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The "Fed Model" and the Predictability of Stock Returns*

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Abstract

The focus of this article is on the predictive role of the stock-bond *yield gap*—the difference between the stock market earnings (dividend) yield and the 10-year Treasury bond yield—also known as the "Fed model". The results show that the *yield gap* forecasts positive excess market returns, both at short and long forecasting horizons, and for both value- and equal-weighted stock indexes, and it also outperforms competing predictors commonly used in the literature. These findings go in line with the predictions from a present-value decomposition. The absence of predictive power for dividend growth, dividend payout ratios, earnings growth, and future one-period interest rates, actually strengthens the return predictability associated with the *yield gap* at very long horizons. By performing an out-of-sample analysis, the results show that the *yield gap* has reasonable out-of-sample predictability for the equity premium when the comparison is made against a simple historical average, especially when one imposes a restriction of positive equity premia. Furthermore, the *yield gap* proxies generally show greater out-of-sample forecasting power than the alternative state variables. An investment strategy based on the forecasting ability of the *yield gap* produces significant gains in Sharpe ratios.

> The Fed's model arrives at its conclusions by comparing the yield on the 10-year Treasury note to the price-to-earnings ratio of the S&P 500 based on expected operating earnings in the coming 12 months. To put stock and bonds on the same footing, the model uses the "earnings yield" on stocks, which is the inverse of the P/E

—Barron's online

1. Introduction

The dividend-to-price and earnings-to-price ratios[1] have been widely used in the academic literature as predictors of future stock market excess returns.[2] In addition, yield spreads related to Treasury and corporate bond yields have also been used to forecast the equity premium (Keim and Stambaugh, 1986; Campbell, 1987; Fama and French, 1989, among others).

This article focuses instead on the *yield gap*, which corresponds to the difference between the earnings yield (or dividend yield) on a stock market index and the long-term yield on Treasury bonds, which is also known as the "Fed model". Over the last decades, this variable has been widely referred in the financial press and is used by practitioners to forecast stock returns. Moreover, it was used in official testimonies by Fed's chairman Alan Greenspan in the late 1990s to argue for the overvaluation of the US stock market.[3] Despite the importance of this variable in the financial industry, for a long time little attention has been devoted to it in the academic literature, with Asness (2003), Campbell and Vuoteenaho (2004b), Koivu, Pennanen, and Zeimba (2005), Polk, Thompson, and Vuoteenaho (2006), Estrada (2006, 2009), and Bekaert and Engstrom (2010) representing recent exceptions.

The Fed model postulates that stocks and long-term bonds are competing assets in the portfolios of many important investors (e.g., pension funds or insurance companies), and thus the earnings or dividend yields associated with stocks should be approximately equal to the yields on nominal bonds in the long-run, or at least should be strongly correlated. During the 1990s, a common argument among practitioners to justify the historical high US stock prices is that long-term bond yields were at very low levels, in part due to very low expected inflation, and thus stock earnings or dividend yields should also be at very low levels. Several authors (Asness, 2003; Campbell and Vuolteenaho, 2004b; Estrada, 2009, among others) have questioned the theoretical validity of the Fed model as a model of stock valuation, since we cannot compare a real variable (earnings yield) with a nominal variable (bond yield). However, recently, Bekaert and Engstrom (2010) show that the correlation between stock and bond yields observed in the data, associated with a comovement with expected inflation, has a rational asset pricing explanation: periods of high expected inflation (and thus high long-term

This article takes a different approach than most of the literature on the Fed model. Rather than focusing on the correlation between stock and bond yields, and whether the two yields should be approximately equal or strongly correlated, this article focuses instead on the forecasting ability of the *yield gap* for the aggregate equity premium. By using the definition of stock return, I derive a dynamic accounting decomposition for the *yield gap* proxy based on the earnings yield, as a function of future equity premia, future short-term interest rates, future earnings growth, and future dividend payout ratios. A second *yield gap* based on the dividend yield is correlated with future equity premia, future short-term interest rates, and future dividend growth. These dynamic present-value relations represent the rationale for the predictive role of the *yield gap* for equity premia, and both are generalizations of the Campbell and Shiller (1988a) present-value decomposition when one works with excess stock returns rather than stock returns. Hence, the *yield gap* should have greater forecasting power than either the earnings yield or dividend yield for the equity premium. Although other authors have looked at the predictive role of the Fed model for the equity premium (Asness, 2003; Koivu, Pennanen, and Ziemba, 2005), the analysis in this article differs from those articles in the proxies that are used for the *yield gap*; the theoretical framework justifying the predictability of the Fed model; and the empirical methodology, which is in line with the recent literature on the predictability of stock returns.

The empirical results show that at the 1-month horizon, the *yield gap* has significantly greater forecasting power for the equity premium than both the earnings- (e−p) and dividend-to-price ratios (d−p). Moreover, the *yield gap* outperforms other popular predictors from the predictability literature—the term spread, the default spread, and the dividend payout ratio. These results are robust to the finite-sample bias associated with persistent predictors and the cross-correlation between shocks to both returns and the predictor.

The results from long-horizon regressions show that the *yield gap* has significant forecasting power for the equity premium at horizons between 3 months and 5 years. Moreover, it outperforms both e−p and d−p and other predictors at most forecasting horizons. Hence, these results provide evidence that if one wants to predict excess stock returns (rather than returns) at long horizons, then the *yield gap* should be a better predictor than both e−p and d−p. These results are robust for both the value- and equal-weighted equity premium.

I follow Cochrane (2008) in analyzing the joint return–dividend–earnings for these alternative variables actually strengthens the return predictability associated with the log *yield gap* at very long horizons, reinforcing the evidence from the long-horizon regressions.

By performing an out-of-sample forecasting analysis, the results show that the *yield gap* has reasonable out-of-sample predictability for the equity premium when the comparison is made against a simple historical average. This evidence is especially important when one imposes a constraint of nonnegative forecasted excess returns, as in Campbell and Thompson (2008). Furthermore, the *yield gap* proxies have greater out-of-sample predictability power than the alternative forecasting variables commonly used in the predictability literature. The out-of-sample forecasting power of the *yield gap* is economically significant, as indicated by the significant gains in the Sharpe ratios, as well as positive certainty equivalent estimates, associated with dynamic trading strategies based on the predictive ability of the *yield gap*. Thus, the *yield gap* can be an important state variable to be used in dynamic portfolio choice.

The remainder of this article is organized as follows. Section 2 presents the theoretical motivation, and Section 3 describes the data and variables. Sections 4 and 5 present the results for the short-run and long-horizon forecasting regressions, whereas Section 6 analyzes the joint return–dividend–earnings predictability. Section 7 performs the out-of-sample predictability evaluation, while Section 8 evaluates the economic significance associated with the out-of-sample predictive role of the *yield gap*. Finally, Section 9 concludes.

2. Theoretical Framework

In this section, I derive present-value relations that justify why the *yield gap* should contain information about future expected excess stock returns. I present three different proxies for the *yield gap*. The first proxy corresponds to the difference between the log earnings-to-price ratio and the log yield on a n-period maturity bond, and is denoted by yg. In the Supplementary Appendix, I derive the following dynamic accounting identity for yg:

$$\mathrm{yg}_t \equiv e_t - p_t - \mathrm{ny}_{\mathrm{nt}} = \frac{-k}{1-\rho} + \mathrm{E}_t \sum_{j=0}^{\infty} \rho^j \Big[r^e_{t+1+j} - (1-\rho)(d_{t+1+j} - e_{t+1+j})$$

$$-\Delta e_{t+1+j}\Big] + \mathrm{E}_t \sum^{\infty} \rho^j r_{f,t+1+j},$$

represents the log earnings-to-price ratio associated with the stock market index; and $y_{nt} \equiv \ln(1 + Y_{nt})$ is the log yield at time t of a zero-coupon bond with maturity n.

Equation (1) postulates that high values of yg (log earnings-to-price ratio is high relative to the log bond yield) are associated with a combination of higher expected future excess log stock returns (r^e_{t+1+j}); lower expected future log dividend-to-earnings payout ratios ($d_{t+1+j} - e_{t+1+j}$); lower expected future log growth rates on equity earnings (Δe_{t+1+j}); and also higher expected future log short-term interest rates ($r_{f,t+1+j}$).[4] Thus, conditional on future dividend payout ratios, future earnings growth, and future interest rates, yg forecasts higher equity premia. This equation will be used to interpret the predictive regressions in the next sections, particularly at long horizons, and only assumes the Log Pure Expectations Hypothesis of the term structure (Campbell, Lo, and Mackinlay, 1997, Chapter 10)[5], and is also based on the definition of stock returns and a terminal condition that the log earnings-to-price ratio does not grow faster than the discount factor, ρ.[6]

Equation (1) also represents a generalization of the present-value relation for the log earnings-to-price ratio, as shown in the Supplementary Appendix:

$$e_t - p_t = \frac{-k}{1-\rho} + \mathrm{E}_t \sum_{j=0}^{\infty} \rho^j \left[r_{t+1+j} - (1-\rho)(d_{t+1+j} - e_{t+1+j}) - \Delta e_{t+1+j} \right]. \tag{2}$$

By comparing Equations (1) with (2), the main difference is that in the first identity yg is positively correlated with future equity premia, $\mathrm{E}_t \sum_{j=0}^{\infty} \rho^j r^e_{t+1+j}$, whereas in the second identity, e−p is positively correlated with future expected stock returns, $\mathrm{E}_t \sum_{j=0}^{\infty} \rho^j r_{t+1+j}$. Hence, yg should be a better predictor for future expected excess stock returns while e−p should track more closely the variation in future expected stock returns.

The second *yield gap* proxy represents the spread between the log dividend-to-price ratio and the log bond yield, denoted by yg*. Similarly to yg, yg* satisfies the following approximate decomposition (also derived in the Appendix):

Hence, conditional on expected future log dividend growth rates, $\mathrm{E}_t \sum_{j=0}^{\infty} \Delta d_{t+1+j}$, and expected future log interest rates, $\mathrm{E}_t \sum_{j=n}^{\infty} \rho^j r_{f,t+1+j}$, yg* is positively correlated with future equity premia. By comparing the two *yield gap* proxies (1) and (3), if expected future dividend payout ratios and earnings growth are more variable (and more correlated with the left-hand side variable) than expected future dividend growth, then yg* should be a more powerful predictor of future equity premia than yg, specially at longer horizons. Equation (3) represents a generalization of the decomposition for the log dividend-to-price ratio derived by Campbell and Shiller (1988a):

$$d_t - p_t = \frac{-k}{1-\rho} + \mathrm{E}_t \sum_{j=0}^{\infty} \rho^j \left(r_{t+1+j} - \Delta d_{t+1+j} \right). \tag{4}$$

Thus, similarly to the comparison between yg and e−p, yg* should be a better proxy to forecast equity premia than d−p, while d−p is likely to be more correlated with future expected stock returns. Both yg and yg* contain an adjustment to e−p and d−p, respectively, due to the fact that one is working with excess stock returns rather than returns. However, if we state the dynamic decompositions in terms of future stock returns then the identity associated with yg (yg*) will collapse to e−p (d−p).

The previous dynamic identities arise from a log-linearization of the stock market (excess) return and can be seen as a generalization of the simple Gordon model, by allowing for time variation in expected (excess) returns, dividend payout ratios, earnings and dividend growth rates, and short-term interest rates. In alternative, one can motivate the predictability of the *yield gap* (in levels) for excess stock returns by using the Gordon model itself. Following Campbell and Thompson (2008), in the long-run steady-state equilibrium the simple equity market return is equal to the aggregate earnings-to-price ratio (in levels):

$$R = \exp(\mathrm{e} - \mathrm{p}), \tag{5}$$

and if we subtract both sides by the holding-period return on a long-maturity bond, R_n, (equal states that positive perturbations in exp(e−p) - Y_n translate positively on excess stock returns.[7] I use YG ≡ exp(e−p) - Y_n as the third *yield gap* proxy, and it represents the difference between the earnings-to-price ratio (in levels) and the bond yield. This measure allows us to compare directly the yields on the two assets, following the prevailing idea by practitioners that both stocks and long-term bonds represent competing assets, and hence, should earn approximate returns (or yields) in the long-run. Since YG is not associated with a dynamic present-value relation, one should expect that the forecasting power for the equity premium at long horizons should be lower in comparison with both yg and yg*. On the other hand, since YG is not theoretically related with long-run variation in excess returns it can potentially represent a better proxy for predicting the equity premium at shorter horizons, especially if bond yields have forecasting power for future short-term interest rates.

In the Supplementary Appendix, I present an alternative explanation for the time-series predictability associated with the *yield gap* for the equity premium by deriving a conditional Capital Asset Pricing Model (CAPM) with time-varying and countercyclical risk-aversion.

3. Variables and Data

3.1 DATA

Monthly data on prices, earnings, and dividends associated with the Standard & Poor's (S&P) 500 Index are obtained from Robert Shiller's web page. $p = \ln(P)$ is the log of the S&P 500 Index level; $e = \ln(E)$ is the log of the annual moving average of earnings; and $d = \ln(D)$ is the log annual dividend. Return data on both the value- (R_{vw}) and equal-weighted (R_{ew}) market indexes are obtained from the Chicago Center for Research in Security Prices (CRSP). Interest rate data, including the 10- and 1-year Treasury bond yields, the 3-month Treasury bill rate, and the Moody's seasoned AAA and BAA average corporate bond yields, are all obtained from the FRED database, available from the St. Louis FED's web page. The 1-month Treasury bill rate ($R_{f,t+1}$) is obtained from Kenneth French's web page. The sample is 1953:04 to 2008:12.

3.2 CONSTRUCTION OF VARIABLES AND SUMMARY STATISTICS

beginning of period $t+j$. The log earnings-to-price and log dividend-to-price ratios are computed as e−p and d−p, respectively. The two proxies of the the log *yield gap* are calculated according to the present-value relations (1) and (3), yg = e−p−10y and yg* = d−p−10y, where y denotes the (annualized) log yield on the 10-year treasury bond, $y = \ln(1+Y)$, with Y representing the simple yield. The *yield gap* in levels represents the difference between the original earnings-to-price ratio and the Treasury yield, YG = exp(e−p) – Y. The log growth in earnings is computed as $\Delta e_{t+1} = e_{t+1} - e_t$ and similarly the log change in dividends is given by $\Delta d_{t+1} = d_{t+1} - d_t$.

The other forecasting state variables used to predict excess market returns are the log dividend payout ratio (d−e), the relative Treasury bill rate (RREL), the term-structure spread (TERM), and the default spread (DEF). RREL represents the difference between the 3-month Treasury bill rate (TB3M) and a moving average of TB3M over the previous 12 months, $\mathrm{RREL}_t = \mathrm{TB3M}_t - \sum_{j=1}^{12} \mathrm{TB3M}_{t-j}$. TERM is the difference between the 10- and 1-year Treasury bond yields, and DEF represents the spread between the average yields of BAA and AAA corporate bonds.

Table I reports descriptive statistics for the excess market returns, Δd, Δe, and the predictive variables. By analyzing the correlation coefficients in Panel B we can see that the two proxies for the log *yield gap* are strongly correlated (0.84), while YG is also highly correlated with yg (0.91), as expected. On the other hand, yg is strongly correlated with e−p (0.76) and the same holds for yg* and d−p (0.80). All three measures of the *yield gap* have marginal contemporaneous correlations with excess market returns, dividend growth, and earnings growth.

Table I. Descriptive statistics for returns and forecasting variablesThis table reports descriptive statistics for excess market returns; dividend growth (Δd); earnings growth (Δe); and forecasting variables. The excess returns are on the value-weighted market index (r^e_{vw}) and equal-weighted market index (r^e_{ew}). The forecasting variables are the *yield gap* proxies (yg, yg*, YG); earnings-to-price ratio (e – p); dividend-to-price ratio (d – p); dividend payout ratio ($d-e$); relative short-term interest rate (RREL); term structure spread (TERM); and the default spread (DEF). The sample is 1953:04–2008:12. ϕ designates the first-order autocorrelation coefficient. Panel B contains the correlations among the excess returns, earnings and dividend growth, and the predictors. For details on the variables' construction refer to Section 3.

Panel A

e−p	−2.770	0.381	−3.844	−1.915	0.996
d−p	−3.499	0.400	−4.503	−2.775	0.994
YG	0.003	0.025	−0.044	0.081	0.985
d–*e*	−0.730	0.204	−1.190	0.082	1.006
Δ*d*	0.005	0.005	−0.022	0.022	0.748
Δ*e*	0.004	0.023	−0.225	0.084	0.971
RREL	−0.000	0.010	−0.042	0.046	0.899
TERM	0.008	0.010	−0.031	0.033	0.966
DEF	0.010	0.004	0.003	0.034	0.992
r^e_{vw}	0.004	0.044	−0.261	0.148	0.103
r^e_{ew}	0.006	0.055	−0.324	0.256	0.235

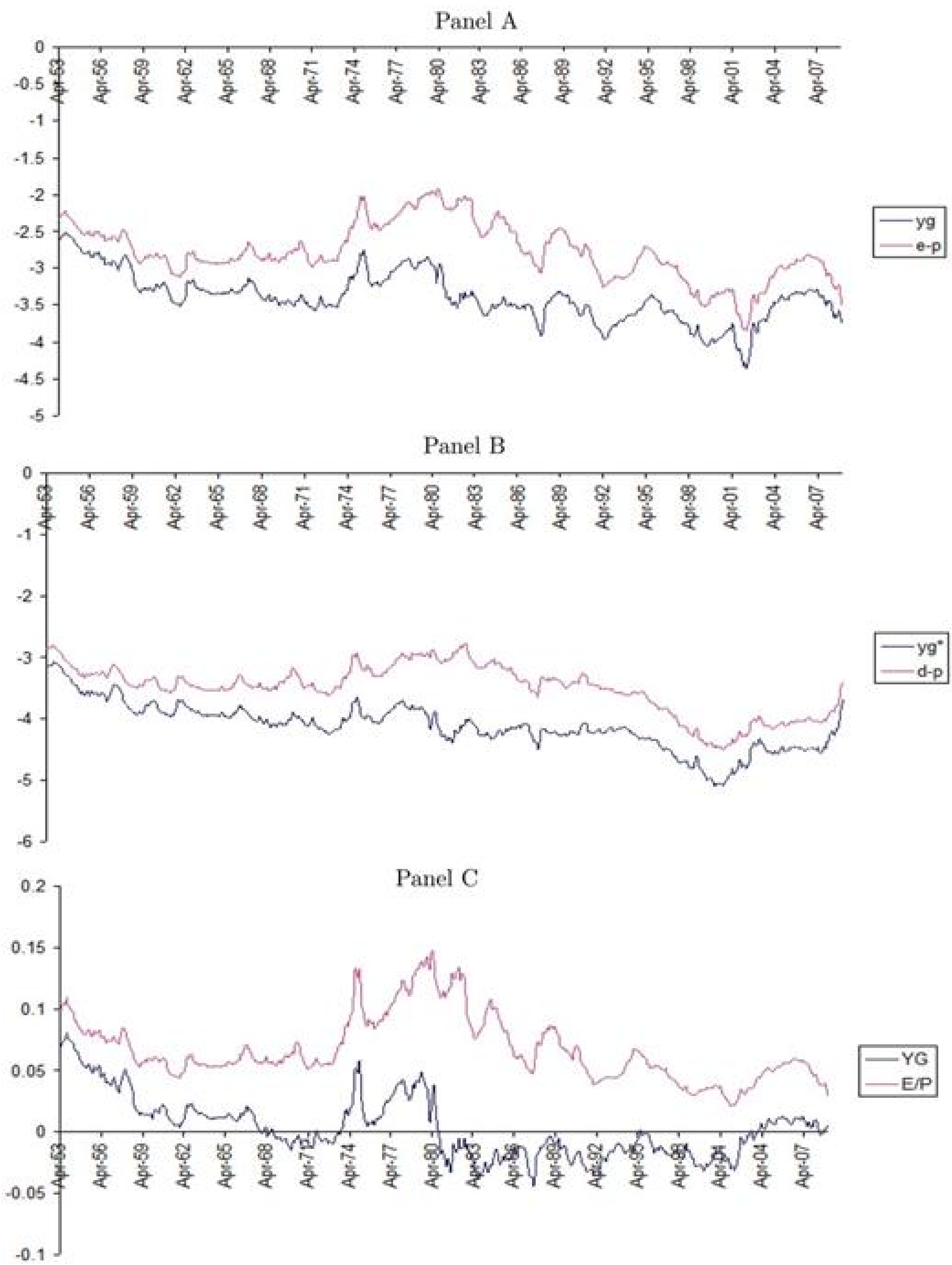
Panel B

	yg	yg*	e−p	d−p	YG	*d*–*e*	Δ*d*	Δ*e*	r^e_{vw}	r^e_{ew}
yg	1.00	0.84	0.76	0.69	0.91	−0.07	0.24	0.11	0.07	0.05
yg*		1.00	0.58	0.80	0.78	0.48	0.02	−0.03	0.05	0.04
e−p			1.00	0.87	0.47	−0.17	0.26	0.12	0.02	0.00
d−p				1.00	0.43	0.35	0.07	0.00	0.02	0.00
YG					1.00	−0.04	0.17	0.05	0.07	0.07
d–*e*						1.00	−0.35	−0.23	−0.01	−0.00
Δ*d*							1.00	0.25	−0.02	−0.02
Δ*e*								1.00	0.08	0.08
r^e_{vw}									1.00	0.87
r^e_{ew}										1.00

The first-order autocorrelation coefficients show that the log *yield gap*, being a function of highly persistent variables (e−p and d−p), is also

Figure 1 presents the time-series evolution of the the *yield gap* measures and the corresponding components. The plots confirm that yg is strongly correlated with e−p, and the same pattern holds for yg* in relation with d−p, but this correlation is far from perfect. Moreover, the magnitudes of *yield gap* and equity yield series are significantly different from each other, which means that the bond yield is an important component of *yield gap*. YG assumes positive values (on average) during the 1960s and 1970s, and negative values during the 1980s and 1990s, which is in part related to the long "bull" stock market in the 1990s that depressed the aggregate earnings-to-price and dividend-to-price ratios.

Figure 1.



4. Short-Run Predictability

4.1 MONTHLY PREDICTIVE REGRESSIONS

I start by investigating the predictability of the *yield gap* for excess market returns at the 1-month horizon, by conducting the following predictive regression:

$$r^{e}_{t+1} = a + \mathbf{b}'\mathbf{x}_t + u_{t+1}, \tag{7}$$

where r^{e}_{t+1} is the future continuously compounded excess market return, and $\mathbf{x}_t$ is a column vector of forecasting state variables known at time *t*. The compounded excess return is multiplied by 12 to measure the annualized effect of the predictors on future excess returns. The statistical inference is based on Newey and West (1987) asymptotic *t*-statistics, computed with one lag.

In addition to the three *yield gap* proxies and their components, e−p and d−p, I use four alternative popular predictors from the literature.[8] The first competing variable is the slope of the Treasury yield curve or term structure spread (TERM, Campbell, 1987; Fama and French, 1989; Estrella and Hardouvelis, 1991). It is important to compare the predictive ability of the *yield gap* with TERM since both depend on the 10-year Treasury bond yield. The second variable is the default spread, (DEF, Keim and Stambaugh, 1986; Fama and French, 1989). The third predictor is the relative or detrended Treasury bill rate (RREL, Campbell, 1991; Hodrick, 1992; Campbell and Ammer, 1993). Finally, I use the aggregate log dividend payout ratio (*d*−*e*), which is advocated by Lamont (1998) to forecast stock returns at short horizons.[9]

The results for the excess value-weighted market return (r^{e}_{vw}) are presented in Table II. Both yg and yg* forecast positive excess market returns, in accordance with the dynamic accounting identities (1) and (3). The coefficient associated with yg is greater than the one for yg*, showing that yg has relatively larger forecasting power at the monthly horizon. Both slope estimates are strongly statistically significant (at the 1% level) as indicated by the asymptotic *t*-stats. In terms of fit, yg and yg* explain 1.57 and 1.26% of the variation in next month's excess market return, respectively. When one uses the third *yield gap* proxy, YG, the slope estimate is 2.48, which is statistically significant at the 1% level. This estimate is economically market return, which is lower than the fit associated with yg, but outperforms slightly the other proxy, yg*.

Table II. Monthly predictive regressions for the value-weighted excess market returnThis table presents 1-month ahead predictive regressions for the excess return on the value-weighted market index. The forecasting variables are the current values of the *yield gap* proxies (yg,yg*,YG); e−p; d−p; *d*–*e*; RREL; TERM; and DEF. The original sample is 1953:04–2008:12. For each predictor, in line 1 are reported the coefficient estimates, and in line 2 are reported the asymptotic Newey–West *t*-statistics (with one lag). The *t*-statistics at bold denote significance at the 1% level, while the underlined ones indicate significance at the 5% level. R^2 denotes the coefficient of determination (in %). For further details see Section 4.

Row	yg	yg*	e−p	d−p	YG	*d*–*e*	RREL	TERM	DEF
1	0.198 (**2.94**)								
2		0.156 (**2.83**)							
3			0.113 (1.76)						
4				0.104 (1.86)					
5	0.237 (2.47)		−0.044 (−0.48)						
6		0.184 (2.02)		−0.033 (−0.36)					
7					2.484 (**2.89**)				
8						0.011 (0.11)			
9							−6.572 (−**3.29**)		
10								3.949 (1.88)	
11									2.926 (0.50)
12	0.271 (**3.96**)						−6.047 (−2.08)	3.600 (1.26)	−0.79 (−0.14

When one uses the components of the log *yield gap*, e−p and d−p, the respective slopes are significantly smaller than the slopes for either yg or yg*, and these estimates are not statistically significant at the 5% level. Moreover, the forecasting ratio for e−p is less than half the corresponding fit for yg, whereas in the case of d−p the R^2 estimate is around half the fit associated with yg*. In Rows 5 and 6, I conduct bivariate regressions of yg with e−p, and alternatively, yg* with d−p. This allows one to assess whether e−p adds predictive power in the presence of yg, and similarly for d−p relative to yg*. The slopes for both e−p and d−p have the wrong signs and are strongly nonsignificant. On the other hand, the coefficient estimates for both yg and yg* actually increase relative to the point estimates in the univariate regressions, and are statistically significant at the 5% level. The R^2 estimates in both bivariate regressions are very similar to the corresponding forecasting ratios in the univariate regressions for yg and yg*, showing that e−p and d−p do not add forecasting power in the presence of the log *yield gap* proxies.

In Rows 8–11, I conduct univariate predictive regressions for four popular forecasting variables from the predictability literature, *d*−*e*, RREL, TERM, and DEF. Among these alternative predictors of stock returns, only the relative bill rate is able to outperform the forecasting power of the *yield gap*, with a R^2 estimate of 1.67%, while *d*−*e*, TERM, and DEF clearly underperform the three *yield gap* proxies. The relatively large forecasting power of RREL at the 1-month horizon is consistent with previous evidence that short-term interest rates forecast excess stock returns at short horizons (Fama and Schwert, 1977; Campbell, 1991; Hodrick, 1992; Patelis, 1997; Ang and Bekaert, 2007, among others). Rows 12 and 13 show the results for multiple regressions including the log *yield gap* in addition to RREL, TERM, and DEF. We can see that conditional on these three variables, the slopes for both yg and yg* remain significant at the 1% level.

The Supplementary Appendix presents results for bivariate regressions in which the predictors are the *yield gap* components, that is, these regressions correspond to an unrestricted version of the *yield gap* in which the slopes associated with each component (market ratio and bond yield) are unconstrained instead of being symmetric. The results show that the fit is basically the same as in the corresponding regressions for the "restricted" *yield gap* (yg, yg*, YG).[10]

In Table III, I replicate the predictive regressions for the equal-weighted excess market return (r^e_{ew}) as the variable to be forecasted. The motivation stock in the market. Moreover, since the equal-weighted average is more tilted towards small stocks, the analysis of predictability for r^e_{ew} can provide a better indication of return predictability among small stocks. The slope estimates associated with yg and yg* are greater than the corresponding values in Table II, and these estimates are statistically significant at the 5 or 1% levels. The forecasting ratios are 1.31 and 1.12% for yg and yg*, respectively, which are slightly below the corresponding fit in forecasting r^e_{vw}.

Table III. Monthly predictive regressions for the equal-weighted excess market returnThis table presents 1-month ahead predictive regressions for the excess return on the equal-weighted market index. In everything else it is identical to Table II.

Row	yg	yg*	e−p	d−p	YG	*d*−*e*	RREL	TERM	DEF
1	0.227 (**2.58**)								
2		0.184 (2.51)							
3			0.113 (1.36)						
4				0.110 (1.46)					
5	0.305 (**2.64**)		−0.089 (−0.80)						
6		0.248 (2.27)		−0.076 (−0.67)					
7					3.396 (**3.11**)				
8						0.032 (0.23)			
9							−10.707 (**−4.02**)		
10								6.578 (2.34)	
11									8.543 (1.12)
12	0.336						−9.415	4.819	2.301

Regarding the components of the *yield gap*, the slope estimates associated with e−p (d−p) are significantly below the counterpart estimates for yg (yg*), and both estimates are not statistically significant at the 5% level. Moreover, the forecasting ratios for both e−p and d−p are less than half the corresponding values for yg and yg*, at 0.43 and 0.45%, respectively. Similar to the case of the value-weighted index, when one conducts bivariate regressions the coefficients associated with e−p and d−p are strongly nonsignificant and have the wrong signs, while the R^2 estimates are only marginally higher than in the univariate regressions for yg and yg*.

The forecasting ability of YG is greater in comparison to the other two measures of the *yield gap* with a explanatory ratio of 1.64%, and the respective slope is significant at the 1% level. Among the alternative forecasting variables, only RREL is able to outperform the *yield gap* with a R^2 estimate of 2.84%. The forecasting power associated with YG and RREL seems to signal that short- and long-term interest rates can predict the equity premia of small stocks at short horizons. Conditional on RREL, TERM, and DEF, both versions of the log *yield gap* remain significant predictors (1% level) of the excess equal-weighted return.

4.2 SMALL-SAMPLE BIAS

The asymptotic inference conducted above might not represent a convenient approximation to the finite sample distribution of the slope estimates in the predictive regression (7). Specifically, shocks to financial ratios (like yg, yg*, d−p, or e−p) are likely to be negatively correlated with shocks to (excess) returns, and this implies that the regressor in the predictive regression will be correlated with the lagged shock to (excess) returns. In addition, since the predictor is often persistent, the regressor will also be correlated with past shocks to returns at several lags, $\mathrm{E}(x_t u_{t+1-i}) < 0$, $i > 0$. This violates one of the assumptions of the finite-sample OLS distribution, which requires that the regressor is orthogonal to the error term at all leads and lags, and not just at contemporaneous observations.[11] Thus, although the OLS estimate for the slope in the predictive regression will still be consistent, it will have an upwards bias in finite samples. By assuming that the forecasting variable follows an AR(1) process, Stambaugh (1999) shows that this finite-sample bias increases with the persistence in the predictor, the correlation between the shocks to returns and the predictor, and decreases with the sample size.[12]

However, Lewellen (2004) argues that this adjustment to the finite-sample

$$r^e_{t+1} = a + bx_t + u_{t+1}, x_{t+1} = \psi + \phi x_t + v_{t+1}, \quad (8) \quad (9)$$

Lewellen focuses on the distribution of the slope estimate, b, conditional on the information about the persistence of the predictor, ϕ. The idea is that we cannot conduct inference about b in isolation, but rather have to incorporate the information about ϕ, and specifically the fact that most predictors are stationary, and thus have $\phi < 1$. In the case of financial ratios as predictors, the estimate for b is likely to be high only when the estimate for ϕ is very low, thus it is unlikely that (in the population) we have large estimates for both the predictive slope and autoregressive coefficient (close to one). In other words, in a sample with large estimates for both b and ϕ, we should reject the joint null hypothesis, $b = 0$, $\phi < 1$, and this provides evidence that $b \neq 0$, since the predictor should a priori be stationary.

The adjusted point estimate for the slope is given by

$$\widehat{b^*} = \widehat{b} - \widehat{\gamma}\,(\widehat{\phi} - \phi), \quad (10)$$

where $\widehat{\gamma}$ comes from a regression in the errors associated with the predictive model above:

$$u_{t+1} = \gamma v_{t+1} + \varepsilon_{t+1}. \quad (11)$$

The standard error for the slope estimate is given by

$$\mathrm{Var}\,(\widehat{b^*}) = \sigma^2_\varepsilon (\mathbf{X}'\mathbf{X})^{-1}_{(2,2)}, \quad (12)$$

where $\sigma_\varepsilon^2 \equiv \mathrm{Var}\,(\varepsilon_{t+1})$ and $\mathbf{X}$ is the data matrix associated with the predictive regression. Under the null, the t-statistic for $\widehat{b^*}$ is exactly distributed as a Student t, $t(T - 3)$, where T is the sample size. Similarly to Lewellen (2004), ϕ is calibrated at 0.9999.

The results are available in Table IV. In the case of the value-weighted excess also statistically significant at the 5% level, d−p is insignificant with a *p*-value of 0.10. The negative estimates for γ across all five predictors confirm that innovations to these variables are negatively correlated with innovations to returns, as expected. The results for the equal-weighted excess return show that the three *yield gap* proxies are statistically significant, while both e−p, and especially d−p, are not significant at the 5% level. In sum, these results provide evidence that after adjusting for the finite-sample bias in the slope of the predictive regression, *yield gap* remains a significant predictor of future equity premia, while in the cases of e−p and d−p, the evidence of predictability is rather weak.

Table IV. Adjusting for finite-sample biasThis table presents slope estimates associated with the 1-month predictive regressions on the value- (Panel A) and equal-weighted equity premium (Panel B), which are adjusted for finite-sample bias. $\widehat{b^*}$ denotes the adjusted slope estimate, while $t(\widehat{b^*})$ and $p(\widehat{b^*})$ denote the respective *t*-statistic and (one-sided) *p*-value, respectively. $\hat{\phi}$ stands for the autoregressive coefficient of the predictors, and $\hat{\gamma}$ denotes the OLS slope estimate of a regression containing the residuals of the predictive regression and the AR(1) process for the predictor. The forecasting variables are the current values of the *yield gap* proxies (yg, yg*, YG); e−p; and d−p. The original sample is 1953:04–2008:12. For further details see Section 4.

Row	$\widehat{b^*}$	$t(\widehat{b^*})$	$p(\widehat{b^*})$	$\hat{\phi}$	$\hat{\gamma}$
Panel A (VW)					
yg	0.137	2.49	0.01	0.988	−0.444
yg*	0.094	2.03	0.02	0.990	−0.531
e−p	0.085	1.98	0.02	0.996	−0.634
d−p	0.046	1.27	0.10	0.994	−0.853
YG	1.726	2.24	0.01	0.985	−4.114
Panel B (EW)					
yg	0.141	2.11	0.02	0.988	−0.615
yg*	0.099	1.76	0.04	0.990	−0.729
e−p	0.078	1.45	0.07	0.996	−0.803
d−p	0.035	0.79	0.22	0.994	−1.080
YG	2.380	2.44	0.01	0.985	−6.005

5.1 LONG-RUN REGRESSIONS

In this section, I use univariate long-horizon regressions (Fama and French, 1988, 1989, among many others) to assess the forecasting power of the log *yield gap* (yg, yg*) for future excess market returns at several horizons, in accordance to the dynamic accounting identities presented in Equations (1) and (3). Following these present-value relations, both yg and yg* should be better proxies to forecast the equity premium at longer horizons rather than 1-month ahead excess returns, and the same argument holds for both e−p and d−p based on the dynamic decompositions in (2) and (4). If expectations about future dividend growth and short-term interest rates are not too volatile, and not strongly correlated with yg*, then yg* should track relatively well future long-horizon expected excess returns. Similarly, if expectations about future earnings growth and payout ratios do not change significantly over time, yg should be correlated with the equity premium at future periods.

The typical specification used is

$$r^e_{t+1,t+K} = a_K + b_K x_t + u_{t+1,t+K}, \tag{13}$$

where $r^e_{t+1,t+K}$ is the continuously compounded excess return measured over K months in the future, and x_t is a forecasting variable known at time t. I use forecasting horizons of 3, 12, 24, 36, 48, and 60 months ahead. The compounded excess return $r^e_{t+1,t+K}$ is multiplied by (12/K) for the slope coefficients, b_K, to measure the annualized effect of the predictors on future returns.

Given the well known poor small-sample properties of the asymptotic t-stats for long-horizon regressions (see Hodrick, 1992; and Nelson and Kim, 1993, among others), in addition to the Newey and West (1987),t-statistics, I compute empirical p-values for the slope estimates from a Bootstrap experiment. The Newey–West standard errors are calculated using K lags, that is, the forecasting horizon associated with each regression. The bootstrap simulation allows one to obtain an empirical distribution that better approximates the finite sample distribution of the coefficient estimates in the regression above. I follow the approach conducted in Kilian (1999), Goyal and Santa-Clara (2003), Goyal and Welch (2008), among others, in which the excess return and forecasting variable are simulated (10,000 times) under the null of no predictability of the (excess) return and assuming that the predictor, x_t, follows an AR(1) process:

$$r^e_{t+1,t+K} = a_K + u_{t+1,t+K}, x_{t+1} = \psi + \phi x_t + v_{t+1}.$$

(14) (15)

This bootstrap procedure allows for the high persistence of the forecasting variable and the cross-correlation between the two residuals. Details of the bootstrap algorithm are provided in the Supplementary Appendix.

The results for the long-horizon regressions in the case of the value-weighted excess return are displayed in Table V. The (annualized) slope estimates associated with yg decline with the forecasting horizon, varying between 0.19 ($K = 3$) and 0.04 ($K = 60$). These estimates are statistically significant at the 5 or 1% levels for horizons up to 36 months, according to both the asymptotic t-stats and empirical p-values. However, for $K = 48$ and $K = 60$, the slopes are significant only based on the bootstrapped p-values. The forecasting ratio has a hump-shaped pattern, peaking at 8.97% ($K = 36$) and declining thereafter to 6.61% ($K = 60$). The coefficients associated with yg* have a monotonic declining pattern similar to yg, but these estimates are statistically significant at all horizons, based on both the asymptotic and bootstrap inference. The fit of the regression increases from 3.20% ($K = 3$) to reach a maximum of 12.81% ($K = 36$), and declines thereafter. Interestingly, after $K = 3$, the forecasting ratio associated with yg* consistently outperforms the corresponding fit from yg, which means that yg* has greater forecasting power at longer horizons. This finding is consistent with the dynamic relations (1) and (3), if the correlation between yg and future earnings growth is greater than the correlation between yg* and future dividend growth.

Table V. Long-horizon regressions for the value-weighted excess market returnThis table presents long-horizon regressions for the monthly continuously compounded excess return on the value-weighted market index, at horizons of K=3,12,24,36,48,60 months ahead. The forecasting variables are the current values of the *yield gap* proxies (yg,yg*,YG); e – p; d – p; *d–e*; RREL; TERM; and DEF. The original sample is 1953:04–2008:12. For each predictor, in line 1 are reported the coefficient estimates, and in line 2 are reported the asymptotic Newey–West *t*-statistics (with *K* lags). In line 3 are presented the *p*-values (in brackets) from a bootstrap experiment. The *t*-statistics at bold denote significance at the 1% level, while the underlined ones indicate significance at the 5% level. R^2 denotes the coefficient of determination (in %). For further details see Section 5.

	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R^2(%)	3.71	8.90	8.71	8.97	7.25	6.61
yg*	0.152	0.138	0.100	0.076	0.059	0.055
	(**3.29**)	(**3.09**)	(2.34)	(2.32)	(2.54)	(**3.15**)
	[0.04]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R^2(%)	3.20	10.45	12.56	12.81	11.66	12.49
e−p	0.114	0.094	0.064	0.050	0.039	0.037
	(2.03)	(2.00)	(1.63)	(1.50)	(1.39)	(1.60)
	[0.09]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]
R^2(%)	1.84	4.87	5.29	5.83	5.42	5.99
d−p	0.109	0.107	0.082	0.065	0.054	0.056
	(2.26)	(2.29)	(1.88)	(1.86)	(2.13)	(**3.10**)
	[0.18]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R^2(%)	1.89	7.07	9.53	10.34	10.66	13.33
YG	2.260	1.844	1.138	0.807	0.580	0.505
	(**3.25**)	(**2.99**)	(1.98)	(1.75)	(1.41)	(1.19)
	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R^2(%)	3.07	8.02	7.19	6.52	5.20	4.84
d–e	0.029	0.094	0.099	0.079	0.075	0.088
	(0.33)	(1.16)	(1.27)	(1.14)	(1.36)	(1.83)
	[0.71]	[0.09]	[0.00]	[0.00]	[0.00]	[0.00]
R^2(%)	0.03	1.36	3.30	3.37	4.33	6.68
RREL	−5.246	−4.045	−1.300	−0.782	−0.653	−0.796
	(−**2.99**)	(−2.39)	(−1.51)	(−1.63)	(−1.61)	(−2.20)
	[0.01]	[0.00]	[0.06]	[0.07]	[0.06]	[0.02]
R^2(%)	2.87	6.70	1.63	1.06	1.15	2.09
TERM	3.471	3.291	2.074	2.003	1.883	1.893

R^2(%)	1.27	4.44	4.11	6.80	9.29	10.97
DEF	2.808	2.341	−0.511	−0.187	0.580	1.542
	(0.50)	(0.57)	(−0.21)	(−0.09)	(0.28)	(0.85)
	[0.32]	[0.22]	[0.69]	[0.83]	[0.40]	[0.03]
R^2(%)	0.13	0.35	0.04	0.00	0.14	1.21

The results of the long-horizon regressions for the components of the *yield gap* show that e−p (d−p) have lower forecasting power than yg (yg*) at all horizons, with the sole exception of the comparison between d−p and yg* at the 5-year horizon. Moreover, the slopes associated with e−p are not statistically significant for horizons beyond 1 year, based on the asymptotic *t*-stats. Hence, these results provide evidence that if one wants to predict excess stock returns at long horizons, then yg (yg*) should be a better predictor than e−p (d−p). Similarly to the case of yg versus yg*, d−p outperforms e−p in forecasting multi-period excess returns at all horizons, and this is also consistent with the present-value relations (2) and (4), if forecasts of future earnings growth and payout ratios are more volatile than the corresponding forecasts of future dividend growth.

The long-horizon regressions associated with the third *yield gap* proxy, YG, show that it underperforms yg, especially at horizons greater than two years. This is not surprising, since according to Equation (1), yg should be more suitable to track variations in long-term excess stock returns than YG, while YG should be a better predictor of short-horizon returns, following Equation (6). In fact, the forecasting ratio increase from 3.07% at the 3-month horizon to 7.19% at $K = 24$, and declines thereafter to 4.84% at $K = 60$. Thus, the forecasting power of YG is greater and with larger statistical significance at the near horizons, being less relevant for forecasting more distant ahead excess returns. Regarding the four alternative predictors, these variables underperform the three *yield gap* proxies at most horizons. The only relevant exception is TERM, which outperforms yg and YG at very long horizons, but still lags behind yg*.

The results for the equal-weighted excess return are reported in Table VI, which is similar to Table V. The explanatory ratios associated with yg vary between 2.97% ($K = 3$) and 6.32% ($K = 36$), whereas the range associated with yg* is 2.67% ($K = 3$) to 7.88% ($K = 12$). These R^2 estimates are lower than in the regressions for r^e_{vw}, especially in the case of yg* in which the difference near horizons, based on both the asymptotic and bootstrap inferences, although for the longer horizons these estimates are only significant according to the empirical p-values.

Table VI. Long-horizon regressions for the equal-weighted excess market returnThis table presents long-horizon regressions for the monthly continuously compounded excess return on the equal-weighted market index. In everything else it is identical to Table V.

	$K=3$	$K=12$	$K=24$	$K=36$	$K=48$	$K=60$
yg	0.226	0.169	0.099	0.079	0.059	0.050
	(**2.91**)	(**3.02**)	(1.81)	(1.65)	(1.29)	(1.22)
	[0.03]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R^2(%)	2.97	6.85	5.70	6.32	5.19	4.87
yg*	0.188	0.159	0.097	0.062	0.038	0.033
	(**3.06**)	(**3.58**)	(**2.72**)	(1.97)	(1.25)	(1.02)
	[0.08]	[0.00]	[0.00]	[0.01]	[0.03]	[0.03]
R^2(%)	2.67	7.88	6.96	4.91	2.76	2.44
e−p	0.125	0.102	0.056	0.038	0.021	0.015
	(1.67)	(1.76)	(1.14)	(0.86)	(0.53)	(0.42)
	[0.18]	[0.01]	[0.03]	[0.04]	[0.13]	[0.22]
R^2(%)	1.20	3.22	2.35	1.88	0.90	0.55
d−p	0.124	0.116	0.068	0.035	0.013	0.006
	(1.90)	(2.25)	(1.71)	(0.97)	(0.39)	(0.21)
	[0.28]	[0.01]	[0.01]	[0.05]	[0.32]	[0.55]
R^2(%)	1.32	4.73	3.87	1.71	0.32	0.10
YG	3.271	2.646	1.717	1.413	1.182	1.053
	(**3.45**)	(**3.96**)	(**3.06**)	(**3.01**)	(**2.61**)	(2.51)
	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R^2(%)	3.49	9.44	9.63	11.50	11.87	11.70
d–*e*	0.049	0.104	0.073	−0.003	−0.040	−0.044

R^2(%)	0.05	0.95	1.05	0.00	0.67	0.95
RREL	−9.062	−6.252	−1.976	−0.934	−0.544	−0.561
	(−**3.70**)	(−**3.27**)	(−1.55)	(−1.07)	(−0.76)	(−0.87)
	[0.00]	[0.00]	[0.04]	[0.12]	[0.28]	[0.21]
R^2(%)	4.64	9.15	2.21	0.87	0.44	0.58
TERM	5.648	4.285	1.708	1.017	0.634	0.668
	(<u>2.26</u>)	(<u>2.04</u>)	(1.15)	(0.89)	(0.62)	(0.63)
	[0.01]	[0.00]	[0.03]	[0.07]	[0.15]	[0.09]
R^2(%)	1.83	4.30	1.64	1.01	0.58	0.76
DEF	8.899	6.268	0.358	−0.677	−1.252	−1.041
	(1.16)	(1.15)	(0.11)	(−0.21)	(−0.43)	(−0.42)
	[0.03]	[0.02]	[0.84]	[0.57]	[0.21]	[0.25]
R^2(%)	0.71	1.42	0.01	0.07	0.36	0.31

The third *yield gap* proxy, YG, shows a substantial greater forecasting power for r^e_{ew} than both yg and yg*, with forecasting ratios that vary between 3.49% ($K = 3$) and 11.87% ($K = 48$). This fit is also significantly larger than the corresponding fit associated with YG in forecasting r^e_{vw}. Thus, YG forecasts relatively better the excess return of the average stock in the market, in contrast with both yg and yg*, which do a better job in predicting the excess return of the value-weighted index. In other words, since the value-weighted index is tilted toward large caps, YG outperforms the other *yield gap* proxies in predicting equity premia for small stocks. The slopes associated with YG decline with the horizon, but are statistically significant at all horizons.

The components of the log *yield gap* have weak forecasting power for r^e_{ew}, with R^2 estimates varying between 0.55% ($K = 60$) and 3.22% ($K = 12$) in the case of e−p, while in the case of d−p the range is between 0.10% ($K = 60$) and 4.73% ($K = 12$). The alternative four predictors have also significantly lower predictive power than all three *yield gap* proxies, the sole exception being RREL at short horizons ($K = 3, 12$). Overall, YG is the predictor with better predictive performance for r^e_{ew} at most horizons.

5.2.a Implied long-horizon R^2 estimates

Several authors have cast some doubts on the robustness of the results from long-horizon regressions, specifically on the respective statistical power (Richardson and Stock, 1989; Valkanov, 2003; Torous, Valkanov, and Yan, 2004; Boudoukh, Richardson, and Whitelaw, 2008, among others). Specifically, Boudoukh et al. show that under some assumptions, the R^2 estimates at long horizons ($R_K^{\ 2}$) are mechanically related with the R^2 estimate from the one-period regression ($R^2_{\ 1}$):

$$E(R_K^2|R_1^2) = \frac{\left[1+\frac{\phi(1-\phi^{K-1})}{1-\phi}\right]^2}{K} R_1^2, \quad (16)$$

where ϕ stands for the autocorrelation coefficient of the forecasting variable. According to (16), for a highly persistent predictor ($\phi \simeq 1$) the R^2 estimates increase almost linearly with the horizon.[15]

I compute the implied R^2 estimates, whose results appear in Table VII. The results associated with r^e_{vw} show that the values for $E(R^2_{\ K}|R^2_{\ 1})$ associated with both yg and yg* increase monotonically with the horizon. However, these implied estimates are significantly different than the actual estimates reported in Table V, particularly at longer horizons. Specifically, the actual estimates do not show the kind of monotonic behavior associated with the simulated R^2. This is also true for YG, where the actual forecasting ratios exhibit a clear hump-shaped pattern. On the other hand, e−p, and especially d−p, have a more clear monotonic behavior of their actual R^2 estimates, in line with the simulated values. In the case of the equal-weighted excess return, there is also a substantial difference between the actual and simulated R^2 estimates associated with the *yield gap*. Thus, it seems that the kind of assumptions and results found by Boudoukh, Richardson, and Whitelaw (2008) are not consistent with the long-run predictability of the *yield gap*. In the next section, I discuss predictability at very longer horizons, similarly to the analysis conducted by Cochrane (2008).

Table VII. Implied long-horizon R^2 estimates from 1-month estimatesThis table presents simulated long-horizon R^2 estimates (in %) at horizons of K=3,12,24,36,48,60 months ahead, for regressions on the value-weighted (Panel A) and equal-weighted equity premium (Panel B). The forecasting variables are the current values of the *yield gap* proxies

Panel A (VW)						
yg	4.60	16.59	28.96	38.04	44.56	49.09
yg*	3.71	13.59	24.23	32.47	38.77	43.50
e−p	2.01	7.79	14.90	21.39	27.30	32.68
d−p	1.90	7.22	13.48	18.88	23.53	27.51
YG	4.01	13.98	23.39	29.53	33.33	35.47
d–*e*	0.00	0.02	0.05	0.08	0.11	0.15
RREL	4.09	7.11	5.81	4.35	3.37	2.72
TERM	1.73	5.16	7.14	7.62	7.41	6.93
DEF	0.16	0.62	1.12	1.54	1.89	2.16
Panel B (EW)						
yg	3.84	13.84	24.16	31.74	37.18	40.96
yg*	3.29	12.05	21.47	28.78	34.36	38.55
e−p	1.28	4.97	9.50	13.64	17.41	20.83
d−p	1.34	5.07	9.47	13.27	16.53	19.33
YG	4.78	16.68	27.91	35.23	39.76	42.30
d–*e*	0.03	0.12	0.26	0.41	0.59	0.79
RREL	6.93	12.04	9.83	7.37	5.71	4.61
TERM	3.06	9.13	12.64	13.49	13.13	12.27
DEF	0.90	3.35	6.12	8.40	10.26	11.77

5.2.b VAR-based predictability

An alternative approach to the long-horizon regressions is to estimate the implied long-run effects of the predictive variables on excess returns from a short-run vector autoregression (VAR). This method allows one to avoid the small-sample biases associated with the long-horizon regressions, especially when the forecasting horizon is large and hence the number of usable observations is relatively small. I follow Hodrick (1992) and Lettau and Ludvigson (2001), among others, in computing implied long-horizon R^2

estimates from a first-order VAR that includes the forecasting variable (x_t) and the equity premium:[16]

$$\mathbf{z}_t = [x_t, r^e_t]'. \tag{17}$$

The results are displayed in Table VIII. In the case of r^e_{vw} (Panel A), the implied R^2 estimates associated with both yg and yg* increase monotonically with horizon. The range for yg is between 3.48% ($K = 3$) and 31.67% ($K = 60$), while the corresponding range for yg* is 2.62–27.74%. The magnitude of this forecasting power is substantially larger than the fit from the long-horizon regressions with the sole exception of the 3-month (for both yg and yg*) and 12-month horizons (only in the case of yg*). The implied R^2 estimates associated with YG also increase significantly relative to the forecasting ratios in the long-horizon regressions, varying between 2.65% ($K = 3$) and 20.45% ($K = 60$). Moreover, at most horizons the implied R^2 estimates associated with e–p (d–p) underperform the corresponding fit associated with yg (yg*). The alternative predictors also lag behind in comparison to *yield gap*, the sole exception being RREL at the 3-month horizon.

Table VIII. VAR implied long-horizon R^2 estimatesThis table presents VAR implied long-horizon R^2 estimates (in %) at horizons of K=3,12,24,36,48,60 months ahead, when the predicted variables are the value-weighted (Panel A) and equal-weighted equity premium (Panel B). The forecasting variables are the current values of the *yield gap* proxies (yg,yg*,YG); e−p; d−p; *d*–*e*; RREL; TERM; and DEF. For each predictor, a bivariate first-order VAR containing the forecasting variable and the equity premium is estimated, $\mathbf{z}_t=[x_t,r_t^e]'$. The original sample is 1953:04–2008:12. For further details see Section 5.

	***K*=3**	***K*=12**	***K*=24**	***K*=36**	***K*=48**	***K*=60**
Panel A (VW)						
yg	3.48	11.36	19.49	25.24	29.15	31.67
yg*	2.62	8.61	15.35	20.63	24.69	27.74
e−p	2.79	9.19	16.93	23.54	29.14	33.85
d−p	1.77	5.59	10.44	14.69	18.41	21.64
YG	2.65	8.24	13.70	17.21	19.32	20.45

DEF	0.97	2.24	3.89	5.22	6.25	7.05
Panel B (EW)						
yg	4.52	9.28	15.63	20.26	23.49	25.62
yg*	3.98	7.57	13.09	17.50	20.88	23.42
e−p	3.89	6.81	12.13	16.89	21.06	24.66
d−p	3.18	4.48	7.88	10.98	13.68	16.03
YG	4.54	9.21	14.90	18.58	20.75	21.87
d–*e*	2.26	0.51	0.25	0.17	0.13	0.10
RREL	6.41	7.09	5.29	3.83	2.91	2.32
TERM	4.13	5.54	6.72	6.76	6.32	5.75
DEF	4.86	9.20	15.03	19.19	22.02	23.87

The results for r^e_{ew} (Panel B) are qualitatively similar to those from r^e_{vw}. The implied fit associated with yg, yg*, e−p, and d−p in forecasting r^e_{ew} decreases relative to the case of r^e_{vw} for horizons beyond 3 months, as in the long-horizon regressions. In contrast, the implied forecasting ratios associated with YG are greater than in the case of r^e_{vw}, similarly to the long-horizon regressions. As in the case of r^e_{vw} it turns out that yg (yg*) outperforms e−p (d−p) at all horizons, especially in the comparison between yg* and d−p. With the exception of DEF, the alternative predictors have lower forecasting power than the *yield gap* proxies after the 3-month horizon.

In the Supplementary Appendix, I analyze the impact of the *yield gap* for a return decomposition of the stock index in terms of discount-rate (expectations about future excess stock returns) and cash-flow news (expectations about future cash flows), as in Campbell (1991). The results show that, similar to the traditional ratios, d−p and e−p, in the variance decompositions based on the log *yield gap* the main driver of stock market returns is discount-rate news rather than cash-flow news.[17]

6. Joint Predictability of Returns, Dividends, and Earnings

dividend growth, earnings growth, dividend payout ratios, or future short-term interest rates, depending on the specific forecasting variable being analyzed. Hence, one can investigate the joint predictability of each of these predictors for all the respective components, not just future equity premia. For example, one can formulate a joint test of the predictability of yg* for future expected excess returns, expected dividend growth, and expected short-term interest rates. If yg* has no forecasting power for future dividend growth and future interest rates, then it must forecast future excess stock returns, thus reinforcing the return predictability associated with yg* found in the previous section. This is the approach conducted by Cochrane (2008) for the dividend-to-price ratio, since according to Equation (4), d−p must forecast long-horizon (excess) returns, long-horizon dividend growth or both.[18] Cochrane finds that the predictability of d−p for future dividends is rather weak, thus reinforcing the long-run return predictability associated with that predictor.

In this section, I follow and extend the approach conducted by Cochrane (for d−p) to the *yield gap* proxies, yg and yg*. I focus only on long-run predictability since, unlike d−p and e−p, there are no approximate decompositions associated with either yg or yg* at the one−period horizon, as shown in Section 2 and in the Supplementary Appendix, that is, the identities (1) and (3) are only valid at multiple horizons.

Cochrane (2008) derives the following identity for long-run predictive coefficients associated with d−p:

$$\begin{aligned} 1 &= b_r^{lr} - b_d^{lr}, \\ b_r^{lr} &\equiv \frac{b_r}{1-\rho\phi}, \\ b_d^{lr} &\equiv \frac{b_d}{1-\rho\phi}, \end{aligned} \tag{18}$$

where b_r^{lr} and b_d^{lr} denote the slopes of regressions of long-run excess returns and dividend growth on d−p, respectively, while b_r and b_d denote the one−period predictive coefficients.

This identity for coefficients is based on the dynamic present-value relation associated with d−p in (4), and it should work better with returns than excess returns since Equation (4) is only (approximately) valid for returns.

growth and equity premia are not independent, that is, we cannot have absence of forecasting power for both future (excess) returns and dividend growth.

Similarly to the dividend-to-price ratio, one can derive the following identity for the long-run coefficients associated with yg*:

$$
\begin{aligned}
1 &= b_r^{lr} - b_d^{lr} + b_f^{lr}, \\
b_r^{lr} &\equiv \frac{b_r}{1-\rho\phi}, \\
b_d^{lr} &\equiv \frac{b_d}{1-\rho\phi}, \\
b_f^{lr} &\equiv (\rho\phi)^n \frac{b_f}{1-\rho\phi},
\end{aligned}
\tag{19}
$$

where the one–period regression coefficients are

$$r^e_{t+1} = a_r + b_r \mathrm{yg}^*_t + \varepsilon^r_{t+1}, \tag{20}$$

estimated from the following first-order VAR:

$$\Delta d_{t+1} = a_d + b_d \mathrm{yg}^*_t + \varepsilon^d_{t+1}, \tag{21}$$

$$r_{f,t+1} = a_f + b_f \mathrm{yg}^*_t + \varepsilon^f_{t+1}, \tag{22}$$

$$\mathrm{yg}^*_{t+1} = a_{\mathrm{yg}} + \phi \mathrm{yg}^*_t + \varepsilon^{\mathrm{yg}}_{t+1}. \tag{23}$$

The full derivation of Equation (19) is presented in the Supplementary Appendix. The main difference relative to the identity for d−p is the long-run coefficient associated with future interest rates, b_f^{lr}, which comes from the fact that the predictor is yg* rather than d−p and the original dynamic

I estimate the VAR above, equation-by-equation, using Newey and West (1987) standard errors (with one lag) as in the 1-month predictive regressions in Section 4. To compute the standard errors associated with the long-run coefficients, I use the delta method as in Cochrane (2008).[19] In the computation of the long-run interest coefficient, b_f^{lr}, I set $n = 120$, which is consistent with the 10-year (annualized) bond yield used in the construction of the *yield gap*.[20]

I focuses the analysis on the long-run predictability of equity premia (rather than stock returns) since it has been the focus of the literature, and it is also consistent with the dynamic decompositions for the log *yield gap*, as shown in Section 2. Table IX presents the estimates of the long-run slopes.[21] I test the following two null hypotheses, which are consistent with the identity (19):

$$H_0: b_r^{lr} = 0, b_d^{lr} = -1, b_f^{lr} = 0, \tag{24}$$

$$H_0: b_r^{lr} = 0, b_d^{lr} = 0, b_f^{lr} = 1. \tag{25}$$

Table IX. Long-run predictability for returns and dividend growthThis table presents long-run regression coefficients in forecasting the value-weighted equity premium ($b_{r,\mathrm{VW}}^{lr}$); equal-weighted equity premium ($b_{r,\mathrm{EW}}^{lr}$); dividend growth (b_d^{lr}); and future short-term interest rates (b_f^{lr}). The forecasting variable is the log *yield gap* (yg*). In the first line are reported the coefficient estimates, and below (in parenthesis) are reported asymptotic Newey–West *t*-statistics (calculated with the delta method) associated with the specific null hypotheses (H_0) being tested. The *t*-statistics at bold denote significance at the 1% level, while the underlined ones indicate significance at the 5% level. The original sample is 1953:04–2008:12. For further details see Section 6.

H_0	$b_{r,\mathrm{VW}}^{lr}$	$b_{r,\mathrm{EW}}^{lr}$	b_d^{lr}	b_f^{lr}
	1.058	1.247	0.016	−0.021
b_r=0, b_d=−1, b_f=0	(**3.51**)	(**3.04**)	(**14.64**)	(−1.06)
b_r=0, b_d=0, b_f=1	(**3.51**)	(**3.04**)	(0.23)	(−**50.79**)

In the first null hypothesis, yg* only forecasts future dividend growth, whereas in the second null hypothesis, yg* is only correlated with future market proxy is the equal-weighted excess return, the long-run return slope is actually larger than for r^e_{vw} (1.25) and also strongly significant. Thus for both equity premia proxies, more than 100% of the variance of yg* is attributed to time-varying expected excess stock returns. The long-run dividend coefficient has the wrong sign (0.02), and the null hypothesis, b^{lr}_d = -1 is strongly rejected (*t*-stat = 14.64), while the null b^{lr}_d = 0 is not rejected (*t*-stat = 0.23). The long-run interest coefficient has also the wrong sign (-0.02), and one does not reject the null, b^{lr}_f = 0, while the null b^{lr}_f = 1 is largely rejected (*t*-stat = -50.79). Therefore, the variation in yg* is not attributed to time-varying expected dividend growth or time-varying expected short-term interest rates, thus reinforcing the predictability of yg* for long-run equity premia. The sum $b^{lr}_r - b^{lr}_d + b^{lr}_f$ is close to one (1.02) in the case of r^e_{vw}, which shows that the long-run identity associated with yg* is relatively accurate. However, in the case of r^e_{ew}, we have $b^{lr}_r - b^{lr}_d + b^{lr}_f$ = 1.21, which comes from the large magnitude of the long-run return coefficient.[22]

In the Supplementary Appendix of this article, I present a similar variance decomposition for the other *yield gap* proxy, yg. The results for this decomposition show that more than 100% of the variance of yg is associated with time-varying equity premia.[23] Overall, the results of this section show that when one imposes the restrictions that the log *yield gap* should forecast other variables aside equity premia—dividend growth, dividend payout ratios, earnings growth, one–period interest rates—the absence of predictive power for these alternative variables actually strengthens the return predictability associated with the log *yield gap* at long horizons. Thus, these results reinforce the evidence from long-horizon regressions in the previous section.

7. Out-of-Sample Predictability

7.1 UNCONSTRAINED OUT-OF-SAMPLE REGRESSIONS

The results in Sections 4–6 show that the *yield gap* forecasts in-sample (IS) the excess returns on both the value- and equal-weighted stock market index. In this section, and following the work of Bossaerts and Hillion (1999), Lettau and Ludvigson (2001), Goyal and Welch (2003, 2008), Guo (2006), Campbell and Thompson (2008), Rapach, Strauss, and Zhou (2010), parameter instability in these regressions. To be consistent with Goyal and Welch (2008) and Campbell and Thompson (2008), the focus of the analysis is on the one-period ahead OS predictability, and in the Supplementary Appendix, robustness checks associated with other forecasting horizons are provided.

To assess the OS predictability of the *yield gap*, and other competing state variables, the null (or restricted) model considered is the constant model, that is, a regression containing just a constant in which the best forecast of future excess returns is the corresponding historical average (Lettau and Ludvigson, 2001; Goyal and Welch, 2008; Campbell and Thompson, 2008):

$$\begin{aligned} H_0 &: r_{t+1} = a + u_{t+1}, \\ H_a &: r_{t+1} = a + bx_t + u_{t+1}, \end{aligned} \tag{26}$$

where H_a corresponds to the alternative or unrestricted model, and x_t represents the forecasting state variable having a slope of b.

The first major measure of OS performance analyzed is the OS coefficient of determination, calculated as

$$R^2_{OS} = 1 - \frac{\mathrm{MSE}_U}{\mathrm{MSE}_R}, \tag{27}$$

where $\mathrm{MSE}_U = \frac{1}{T_{OS}} \sum_{t=1}^{T_{OS}} \widehat{u}^2_{Ut}$ denotes the mean-squared (forecasting) error associated with the unrestricted model, and MSE_R represents the same for the restricted model. T_{OS} represents the number of observations on the evaluation (or out-of-sample) period. The OS R^2 is positive whenever $\mathrm{MSE}_U < \mathrm{MSE}_R$, i.e., the forecasting squared errors associated with the unrestricted model have lower magnitude than those corresponding to the restricted model.

The second OS evaluation measure is the F-test from McCracken (2007):

$$\text{MSE-}F = T_{OS} \frac{\mathrm{MSE}_R - \mathrm{MSE}_U}{\mathrm{MSE}_U},$$

which tests the null hypothesis that

is that the MSE associated with the unrestricted model is lower in comparison to the restricted model.

The third OS test statistic is the encompassing test proposed by Harvey, Leybourne, and Newbold (1998) and Clark and McCracken (2001):

$$\text{ENC-NEW} = \frac{\sum_{t=1}^{T_{OS}} \left(\widehat{u}_{Rt}^{2} - \widehat{u}_{Rt}\widehat{u}_{Ut}\right)}{\text{MSE}_U}, \tag{29}$$

in which the null hypothesis is that the restricted model encompasses the unrestricted model, that is, the unrestricted model cannot improve the forecast associated with the restricted model. The alternative hypothesis is that the unrestricted model has additional information that can improve the forecast obtained from the restricted model. The statistical inference associated with MSE-*F* and ENC-NEW is based on the critical values derived in McCracken (2007) and Clark and McCracken (2001), respectively, which are obtained from Monte-Carlo simulations.

The OS statistics associated with forecasting the excess market return are provided in Table X. The forecasting variables are the three proxies for the *yield gap* (yg, yg*, YG), and the alternative predictors considered in the previous sections: e −p,d −*p*,*d*- *e*, RREL, TERM, DEF. The initial estimation period is 10 years (120 observations), which represents a compromise between the low statistical power of the OS regressions and the parameter instability over time. The results for the value-weighted return (Panel A) show that, in most cases, the models including the forecasting variables perform worse than the constant model, as indicated by the negative estimates for both R^2_{OS} and MSE-*F*. The sole exceptions are the models containing yg and YG, in which cases we have positive estimates for both R^2_{OS} (0.54 and 0.14%) and MSE-*F*(2.97 and 0.79). The estimate of MSE-*F* in the case of yg is statistically significant at the 5% level. Regarding the ENC-NEW statistic, in general, one tends to reject the null that the restricted model encompasses the unrestricted model, at the 5% level. The exception is the regression with e−p, in which case one accepts the null that this variable does not add forecasting power to the null model. Thus, in this application, the ENC-NEW statistic tends to reject the null much more often than the MSE-*F* statistic.

Table X. Out-of-sample predictabilityThis table presents out-of-sample evaluation statistics for predictability of the excess returns on the value- (Panel A) and equal-weighted (Panel B) market indexes, one period ahead. The forecasting variables are the current values of the *yield gap* proxies (yg,yg*,YG); e−p; d−p; *d–e*; RREL; TERM; and the DEF. R^2_{OS} denotes the out-of-sample coefficient of determination (in %); MSE-*F* is the McCracken (2007),*F*-statistic; and ENC-NEW stands for the encompassing test proposed by Clark and McCracken (2001). CV denotes the 95% critical values associated with MSE-*F* and ENC-NEW. The total sample is 1953:04–2008:12, and the initial estimation period is 1953:04–1963:03. For further details see Section 7.

	R^2_{OS}(%)	MSE−*F*	*CV*	ENC−NEW	CV
Panel A (VW)					
yg	0.54	2.97	1.52	6.81	2.37
yg*	−0.23	−1.24	1.52	9.06	2.37
e−p	−0.22	−1.19	1.52	0.87	2.37
d−p	−0.34	−1.88	1.52	4.89	2.37
YG	0.14	0.79	1.52	6.46	2.37
d–e	−0.91	−4.97	1.52	2.50	2.37
RREL	−0.70	−3.80	1.52	7.79	2.37
TERM	−2.30	−12.33	1.52	9.89	2.37
DEF	−0.84	−4.57	1.52	2.65	2.37
Panel B (EW)					
yg	0.73	4.01	1.52	7.51	2.37
yg*	0.26	1.42	1.52	9.39	2.37
e−p	−0.13	−0.71	1.52	1.69	2.37
d−p	−0.03	−0.18	1.52	6.09	2.37
YG	0.88	4.88	1.52	7.82	2.37
d–e	−0.93	−5.05	1.52	0.55	2.37
RREL	0.55	3.01	1.52	12.76	2.37
TERM	−1.56	−8.43	1.52	8.79	2.37
DEF	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

estimates for R^2_{OS}: 0.73, 0.26, and 0.88% for yg, yg*, and YG, respectively. The corresponding estimates associated with MSE-*F* are 4.01, 1.42, and 4.88, respectively, and these are statistically significant in the cases of yg and YG. Similarly to the value-weighted excess market return, the ENC-NEW statistic rejects the null when the forecasting variables are the three *yield gap* proxies. On the other hand, when the forecasting variables are e−p, d−e, and DEF, one does not reject the null hypothesis that the model with constant expected returns encompasses the model with time-varying expected returns.

The results presented in this subsection show that the *yield gap* has significantly greater OS predictability for excess market returns than the alternative forecasting variables. Moreover, the OS predictability is stronger in the case of r^e_{ew} than for r^e_{vw}, which shows that the value-weighted return (and thus, the returns of big capitalization stocks) is relatively more difficult to forecast out-of-sample at the one-month horizon.

7.2 COMPARISONS ACROSS FORECASTING VARIABLES

The test statistics used above are associated with univariate OS regressions. However, one might be interested in comparing the OS performance of two alternative variables, for example, yg versus e−p. In the forthcoming analysis, the alternative model is some measure of the *yield gap*, and the null model is one of the competing variables. For example, in the comparison between yg and e−p, the competing models are

$$\begin{aligned} H_0 &: r_{t+1} = a + b(e_t - p_t) + u_{t+1}, \\ H_a &: r_{t+1} = c + d\mathrm{yg}_t + u_{t+1}. \end{aligned} \tag{30}$$

To test this hypothesis, I use the encompassing test statistic proposed by Diebold and Mariano (1995) and Harvey, Leybourne, and Newbold (1998):

$$\text{ENC-T} = \sqrt{\frac{T_{OS}-1}{T_{OS}}}\,\frac{\sum_{t=1}^{T_{OS}}\left(\widehat{u}^2_{Nt} - \widehat{u}_{Nt}\widehat{u}_{At}\right)}{\sqrt{\sum_{t=1}^{T_{OS}}\left(\widehat{u}^2_{Nt} - \widehat{u}_{Nt}\widehat{u}_{At}\right)^2 - \overline{c}^2}},$$

$$\overline{c} \equiv \frac{1}{T_{OS}}\sum^{T_{OS}}\left(\widehat{u}^2_{Nt} - \widehat{u}_{Nt}\widehat{u}_{At}\right),$$

respectively. The statistical inference is based on the critical values derived in Clark and McCracken (2001). This test is about the covariance between $\widehat{u}_{Nt}$ and $\widehat{u}_{Nt} - \widehat{u}_{At}$. The null hypothesis is that the null model (the model with the alternative predictor) encompasses the preferred model (containing the *yield gap* measure). The alternative hypothesis is that the preferred model contains information that can improve the forecast of the null model.

The results associated with the test-statistic (31) are presented in Table XI. Both yg and YG are compared against the alternative predictors, e−p, *d*−*e*, RREL,TERM,DEF, while yg* is compared against d−p, *d*−*e*, RREL, TERM, DEF, since d−p (rather than e−p) is a component of yg*. The results for the value-weighted excess market return (Panel A) show that in all cases the ENC-T statistic assumes positive values, and most importantly, one rejects the null hypothesis at the 5% level. In other words, all *yield gap* proxies have forecasting power in addition to the alternative predictors. The results in the case of the equal-weighted excess market return (Panel B) are qualitatively very similar to those in Panel A. In summary, the results in this subsection provide further evidence that the *yield gap* proxies have greater OS predictability power than popular forecasting variables from the predictability literature.

Table XI. Out-of-sample predictability: comparison across modelsThis table compares different predictors in relation to the out-of-sample predictability of excess market returns. The forecasted excess returns are on the value-weighted market index (Panel A) and equal-weighted market index (Panel B). The competing forecasting models are the *yield gap* proxies (yg,yg*,YG); e − p; d − p; *d*–*e*; RREL; TERM; and DEF. ENC-T stands for the Harvey et al. (1998) test statistic, with CV denoting the respective 95% critical value. The total sample is 1953:04–2008:12, and the initial estimation period is 1953:04–1963:03. For further details see Section 7.

	ENC-T	CV
Panel A (VW)		
yg versus e − p	1.84	1.33
yg versus *d*–*e*	2.45	1.33
yg versus RREL	3.40	1.33
yg versus TERM	4.00	1.33
yg versus DEF	2.72	1.33
yg* versus d − p	2.01	1.33

yg* versus TERM	4.06	1.33
yg* versus DEF	2.83	1.33
YG versus e – p	1.83	1.33
YG versus *d*–*e*	2.28	1.33
YG versus RREL	3.30	1.33
YG versus TERM	3.96	1.33
YG versus DEF	2.78	1.33
Panel B (EW)		
yg versus e – p	1.99	1.33
yg versus *d*–*e*	2.41	1.33
yg versus RREL	3.17	1.33
yg versus TERM	4.02	1.33
yg versus DEF	3.02	1.33
yg* versus d – p	2.10	1.33
yg* versus *d*–*e*	2.24	1.33
yg* versus RREL	3.14	1.33
yg* versus TERM	4.13	1.33
yg* versus DEF	3.17	1.33
YG versus e – p	2.39	1.33
YG versus *d*–*e*	2.45	1.33
YG versus RREL	3.25	1.33
YG versus TERM	4.15	1.33
YG versus DEF	3.37	1.33

7.3 CONSTRAINED OUT-OF-SAMPLE REGRESSIONS

As pointed out by Campbell and Thompson (2008), the OS predictability evaluation can suffer from some distortions. For example, the estimation of forecasts of the equity premium, which are not confirmed ex post, leading to a downward bias in the OS performance. To overcome this issue, I impose the prior restriction that the forecasted market equity premium cannot be negative, that is, a investor would rule out a model that forecasts negative equity risk premia.

Table XII reports estimates for R^2_{OS} when the restriction of a nonnegative forecasted excess return is imposed, i.e., whenever the unrestricted model forecasts a negative excess return, this estimate is truncated to zero. The results for the value-weighted excess market return show that the three *yield gap* proxies produce positive R^2_{OS} estimates: 0.59, 0.47, and 0.64% for yg, yg*, and YG, respectively. Regarding the alternative predictors, only d−p and RREL present positive explanatory ratios, although of lower magnitude than the *yield gap*. In the case of the equal-weighted market return, the R^2_{OS} estimates associated with the *yield gap* increase slightly to 1.01, 0.53, and 1.03% for yg, yg*, and YG, respectively. In this case, only RREL produces a larger explanatory ratio (1.88%), whereas the values associated with *d−e*, TERM, and DEF continue to be negative. Overall, these results confirm the findings in Campbell and Thompson (2008) that by imposing the constraint of positive predicted equity risk premium, the OS performance of the forecasting variables tends to improve.

Table XII. Out-of-sample predictability: positive equity premiumThis table presents out-of-sample estimates for the coefficient of determination (in %) when the predicted (one period ahead) stock risk premium is restricted to be positive. The forecasted excess returns are on the value-weighted market index (VW) and equal-weighted market index (EW). The forecasting variables are the *yield gap* proxies (yg,yg*,YG); e−p; d−p; *d–e*; RREL; TERM; and DEF. The total sample is 1953:04–2008:12, and the initial estimation period is 1953:04–1963:03. For further details see Section 7.

	R^2_{OS}(%), VW	R^2_{OS} (%), EW
yg	0.59	1.01
yg*	0.47	0.53
e−p	−0.26	0.01
d−p	0.09	0.68
YG	0.64	1.03
d–e	−0.12	−0.29

DEF	−0.84	−0.83

The Supplementary Appendix presents additional results regarding the OS forecasting power of the *yield gap*, specifically, using longer horizons in the OS predictive regressions, and computing the Lewellen (2004) adjustment for the slopes in the OS regressions.

Overall, the results of this section show that the *yield gap* has a reasonable OS performance in forecasting both value- and equal-weighted excess market returns, but given the low statistical power associated with OS predictability tests, as argued by Inoue and Kilian (2004), Campbell and Thompson (2008), and Cochrane (2008), among others, these results per se should be interpreted with some caution, and be rather interpreted as a robustness check to the IS predictability from the previous sections.

8. Economic Significance

In this section, I evaluate the economic significance associated with the OS predictive power of the *yield gap* for stock market excess returns. Following Breen, Glosten, and Jagannathan (1989), Pesaran and Timmermann (1995), Goyal and Santa-Clara (2003), Campbell and Thompson (2008), among others, I define an "active" trading strategy based on the OS 1-month ahead forecasting ability of the *yield gap* (and other state variables) for excess returns. At each time t, I conduct the following 1-month predictive regression:

$$r_{t+1} = a + bx_t + u_{t+1}, \quad (32)$$

and the forecasted excess return is calculated as $\widehat{r}_{t+1} = \widehat{a} + \widehat{b}x_t$, where $\widehat{a}$ and $\widehat{b}$ are the estimated coefficients from the above regression, and r_{t+1} denotes the simple excess return on the stock index.[24] Then, the trading strategy allocates 100% in the market portfolio if the forecasted excess return $(\widehat{r}_{t+1})$ is positive, and otherwise, it invests 100% in the risk-free rate. In symbols, the strategy can

$$S_t = \begin{cases} \omega = 1 \ if \ \widehat{r}_{t+1} \geq 0 \\ \omega = 0 \ if \ \widehat{r}_{t+1} < 0. \end{cases}$$

$$R_{p,t+1} = \omega R_{t+1} + (1-\omega) R_{f,t+1},$$

(34)

where R_{t+1} denotes the simple return on the risky asset, and $R_{f,t+1}$ represents the simple risk-free rate. By iterating this process forward and using an expanding sample for the predictive regressions, as in the last section, one obtains a time-series of realized returns on the trading strategy, which are compared to a "passive" investment strategy ("buy-and-hold") that invests in the stock index. I conduct this strategy for both the value- and equal-weighted market indexes as the two proxies for the risky asset.

Following Campbell and Thompson (2008), I extend the strategies presented above to take into account the possibility of short-selling the stock index. The active trading strategy is now given by

$$S_t = \begin{cases} \omega = 1.5 \ \mathit{if} \ \widehat{r}_{t+1} \geq 0 \\ \omega = -0.5 \ \mathit{if} \ \widehat{r}_{t+1} < 0 \end{cases}.$$

(35)

Under this strategy, the investor allocates 150% to the risky asset if its forecasted excess return is positive, selling short the risk-free asset (borrow) at 50% (maximum leverage), and otherwise, he sells short the risky asset and invests the proceedings in the risk-free asset. The return on this active strategy is compared to the return on a passive strategy that allocates 150% to the stock index:

$$\widetilde{R}_{p,t+1} = 1.5 R_{t+1} - 0.5 R_{f,t+1}.$$

(36)

To have an initial sample of 120 months to conduct the first predictive regression, the active strategy starts at 1963:04. The passive strategy is compared to the trading strategies based on the conditioning state variables analyzed in the last section, yg, yg*, YG, e−p, d−p, $d-e$, RREL, TERM, and DEF. For each variable, I compute the average return, standard deviation, and Sharpe ratio (ratio of average return to standard deviation) associated weighted index the trading strategies based on yg (0.70%), yg* (0.75%), and YG (0.72%) have slightly lower average returns than the passive strategy (0.84%), but they also have significant lower volatilities. Hence, all the trading strategies based on the *yield gap* measures produce greater Sharpe ratios than the buy-and-hold strategy. Specifically, the monthly Sharpe ratios associated with yg, yg*, and YG are 0.21, 0.29, and 0.20, respectively, which compare to 0.19 for the buy-hold strategy. On the other hand, the Sharpe ratio associated with e−p (0.20) is slightly below the Sharpe ratio for yg, while the difference in performance ratios between d−p (0.18) and yg* is much wider. In what concerns the alternative predictors, the Sharpe ratio associated with TERM (0.24) outperforms yg and YG, but lags behind yg*.

Table XIII. Trading strategies based on the OS forecasting ability of the *yield gap*This table reports descriptive statistics and the associated Sharpe ratios for trading strategies based on the out-of-sample forecasting power of the *yield gap* (and other forecasting variables) for excess market returns. Buy-hold denotes the passive strategy associated with holding the risky asset. The risky assets used in the portfolio choice are the value-weighted index (Panels A, C) and equal-weighted index (Panels B, D). In Panels A and B, short-sales are not allowed whereas in Panels C and D the trading strategies are constructed with short-selling. The forecasting variables are the *yield gap* proxies (yg,yg*,YG); e − p; d − p; *d–e*; RREL; TERM; and DEF. The total sample is 1953:04–2008:12, and the initial estimation period is 1953:04–1963:03. For further details see Section 8.

	Buy-hold	**yg**	**yg***	**e − p**	**d − p**	**YG**	***d–e***	**RREL**	**TERM**
Panel A (VW, no short-sales)									
Mean (Std. Dev.) (%)	0.84 (4.44)	0.70 (3.37)	0.75 (2.59)	0.86 (4.34)	0.69 (3.79)	0.72 (3.56)	0.79 (3.89)	0.85 (4.05)	0.94 (3.86)
Sharpe	0.19	0.21	0.29	0.20	0.18	0.20	0.20	0.21	0.24
Panel B (EW, no short-sales)									
Mean (Std.	1.12 (5.69)	1.01 (4.67)	1.17 (4.37)	1.06 (5.52)	1.03 (4.93)	0.98 (4.92)	1.11 (5.21)	1.08 (5.20)	1.11 (4.88)

Panel C (VW, short-sales)									
Mean (Std. Dev.) (%)	1.03 (6.66)	0.75 (5.27)	0.85 (4.29)	1.06 (6.52)	0.74 (5.81)	0.80 (5.51)	0.93 (5.94)	1.05 (6.15)	1.23 (5.89)
Sharpe	0.16	0.14	0.20	0.16	0.13	0.14	0.16	0.17	0.21
Panel D (EW, short-sales)									
Mean (Std. Dev.) (%)	1.45 (8.54)	1.22 (7.21)	1.54 (6.80)	1.32 (8.32)	1.27 (7.55)	1.16 (7.53)	1.42 (7.91)	1.37 (7.90)	1.42 (7.47)
Sharpe	0.17	0.17	0.23	0.16	0.17	0.15	0.18	0.17	0.19

In the case of the equal-weighted index, yg and yg* with Sharpe ratios of 0.22 and 0.27, respectively, both outperform the passive strategy (0.20), while YG has identical performance. This positive performance is a consequence of lower volatilities (both yg and yg*) and higher mean returns than the passive strategy (in the case of yg*). As in the case of the value-weighted index, e−p (d−p) underperform relative to yg (yg*), while the performance of TERM is slightly above to that of both yg and YG, but underperforms relative to yg*. The lower volatilities associated with the active strategies based on *yield gap*, compared to the passive strategy, can be (partially) related with the forecasting ability of the *yield gap* for the equity premium, and is consistent with previous evidence showing that the volatility of stock prices (returns) is negatively correlated with the level of realized prices (returns) (French, Schwert, and Stambaugh 1987). Specifically, if the *yield gap* is relatively successful in forecasting the sign of the equity premium, that is, the positive predicted equity premium is matched by an ex post positive realized return, then the volatility of the returns of the dynamic strategies will be adjusted downwards, since in many periods of negative realized returns (and thus, high stock price volatility) the active strategy does not hold the stock index.

outperforms significantly the passive strategy with a Sharpe ratio of 0.20 (compared to 0.16 for the passive strategy) in the case of the value-weighted index, whereas in the case of the equal-weighted index the Sharpe ratio is 0.23 (versus 0.17 for the benchmark). In fact, apart from the case of the value-weighted index with short-sales, yg* has the largest Sharpe ratio among all the forecasting variables. Across all predictors, the Sharpe ratios are in general lower than the corresponding estimates with no short-selling, which is the result of the higher volatility when short-sales are available (associated with higher leverage), despite the increase in average returns associated with the dynamic strategies.

The Supplementary Appendix presents utility-based metrics of economic significance for the trading strategies associated with the *yield gap* and alternative predictors. The results show that for levels of relative risk aversion between three and five, the change in average utility for active strategies associated with the *yield gap* (relative to the passive strategy) are generally positive and economically significant.

In sum, the results of this section indicate that the OS predictive power associated with the *yield gap* is economically significant and relevant in terms of asset allocation/portfolio choice, as showed by the gains in the Sharpe ratio and average utility.

9. Conclusion

This article conducts a comprehensive analysis of the forecasting ability of the "Fed model" for the equity premium. The key variable is the difference between the earnings-to-price (or dividend-to-price) ratio and the long-term bond yield, termed by *yield gap*. I derive a dynamic accounting decomposition for the *yield gap* proxy based on the log earnings yield, as a function of future equity premia, future short-term interest rates, future earnings growth, and future dividend payout ratios. A second *yield gap* based on the log dividend yield is correlated with future equity premia, future short-term interest rates, and future dividend growth. These dynamic present-value relations represent the rationale for the predictive role of the *yield gap* for equity premia at multiple horizons.

At the 1-month horizon, the *yield gap* has significantly greater forecasting power for the equity premium than both the earnings- (e−p) and dividend-to-price ratios (d−p). Moreover, the *yield gap* outperforms other popular horizon regressions, the *yield gap* has significant forecasting power for the equity premium at horizons between 3 months and 5 years. Moreover, it outperforms both e−p and d−p, and other predictors, at most forecasting horizons. Hence, these results provide evidence that if one wants to predict excess stock returns (rather than returns) at long horizons, then the *yield gap* should be a better predictor than both e−p and d−p.

I follow Cochrane (2008) in analyzing the joint return−dividend−earnings predictability associated with the *yield gap*. The results show that when one imposes the restrictions that the log *yield gap* should forecast other variables aside equity premia—dividend growth, dividend payout ratios, earnings growth, one-period interest rates—the absence of predictive power for these alternative variables actually strengthens the return predictability associated with the *yield gap* at very long horizons, reinforcing the evidence from the long-horizon regressions.

By performing an out-of-sample analysis, the results show that the *yield gap* has reasonable out-of-sample predictability for the equity premium when the comparison is made against a simple historical average, especially when one imposes a constraint of nonnegative forecasted excess returns. Furthermore, the *yield gap* proxies have greater out-of-sample predictability power than the alternative forecasting variables commonly used in the literature. The out-of-sample forecasting power of the *yield gap* is economically significant, as indicated by the significant gains in the Sharpe ratios, as well as positive certainty equivalent estimates, associated with dynamic trading strategies based on the predictive ability of the *yield gap*.

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[1] In the article, I use both dividend (earnings)-to-price ratio and dividend (earnings) yield to

(1988a), Cochrane (1992); Goetzmann and Jorion (1993, 1995); Kothari and Shanken (1997); Goyal and Welch (2003); Robertson and Wright (2006); Lettau and Van Nieuwerburgh (2008); Chen (2009), among others. For the earnings-to-price ratio, see Fama and French (1988); Campbell and Shiller (1988b, 1998); Campbell and Vuolteenaho (2004a); Campbell and Yogo (2006); Boudoukh, Richardson, and Whitelaw (2008), among others.

[3] There is no official information or evidence showing that the Federal Reserve uses the Fed model as an instrument of monetary policy.

[4] Lowercase letters represent the logs of uppercase letters.

[5] If we relax the assumption that the Expectations Hypothesis of the term structure holds, there would be a bond risk premia term on the right-hand side of this decomposition. Thus, such dynamic decomposition would also justify the predictability of yg for bond risk premia. However, this analysis is beyond the scope of this article, which focuses on stock return predictability.

[6] Bekaert and Engstrom (2010) use standard present-value relations for the dividend yield and bond yield, and employ a vector autoregression (VAR) to estimate the respective components, and ultimately analyze which components drive the correlation between both yields. Their focus is on explaining what drives the correlation between equity and bond yields, while my analysis is focused on a linear function of these yields that should forecast equity premia.

[7] The gross simple return on a *n*-maturity zero-coupon bond is given by

$$1 + R_{n,t+1} = \frac{(1 + Y_{nt})^n}{\left(1 + Y_{n-1,t+1}\right)^{n-1}},$$

and in the steady-state equilibrium we have, $R_{n,t+1}=R_n$ and $Y_{nt}=Y_{n-1,t+1}=Y_n$, and hence, the previous equation reduces to

$$R_n = Y_n.$$

[8] Ang and Bekaert (2007) also compute predictive regressions with the dividend yield and interest rate on the right-hand side. However, this approach differs from the regressions on yg* in two ways. First, they use the short-term interest rate rather than the long-term bond yield used in the computation of yg*. Second, the regression on yg* can be interpreted as a constrained version of their regression, since the coefficients associated with the two

in the predictability literature (see Lettau and Ludvigson, 2001; Rangvid, 2006; Cooper and Priestley, 2009; Hsu, 2009, among others).

[10] I thank the referee for making this suggestion.

[11] In the language of Econometrics, the regressor is predetermined (since it is orthogonal to the contemporaneous error term) but it does not satisfy the strict exogeneity property (see Campbell, Lo, and Mackinlay, 1997, Chapter 7, or in alternative, Hayashi, 2000, Chapters 1 and 2, for a more formal discussion).

[12] The assumption of an AR(1) process for the predictor is standard in the literature. Pastor and Stambaugh (2009) analyze the moving-average (MA) representation of the AR(1) process.

[13] Other papers that use alternative methods to correct for the finite-sample bias associated with predictive regressions include Campbell and Yogo (2006), Polk, Thompson, and Vuolteenaho (2006) and Amihud, Hurvich, and Wang (2009).

[14] As in Lewellen (2004), I use one-sided *p*-values since with financial ratios as forecasting variables, the alternative hypothesis should be $b > 0$, as shown in Section 2.

[15] It is possible to show that $\lim_{\phi \to 1} \mathrm{E}(R^2_K | R^2_1) = KR^2_1$. The proof is available upon request.

[16] See Hodrick (1992) for a detailed description.

[17] I thank Burton Hollifield (the editor) for making this suggestion.

[18] Binsbergen and Koijen (2010) also look at the interaction between return and dividend predictability associated with the dividend-to-price ratio, but they threat expected return and expected dividend growth as latent processes.

[19] The derivation of the standard errors is available upon request.

[20] Notice that the 1-month Treasury bill rate used to calculate excess stock returns is not annualized.

[21] To save space, I do not report the one-period slope estimates from the VARs. Results are available upon request.

[22] The VAR estimation is based on monthly returns and interest rates, on one hand, and annualized dividends and earnings, on the other hand, to be consistent with the analysis in the previous sections. For this reason, the identity involving the long-run coefficients cannot be totally accurate. Moreover, the data on dividend and earnings are for the S&P 500 index, which is tilted towards large caps, implying that the coefficient decomposition works better with value-weighted returns than equal-weighted returns.

returns from the log *yield gap*, it is still significantly lower than the share of equity premia predictability.

[24] In this section, r_{t+1} stands for the excess (simple) return instead of excess log return, and R_{t+1} denotes the nominal (simple) return.

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- Supplementary data

Supplementary data

Supplementary Data - zip file