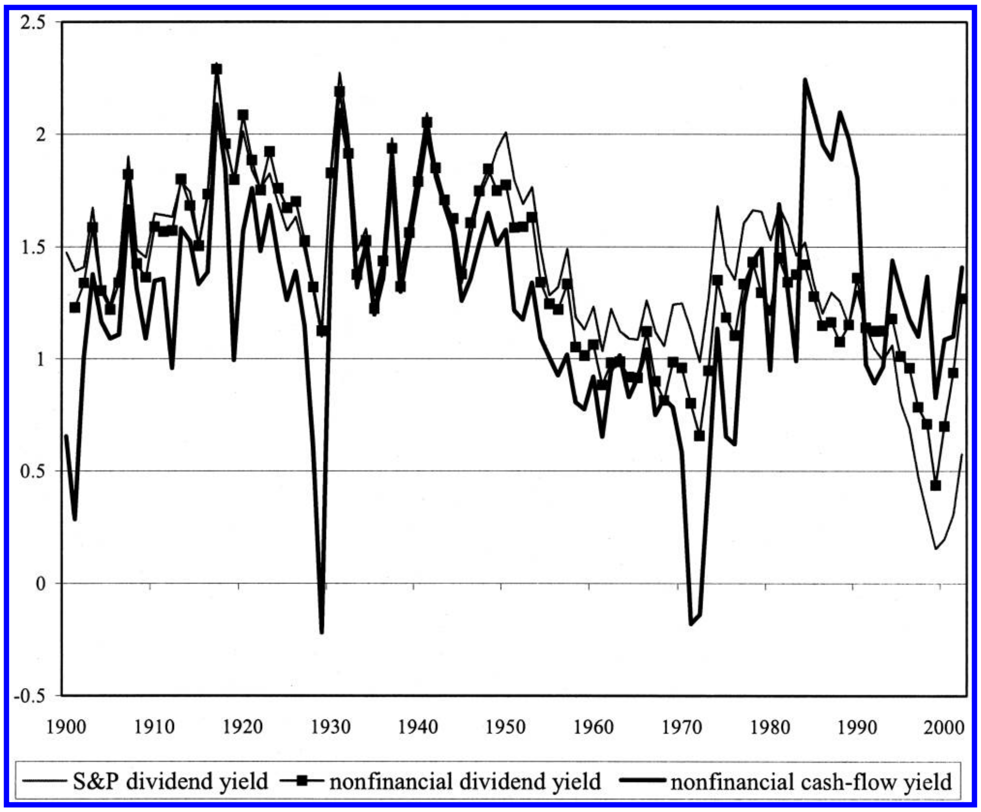
FIGURE 1.—ALTERNATIVE MEASURES OF THE DIVIDEND YIELD



from 1929 to 1945 the (virtually identical) series from the National Income and Product Accounts Table 1.16, for the total nonfinancial corporate sector. Before 1929, the series is constructed using data from Kuznets (1941), Goldsmith (1955), and Cowles (1938) (for details, see Wright, 2004). All series net out intercorporate dividend payments and thus are consistent with market value data.

- *Real net new issues* (N_t): From 1946 to 2002, the nominal value of this series equals (net) nonfinancial corporate equity issues from Flow of Funds Table R102 (line 11). In recent years, these figures have been consistently negative, implying net corporate purchases, due to the combined effect of repurchases and cash-financed mergers and acquisitions. Before 1946, data on these last two components are not available, but they are assumed to be empirically negligible.[5] Wright (2004) constructs a series for new issues for this earlier period with data from various sources [Miller (1963); *Historical Statistics;* and, for the first decade of the twentieth century, editions of the *Commercial and Financial Chronicle*].

Wright (2004) derives implied series for the aggregate real stock price index, the aggregate real return for the total nonfinancial corporate sector, and real dividends per share (none of which are directly published), all of which can be derived from the three core series above. Total real cash flow can also be derived as $C_t = D_t - N_t$, and the real nonfinancial return by $1 + R_t = (V_t + C_t)/V_{t-1}$.[6]

B. *Alternative Measures of the Dividend Yield*

Figure 1 shows the conventional measure of the nonfinancial dividend yield (ratio of dividend per share to price), alongside our alternative *cash-flow yield* (defined as C_t/V_t) using our data set, over the course of our sample. For comparison we also show the yield on the S&P composite index. The two conventional measures are, as might be expected, very similar.[7] The cash-flow yield has a very similar mean to the conventional yield, but at times distinctively different properties. It is noteworthy that these differ-

[5] Allen and Michaely (2002) note that before 1983 repurchases were barely legal, and as a result very uncommon. In the period of overlap with Fed data the alternative sources for new issues that we rely on in earlier periods yield very similar figures, suggesting that the omission of cash-financed acquisitions before 1946 is not empirically significant either.

[6] Following Miller and Modigliani (1961), Wright (2004) shows that this is identical to the more common definition using dividends per share.

[7] Following standard practice (for example, Shiller, 2000; Goyal & Welch, 2004), the S&P yield is extrapolated backward before 1925 using the equivalent series from Cowles (1938). The decline in the yield in the 1990s for all nonfinancial companies was not as marked as for the S&P 500 companies, largely due to a distinct divergence in tax incentives for smaller companies, which encouraged 100% payout ratios.

TABLE 1.—CORRELATIONS ACROSS DIFFERENT DATA SETS: ANNUAL DATA, 1901–2002

	Return	S&P Return	Cash-flow Yield	Nonfin. Div. Yield	S&P Div. Yield
A. Unconditional Correlations					
Return	1.000	0.976	−0.281	−0.355	−0.314
S&P Return		1.000	−0.281	−0.341	−0.310
Cash-flow Yield			1.000	0.632	0.475
Nonfin. Div. Yield				1.000	0.898
S&P Div. Yield					1.000
B. Correlations between Innovations					
Return	1.000	0.976	−0.627	−0.849	−0.838
S&P Return		1.000	−0.626	−0.858	−0.834
Cash-flow Yield			1.000	0.683	0.717
Nonfin. Div. Yield				1.000	0.945
S&P Div. Yield					1.000

Panel A shows unconditional correlations between log yields and log real returns. Panel B shows correlations between innovations when log returns are regressed on a constant and yields are modeled as AR(1) processes.

ences were not just evident in the last two decades of the sample.

For much of the sample, the difference between the two series reflected surges in new issues at certain periods (most strikingly in 1929, and also in the early 1970s) that lowered the cash-flow yield significantly, by lowering the net transfer of cash from firms to shareholders. In other periods (most notably the 1930s and early 1940s), new issues essentially collapsed to zero and the cash-flow and conventional yields were nearly identical. However, in the last two decades of the century there was a clear shift, with the difference between the two yields switching sign, as firms engaged in significant levels both of repurchases and of geared acquisitions, which more than offset minimal levels of new issues. The effect of the implied adjustment to the dividend yield in recent years is more significant than in estimates based solely on data for repurchases, as in, for example, Fama and French (2001); Liang and Sharpe (1999), and Boudoukh et al. (2004). Though there are data coverage differences, the primary explanation is the effect of cash-financed acquisitions in the Fed data.[8]

The chart also shows that, though the cash-flow yield is distinctly more volatile than the per share yield, it appears to have a stronger tendency to mean reversion than either of the two conventional measures. This is important because persistence of the dividend yield has been pointed to as a cause for the inferential problems in predictive regressions.

The downward drift in both conventional measures of the dividend yield in the latter part of the sample reflected, at least in part, the surge in the stock market during the course of the 1990s. Strikingly, however, this tendency was not evident in the cash-flow yield, which, at the peak of the market in 2000, was close to its mean, because cash flow from the corporate sector to equity holders grew as rapidly as the stock market during the 1990s, due to the strength of M&A activity and repurchases.

In Robertson and Wright (2004) we argue that good theoretical grounds exist for expecting stronger evidence of mean reversion for the cash-flow yield than for conventional measures. We show that the mean value of the conventional yield may be subject to permanent shocks if permanent shifts occur between dividend and nondividend methods of cash transfer to shareholders, as figure 1 strongly suggests has been the case. The mean cash-flow yield will however be immune to such shifts. Empirically this seems to be borne out in our data set: the estimated AR(1) coefficients for the S&P and nonfinancial dividend yield are 0.87 and 0.81 respectively, whereas that for the cash-flow yield is only 0.63. In Robertson and Wright (2004) we show that the unit root restriction cannot be rejected for conventional yields, but is strongly rejected for the cash-flow yield.[9]

C. *Correlations across Different Data Sets*

Table 1 shows correlations between the key data series used in the predictive regressions. Panel A shows unconditional correlations. The two measures of real returns are very highly correlated, and the two comparable measures of the conventional dividend yield only somewhat less so. Panel B shows conditional correlations between innovations to each of the five series, assuming for simplicity that returns are white noise and yields are AR(1) processes. The conditional correlation between the two conventional yield series is even stronger than the unconditional correlation (which is lowered primarily by the somewhat lower persistence of the nonfinancial yield). Panel B also shows a very high negative correlation between innovations to conventional yields and to returns, which, as discussed in the next

[8] The Federal Reserve does not publish a breakdown of net aggregate corporate equity purchases into new issues, repurchases, and geared mergers and acquisitions (M&A). Allen and Michaely (2002) provide aggregate data on all three elements, for quoted companies, that show similar patterns to those in the Fed data. Wright (2004) provides comparative analysis of Allen and Michaely's data set and the Fed data.

[9] See the appendix for discussion of the impact on AR(1) coefficients of imposing the null of no predictability.

section, is a source of bias in predictive regressions. In contrast, the conditional correlation between the cash-flow yield and returns is distinctly less strong.

III. Predictive Return Regressions

A. Full Sample Estimates

Most tests of predictability rely on regressions of the form

$$r_{t,h} = \alpha + \beta_h x_t + u_{t,h}, \tag{1}$$

$$x_t = \gamma + \lambda x_{t-1} + v_t, \tag{2}$$

where $r_{t,h}$ is the h-period-ahead log return at time t, and x_t is some predictor variable (most commonly the dividend yield) observed at t. The hypothesis of interest is typically a test of H_0:$\beta_h = 0$, with a rejection being interpreted as evidence of predictability. A number of problems with inference in this framework have been pointed out. First, if $h > 1$, then $u_{t,h}$ will usually be serially correlated due to overlapping observations, and this will affect estimates of the standard error of the estimate of β_h. Second, if we search for predictability at various different horizons h, we need to take account of the multiplicity of tests and look at the implied joint hypothesis. Third, according to Stambaugh (1999) it is necessary to take account of the time series properties of the predictor variable, because biases in the estimation of λ are transmitted to estimates of β_h, with the magnitude of the bias depending on the degree of correlation between v_t and $u_{t,h}$.[10] Together these problems mean that the conventional t-statistic will not be reliable, because the point estimate may be biased and the OLS standard errors incorrect. Solutions to the problem of serial correlation in the residuals have been much discussed, usually by correcting the estimated standard errors through some Newey-West-type adjustment—Ang and Bekaert (2004) argue that Hodrick (1992) standard errors provide the most reliable inference, and we present these. The estimates of β_h can also be bias-adjusted (see Stambaugh, 1999; Lewellen, 2004; Campbell & Yogo, 2002). In this paper however we follow Nelson and Kim (1993) and Ang and Bekaert (2004) in relying primarily on simulation methods to obtain p-values that will largely correct for these difficulties.

In table 2 we report the results of estimating the equation for $h = 1, \ldots, 10$ years where $r_{t,h} = \frac{1}{h}\sum_{i=1}^{h} r_{t+i}$ is the average h-period-ahead return; $r_t = log(1 + R_t)$ is the 1-period log return, and x_t is one of the three log dividend yield measures. We report p-values for the test of the null hypothesis H_0:$\beta_h = 0$, using both OLS and Hodrick (1992) standard errors. We also report Monte Carlo-derived p-values obtained by simulating the set of equations under the null $\beta_h = 0$ for all h, thus dealing simultaneously with the bias and overlapping-observation problems; and bootstrapped p-values where the actual residuals (under the null) are sampled to generate the simulated data.[11]

Given the known problems of focusing on results for individual horizons, the final column of table 2 reports conventional and simulated p-values for joint tests of the null of no predictability at all horizons from 1 to 5 and from 1 to 10 years. Our test procedure exploits an equivalence between two ways of representing horizon return predictability. The standard approach in equation (1) is in terms of the h-period real return $r_{t,h} = \frac{1}{h}\sum_{i=1}^{h} r_{t+i}$, where r_t is the 1-period real return; but this has the problem that the errors are MA processes. An alternative representation is

$$r_{t+h} = \gamma_h x_t + \omega_{t,h}, \tag{3}$$

which has the advantage that under the null of no predictability the γ_h are zero and the $\omega_{t,h}$ are white noise. Because the implied coefficients in equation (3) can be derived by $\beta_h = \sum_{i=1}^{h} \gamma_i$, the joint null H_0:$\beta_h = 0$ for all $h = 1, \ldots, H$ is equivalent to the joint null H_0:$\gamma_h = 0$ for all $h = 1, \ldots, H$. We can estimate the set of equations of the form (3) for $h = 1, \ldots, H$ as a system, and because all equations have the same regressor, the FIML, SUR, and OLS estimates will be the same and will imply identical estimates of the β_h to those derived by direct estimation. We therefore test the joint null by estimating restricted and unrestricted systems for $H = 5$ and 10, and test the null by likelihood ratio. Given the bias problems caused by the correlation of x_t with r_t, the size of the resulting test statistic will be incorrect, but we again run Monte Carlo and bootstrapped simulations under the null of no predictability to estimate the true size.

Panels A and B of table 2 replicate the known results on the fragility of the evidence that the conventional dividend yield predicts returns, with very similar results for both measures. The estimated coefficients show the well-known horizon effect—the OLS p-values drop with increasing horizon, so that a null hypothesis of no predictability would be rejected strongly at conventional significance levels at longer horizons. However, p-values using Hodrick standard errors show the importance of controlling for serial dependence in the long-horizon prediction regressions: the extent of predictability is brought down to at best marginal significance. The simulated p-values reinforce this conclusion, and indeed show that even the Hodrick correction understates the size distortion. Concerns about nonnormality of the data are shown to be of little consequence, as the Monte Carlo and bootstrapped p-values differ only marginally. For neither measure do simulated p-values fall below 5% at any individual horizon; and the more robust joint tests fail to reject the null of no predictability once the (again, very significant) size distortion is corrected.

[10] Thus bias is less of a problem for the cash-flow yield than for conventional yields, since, as shown in table 1B, there is a much weaker conditional correlation with returns.

[11] For details of simulations see the appendix.

TABLE 2.—TESTING PREDICTIVE RETURN REGRESSIONS AT DIFFERENT HORIZONS, 1901–2002

			p-Values				
h	Obs.	Coeff.	OLS	Hodrick	Monte Carlo	Bootstrap	Joint Tests
			A. S&P Real Return and Dividend Yield				
1	101	0.0853	0.087	0.059	0.136	0.133	$h = 1, \ldots, 5$:
2	100	0.100	0.007	0.046	0.083	0.079	$p_{sur} = 0.003$
3	99	0.076	0.010	0.113	0.150	0.147	$p_{mc} = 0.108$
4	98	0.067	0.012	0.173	0.182	0.185	$p_{bs} = 0.100$
5	97	0.074	0.003	0.159	0.140	0.139	
6	96	0.070	0.003	0.187	0.154	0.153	$h = 1, \ldots, 10$:
7	95	0.066	0.002	0.167	0.162	0.158	$p_{sur} = 0.001$
8	94	0.079	0.000	0.058	0.085	0.083	$p_{mc} = 0.154$
9	93	0.079	0.000	0.037	0.077	0.074	$p_{bs} = 0.151$
10	92	0.075	0.000	0.033	0.078	0.081	
			B. Nonfinancial Real Return and Dividend Yield				
1	100	0.095	0.095	0.080	0.129	0.135	$h = 1, \ldots, 5$:
2	99	0.119	0.004	0.020	0.066	0.067	$p_{sur} = 0.006$
3	98	0.090	0.004	0.045	0.121	0.120	$p_{mc} = 0.088$
4	97	0.071	0.008	0.112	0.191	0.188	$p_{bs} = 0.084$
5	96	0.072	0.003	0.093	0.171	0.168	
6	95	0.064	0.003	0.134	0.210	0.201	$h = 1, \ldots, 10$:
7	94	0.055	0.005	0.151	0.263	0.257	$p_{sur} = 0.006$
8	93	0.062	0.001	0.047	0.205	0.202	$p_{mc} = 0.088$
9	92	0.059	0.001	0.044	0.213	0.209	$p_{bs} = 0.084$
10	91	0.053	0.001	0.070	0.250	0.245	
			C. Nonfinancial Real Return and Cash-Flow Yield				
1	101	0.144	0.001	0.005	0.003	0.003	$h = 1, \ldots, 5$:
2	100	0.151	0.000	0.000	0.001	0.001	$p_{sur} = 0.000$
3	99	0.112	0.000	0.001	0.003	0.003	$p_{mc} = 0.004$
4	98	0.086	0.000	0.002	0.012	0.012	$p_{bs} = 0.004$
5	97	0.082	0.000	0.000	0.011	0.010	
6	96	0.071	0.000	0.000	0.019	0.017	$h = 1, \ldots, 10$:
7	95	0.061	0.000	0.000	0.040	0.033	$p_{sur} = 0.000$
8	94	0.063	0.000	0.000	0.025	0.020	$p_{mc} = 0.009$
9	93	0.060	0.000	0.000	0.027	0.021	$p_{bs} = 0.009$
10	92	0.057	0.000	0.000	0.026	0.022	

Estimates of the h-period return regression $r_{t,h} = \alpha + \beta_h x_t + u_{t,h}$ where $r_{t,h} = \frac{1}{h}\Sigma_{i=1}^{h} r_{t+i}$ is the average real log return over the next h years, r_t is the 1-period real log return, and x_t is one of the three yield measures. We report the OLS estimate of the coefficient β_h at various horizons, and the the p-values of the test of the null hypothesis $H : \beta_h = 0$ using OLS standard errors; Hodrick (1992) autocorrelation-corrected standard errors; p-values from Monte Carlo simulations of the model under the null where x_t follows an AR(1) $x_t = \gamma + \lambda x_{t-1} + \upsilon_t$ and the residuals are assumed normal with covariance structure matching the data; and finally a bootstrap simulation where the residuals are sampled with replacement from the actual equation residuals. The simulations are based on 10,000 repetitions. The final column reports p-values of the joint tests that $\beta_h = 0$ for horizons $h = 1, \ldots, H$ for $H = 5$ and 10 as described in section III A: p_{sur} is the conventional p-value for the LR statistic [χ^2 (H)] when the restricted and unrestricted systems are estimated by SUR; p_{mc} and p_{bs} are implied p-values from Monte Carlo and bootstrapped simulations of the null model as given above.

In contrast, our alternative cash-flow yield demonstrates much more robust performance. Monte Carlo results show that the size distortion of OLS and Hodrick p-values remains, but even allowing for this, the null of no predictability is strongly rejected at all individual horizons and in both joint tests. A further contrast with conventional yields is that the strongest predictive power is evident at short horizons.

B. *Subsample and Recursive Estimates*

Although table 2 shows that the cash-flow yield maintains predictability even when we allow for serial correlation properties, problems are still possible with data mining by choice of sample period or lookahead bias. Would an investigator analyzing these data earlier in the sample period have found significant predictive ability from the cash-flow yield, or is the predictability evident in table 2 an artificial construct of the period chosen?

Table 3 provides a full set of estimates of coefficients β_h for $h = 1, \ldots, 10$, in horizon regressions of the form (1), and the same set of diagnostic statistics as in panel C of table 2, for three different subsamples. The first two subsamples are chosen to reflect discontinuities in underlying data sources used in the Wright (2004) data set: BEA national income statistics only become available from 1929 onward, and Flow of Funds statistics from 1946 onward. Additionally, panel C shows results for the commonly used sample (cf. Lewellen, 2004; Goyal & Welch, 2003, 2004; Ang & Bekaert, 2004) from 1963 onward. Point estimates of coefficients at different horizons are very similar in all three subsamples to those shown in table 2C for the full sample. Monte Carlo and bootstrapped p-values are somewhat higher than over the full sample, but are still almost invariably significant for all horizons at conventional levels, even in the shortest sample. The joint tests continue to reject the null of no predictability at least at the 5% level, except (barely) in the case of the very short sample shown in panel C.

TABLE 3—TESTING PREDICTIVE RETURN REGRESSIONS USING CASH-FLOW YIELD OVER SUBSAMPLES

h	Obs.	Coeff.	p-Values OLS	Hodrick	Monte Carlo	Bootstrap	Joint Tests
			A. 1929–2002				
1	73	0.154	0.001	0.007	0.006	0.005	$h = 1, \ldots, 5$:
2	72	0.152	0.000	0.000	0.002	0.002	$p_{sur} = 0.000$
3	71	0.119	0.000	0.000	0.006	0.007	$p_{mc} = 0.009$
4	70	0.089	0.000	0.000	0.024	0.026	$p_{bs} = 0.009$
5	69	0.082	0.000	0.000	0.026	0.030	
6	68	0.068	0.000	0.003	0.053	0.055	$h = 1, \ldots, 10$:
7	67	0.062	0.000	0.004	0.065	0.068	$p_{sur} = 0.000$
8	66	0.065	0.000	0.000	0.042	0.045	$p_{mc} = 0.023$
9	65	0.062	0.000	0.000	0.043	0.046	$p_{bs} = 0.021$
10	64	0.061	0.000	0.000	0.037	0.039	
			B. 1946–2002				
1	56	0.142	0.002	0.008	0.010	0.017	$h = 1, \ldots, 5$:
2	55	0.136	0.000	0.001	0.008	0.014	$p_{sur} = 0.000$
3	54	0.113	0.000	0.001	0.016	0.022	$p_{mc} = 0.020$
4	53	0.090	0.000	0.002	0.035	0.045	$p_{bs} = 0.021$
5	52	0.090	0.000	0.002	0.027	0.034	
6	51	0.085	0.000	0.006	0.027	0.035	$h = 1, \ldots, 10$:
7	50	0.084	0.000	0.001	0.023	0.028	$p_{sur} = 0.000$
8	49	0.083	0.000	0.000	0.019	0.025	$p_{mc} = 0.021$
9	48	0.084	0.000	0.000	0.013	0.020	$p_{bs} = 0.020$
10	47	0.085	0.000	0.000	0.010	0.015	
			C. 1963–2002				
1	39	0.149	0.006	0.014	0.027	0.033	$h = 1, \ldots, 5$:
2	38	0.146	0.000	0.000	0.015	0.023	$p_{sur} = 0.001$
3	37	0.123	0.000	0.000	0.024	0.033	$p_{mc} = 0.044$
4	36	0.097	0.000	0.000	0.055	0.061	$p_{bs} = 0.020$
5	35	0.095	0.000	0.000	0.057	0.053	
6	34	0.090	0.000	0.001	0.057	0.054	$h = 1, \ldots, 10$:
7	33	0.088	0.000	0.000	0.039	0.050	$p_{sur} = 0.000$
8	32	0.084	0.000	0.000	0.040	0.050	$p_{mc} = 0.058$
9	31	0.086	0.000	0.000	0.029	0.039	$p_{bs} = 0.058$
10	30	0.086	0.000	0.000	0.023	0.029	

Estimates of the h-period return regression $r_{t,h} = \alpha + \beta_h x_t + u_{t,h}$, where x_t is the cash-flow yield, over different subsamples. The elements of the table are defined as in panel C of table 2.

Figures 2 and 3 use recursive regressions to show that the predictive power of the cash-flow yield has been evident on a consistent basis over a wide range of sample periods, and therefore does not appear to suffer from lookahead bias. We recursively estimate predictive regressions with $h = 1$, starting with an initial sample of 20 observations and expanding up to the full sample.[12] Figure 2 shows the recursive t-statistic on the predictor variable. There is significant predictive ability from the cash-flow yield throughout the sample, in contrast to the other measures of dividend yield. Figure 3 shows an alternative diagnostic [as suggested by Goyal and Welch (2004)], which displays a very similar pattern. It shows the difference between cumulative sums of squared one-step-ahead recursive residuals from a regression on a constant and from the predictor variable. When the line rises, the residuals from the predictor variable are smaller than those from the constant-mean prediction, indicating additional predictive power.

The S&P and conventional dividend yields gain very much (relative to the constant-expected-return benchmark) around the crash of 1929, but then lose this advantage in the 1930s. They then produce smaller prediction errors until about 1953, when again all advantage is lost by the 1970s. The 1971–1973 crash is again good for the conventional yield, but after that its performance is pretty feeble through to the end of the sample, with its prediction being little better than a constant-mean-return prediction.[13] By contrast, the cash-flow yield also gains in 1929, but then produces roughly comparable prediction errors from 1930 to about 1970, again predicts rather better through the 1971–1973 crash, and then gains almost monotonically in the post-1973 era (the upward-sloping line indicating that the one-step-ahead prediction errors are almost uniformly smaller than those from the constant-mean regression in this period).

Both charts indicate that, had data on the cash-flow yield been available, they would have shown statistically significant evidence of predictive power from the 1950s onward, and that increasing the available data has reinforced, rather than undermined, this evidence. This is again in stark contrast to conventional yield measures.

[12] Results for longer horizons are very similar. Experiments with data after 1929, after 1945, and excluding the 1990s show a very similar pattern.

[13] The pattern shown in figure 3 is very similar to that in Goyal and Welch (2004, figure 1A), derived from predictive regressions for the excess return.

FIGURE 2.—RECURSIVE t-STATISTICS FROM PREDICTIVE REGRESSIONS

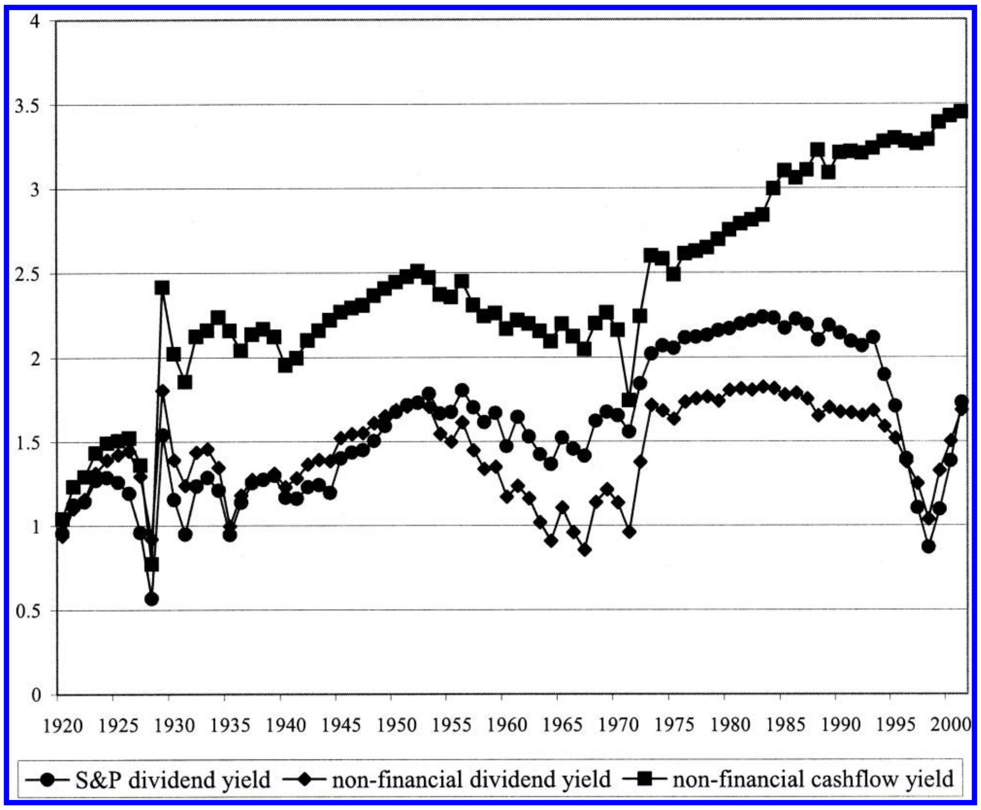
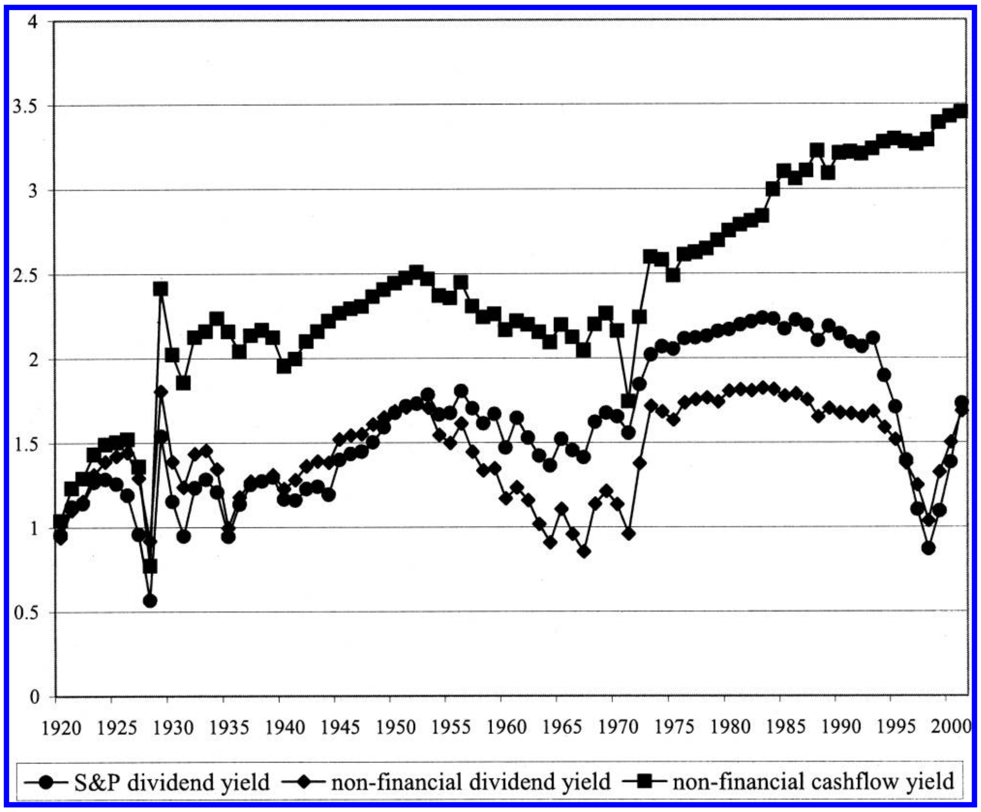


FIGURE 3.—RECURSIVE SUM OF SQUARED RESIDUALS FROM CONSTANT-EXPECTED-MEAN PREDICTIONS MINUS RECURSIVE SUM OF SQUARES FROM PREDICTIVE REGRESSIONS



IV. Conclusions

Recent research has significantly undermined the evidence that conventional dividend yields predict aggregate stock returns. This paper does not take issue with this revisionist view, but shows that robust evidence of predictability is restored if we use a new cash-flow yield that aggregates dividend and nondividend cash flows. Because this alternative measure is also clearly more in line with an economically meaningful measure of corporate cash flows to shareholders (as in Miller & Modigliani, 1961), we do not believe that we can be accused of redefining the data to achieve the desired result. It should be stressed that although the predictive power of the cash-flow yield is stable and statistically significant, the associated predictive regressions do not have very high R^2 values, so that, even supposing such predictability to reflect a degree of market inefficiency (which is of course an open question in itself), any implied trading strategy that exploited this predictability would itself be very risky. Nonetheless, rumors of the death of the predictability literature do appear to have been exaggerated.

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APPENDIX

Monte Carlo and Bootstrapped Simulations

The p-values for the point estimates of the β_h in equation (1) are derived by generating 10,000 samples, each of 103 annual observations, of the system of equations (1) for $h = 1$ and (2) with β_1 set equal to 0. The models for the data-generating process under the null, using the three alternative measures of x_t, were estimated over the sample 1901–2002, and for each replication, equations of the form (1) were estimated for h = 1, . . . ,10. The (two-sided) p-values reported are the proportion of samples in which the squared value of $\hat{\beta}_h$ exceeded the value derived from the historic sample.

The advantage of the Monte Carlo approach is that it deals simultaneously with the bias and overlapping-observation problems. One potential shortcoming of the Monte Carlo approach arises if the generating mechanism of the true data is not well approximated by that chosen [for instance, if x_t is not in fact an AR(1)]; however, we found no evidence in our data that allowing for higher-order processes for x_t made a substantial difference to our results.[14] The Monte Carlo approach also assumes there is no conditional heteroskedasticity in the underlying innovation sequence, but on our annual data set the null of homoskedastic errors cannot

[14] The (partial) correlograms of all three yield series fall essentially to 0 after the first lag.

be rejected. Finally, the Monte Carlo simulations use normally generated error sequences (with covariance structure matching that of the data under the null hypothesis). There is some evidence of nonnormality in the data, so we also report Monte Carlo using bootstrap residuals, that is, the actual residuals from the system (1) are sampled randomly (with replacement) to generate the simulated data. This will ensure that the simulated data match any nonnormality in the data.

It is worth noting that the estimated models used as the DGP in simulations all imply distinctly higher persistence of the three yield measures than when these are estimated as single equations. The AR(1) parameters for the cash-flow, nonfinancial, and S&P yields rise from (0.63, 0.81, 0.87) when estimated by single-equation methods to (0.79, 0.90, 0.95) when estimated jointly with return regressions under the null of no predictability. Thus, imposing the null of no predictability is almost equivalent to imposing unit roots in conventional yields. This is what would be expected if (as is the case) the Campbell-Shiller (1988) log linear approximation for returns is close to holding exactly, and if conventional dividend growth is close to being unforecastable (this is reflected in the very strong negative conditional correlations between conventional yields and returns shown in table 1). Even under the null of no predictability, however, the cash-flow yield remains clearly stationary; for the cash-flow yield has significant predictive power for cash flows, as well as for returns.

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