Stocks versus Bonds: Explaining the Equity Risk Premium

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From the 19th century through the mid-20th century, the dividend yield (dividends/price) and earnings yield (earnings/price) on stocks generally exceeded the yield on long-term U.S. government bonds, usually by a substantial margin. Since the mid-20th century, however, the situation has radically changed. In addressing this situation, I argue that the difference between stock yields and bond yields is driven by the long-run difference in volatility between stocks and bonds. This model fits 1871–1998 data extremely well. Moreover, it explains the currently low stock market dividend and earnings yields. Many authors have found that although both stock yields forecast stock returns, they generally have more forecasting power for long horizons. I found, using data up to May 1998, that the portion of dividend and earnings yields explained by the model presented here has predictive power only over the long term whereas the portion not explained by the model has power largely over the short term.

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The dividend yield on the S&P 500 Index has long been examined as a measure of stock market value. For instance, the well-known Gordon growth model expresses a stock price (or a stock market's price) as the discounted value of a perpetually growing dividend stream:

$$P = \frac{D}{R-G}. \tag{1}$$

where

P = price
D = dividends in Year 0
R = expected return
G = annual growth rate of dividends in perpetuity

Now, solving this equation for the expected return on stocks produces

$$R = \frac{D}{P} + G. \tag{2}$$

Thus, if growth is constant, changes in dividends to price, D/P, are exactly changes in expected (or required) return. Empirically, studies by Fama and French (1988, 1989), Campbell and Shiller (1998), and others, have found that the dividend yield on the market portfolio of stocks has forecasting power for aggregate stock market returns and that this power increases as forecasting horizon lengthens.

The market earnings yield or earnings to price, E/P (the inverse of the commonly tracked P/E), represents how much investors are willing to pay for a given dollar of earnings. E/P and D/P are linked by the payout ratio, dividends to earnings, which represents how much of current earnings are being passed directly to shareholders through dividends. Studies by Sorenson and Arnott (1988), Cole, Helwege, and Laster (1996), Lander, Orphanides, and Douvogiannis (1997), Campbell and Shiller (1998), and others, have found that the market E/P has power to forecast the aggregate market return.

Under certain assumptions, a bond's yield-to-maturity, Y, will equal the nominal holding-period return on the bond.[1] Like the equity yields examined here, the inverse of the bond yield can be thought of as a price paid for the bond's cash flows (coupon payments and repayment of principal). When the yield is low (high), the price paid for the bond's cash flow is high (low). Bernstein (1997), Ilmanen (1995), Bogle (1995), and others, have shown that bond yield levels (unadjusted or adjusted for the level of inflation or short-term interest rates) have power to predict future bond returns.

This article examines the relationship between stock and bond yields and, by extension, the relationship between stock and bond market returns (the difference between stock and bond expected returns is commonly called the equity risk premium). I hypothesize that the relative yield stocks must provide versus bonds today is

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driven by the experience of each generation of investors with each asset class.

The article also addresses the observation of many authors, economists, and market strategists that today's dividend and earnings yields on stocks are, by historical standards, shockingly low. I find they are not.

Finally, I report the results of decomposing stock yields into a fitted portion (i.e., stock yields explained by the model presented here) and a residual portion (i.e., stock yields not explained by the model).

Historical Yields on Stocks and Bonds

As far as yields are concerned, 1927–1998 tells a tale of two periods—as **Figure 1** clearly shows. Figure 1 plots the dividend yield for the S&P 500 and the yield to maturity for a 10-year U.S. T-bond from January 1927 through May 1998.[2] Prior to the mid-1950s, the stock market's yield was consistently above the bond market's yield. Anecdotally, investors of this era believed that stocks should yield more than bonds because stocks are riskier investments. Since 1958, the stock yield has been below the bond yield, usually substantially below. As of the latest data in Figure 1 (May 1998), the stock market yield was at an all-time low of 1.5 percent whereas the bond market yield was at 5.5 percent, not at all a corresponding low point. This observation has led many analysts to assert that the role of dividends has changed and that dividend yields in the late 1990s are not comparable to those of the past. Although this assertion may have some merit, I will argue that it is largely unnecessary to explain today's low D/P.

As did dividend yields, the stock market's earnings yields systematically exceeded bond yields early in the sample period, but as **Figure 2** shows, since the late-1960s, earnings yields have been comparable to bond yields and clearly strongly related (as are dividend yields, albeit from a lower level).[3] **Table 1** presents monthly correlation coefficients for various periods between the levels of D/P and Y and E/P and Y. The numbers in Table 1 clearly bear out what is seen in Figures 1 and 2. For the entire period, D/P and Y were negatively correlated because of their reversals; E/P was essentially uncorrelated with Y. For the later period, however, stock and bond yields show the strong positive relationship many economists and market strategists have noted.

Thus, we are left with several puzzles:

- Why did the stock market strongly outyield bonds for so long only to now consistently underyield bonds?
- Why did stock and bond yields move relatively independently, or even perversely, in the overall 1927–98 period but move strongly together in the later 40 years of this period?
- Perhaps most important, why are today's stock market yields so low and what does that fact mean for the future?

The rest of this article tries to answer these questions.

Figure 1. S&P 500 Dividend Yield and T-Bond Yield to Maturity, January 1927– May 1998
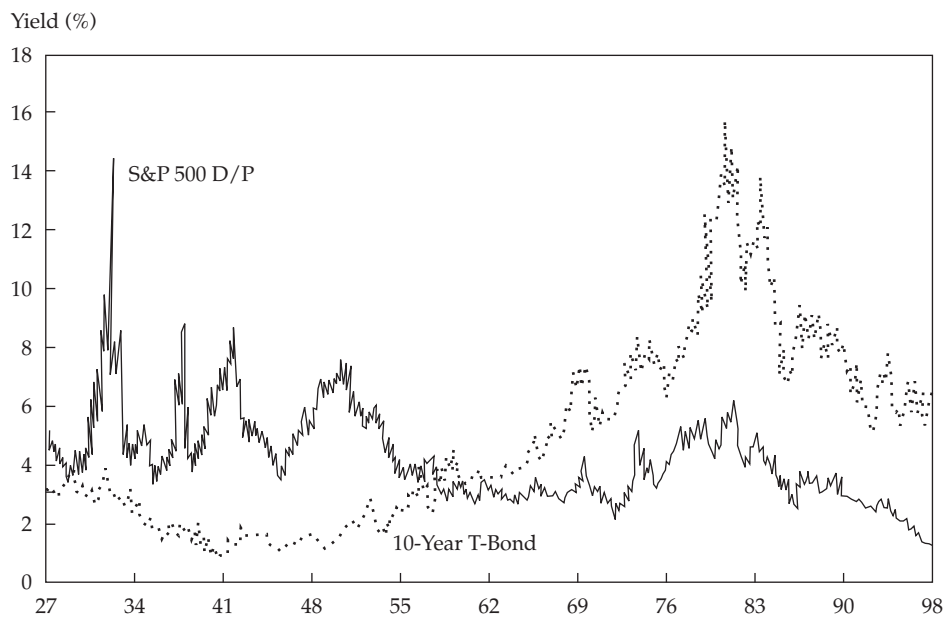
Figure 2. S&P 500 Earnings Yield and T-Bond Yield to Maturity, January 1927–May 1998
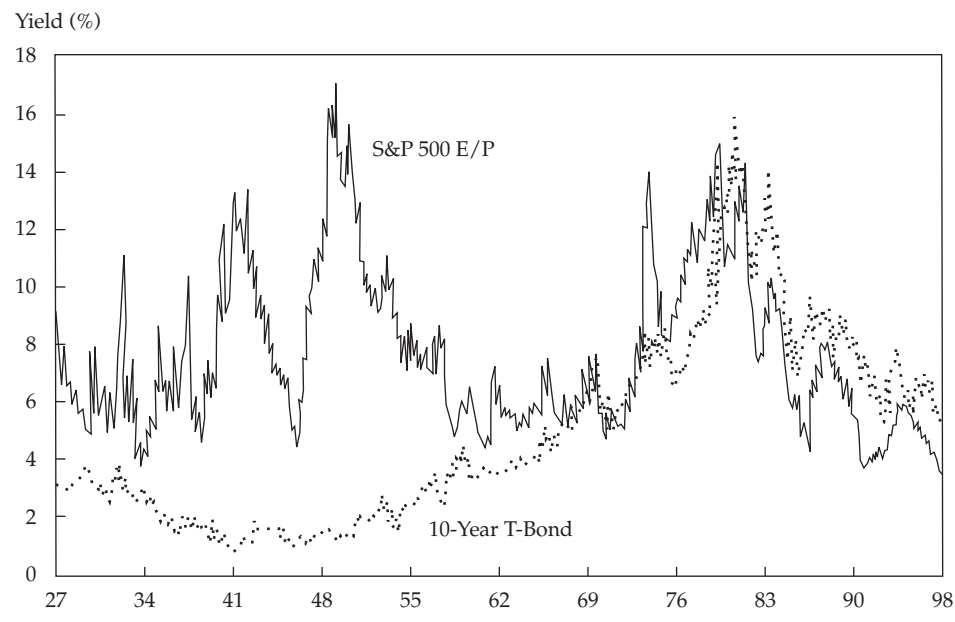
Table 1. Monthly Correlation Coefficients, Various Periods

Period	Correlation of D/P and Y	Correlation of E/P and Y
Full (January 1927–May 1998)	−0.28	+0.08
Early (January 1927–December 1959)	−0.23	−0.49
Late (January 1960–May 1998)	+0.71	+0.69

Model for Stock Market Yields

Researchers have shown a strong link between aggregate dividend and earnings yields and expected stock market returns, especially for long horizons. When stock market yields are high (low), expected future stock returns are high (low). This predictability has two possible explanations that are at least partly consistent with efficient markets (there are many *inefficient*-market explanations). One, investors' taste for risk varies. When investors are relatively less risk averse, they demand less in the way of an expected return premium to bear stock market risk. Fama and French (1988, 1989), among others, explored this hypothesis. Two, the perceived level of risk can change even if investors' taste for risk is constant.

I explore the hypothesis that the perceived level of risk can change (although the two hypotheses are not mutually exclusive). Note that investor perception of long-term risk need not be accurate for this hypothesis to be true. If investor perception of risk is accurate, then the evidence presented here may be consistent with an efficient market. If investor perception of risk is inaccurate but explains the pricing of stocks versus bonds, then the hypothesis

may be deemed accurate but still pose a dilemma for fans of efficient markets.

Consider a simple model in which the required long-term returns on aggregate stocks and bonds vary through time. Expected stock returns, E(Stocks), are assumed to be proportional to dividend yields, whereas expected bond returns, E(Bonds), are assumed to move one-for-one with current bond yields; that is,

$$E(\text{Stocks})_t = a + b(\text{D/P}_t) + \varepsilon_{Stocks,t}, \qquad (3)$$

$$E(\text{Bonds})_t = Y_t + \varepsilon_{Bonds}, \qquad (4)$$

(where a is the intercept, b is the slope, D/P_t is dividend yield at time t, and ε is an error term). The hypothesis is that b is positive, so expected stock returns vary positively with current stock dividend yields, and that the ε terms are identically and independently distributed error terms representing the portion of expected returns not captured by the model.[4]

Now, I assume that expected stock and bond returns are linked through the long-run stock and bond volatility experienced by investors. So,

$$E(\text{Stocks})_t - E(\text{Bonds})_t = c + d\sigma(\text{Stocks})_t + e\sigma(\text{Bonds})_t. \quad (5)$$

The hypothesis is that *d* is positive whereas *e* is negative. That is, I assume that the expected (or required) return differential between stocks and bonds is a positive linear function of a weighted difference of their volatilities.[5] Although Equations 3, 4, and 5 do not represent a formal asset-pricing model, they do capture the spirit of allowing expected returns to vary through time as a function of volatility. Moreover, they yield empirically testable implications.[6]

Rearranging these equations (and aggregating coefficients) produces the following model:

$$D/P = \gamma_0 + \gamma_1 Y + \gamma_2 \sigma(\text{Stocks}) + \gamma_3 \sigma(\text{Bonds}) + \varepsilon_{D/P,t}. \quad (6)$$

Now, the hypothesis is that γ_1 is positive, γ_2 is positive, and γ_3 is negative. This model, and the precisely corresponding model for E/P, is tested in the following section.[7] Other authors (e.g., Merton 1980; French, Schwert, and Stambaugh 1987) have tested the link between expected stock returns and volatility by examining the relationship between realized stock returns and *ex ante* measures of volatility.[8] However, as these authors noted, realized stock returns are a noisy proxy for expected stock returns. I believe that linking Equations 3, 4, and 5 and focusing on the long term will reveal a clearer relationship between stock market volatility and expected stock market returns as represented by stock market yield (D/P or E/P).[9]

Preliminary Evidence

To investigate Equation 6, I defined a generation as 20 years and used a simple rolling 20-year annualized monthly return volatility for $\sigma(\text{Stocks})$ and $\sigma(\text{Bonds})$.[10] The underlying argument is that each generation's perception of the relative risk of stocks and bonds is shaped by the volatility it has experienced. For instance, Campbell and Shiller (1998) mentioned (but did not necessarily advocate) the argument that Baby Boomers are more risk tolerant "perhaps because they do not remember the extreme economic conditions of the 1930s." Another example is Glassman and Hassett (1999), who argued in *Dow 36,000* that remembrances of the Great Depression have led investors to require too high an equity risk premium.

A 20-year period captures the long-term generational phenomenon that I hypothesized.[11] The hypothesis is inherently behavioral because it states that the long-term, slowly changing relationship between stock and bond yields is driven by the long-term volatility of stocks and bonds experienced by the bulk of current investors. Although I believe a 20-year period is intuitively reasonable, given the hypothesis, I am encouraged by the fact

that the results that follow are robust to alternative specifications of long-term volatility (i.e., from 10-year to 30-year trailing volatility) and still showed up significantly when windows as short as 5 years were used.

The regressions in this section are simple linear regressions that do not account for some significant econometric problems; for example, the following regressions have highly autocorrelated independent variables, dependent variables, and residuals. But the goal of these regressions is to initially establish the existence of an economically significant relationship. Because statistical inference is problematic, I do not focus on (but do report) the *t*-statistics. The focus is on the economic significance of the estimated coefficients and R^2 figures. (Subsequent sections explore the issue of statistical significance and report robustness checks.)

Because I required 20 years to estimate volatility and the monthly data began in 1926, I estimated Equation 6 by using monthly data from January 1946 through May 1998. Before examining this equation in full, I first examine the regression of D/P on bond yields only and D/P on the rolling volatility of stock and bond markets only for the 1946–98 period (the first data points are dividend and bond yields in January 1946 and stock and bond volatility estimated from January 1926 through December 1945; the *t*-statistics are in parentheses under the equations. The results are as follows:

$$D/P = 4.10\% - 0.03Y \quad (7)$$
$$(40.72) \quad (-2.26)$$

(with an adjusted R^2 of 0.7 percent) and

$$D/P = 2.02\% + 0.14\sigma(\text{Stocks}) - 0.07\sigma(\text{Bonds}) \quad (8)$$
$$(11.87) \quad (18.96) \quad (-5.24)$$

(with an adjusted R^2 of 43.0 percent).[12]

Equation 7 shows that D/P and Y have a mildly negative relationship for 1946–1998, similar to what I found for the entire 1926–98 period (Table 1). Equation 8 shows that a significant amount of the variance of D/P (note the adjusted R^2) is explained by stock and bond volatility, with D/P rising with stock market volatility and falling with bond market volatility. This relationship is economically significant. An increase in stock market volatility from 15 percent to 20 percent, all else being equal, raises the required dividend yield on stocks by 70 basis points (bps). Now, note the estimate for Equation 6:

$$D/P = 0.00\% + 0.35Y + 0.23\,\sigma(\text{Stocks}) - 0.31\sigma(\text{Bonds}) \quad (9)$$
$$(-0.05) \quad (28.77) \quad (39.51) \quad (-25.69)$$

(with an adjusted R^2 of 75.4 percent).

This result supports the hypothesis. The dividend yield is mildly negatively related to the bond yield when measured alone (Equation 7), but this

negative relationship is a highly misleading indicator of how stock and bond yields covary. When I adjusted for different levels of volatility, I found stock and bond yields to be strongly positively related. My interpretation of this regression is that stock and bond market yields are strongly positively related and the difference between stock and bond yields is a direct positive function of the weighted difference between stock and bond volatility. Intuitively, the more volatile stocks have been versus bonds, the higher the yield premium (or smaller a yield deficit) stocks must offer. In any case, when volatility is held constant, stock yields do rise and fall with bond yields.

Again, these results are economically significant. For example, a 100 bp rise in bond yields translates to a 35 bp rise in the required stock market dividend yield, whereas a rise in stock market volatility from 15 percent to 20 percent leads to a rise of 115 bps in the required stock market dividend yield.

The fact that stock and bond yields are univariately unrelated (or even negatively related) over long periods (Table 1) is a result of changes in relative stock and bond volatility that obscure the strong positive relationship between stock and bond yields. The reason stock and bond yields are univariately positively related over shorter periods (e.g., 1960–1998) is because of the stable relationship between stock and bond volatility over short periods. In other words, a missing-variable problem is not much of a problem if the missing variable was not changing greatly during the period being examined (such as in 1960–1998). The problem is potentially destructive, however, if the missing variable varied significantly during the period (such as in 1927–1998).

Figure 3 presents the actual market D/P and the in-sample D/P fitted from the regression in Equation 9. **Figure 4** presents the residual from this regression (actual D/P minus fitted D/P). For today's reader, perhaps the most interesting part of Figures 3 and 4 is the latest results. The actual D/P at the end of May 1998 (the last data point) is 1.5 percent, a historic low. The forecasted D/P is also at a historic low, however—2.1 percent—which is a forecasting error of only 60 bps.

Simply examining the D/P series leads to a belief that recent D/Ps are shockingly low. These regressions suggest a different interpretation: Given the recent low bond yields and a low realized differential in volatility between stocks and bonds, I would forecast an all-time historically low D/P for stocks as of May 1998. The fact that the model does not forecast the actual low in dividend yield is not statistically anomalous (May's forecast error is about 1 standard deviation below zero) and may be a result of the stories other authors have cited to explain today's low D/P (e.g., stock buy-backs

Figure 3. Actual S&P 500 Dividend Yield and In-Sample Dividend Yield, January 1946–May 1998
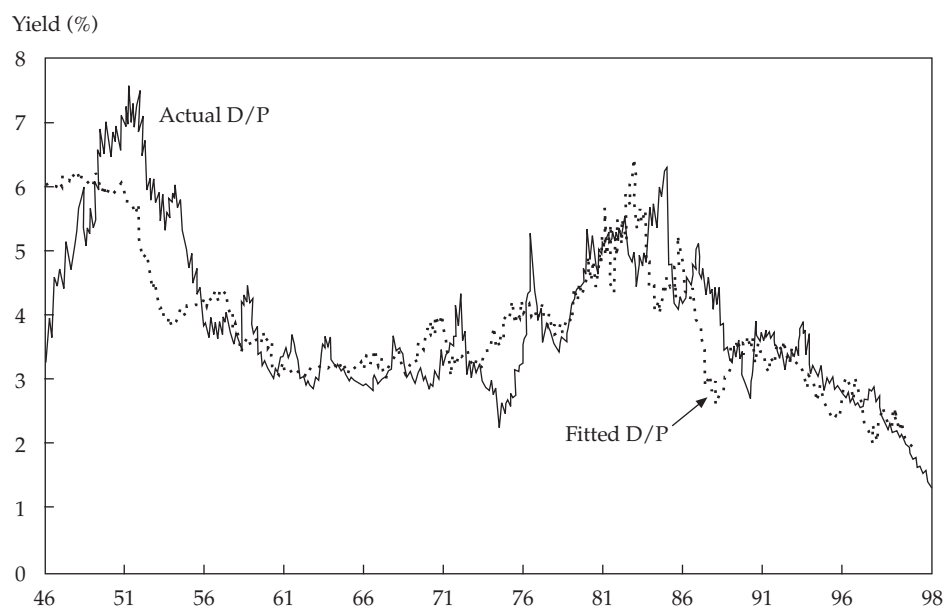
Note: In-sample D/P fitted from the regression in Equation 9.

Figure 4. Regression Residual: Actual D/P minus Fitted D/P, January 1946–May 1998
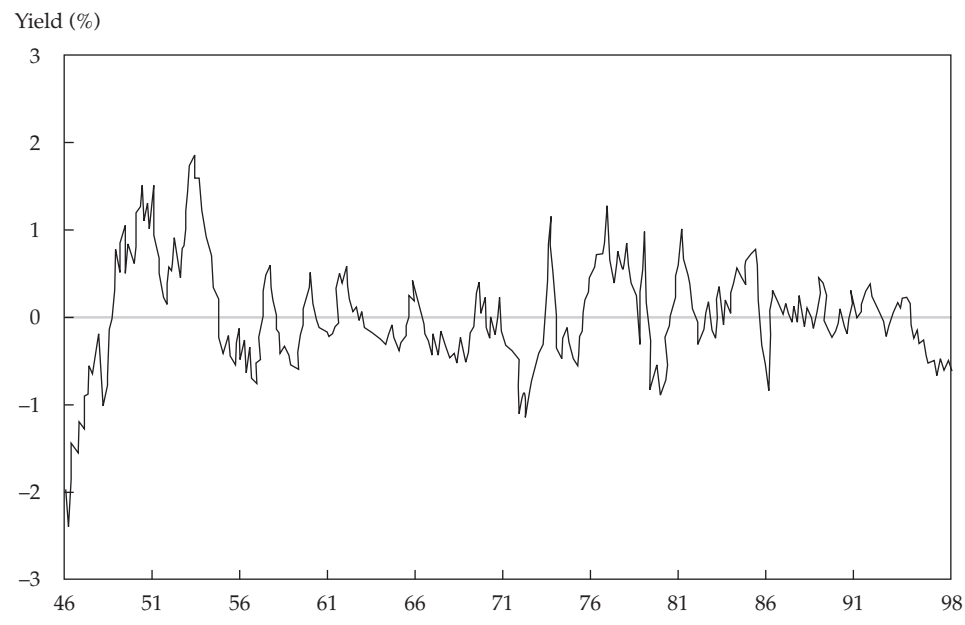
replacing dividends). But these stories might not be at all necessary. For example, the story of stock buybacks replacing dividends has been around since at least the late 1980s (Bagwell and Shoven 1989), yet the average in-sample forecasting error of my model for D/P for 1990–1998 is only –9 bps. Apparently, nothing more than Equation 9 is needed to explain recent low dividend yields.

Running a similar regression for E/P, I obtained the following result:

$$E/P = -1.39\% + 0.96Y + 0.49\sigma(\text{Stocks}) - 0.76\sigma(\text{Bonds}) \quad (10)$$
$$(-3.70) \quad (27.33) \quad (29.58) \qquad (-21.56)$$

(with an adjusted R^2 of 64.8 percent). The model explains about as much of the variance for earnings yield as dividend yield. As of the end of May 1998, the E/P for the S&P 500 was 3.6 percent, corresponding to a P/E of 27.8. The forecasted E/P from the Equation 10 regression is 3.4 percent, or a forecasted P/E ratio of 29.1. Unlike the case for D/P, I am not (even to a small degree) failing to explain the recent high P/Es on stocks; rather, one would have to explain the opposite, because according to the model, the May 1998 P/E of 27.8 is slightly *lower* than it should be.

Again, these results are economically significant: The required earnings yield was moving virtually one-for-one with 10-year T-bond yields and increasing 245 bps for each 5 percent rise in stock market volatility (all else being equal). Examining Figure 2 and Table 1 shows that E/P and Y were strongly positively correlated only for the later period of the sample (in the earlier period, they were actually negatively correlated, and for the whole period, they were close to uncorrelated). When changing stock- and bond-market volatility is accounted for in Equation 10, however, the strong positive relationship between E/P and Y is extended to the full period.

Critique and Further Evidence

The regression results presented in the previous section fit intuition and the hypothesis as formalized in Equation 6, but they are certainly open to criticism. They are in-sample regression results and are thus particularly open to charges of data mining. They are level-on-level regressions, which renders the *t*-statistics invalid and makes the high R^2 figures potentially spurious.[13] Worse, they are level-on-level regressions that use 20-year rolling data and a highly autocorrelated dependent variable.[14] Because the inference is suspect, stock and bond volatility may have followed a pattern that explained a secular-level change in dividend and earnings yield merely by chance.

To examine this possibility, **Figure 5** shows the rolling 20-year volatilities of the stock and bond markets used in the preceding regressions and the ratio of stock to bond volatility. Aside from the very early and very late years of the period, the ratio of rolling 20-year stock volatility to bond volatility was dropping nearly monotonically from 1946 through mid-1998. Thus, a hypothesis that fits the regression results and Figure 5 is that stock yields and bond yields are positively related but, exogenous to this relationship, the level of stock yields has been declining over time.

Figure 5. Rolling 20-Year Volatilities of Stock and Bond Markets and Ratio of Stock to Bond Volatility, January 1946–May 1998
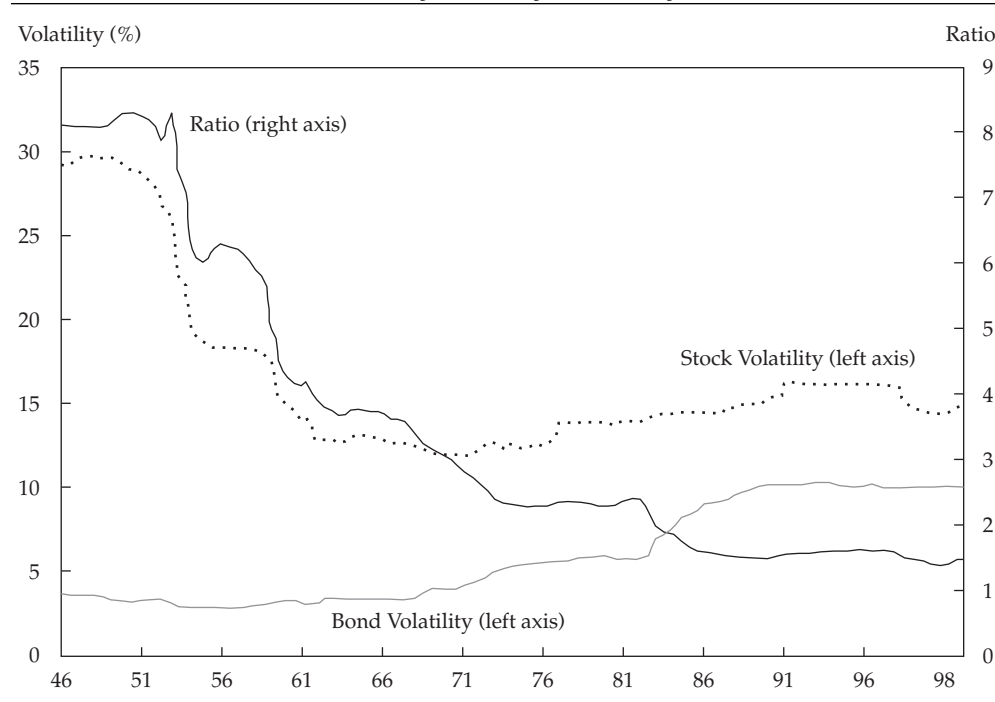
The issue is one of causality. Was the drop in the level of stock yields versus that of bond yields occurring because of changes in their relative experienced volatilities (as I hypothesize), or were other factors causing this drop through time and thus producing spurious regression results? A 50-year regression that uses 20-year rolling data makes answering this question difficult. So, the next subsections attempt to explore this critique.

Performance of the Model versus a Time Trend. If the drop in stock yields versus bond yields is coincidentally, not causally, related to volatility, then a time trend might do as well as volatility in the regression tests. For ease of comparison, recall the results for D/P regressed on bond yields and stock and bond volatility; Equation 9 was

$$D/P = 0.00\% + 0.35Y + 0.23\,\sigma(\text{Stocks}) - 0.31\sigma(\text{Bonds}),$$
$$(-0.05)\quad (28.77)\quad (39.51)\qquad (-25.69)$$

and the adjusted R^2 was 75.4 percent. The next equations report similar regressions in which, instead of stock and bond volatility, either a linear or loglinear time trend was used:

$$D/P = 6.18\% + 0.25(Y) - 0.00(\text{Linear trend})\qquad (11)$$
$$(51.44)\quad (14.69)\quad (-21.97)$$

(with an adjusted R^2 of 43.8 percent) and

$$D/P = 27.97\% + 0.33(Y) - 0.04(\text{Loglinear trend})\quad (12)$$
$$(32.32)\quad (19.88)\quad (-27.61)$$

(with an adjusted R^2 of 55.1 percent).

The time-trend variables capture much of the effect being studied. That is, the relationship between D/P and Y goes from weakly negative (Equation 7) to strongly positive in the presence of the trend variable—meaning that the expected difference between stock and bond yields was declining through time and, after accounting for this trend, stock and bond yields were positively related. The volatility-based regression, however, is clearly the strongest: The adjusted R^2 is higher, and the coefficient on bond yields is larger and more significant.

Next, the loglinear time trend is added to Equation 9 to see how the volatility variables fare in head-on competition:

$$D/P = -10.00\% + 0.35Y + 0.28\sigma(\text{Stocks})\qquad (9a)$$
$$(-3.98)\quad (28.50)\quad (19.63)$$

$$- 0.46\sigma(\text{Bonds}) + 0.02(\text{Loglinear trend})$$
$$(-11.87)\qquad\qquad (3.99)$$

(with an adjusted R^2 of 76.0 percent).

Clearly, the volatility variables drive out the time trend (analogous results held for the linear time trend) to the point at which the trend's coefficient is slightly positive (the wrong sign). Although the nearly monotonic fall in bond versus stock volatility makes it hard to distinguish between causality and coincidence for the 1946–98 period, the superiority of the volatility-based model over a time trend gives comfort. Analogous results favoring the volatility model were found for E/P.

Rolling Regression Forecasts. I formed rolling out-of-sample forecasts of D/P starting with January 1966. (I began in 1966 because I needed the 20 years from 1926 to 1946 to estimate volatility and the 20 years from 1946 to 1966 to formulate the first predictive regression.) The regressions used an "expanding window" that always started in January 1946 and went up to the month before the forecast.

For comparison purposes, I formed these forecasts based on five models. Model 1 attempted to forecast D/P by using only the average D/P (so the forecast of D/P on January 1966 was the average D/P from January 1946 through December 1965). Model 2 attempted to forecast D/P by using a rolling regression on bond yields only. Model 3 used a rolling version of the complete model from Equation 9 (a regression on bond yields, stock volatility, and bond volatility). Model 4 and Model 5 corresponded to rolling versions of, respectively, the linear trend model in Equation 11 and the loglinear trend model in Equation 12. **Table 2** presents the results of these out-of-sample forecasts.

The volatility-based Model 3 was nearly unbiased over the 1966–98 period, had the lowest absolute bias of any of the five models, and had the lowest standard deviation of forecast error. The out-of-sample rolling regressions thus support the superiority of the volatility model, although again, the time-trend models are somewhat effective when compared with the more naive Models 1 and 2.

Earlier Data. The best response to many statistical problems is extensive out-of-sample testing—that is, tests with data for a previously unexamined period. All of the tests so far used monthly data for the commonly studied period commencing in 1926. For the tests reported in this section, I used earlier data. Although perhaps not as reliable as the modern data, annual data on the aggregate stock and bond markets are available for as early as 1871.[15]

In addition to simply using new data points, examining the older information provides an advantage that is specific to this study. In **Figure 6**, the new data are used to plot the ratio of rolling 20-year stock market volatility to rolling 20-year bond market volatility over the entire 1891–1998 period.[16]

Table 2. Out-of-Sample Forecasts, January 1966–May 1998

Model	Average Forecasting Error	σ(Forecasting error)
1. Using average D/P	–0.56%	0.97%
2. Using regression on Y	0.29	1.38
3. Using the full model	0.14	0.50
4. Using linear time trend	0.71	0.66
5. Using loglinear time trend	0.54	0.62

Figure 6. Ratio of Rolling 20-Year Stock Market Volatility to Bond Market Volatility, January 1891–May 1998
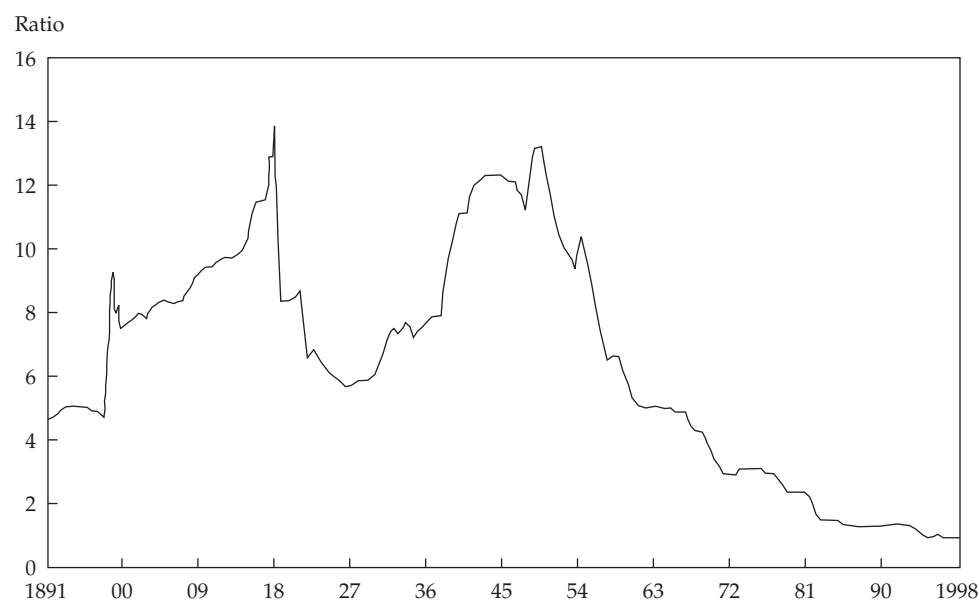
Recall that one problem with testing the hypothesis for 1946–1998 was that the volatility ratio declined nearly monotonically. Figure 6 shows that the new data preserve this property for this same time period but that the 1891–1945 period reflects no monotonic trend. Thus, if the model works for 1891–1945, or 1891–1998, a spurious time trend is not driving the results. I found that dividend yields also trended down strongly over the 1946–98 period but appear much more stationary when viewed over the entire 1891–1998 period (this figure is available upon request).

As a data check, before examining the pre-1946 data, I reexamined the 1946–98 period with the new annual data set. The following are *annual* regressions for the already-studied 1946–98 period:

$$D/P = 4.12\% - 0.04Y \qquad (13)$$
$$(10.78) \quad (-0.65)$$

(with an adjusted R^2 of –1.1 percent);

$$D/P = -1.15\% + 0.29Y + 0.24\sigma(\text{Stocks}) \qquad (14)$$
$$(-1.64) \quad (6.07) \quad (8.03)$$
$$- 0.16\sigma(\text{Bonds})$$
$$(-4.88)$$

(with an adjusted R^2 of 66.0 percent;

$$E/P = 6.98\% + 0.13Y \qquad (15)$$
$$(7.57) \quad (0.95)$$

(with an adjusted R^2 of –1.8 percent);

$$E/P = -3.12\% + 0.85Y + 0.46\sigma(\text{Stocks}) \qquad (16)$$
$$(-1.64) \quad (6.07) \quad (8.03)$$
$$- 0.40\sigma(\text{Bonds})$$
$$(-4.88)$$

(with an adjusted R^2 of 48.9 percent).

Although not precisely the same as the monthly regressions presented earlier, the annual regressions on the new data set are similar enough to be encouraging.

Now, consider the results for these same regressions for the earlier 1891–1945 data:

$$D/P = 2.60\% + 0.77Y \qquad (17)$$
$$(2.70) \quad (2.72)$$

(with an adjusted R^2 of 10.6 percent);

$$D/P = -1.65\% + 1.36Y + 0.19\sigma(\text{Stocks}) \qquad (18)$$
$$(-1.18) \quad (5.00) \quad (4.75)$$
$$- 0.53\sigma(\text{Bonds})$$
$$(-2.10)$$

(with an adjusted R^2 of 35.7 percent);

$$E/P = 4.20\% + 1.06Y \qquad (19)$$
$$(2.20) \quad (1.90)$$

(with an adjusted R^2 of 4.6 percent);

$$E/P = 2.90\% + 1.68Y + 0.25\sigma(\text{Stocks}) \qquad (20)$$
$$(1.05) \quad (3.13) \quad (3.15)$$
$$- 2.23\sigma(\text{Bonds})$$
$$(-4.50)$$

(with an adjusted R^2 of 31.5 percent).

These regressions provide bad news and good news. The bad news is that some of the regression coefficients are very different for the 1891–1945 period from what they were for the 1946–98 period. Apparently, the (admittedly simple) model is not completely stable over time. Given changes in the world economy from 1871 to 1998, to think that the coefficients would be completely stable is perhaps wildly optimistic.[17] The good news is that, although over the 1891–1945 period the stock market's D/P and E/P were univariately weakly positively related to Y (see Equations 17 and 19), this relationship became much more strongly positive when I allowed for changing relative stock and bond market volatilities (as in the completely separate 1946–98 period). This relationship was, as my hypothesis forecasted, a strong positive function of the previous 20 years' relative stock versus bond volatility.

Finally, I present the regressions for D/P for the full 1891–1998 period. For comparison, I also present full-period tests of the time-trend variables (the E/P results were highly analogous for all regressions):[18]

$$D/P = 5.20\% - 0.14Y \qquad (21)$$
$$(17.79) \quad (-2.53)$$

(with an adjusted R^2 of 4.8 percent);

$$D/P = 5.90\% + 0.03Y - 0.00\text{Linear trend} \qquad (22)$$
$$(17.32) \quad (0.42) \quad (-3.54)$$

(with an adjusted R^2 of 14.1 percent);

$$D/P = 7.75\% - 0.06Y - 0.07\text{Loglinear trend} \qquad (23)$$
$$(6.09) \quad (-0.91) \quad (-2.06)$$

(with an adjusted R^2 of 7.6 percent);

$$D/P = 1.98\% + 0.26Y + 0.14\sigma(\text{Stocks}) \qquad (24)$$
$$(2.96) \quad (3.52) \quad (4.95)$$
$$- 0.29\sigma(\text{Bonds})$$
$$(-5.65)$$

(with an adjusted R^2 of 35.5 percent).

The earlier data and the full-period data strongly support the central tenet of the hypothesis: Without adjusting for volatility and with or without a time trend (Equations 21–23), either a negative or flat relationship appears between D/P and bond yields over the entire period. After adjustment for relative stock and bond volatility, this relationship is strongly positive (Equation 24). Unlike the 1946–98 results, these results are clearly present in the absence of a significant trend in the

ratio of stock to bond market volatility and despite any changes in the world economy from 1871 to 1998. In fact, unlike the volatility-based model, the time trends utterly fail to resurrect the positive relationship between stock and bond yields over the full period. When I used the data for 1946–1998, I introduced the issue of distinguishing whether the volatility-based model was spuriously supported because the changes in relative volatility approximated a time trend. The earlier and full-period evidence powerfully indicates that it is the time trend whose efficacy is spurious for 1946–1998, not the volatility-based model.

Full-Period Scatter Plots. As a final and perhaps most compelling test, I examined nonoverlapping 20-year periods from 1878 until 1998. I report the results for the resulting six observations in **Figure 7**. Figure 7 plots the ratio of annualized monthly stock market volatility over corresponding monthly bond volatility for the 20 years ending before the labeled year against the excess of stock market earnings yields over bond yields for the year in question. I chose earnings yields for this investigation because the evidence is that they are directly close to being comparable to bond market yields whereas dividend yields move as a dampened function of bond yields (that is, the coefficient on Y in Equation 10 is nearly 1.0, which makes the simple difference relevant to examine).

Figure 7 clearly supports the model: The greater stock volatility is versus bond volatility, the higher E/P must be versus Y. In contrast to the earlier regression tests, which were admittedly an econometric nightmare, nonoverlapping observations were used for Figure 7, and the autocorrelation of both the dependent and independent series was close to zero.[19] Thus, any need for econometric corrections (e.g., first differencing) was avoided.

The problem now is that I have only six observations, so the tests might lack power, but this is not the case. The t-statistic of the regression line is +7.64, and the adjusted R^2 is 92.0 percent. With six observations, a t-statistic must exceed +2.45 to be significant at a p value of 2.5 percent in a one-tailed test. Clearly, the t-statistic for this test is well past this level of significance.

As a robustness check, I recreated Figure 7 but starting 10 years later (resulting in only five observations over this period). The results are in **Figure 8**. This figure is even more striking than Figure 7 (the t-statistic in Figure 8 is +12.46, and the adjusted R^2 is 97.5 percent). Note from Figure 6 (the graph of the rolling volatility ratio) that two peaks are visible in the ratio of stock to bond volatility. These peaks roughly correspond to the right side of, respectively, Figures 7 and 8. In both cases, the model fits these extreme observations exceptionally well (that is, the largest volatility ratio corresponded to the largest end-of-period gap of stock earnings yield over bond yield). Also note that these two periods (the 20 years ending in 1918 and the 20 years ending in 1948) share no overlapping observations, yet the model fits both perfectly.

Figure 7. Ratio of Annualized Monthly Stock Market Volatility to Corresponding Monthly Bond Volatility versus Excess of Stock Market Earnings Yield over Bond Yield, 1871–May 1998
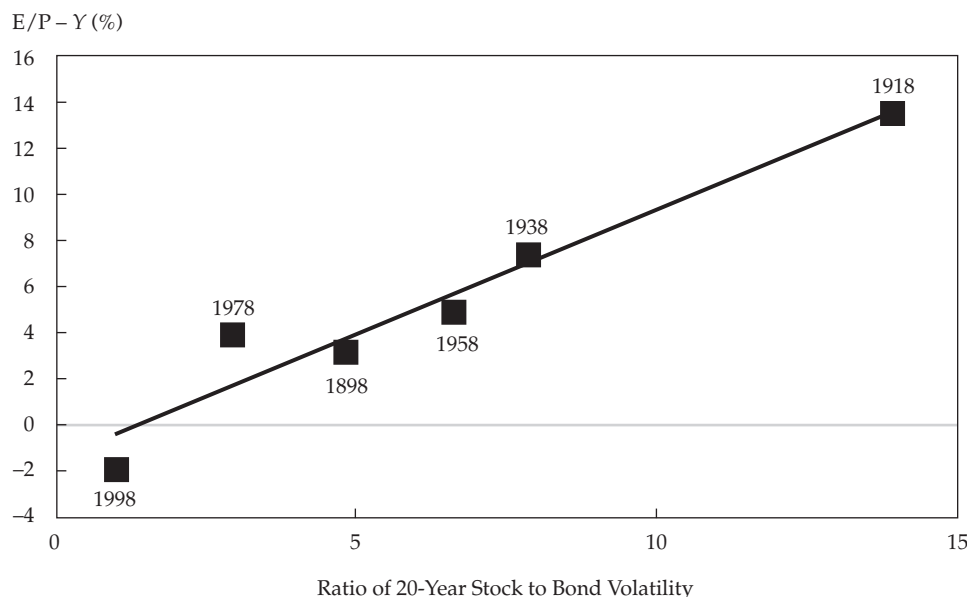
Figure 8. Ratio of Annualized Monthly Stock Market Volatility to Corresponding Monthly Bond Volatility versus Excess of Stock Market Earnings Yield over Bond Yield, 1881–May 1998
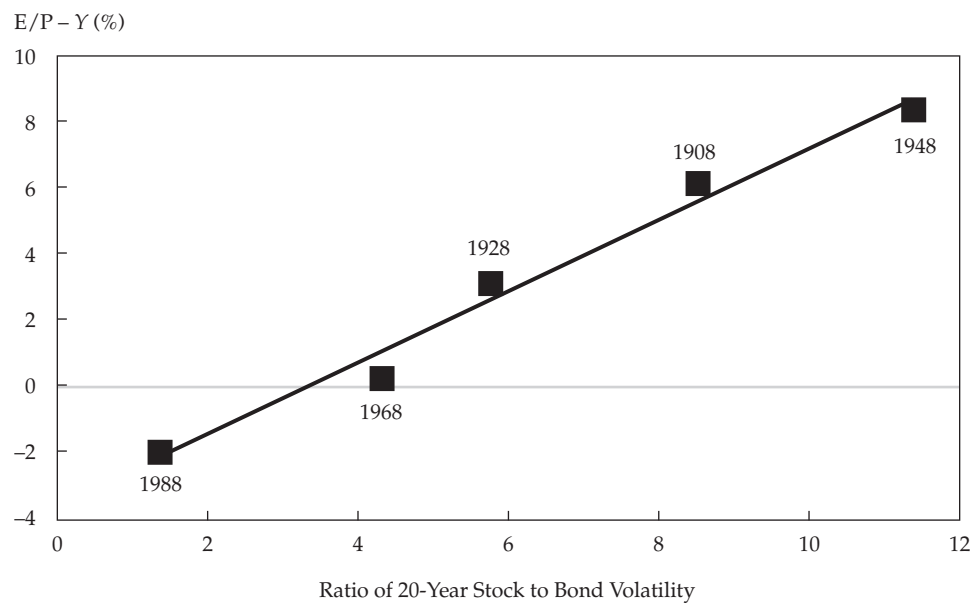
Finally, for completeness, I present in **Table 3** the adjusted R^2 and *t*-statistics for each of eight possible regressions on nonoverlapping periods for which I have six 20-year data points (each row in Table 3 presents the results of a regression that differs by one year in its starting and ending point from the prior/next row). Only one of these eight regressions produced results well below traditional levels of significance, and even in this case, the sign is correct.[20]

We believe these nonoverlapping tests are compelling evidence, irrespective of the econometric problems with our earlier tests, that following long-term periods of high (low) stock market volatility relative to bond market volatility, the required yield on stocks is relatively high (low) versus bonds.

Table 3. Statistics for Eight Regressions

Period	Adjusted R^2	*t*-Statistic
1891–1991	88.5%	+6.28
1892–1992	73.7	+3.87
1893–1993	81.0	+4.72
1894–1994	45.6	+2.28
1895–1995	9.9	+1.25
1896–1996	91.5	+7.42
1897–1997	78.3	+4.36
1898–1998	92.0	+7.64
Mean	70.1	+4.73
Median	79.7	+4.54

Note: Each row presents the results of a regression that differs by one year in its starting and ending point from the prior/next row.

Market Predictability

Researchers have found that variables D/P and E/P have power to forecast aggregate stock market returns. Moreover, this power appears to increase as time horizon lengthens (e.g., Fama and French 1988, 1989). I tested this finding for 1946–1998 using predictive regressions of excess monthly and annualized 5- and 10-year compound S&P 500 returns on aggregate D/P (*t*-statistics on all multiperiod regressions were adjusted for overlapping observations and heteroscedasticity). Here are the findings:

$$\text{S\&P monthly return} = -0.56\% + 0.32\text{D/P} \qquad (25)$$
$$(-1.03) \quad (2.38)$$

(with an adjusted R^2 of 0.7 percent);

$$\text{S\&P 5-year return} = -4.13\% + 4.09\text{D/P} \qquad (26)$$
$$(-0.88) \quad (4.77)$$

(with an adjusted R^2 of 56.1 percent);

$$\text{S\&P 10-year return} = -1.443\% + 3.22\text{D/P} \qquad (27)$$
$$(-0.38) \quad (4.34)$$

(with an adjusted R^2 of 58.7percent).

Equations 25–27 verify the findings of other authors that D/P has weak, but statistically significant, power for forecasting monthly returns and strong statistically significant power for forecasting longer-horizon returns.

Now, a new predictive variable, D/P(Error), is introduced. It is the in-sample residual term from the regression of D/P on Y, σ(Stocks), and σ(Bonds) for the 1946–98 period (Equation 9). It represents the

D/P on the S&P 500 in excess or deficit of what I would have predicted had I been using this model to forecast D/P (i.e., the unexplained portion). The results of the same regression tests as done for Equations 25–27 on this new variable are as follows (all results of this section were analogous when tested on E/P):

$$\text{S\&P monthly return} = 0.67\% + 1.75\,\text{D/P(Error)} \quad (28)$$
$$(4.29) \quad (6.74)$$

(with an adjusted R^2 of 6.6 percent);

$$\text{S\&P 5-year return} = 12.60\% + 4.65\,\text{D/P(Error)} \quad (29)$$
$$(6.50) \quad (3.00)$$

(with an adjusted R^2 of 21.2 percent);

$$\text{S\&P 10-year return} = 12.08\% + 2.01\,\text{D/P(Error)} \quad (30)$$
$$(5.64) \quad (1.35)$$

(with an adjusted R^2 of 7.1 percent).

Comparing the results for D/P(Error) with D/P shows that D/P(Error) has far more predictive power than D/P at short (monthly) horizons but far less power at longer horizons.[21] The power of D/P(Error) to forecast short-horizon returns can be interpreted as picking up time-varying risk aversion or, alternatively, as market mispricing (I leave this decision to future work). In either case, when D/P(Error) is high, stocks are selling for lower prices than is usual in the same interest rate and volatility environment and those low prices indicate higher short-horizon expected returns (and vice versa).

Finally, I formed D/P(Fit) as the fitted values from regression Equation 9. D/P(Fit) can be interpreted as the normal dividend yield as forecasted by the model considering the level of bond yields and stock and bond market volatility. By construction, the following relationship holds:

$$\text{D/P} = \text{D/P(Fit)} + \text{D/P(Error)}. \quad (31)$$

By regressing stock returns on both D/P(Fit) and D/P(Error), I decomposed the forecasting power of D/P into a portion coming from fitted D/P and a portion coming from residual D/P. The following regressions were carried out for 1946–98 data:[22]

$$\text{S\&P monthly return} = 1.25\% - 0.15\,\text{D/P(Fit)} \quad (32)$$
$$(2.07) \quad (-0.99)$$
$$+ 1.75\,\text{D/P(Error)}$$
$$(6.74)$$

(with an adjusted R^2 of 6.6 percent);

$$\text{S\&P 5-year return} = -2.80\% + 3.77\,\text{D/P(Fit)} \quad (33)$$
$$(-0.56) \quad (3.93)$$
$$+ 4.96\,\text{D/P(Error)}$$
$$(4.97)$$

(with an adjusted R^2 of 57.1 percent);

$$\text{S\&P 10-year return} = -3.00\% + 3.61\,\text{D/P(Fit)} \quad (34)$$
$$(-0.76) \quad (4.81)$$
$$+ 2.29\,\text{D/P(Error)}$$
$$(2.00)$$

(with an adjusted R^2 of 61.1 percent).

Clearly, the power of D/P for predicting short-run (monthly) S&P 500 returns is driven by D/P(Error). As horizon lengthens, D/P(Fit) becomes more and more important, and at the 10-year horizon, D/P(Fit) is considerably more important.

To examine even longer forecast horizons and over longer periods, I again used annual data back to 1871 and formed D/P(Fit) and D/P(Error) from Equation 24. Recall that the first 20 years are needed to estimate volatility, so the following regressions are for 1891–1998 (all returns are annualized compound returns):

$$\text{S\&P annual return} = 18.1\% - 1.46\,\text{D/P(Fit)} \quad (35)$$
$$(1.89) \ (-0.71)$$
$$+ 2.89\,\text{D/P(Error)}$$
$$(1.91)$$

(with an adjusted R^2 of 2.0 percent);

$$\text{S\&P 5-year return} = 5.32\% + 0.99\,\text{D/P(Fit)} \quad (36)$$
$$(0.59) \quad (0.51)$$
$$+ 2.32\,\text{D/P(Error)}$$
$$(3.67)$$

(with an adjusted R^2 of 12.2 percent);

$$\text{S\&P 10-year return} = -1.78\% + 2.43\,\text{D/P(Fit)} \quad (37)$$
$$(-0.21) \quad (1.43)$$
$$+ 0.81\,\text{D/P(Error)}$$
$$(1.89)$$

(with an adjusted R^2 of 12.4 percent);

$$\text{S\&P 15-year return} = -10.89\% + 4.24\,\text{D/P(Fit)} \quad (38)$$
$$(-3.91) \quad (9.72)$$
$$+ 0.18\,\text{D/P(Error)}$$
$$(0.43)$$

(with an adjusted R^2 of 33.7 percent);

$$\text{S\&P 20-year return} = -8.66\% + 3.74\,\text{D/P(Fit)} \quad (39)$$
$$(-2.36) \quad (5.58)$$
$$- 0.29\,\text{D/P(Error)}$$
$$(-2.08)$$

(with an adjusted R^2 of 42.2 percent).

The estimated coefficients of D/P(Fit) and D/P(Error) for each of the forecast horizons (regression Equations 35–39) are plotted in **Figure 9**. Although annual predictability (Equation 35) is weak, the short-term predictability present is clearly driven by D/P(Error). The story changes dramatically as horizon increases, until at long

Figure 9. Estimated Coefficients of D/P(Fit) and D/P(Error) for Each Forecast Horizon, 1891–1998
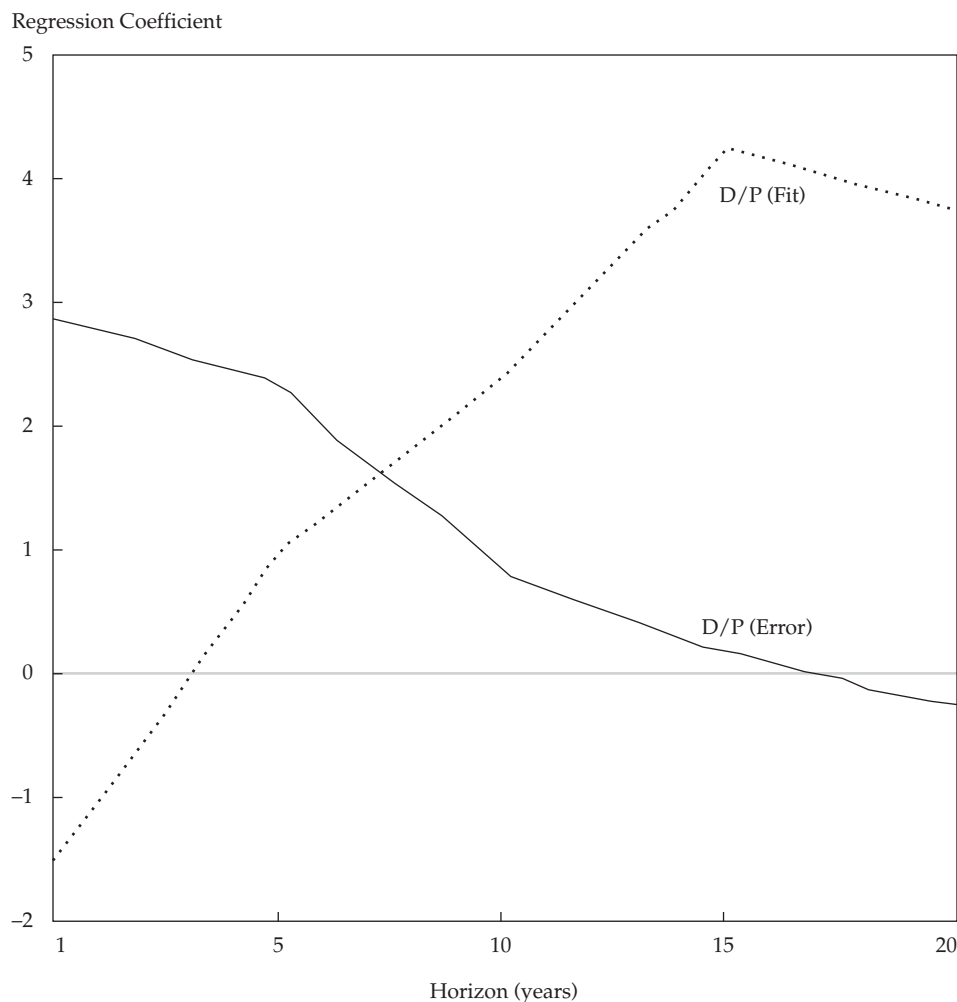
Note: All returns are annualized compound returns.

horizons (15 years and 20 years), D/P(Fit) is clearly adding considerable predictive power whereas D/P(Error) is adding none. Figure 9 tells a clear story that at short horizons, D/P(Error) is what counts but at long horizons, what counts is D/P(Fit). (Analogous results held for E/P.)

To sum up, the forecasting power of D/P can be decomposed into the forecasting power of D/P(Fit) and D/P(Error). In the model, D/P(Fit) is the normal or expected dividend yield, and D/P(Error) is interpreted as the D/P in excess (or deficit) of normal. Evidence presented here indicates that D/P itself forecasts stock returns at both long and short horizons but for different reasons. D/P(Fit) forecasts long-horizon stock returns but has almost no power for the short term. D/P(Error) forecasts short-horizon stock returns but has little power for the long term.

Do Stock Yields Have Farther to Fall?

Many have wondered lately why the market is currently selling at such a historically low D/P and E/P (or high P/D and P/E). In particular, in the book *Dow 36,000*, Glassman and Hassett came to an extreme conclusion. They argued that the reason stock prices seem so high relative to measures such as dividends and earnings is that the expected (or required) return on the stock market is going down as investors realize that the stock market is less risky in relation to the bond market than previously thought. Furthermore, they reasoned that this fall in expected returns is not over yet and concluded that it will not stop until stock and bond market expected returns are equal (a point at which, by their calculations, the Dow will reach approxi-

mately 36,000). Part of their reasoning sounds much like the arguments advanced here. Well, part of it is, and part of it is not.

Their first conclusion is 100 percent consistent with this article: the conclusion that stocks have low yields now because they are perceived to be less risky versus bonds than historically normal. In fact, my central thesis is that the return required by investors to own stocks versus bonds varies directly with the perceived relative risk of the two assets (for which I used their respective rolling 20-year volatilities as proxies). I believe that my model, coupled with currently low bond market yields and a low perceived risk of stocks versus bonds, entirely explains, within the bounds of statistical error, today's low yields on stocks (and, according to the model, the low long-term expected returns that come with low yields). Thus, my work strongly supports one aspect of the argument in *Dow 36,000*, namely, that stock market expected returns versus bonds have come down as investor perceptions of the relative risk of stocks versus bonds have changed.

My conclusions differ, however, from the next conclusion of *Dow 36,000*. Glassman and Hassett extrapolated the trend in lowered return-premium expectations to continue, but my model offers them no support. The authors of *Dow 36,000* stated that the fall in stock expected returns is not over yet and will not be complete until the expected return on stocks is the same as bonds (presumably not yet the case) because the authors believe that stocks are no riskier than bonds in the long term. This hypothesis is quite provocative. If stocks are no riskier than bonds, then stock prices should rise as investors realize stocks are currently priced as if they are more risky. Now, much debate involves the long-run risk of stocks versus bonds, and to review or settle this matter is not the province of this paper.[23] However, much of the reason behind the current prominence of this debate in the first place is how different today appears from the past (i.e., today's historically high stock prices versus dividends or earnings). My conclusion is that, in fact, the structure of the world really is not much different today; only the inputs to the model have changed. In other words, stock yields (and required returns) have always moved with bond yields, and the relative difference between them has always been a function of their relative perceived volatility. In fact, when I directly estimated this relationship, I found that it fits well for the long term and fits well today.

The reason the study reported here is a problem for theories like those proposed in *Dow 36,000* is that I say the rise in stock prices today, rather than simply beginning as investors start to perceive how safe stocks really are, is actually proceeding much as it has throughout financial history. According to the model, investors have repriced stocks to reflect a lower perception of stock market risk, but any farther drop in the required return on stocks (and concurrent rise in stock prices) must come from a further reduction in actual stock volatility (versus bond volatility) or a reduction in bond yields. If investors have been all along implicitly using the relationship hypothesized here to price stocks (as the data strongly support they have since at least 1891), then they have acted consistently in recently raising the price of equities. But we can expect no more such rises unless either interest rates or realized relative volatility change.[24] The model discussed here suggests that unless the inputs to the model change, any repricing of equities is approximately complete.

Finally, if the model is accurate, a belief that a near-term windfall profit of about three times your money is currently available in the broad stock market, a belief held by Glassman and Hassett, is dangerous. First, investors who believe in the windfall possibility may overallocate to stocks.[25] Second, short-term pricing errors induced by believers in this argument (or "bubbles") can be dangerous to the real economy. Third, and perhaps most worrisome, if the model presented and tested in this paper is correct, the belief that stocks stand to receive a one-time enormous windfall profit is not simply wrong, it is backward. The low stock yields of today are fully explained by the model, meaning that the forecast of short-term stock returns is about average.[26] Moreover, if the conclusion here is true that the best forecasting variable for long-term stock returns is the absolute level of stock yields, then today's low yields (both D/P and E/P) point to a poor forecast for the long-term return on stocks.

Conclusion

Each of the puzzles stated at the beginning of this article can be resolved by using the model provided in Equation 6 for the required yield on stocks. Consider the first question: Why did the stock market strongly outyield bonds for so long only to now consistently underyield bonds? The model states that (1) the higher bond yields are and (2) the higher perceived stock market volatility versus bond market volatility is, then the higher stock yields must be. For a long time (before the 1950s), stocks outyielded bonds because the realized volatility of stocks versus bonds was much higher than in modern times.

Consider the second question: Why did stock and bond yields move relatively independently, or

even perversely, in the 1927–98 period but strongly move together in the later 40 years of this period? Stock and bond yields appear to move independently or even perversely over long periods (e.g., 1926–1998), but this appearance is an artifact of missing a part of their structural relationship. If the impact of changing volatility is taken into account, stock and bond yields are strongly positively correlated over the entire period for which we have data, which many strategists and economists would have hypothesized.

Finally, consider the third question: Why are today's stock market yields so low and what does that fact mean for the future? Today's stock market yields are so low simply because bond yields are low and recent realized stock market volatility has been low when compared with bond market volatility. I do not need to resort to "the world has changed" types of arguments to explain today's low yields. The model fully explains them. And the model indicates that they will not go much lower unless realized stock versus bond volatility or interest rates fall farther.

Although testing a long-term, slowly changing relationship has statistical difficulties, the model easily survived every reasonable robustness check, including out-of-sample testing of a previously untouched period (1871–1945) and the formation of completely nonoverlapping, nonserially correlated independent and dependent variables for the entire 1871–1998 period.

This work has strong theoretical implications. A link between volatility and expected return is one of the strongest implications of modern finance.[27] Researchers have found compelling evidence of this phenomenon in comparing asset classes (i.e., stocks versus bonds), but evidence of a link *within* asset classes (e.g., testing the capital asset pricing model for stocks) or an intertemporal link within one asset class has been weak. This article addresses the intertemporal link. Past studies failed to convincingly link expected stock returns to *ex ante* volatility through realized stock returns.[28] However, realized stock returns are very noisy. I hypothesized that D/P (or E/P) is a proxy for expected stock returns and that Y is a proxy for expected bond returns and found strong confirmation that the difference between these proxies is a positive function of differences in experienced volatility. In other words, unlike many other studies, I have documented a strong positive intertemporal relationship between expected return and perceived risk.

This article demonstrated that the relative long-term volatility experienced by investors is a strong driver of the relative yields they require on stocks versus bonds; it did *not* show that these long-term realized volatility figures are accurate forecasts of future volatility. Thus, I have clearly identified a behavioral relationship that I believe is important, but I offer no verdict on market efficiency.[29]

The bottom line is that today's stock market (as of May 1998) has very low yields (D/P and E/P) for the simple reason that bond yields are low and stock volatility has been low as compared with bond volatility. These conditions historically lead investors to accept a low yield (and expected return) on stocks. If one is a short-term investor, knowing that these low yields are not abnormal may be comforting. A long-term investor, however, might be very nervous, because raw stock yields (D/P and E/P) are the best predictors of long-term stock market returns and these raw yields are currently at very low levels.

Notes

1. A set of assumptions sufficient for this equality to hold for coupon-bearing bonds is that the yield curve be flat and unchanging.

2. The sources and/or construction of the data for this article are as follows: For stocks, return and earnings yield data on the S&P 500 came from Datastream and dividend yields from Ibbotson Associates. For bonds, return data for January 1980 to May 1998 are from the J.P. Morgan Government Bond Index levered to a constant duration of 7.0 (i.e., the monthly return used is the T-bill rate plus 7.0 divided by the beginning-of-the-month J.P. Morgan duration times the return on the J.P. Morgan index minus the T-bill return). I constructed a constant-duration bond in the hopes of making my bond return series more homoscedastic. The choice of a duration of 7.0 was arbitrary and had no effect on the results. I performed the regression of this excess return series on the excess monthly return of the Ibbotson Associates long- and intermediate-term bond series for January 1980 to May 1998. For January 1926 to December 1979, I used the fitted values on the Ibbotson return series to approximate the 7.0-year duration J.P. Morgan government bond series. For bond yields, I used the 10-year benchmark yield from Datastream from January 1980 to May 1998. For January 1926 to December 1979, I used the fitted multiple regression forecast (fitted from the regression over the January 1980– May 1998 period) of the 10-year yield on the Ibbotson

short-, intermediate-, and long-term government bond series. The results are not sensitive to precise definitions of the bond yield or return.

3. The earnings yield I used is prior year's earnings over current price. All the economic results in this article are robust to using either a 3- or 10-year moving average of real earnings in the numerator.

4. Equation 3 almost assuredly should be augmented with variables proxying time-varying expected dividend growth (see Fama and French 1988). I have tested such proxies and found them to be statistically significant, but I omitted them from this article because they affect none of the results or conclusions significantly.

5. Bernstein (1993, 1997) examined a related (although slightly different) model and came to some of the same conclusions.

6. The results presented here were insensitive to assuming other reasonable functional forms for this relationship (for example, assuming linearity in the log of the volatilities rather than the levels).

7. Kane, Marcus, and Noh (1996) examined a related model for the first difference of market P/Es (a somewhat different exercise) and came to some conclusions similar to mine.

8. These studies used forms similar to Equation 5.

9. Another logical extension of Equations 3, 4, and 5 is $Y = c + e\text{T-bill} + d\sigma(\text{Bonds})$. That is, the yield on bonds moves (possibly at a multiple) with the short-term interest rate, and this weighted difference between long-term and short-term yields is a positive function of perceived bond volatility. Although not the focus of this article (but the focus of a future paper), empirical tests of this equation strongly support this specification.

10. This work is not sensitive to the definition of generation as precisely 20 years.

11. Note that I am not attempting to use the best short-term conditional estimate of volatility. Short-term changes in volatility may be mostly transitory. If so, they would have little impact on stock prices and required stock yields (see, for instance, Poterba and Summers 1986).

12. All R^2 values were adjusted for degrees of freedom.

13. Granger and Newbold (1974) found that in regressions of one random walk on another, rejection of the null hypothesis is more the rule than the exception. Also see Kirby (1997) or Goetzmann and Jorion (1993).

14. As mentioned previously, the results of this article are not very sensitive to the choice of a 20-year window for volatility. For instance, using a 10-year window for volatility estimation greatly reduced (but did not eliminate) the degree of autocorrelation in the right-hand variables. When I reestimate Equation 9 using 10-year rolling volatility (which also added 10 more years, 1936–1945, to the regression), the t-statistics did not materially change; the t-statistics on Y, $\sigma(\text{Stocks})$, and $\sigma(\text{Bonds})$ were, respectively, +10.00, +14.45, and –14.75. Using a 7-year window (now adding data from 1933–1945 to the regression), the t-statistics were +5.21, +11.54, and –10.93. A later section addresses this issue more directly by using longer-term data and analyzing nonoverlapping 20-year periods.

15. The sources for these data are Robert J. Shiller's Web page (an update of the data in Chapter 26 of Shiller 1989) and the company Global Financial Data.

16. These ratios are somewhat higher than reported in Figure 5 because the duration of the bond used in these annual tests was, on average, somewhat shorter than the duration of 7.0 years used in the monthly tests. Thus, bond volatility is somewhat lower in these annual tests. This change is only a matter of scale and has no economic effect on the tests.

17. For instance, Fama and French (1988) found that the parameters of the Lintner (1956) model for explaining dividend changes changed radically during the 1927–86 period.

18. As a final check, I reestimated Equation 24 using the Cochrane–Orcutt procedure to adjust for first-order auto-

19. correlation in the residuals. Each coefficient was essentially the same and remained statistically significant, whereas the first-order annual residual autocorrelation was highly statistically significant at 0.55.

19. This low autocorrelation matches the results of Poterba and Summers, who found only very short-term persistence in market volatility. Interestingly, I found that long-term rolling estimates of volatility seem to be crucial in determining the required expected return on the market but do not forecast the next period of long-term volatility itself. Thus, although investor perceptions of volatility drive market expected returns, those perceptions have not necessarily been accurate. My model might correctly describe investor behavior, but reconciling this behavior with market efficiency may be difficult (although not necessarily impossible). I leave this endeavor to future work.

20. In fact, the failure of the one regression (1895–1995) was driven by the 1975 observation (without this observation, the regression had an R^2 of 89.5 percent and a t-statistic of +5.93). Furthermore, by the luck of the draw, this regression did not include values for either the x or y variable as extreme as in Figures 7 and 8, which lowered the power of this test.

21. These regression results should not be considered an accurate test of a short- or long-term trading strategy. First, the regressions used D/P, which because it has price in the denominator, is known to induce a small bias toward finding a positive coefficient. The regressions also used the full-period data to form D/P(Error), which would not have been known prior to the end of the period. Finally, of course, the regressions do not account for trading costs. These regressions are meant to be indicative of the forecasting power of the model versus traditional models. Formal tests of a trading strategy based on these methods are not available from the author; trying to profit from such strategies is what I do for a day job.

22. These tests were carried out on in-sample regression residuals to retain the full 1946–98 period. Analogous significant results (although a bit weaker) were found for 1966–1998 when rolling out-of-sample versions of D/P(Fit) and D/P(Error) were used.

23. Two good sources for a scholarly but readable review of these issues are Siegel (1994) and Cornell (1999).

24. Glassman and Hassett did offer some reasons why stock volatility might be lower in the future than in the past, but their central argument does not need this farther drop to happen because their argument is that stocks are no more risky than bonds right now.

25. In all fairness, the actual practical investment advice in the book *Dow 36,000* appears quite reasonable, although it is still easy to see how an investor who believes in the authors' premise will not act so reasonably.

26. When this article was written, May 1998 data were the latest used. As of November 1999, the model's short-term forecast for stocks had joined the long-term forecast of stocks as below average, although not nearly as severely below average as the long-term forecast. I would be happy to provide a more up-to-date forecast and can be contacted at cliff.asness@aqrcapital.com. Of course, trade on such a forecast at your own risk!

27. This link does not need to hold precisely for inefficient portfolios.

28. An exception is Kane, Marcus, and Noh, who correctly pointed out that this relationship is much clearer in *ex ante* measures than in *ex post* returns.

29. Unfortunately, I also could not determine the rationality of the predictive power of D/P(Error) over short horizons and D/P(Fit) over long horizons. Modigliani and Cohn (1979) argued that when inflation (and presumably bond yields) is low, investors mistakenly (i.e., irrationally or inefficiently) overprice equities (and vice versa). The empirical results of this study support their hypothesis in one way: When volatility is held constant, investors do price stocks at higher P/Es and P/Ds when interest rates are low (and vice versa). This empirical finding is an important contribution, because more-naive tests (which fail to account for relative volatility changes) do not pick up this relationship. However, distinguishing whether the short-term predictive power of D/P(Error) or the long-term predictive power of D/P(Fit) is coming from such mispricing or rational variance in expected return (perhaps caused by changing risk aversion) is beyond the scope of this article.

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