Government Bonds and the Cross-Section of Stock Returns*

Malcolm Baker
Harvard Business School and NBER

Jeffrey Wurgler
NYU Stern School of Business and NBER

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* Corresponding Author: Malcolm Baker, Baker Library 261, Harvard Business School, Boston, MA 02163, phone: 617-495-6566, fax: 617-495-6198, email: mbaker@hbs.edu.

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Abstract

We study basic return comovement and predictability patterns in U.S. government bonds and the cross-section of stocks. Government bonds comove most strongly with bond-like stocks, i.e. stocks of large, mature, low-volatility, profitable, dividend-paying firms that are neither high growth nor distressed. Government bonds and bond-like stocks are also copredictable in the sense that time-series variables that predict returns on one asset class also predict returns on the other. In addition to traditional explanations for comovement and copredictability, the evidence is particularly consistent with the hypothesis that fluctuations in investor sentiment affect the demand for both bonds and bond-like stocks relative to the demand for speculative stocks.

I. Introduction

This paper examines some new and basic empirical links between government bond returns and the cross-section of stock returns. The motivation for the study is that bonds and stocks are typically studied in isolation, and when they are studied together, stocks are generally considered at only the aggregated index level. Yet, there are three non-exclusive reasons why stocks might differ in how they comove with government bonds.

One channel works through common shocks to real cash flows. Some stocks have real cash flows that more closely resemble those on bonds. For example, a business cycle contraction may be associated with lower inflation and rising bond prices. A contraction may also have less of an impact on real cash flows of stable, mature firms versus more speculative growth firms or already-distressed firms. If this is the case, then the stocks of stable, mature, and (informally) "bond-like" firms would be expected to comove relatively more strongly with bonds.

A second channel works through common shocks to rationally required returns. Bonds and certain stocks may experience common shocks to rational discount rates. Such shocks are the other cause of return comovement in efficient markets. For example, an increase in aggregate risk aversion increases the market risk premium and may lead to better performance of long-term bonds and the stocks of stable, mature firms than the stocks of more speculative firms. Similarly, holding the risk premium constant, the betas of government bonds may be more closely linked over time to the betas on stocks of stable, mature firms than to the betas of stocks of more speculative firms.

The third channel works through investor sentiment. Bonds and certain stocks may be affected by sentiment in similar ways. Baker and Wurgler (2006) find that stocks that are hard to value and hard to arbitrage, such as speculative growth firms and distressed firms, tend to be overpriced relative to other stocks when sentiment is high. Likewise, such stocks are relatively underpriced when sentiment is low. This idea can easily extend to include bonds. High sentiment may be associated with high demand for speculative stocks relative to demand for stable, mature firms *and* government bonds. Likewise, in the reverse direction, "flights to quality," such as those alleged in August 1998 and around other crashes and crises, may be best explained as dips in sentiment in which investors shift money toward what appear to be "safe" assets without a sophisticated eye to expected risks and returns.

We start by documenting an intuitive but apparently novel return comovement pattern between government bonds and the cross-section of stocks: government bonds comove much more strongly with "bond-like" stocks. That is, large stocks, long-listed stocks, low volatility stocks, stocks of profitable and dividend-paying firms, and stocks of firms with mediocre growth opportunities are more positively correlated with government bonds, controlling for overall stock market returns. Stocks of smaller, newly-listed firms, highly volatile stocks, and stocks of firms with extremely strong growth opportunities *or* those in distress, display a considerably lower correlation to bonds. The single most important characteristic governing a stock's comovement with bonds seems to be simply its total return volatility.

We then document new predictability patterns that further unify bonds and bond-like stocks. We focus on whether bonds and bond-like stocks are "copredictable" in the sense that they can be forecast by the same predictor. Such a pattern would be consistent with two out of the three channels outlined above—time-variation in rationally required returns, assuming the predictor captures a state variable related to risk premia; and, the correction of sentiment-driven mispricings, assuming the predictor captures the state of sentiment. We find clear evidence of such copredictability. The same yield curve variables often used to predict returns on bonds, such as the term spread (Fama and French (1989) and Campbell and Shiller (1991)) and combinations of forward rates (Cochrane and Piazzesi (2005)), also predict returns on bond-like stocks relative to more speculative stocks. Further, in the other direction, the sentiment index that Baker and Wurgler (2006) use to predict the relative returns on bond-like and speculative stocks also has predictive power for bond returns.

These empirical connections between bonds and bond-like stocks may reflect any or all of the three mechanisms outlined above. A complete, unambiguous attribution is not feasible. But for starters, the copredictability facts point to at least some role for either time-varying required returns or sentiment-induced mispricing. So, after documenting the main empirical patterns, we consider which of these two channels is more consistent with the data.

Several aspects of the data that suggest that sentiment is partly responsible for the link between bonds and bond-like stocks. The time-varying rationally required returns story would imply either time-varying betas or market risk premia. We test for time-varying market betas directly and find a change in the right direction, with betas of bond-like stocks falling when predicted bond returns are low. However, simple calibrations suggest that betas do not change by nearly enough to generate the observed magnitude of predictability with a constant market risk premium. The other possibility is a time-varying risk premium. But, variation in the market risk premium is also unable to explain our findings: Higher beta (or smaller, high-volatility, nonpaying, unprofitable) firms are often predicted to have *lower* returns than ostensibly lower-risk types of stocks.

Furthermore, we conduct a calibration in the spirit of Campbell and Thompson (2007), asking how much a rational investor could increase his average portfolio return by exploiting the observed degrees of predictability. The exercise suggests that bond returns appear to be too predictable to be consistent with rationality—although data mining remains a possibility. Finally, we factor analyze mutual fund flows as in Goetzmann, Massa, and Rouwenhorst (2000). The results are consistent with a sentiment or flight-to-quality factor in flows across fund categories, and presumably in small investor trading patterns more broadly. In particular, the second principal component of fund flows has positive loadings on speculative stock fund categories (growth, aggressive growth) but negative loadings on government bond funds and bond-like stock fund categories (income, income equity).

To summarize our findings, there are large cross-sectional differences in the relationship between government bonds and stocks; bonds are more like bond-like stocks than speculative stocks in terms of their comovement and predictability patterns; and, shifting investor sentiment may help to explain these patterns.

The paper contributes to a prior literature that considers stocks and government bonds in the same study but, as mentioned above, focuses on stock indexes. Fama and Schwert (1977), Keim and Stambaugh (1986), and Campbell (1987) started a literature that used dividend yields and interest rates to forecast stock and bond index returns. For example, using the term spread, the default spread, and the dividend yield, Fama and French (1989) find common predictable components in bond and stock indexes. Shiller and Beltratti (1992) and Campbell and Ammer (1993) use present-value relations in an effort to decompose stock and bond index returns into shocks related to real cash flows and discount rates. It is worth noting that our results do not support a specific interpretation of term-spread-based predictability that has appeared in this literature. That is, Fama and French (1989) and Cochrane and Piazzesi (2005) suggest that the fact that a countercyclical term spread predicts both bond and stock index returns means that it captures rational variation in an economy-wide risk premium that affects all risky assets. But this is hard to square with our cross-sectional results which show that the term-spread-based predictability is actually stronger for safer stocks than risky stocks.

One exception to the focus on stock market indexes is Fama and French (1993). Among the many discoveries in their paper, Fama and French find that the term spread and the default spread have strong contemporaneous relationships to several size- and book-to-market-based stock portfolios. However, they do not develop or interpret the cross-sectional differences in the relationships, as their main focus is on documenting a positive covariance between yield-curve variables and a broad range of stock portfolios.

Perhaps the most notable omission in the prior literature that we address here is formal consideration of the hypothesis that shifting sentiment or flights to quality generate mispricing. Relative to the many media claims of sentiment-driven shifts in demand from speculative and safer stocks and bonds, there is little formal consideration on this mechanism in the literature.[1] One exception is Connolly, Stivers, and Sun (2005), who find that government bond returns tend to be high, relative to stock index returns, on days when the implied volatility of equity index options increases. Also, Gulko (2002) finds that the unconditional slightly positive correlation between stocks and bonds becomes negative in stock market crashes.

Finally, this paper contributes to a smaller prior literature on supply and demand effects in bond prices that dates back to Modigliani and Sutch (1966). Vayanos and Vila (2007) develop a theoretical model where investors have an exogenous preference for specific maturities, and

[1] The financial press often refers to August 1998, when Russia devalued its currency and defaulted on some debt, leading to the collapse of Long-Term Capital Management, in terms of a "flight to quality." Investors are said to have fled to safer markets and to safer securities within markets. Similar allegations occurred in October 1987, which included the largest one-day crash in U.S. history. "When investors are scared, they look for safety. They adjust their portfolios to include more safe assets and fewer risky assets. … This kind of movement is usually referred to as a 'flight to quality.' Government bond prices go up, stock prices fall." *Chicago Federal Reserve Bank News Letter*, December 1987, as cited by Barsky (1989). Or, "When stocks are expected to show weakness, investment funds often flow to the perceived haven of the bond market, with that shift usually going into reverse when, as yesterday, equities start to strengthen." John Parry, *The Wall Street Journal*, August 1, 2001, page C1, as cited by Chordia, Sarkar, and Subrahmanyam (2005).

Greenwood and Vayanos (2007) examine the related empirical effects of shifts in the supply of government bonds. Here, our focus is on sentiment-induced variation over time in the demand for bonds.

The paper proceeds as follows. Section II describes the data and the basic empirical relationships between government bonds and the cross-section of stocks. Section III discusses overlapping predictability patterns. Section IV discusses interpretations based on required returns and sentiment. Section V concludes.

II. Comovement of bonds and the cross-section of stocks

To characterize how the cross-section of stock returns covaries with bond returns, we study a broad range of stock portfolios, including portfolios based on firm size, firm age (period since first listing on a major exchange), profitability, dividend policy, and growth opportunities and/or distress. We first describe the data and then the basic regression results.

A. Data on stock portfolios and stock and bond indexes

The stock portfolio constructions follow Fama and French (1992) and Baker and Wurgler (2006). The firm-level data is from the merged CRSP-Compustat database. The sample includes all common stock (share codes 10 and 11) between 1962 through 2005. Accounting data for fiscal year-ends in calendar year t-1 are matched to monthly returns from July t through June t+1.

Table 1 shows average monthly returns and standard deviations for the stock portfolios. Size and age characteristics include market equity *ME* from June of year t, measured as price times shares outstanding from CRSP. *ME* is matched to monthly returns from July of year t through June of year t+1. *Age* is the number of years since the firm's first appearance on CRSP, measured to the nearest month. Return volatility, denoted by σ, is the standard deviation of (raw) monthly returns over the twelve months ending in June of year *t*. If there are at least nine returns to estimate it, σ is matched to monthly returns from July of year *t* through June of year *t*+1. Of the three, size exhibits the most unconditional predictive power.

Profitability is measured by the return on equity *E/BE*. Earnings (*E*) is income before extraordinary items (Item 18) plus income statement deferred taxes (Item 50) minus preferred dividends (Item 19), if earnings are positive; book equity (*BE*) is shareholders equity (Item 60) plus balance sheet deferred taxes (Item 35). Dividends are dividends to equity *D/BE*, which is dividends per share at the ex date (Item 26) times Compustat shares outstanding (Item 25) divided by book equity. For dividends and profitability, there is a salient distinction at zero, so we split dividend payers and profitable firms into deciles and study nonpayers and unprofitable firms separately. Neither characteristic gives a large unconditional effect in average returns.

Characteristics indicating growth opportunities, distress, or both include book-to-market equity *BE/ME*, whose elements are defined above. External finance *EF/A* is the change in assets (Item 6) minus the change in retained earnings (Item 36) divided by assets. Sales growth (*GS*) is the change in net sales (Item 12) divided by prior-year net sales. Table 1 shows that each of these three variables displays some unconditional predictive power, as in prior work.

As always, the growth and distress variables capture several effects simultaneously. With book-to-market, high values may indicate distress and low values may indicate high growth opportunities. Also, as a scaled-price variable, book-to-market is a generic valuation indicator, varying with any source of mispricing or rationally required returns. Likewise, low values of sales growth and external finance (i.e., negative numbers) may indicate distress, while high values may reflect growth opportunities. To the extent that external finance is driven by investor demand and/or market timing, it is also a generic misvaluation indicator.

Table 2 summarizes stock and bond index data. Monthly excess returns on intermediate-term government bonds and long-term government bonds are constructed using data from Ibbotson Associates (2005). Monthly excess returns on the value-weighted NYSE/Amex/Nasdaq stock market are from CRSP.[2]

B. Comovement evidence

Table 3 reports the basic comovement results. The approach is to regress monthly excess stock portfolio returns on contemporaneous excess long-term bond returns while controlling for overall stock market returns:

$$r_{pt} - r_{ft} = a_p + \beta_p \left(r_{mt} - r_{ft} \right) + b_p \left(r_{bt} - r_{ft} \right) + u_{pt} . \tag{1}$$

Panel A shows the cross-sectional pattern of stock market beta loadings β_p. This mainly allows the reader to get some intuition about the composition of the portfolios, but one result that we will mention later on in the paper is that sorting on ex ante measures of total return volatility leads to good ex post separation according to market beta.

We focus primarily on the coefficient b_p, which tells us the relationship between stock portfolio p and government bonds that arises over and above their relationship through general stock market returns. In this way, we document cross-sectional differences in comovement with bonds. Panels B and C of the table reveal a novel but very intuitive comovement pattern, namely, that stock portfolios that are more "speculative" have a lower partial correlation with bond returns. Small-capitalization stocks, young stocks, high-volatility stocks, non-dividend paying stocks, and unprofitable stocks all display strongly negative coefficients b_p. The minimum coefficient of -0.45 is on the unprofitable stocks portfolio. In other words, a one percentage point

[2] We don't consider corporate bonds at length because they are intuitively spanned by government bonds and the wide cross-section of stocks that we examine. High-grade corporate bonds behave like government bonds, while junk bonds behave somwehat more like speculative stocks, and none of this will be surprising. Nonetheless, we will briefly examine the predictability of junk bonds later in the paper.

higher excess return on long-term bonds is associated with a 0.45 percentage point lower excess return on unprofitable stocks, controlling for general stock market returns. The second-lowest coefficient in the table is the -0.44 coefficient on the most volatile stocks.

In contrast, stock portfolios that contain less speculative stocks—or, more succinctly, "bond-like" stocks—show higher partial correlations with lond-term bond returns. Such bond-like stocks include large stocks, low-volatility stocks, and high-dividend stocks. The maximum coefficient in Table 3 is the 0.17 on the lowest-volatility stocks, indicating that a one percentage point higher excess return on long-term bonds is associated with a 0.17 percentage point higher monthly excess return on low-volatility stocks, controlling for general stock market returns.

The bottom three rows in Panel B indicate a U-shaped pattern in the growth and distress variables' coefficients. This means that both high growth *and* distressed firms are less like bonds than are the stable and mature firms in the middle deciles. This U-shaped pattern mirrors that discussed in Baker and Wurgler (2006, 2007), who find that both high growth and distressed stocks are more sensitive to sentiment than more staid firms. The pattern implies that simple "high minus low" portfolios can hide important aspects of the cross-section.

The stock characteristics examined here are correlated, so a natural question is whether they are associated with independent effects. To examine this question, the left panels of Figure 1 plot the coefficients across stock deciles b_p, as reported in Table 3, while the middle panels plot the coefficients b_p that are estimated after adding Fama and French's (1993) factors *SMB* and *HML* and the momentum factor *UMD* to Eq. (1). The patterns are qualitatively similar, but not surprisingly they are dampened by the inclusion of the additional stock portfolios. For example, comparing Panels A and D, the effect of bond returns on high-volatility stocks goes from -0.44

without the additional controls to -0.15 and a t-statistic of -2.8 with them, while the coefficient for low-volatility stocks falls from 0.17 to 0.16 with a larger t-statistic of 5.1.

Another way of examining the degree of independence of the effects in Table 3 is through a double sort methodology. In particular, since many of the characteristics we examine are correlated with firm size, we perform separate regressions within each size quintile and compute the average coefficient on long-term bonds across the five quintiles. The right panels of Figure 1 show these average coefficients. Again, the pattern is qualitatively quite similar.

Overall, these results significantly develop Fama and French (1993)'s evidence that most stock portfolios formed on size and book-to-market are correlated with bonds. In particular, there is a strong and intuitive cross-sectional pattern in which "bond-like stocks" comove relatively more strongly with bonds. We also found that the characteristic that is most closely associated with bondness is low total return volatility.

III. Copredictability of bonds and bond-like stocks

In this section we examine a second fundamental connection between bonds and bond-like stocks, namely copredictability. We use this term to denote a situation where two return series are individually predictable by the same third series. An equivalent but less elegant phrase would be that two return series "have a common predictable component."

Copredictability tells us much more about how two markets are integrated, because it is implied by two, not all three, of the causes of comovement: time-variation in rationally required returns, when the predictor captures a state variable related to risk premia; and the correction of sentiment-driven mispricings, when the predictor captures the state of sentiment. It is not implied by comovement in real cash flows. In other words, the existence of copredictability would mean that real cash flow comovement cannot by itself explain all of the return comovement in the previous section, though it is certaintly part of the story.

We first lay out the facts, starting with the data on the candidate predictors and then proceeding to various predictive specifications. We leave a detailed interpretation of the findings to the following section.

A. Data on predictors

We construct two types of time-series predictors, those previously used primarily to forecast excess bond returns and those previously used to forecast the time series of the cross-section of stock returns. Starting first with the bond-return predictors, Fama and French (1989) and Campbell and Shiller (1991) find that a large term spread predicts higher excess bond returns, while Fama and Bliss (1987) and Cochrane and Piazzesi (2005) use forward rates to predict bond returns. In particular, Cochrane and Piazzesi find that a tent-shaped function of one- to five-year forward rates forecasts bond returns.

Motivated by these results, we construct four bond-return predictors, using Cochrane-Piazzesi and Campbell-Shiller style regressions to forecast both intermediate and long-term government bond returns. CP_{IT} is the Cochrane-Piazzesi fitted predictor for intermediate term excess bond returns, i.e. the fitted intermediate-term excess bond return using the 1-year rate and the 2- through 5-year forward rates derived from the Fama-Bliss yield curve from CRSP in a monthly forecasting regression. Note that we are interested in forecasting monthly returns, while Cochrane and Piazzesi use their factor to forecast overlapping annual returns from month t+1 through month t+12. To be consistent with the spirit of their predictor, we use 12-month moving averages of the forward rates in the predictive regression. Similarly, CP_{LT} is the Cochrane-Piazzesi fitted predictor for long-term excess bond returns fitted using the same set of interest rates. The coefficients in the predictive regressions are reported in the header in Table 4, confirming the established tent-shaped function of forward rates.

Our third bond return predictor, CS_{IT}, is the Campbell-Shiller-style fitted predictor of intermediate excess bond returns using the risk-free rate, the term spread, the credit spread, and the credit term spread. The risk-free rate is the yield on Treasury bills, and the term spread is the difference between the long-term Treasury bond yield and the T-bill yield, both from Ibbotson Associates (2005). The credit spread is the gap between the commercial paper yield and the T-bill yield. The commercial paper yield series, available on the NBER website, is based on data collected by the Federal Reserve Board. The credit term spread is the difference between Moody's Aaa bond yields, also as reported by the Federal Reserve Board, and the commercial paper yield. Each of the regressors is lagged six months. Finally, CS_{LT} is the Campbell-Shiller-style fitted predictor of long-term excess bond returns using these variables. Again, we report the coefficients in the predictive regressions in the header in Table 4, confirming known results such as the positive coefficients on the short-term rate and the term spread.

There is only a small literature on predicting the time-series of the cross-section of stock returns. One of the most successful predictors here is the investor sentiment index developed in Baker and Wurgler (2006). The index is based on six underlying proxies for sentiment: the closed-end fund discount as available from Neal and Wheatley (1998), CDA/Weisenberger, or the *Wall Street Journal*; the number of and average first-day returns on IPOs from Jay Ritter's website; the dividend premium (the log difference between the value-weighted average market-to-book ratio of dividend payers and nonpayers); the equity share in total equity and debt issues from the *Federal Reserve Bulletin*; and detrended NYSE turnover (the log of the deviation from a 5-year moving average). To further isolate the common sentiment component from common macroeconomic components, each proxy was first orthogonalized to macroeconomic indicators, including industrial production, the NBER recession indicator, and consumption growth.

The sentiment index $SENT^{\perp}$ is the first principal component of the six orthogonalized proxies for investor sentiment, which has the intuitive pattern of positive loadings on the equity issuance and turnover variables and negative loadings on the closed-end fund discount and the dividend premium. Just as prior work lags the yield curve variables several months to a year to optimally capture predictable variation in bond returns, we lag the sentiment index a year when using it as a predictor. Finally, later in the paper, we also use a monthly index of changes in sentiment, $\Delta SENT^{\perp}$, which is based on a similar principal components analysis of changes in the underlying sentiment proxies. Our monthly sentiment series are as used in Baker and Wurgler (2007).[3] As reported there, when the sentiment index takes high values, the future return on hard to arbitrage, hard to value, speculative stocks is low relative to the future return of bond-like stocks over the next twelve months or more. Likewise, such speculative stocks have higher sentiment betas, i.e. higher sensitivities to the changes in the sentiment index. Again, for brevity, we do not reproduce these published results. Glushkov (2006) takes a related approach, reverse engineering the process by first measuring the sentiment beta of individual stocks, and next examining the characteristics of those with high and low sentiment betas.

The predictors are summarized in Table 4 and plotted in Figure 2. The means of the bond-return predictors of course match the means of the bond returns. The sentiment index has zero mean and unit variance by construction. The Cochrane-Piazzesi bond return predictors are more variable than the Campbell-Shiller predictors, reflecting their better forecasting ability. Each predictor is positively correlated with every other predictor at the 1% level, although this is

[3] The data are available at: www.stern.nyu.edu/~jwurgler.

overstated because all of the series are persistent. Nonetheless, these positive correlations suggest that the predictors may have overlapping predictive ability. The bond return predictors and the sentiment index are especially linked in the late-1970s through mid-1980s period in which bond return volatility increased.

B. Bond predictors and the cross-section of stock returns

We start by asking whether predictable variation in bonds extends to bond-like stocks. Few papers have investigated this point, and with no focus on cross-stock differences. Cochrane and Piazzesi (2005) find that their forecasting factor is positively related to annual value-weighted stock returns over the next year, but do not consider other stock portfolios. Fama and French (1989) find that the term spread has similar predictive power for equal- and value-weighted stock indexes, but do not go deeper into the cross-section of stocks.

In Table 5 we regress excess stock portfolio returns on contemporaneous excess stock market returns and the Cochrane-Piazzesi forecast of long-term excess bond returns:

$$r_{pt} - r_{ft} = a_p + \beta_p \left(r_{mt} - r_{ft} \right) + t_p CP_{LTt-1} + u_{pt} . \qquad (2)$$

This specification asks whether the Cochrane-Piazzesi tent-shaped function of forward rates predicts excess returns on portfolio *p* with a differentially higher or lower predictive coefficient for stock portfolio *p* than for the value-weighted average. It thereby tests for cross-sectional differences in the forecasting ability of the bond predictor. t_p measures the percentage increase in stock returns associated with a one-percentage-point increase in the predicted long-term bond return, controlling for the value-weighted stock return.

The results show that predictability in bond returns extends to stock returns but with substantial cross-sectional differences in the relationship. When predicted excess bond returns are high, the returns on the stocks of large, established, low-volatility firms are also higher than the value-weighted average firm, while the stock returns of small, young, nonpaying, unprofitable, high-volatility, and high-growth and distressed firms are significantly lower than the average. As in the comovement coefficients, we find that the total return volatility characteristic produces the greatest range of predictive coefficients. Also as before, the sales growth characteristic produces the most pronounced U-shaped pattern. Interestingly, the t_p coefficient estimates from Eq. (2) are similar in sign but generally larger in magnitude than the b_p coefficients estimated from Eq. (1). Hence stock returns are especially sensitive to the *predictable component* of bond returns as opposed to generic innovations.

Figure 3 plots these coefficients. The left panels plot the coefficients t_p across stock deciles. The middle panels plot the coefficients that are estimated after adding *SMB*, *HML*, and *UMD* to Eq. (2). The right panels plot the coefficients from double sorts that explicitly control for firm size, as described earlier. There is a remarkably similar qualitative relationship between the cross-sectional patterns in Figure 3 and those in Figure 1.

Table 6 shows a different predictive specification in which we use the bond predictors to forecast long-short portfolios. We also control for the *SMB*, *HML*, and *UMD* portfolios to detect distinct predictive power for the portfolio *p*.

$$r_{pt} - r_{ft} = a_p + \beta_p \left(r_{mt} - r_{ft}\right) + h_p HML_t + s_p SMB_t + m_p MOM_t + t_p CP_{LTt-1} + u_{pt} \qquad (3)$$

In Panel A, the dependent variables are top decile minus bottom decile long-short portfolio returns for those characteristics for which there are monotonic patterns in their comovement and predictive coefficients across deciles: size, firm age, volatility, dividend payment, and profitability. In Panel B, we attempt to reduce noise by forming long-short portfolios as the top three minus the bottom three deciles for these characteristics. We also form portfolios as the extremes minus the middle two deciles for the growth and distress characteristics for which there were U-shaped patterns in comovement and predictive coefficients: book-to-market, external finance, and sales growth.

The results show that the Cochrane-Piazzesi factor has incremental predictive power for the top minus bottom portfolios formed on size, volatility and dividends, even controlling for *SMB*, and therefore also controlling for the predictable component of *SMB*. Reducing noise by contrasting the top three and bottom three deciles strengthens these effects and also leads to a marginally significant coefficient for profitability. The middle minus extreme portfolios also generate the expected pattern of results. When bond returns are predicted to be high, so are future returns on steady, slow growing stocks relative to high growth and/or distressed stocks.

Summarizing Tables 5 and 6, the basic finding is that when bond returns are predicted to be high, so are returns on bond-like stocks relative to other stocks. This is intuitively consistent with the connection between the bond predictors and the sentiment index in Figure 2, given that high sentiment has previously been shown to predict high returns on bond-like stocks relative to other stocks. For brevity, we do not present parallel sets of results for the other bond predictors CP_{IT} , CS_{IT}, and CS_{LT}, but they display very similar patterns (available on request).

C. Bond-like stock predictors and bond returns

Now we turn the opposite direction. We ask whether investor sentiment, previously found to be a predictor of the relative return on bond-like stocks and speculative stocks, also predicts bonds. The most general predictive regression is as follows:

$$r_{bt} - r_{ft} = a + \beta(r_{mt} - r_{ft}) + \beta^{s} \Delta SENT_{t}^{\perp} + bCP_{LTt-1} + cSENT_{t-1}^{\perp} + u_{t}\,. \quad (4)$$

A few points are worth discussion. First, we begin with specifications that include the index of sentiment changes. We hypothesize that bonds have negative "sentiment betas," as do the most bond-like stocks in the stock portfolios analyzed in Baker and Wurgler (2007). This is not a test of predictability, but it would support the notion that sentiment is a driver of bond returns, a potential cause of predictability. Second, we control for contemporaneous stock market returns to determine whether sentiment has any predictive power for bonds that is not already coming through its ability to forecast stocks. Third, we include the bond predictions CP_{LT}, CP_{IT} , CS_{IT}, or CS_{LT} to shed light on the extent to which any predictive power of sentiment overlaps with the predictive power of these well-known bond predictors.

Table 7 shows results for intermediate-term bond returns in the top panel and long-term bond returns in the middle panel. The first specification in each panel is a warmup regression that includes only contemporaneous stock returns and the index of contemporaneous changes in sentiment as regressors. As conjectured, bonds exhibit negative sentiment betas, just like, for example, low-volatility stocks as reported in Baker and Wurgler (2007). This provides another novel but intuitive connection between bonds and bond-like stocks.

The remaining columns show predictive regressions. The second columns include the stock market and the sentiment index. The sentiment index has a statistically significant ability to predict intermediate-term and long-term excess bond returns. A one-standard-deviation higher value of $SENT^{\perp}$ is associated with 0.22 percent per month higher excess returns on intermediate-term bonds and 0.31 percent per month higher excess returns on long-term bonds. This is a fairly impressive degree of predictive power. The sentiment index has a clear interpretation, has no mechanical connection to future returns, and was developed in an entirely separate setting; in contrast, the standard bond return predictors are ad hoc combinations of yields that have been explicitly chosen to maximize in-sample predictability.

The last two columns in each panel suggest an independent effect of the sentiment index and the bond-return predictors. As just noted, these specifications should not be viewed as a horse race, as the bond predictors were pre-fitted over the sample to maximize predictability and so are overfit. Inclusion of the bond predictors reduces but does not eliminate the predictive coefficient and significance of sentiment index. Likewise, the inclusion of the sentiment index tends to push the coefficient on the bond predictors below unity. The overall message is that sentiment has variation that predicts bond returns that only partially overlaps with that of the fitted bond predictors. This is consistent with the positive but imperfect correlation in these series in Figure 2.

Finally, in the bottom panel we take a brief look at excess returns on junk bonds. Junk bonds are intuitively spanned by government bonds and risky stocks so we do not consider them at length. A practical limitation is that the Merrill Lynch high yield corporate bond return index that we employ is available only since November 1984.

A priori, one expects junk bonds to behave somewhere between government bonds and speculative stocks, and thus to have less positive coefficients on the predictors such as sentiment and the yield-curve variables, but exactly where they fall in this spectrum is an empirical question. This expectation is borne out. The sentiment beta for junk bonds is essentially zero and the predictive coefficient for sentiment is zero. The coefficients on CP_{LT} and CS_{LT} are lower than for government bonds but remain significant.[4] On the other hand, in light of the in-sample construction of the predictors, this may overstate predictability.

As a rough comparison, the behavior of junk bonds in Table 7 resembles that of stock portfolios based on the second or third volatility deciles, i.e. low but not the lowest volatility stocks. For such stocks, as for junk bonds, sentiment betas are about zero and the predictive

[4] A possible analysis in the context of junk bonds is to form a specific forecast for them based on yield-curve variables. We estimated such a CP_J but found that forward rates did not predict excess junk bond returns in a tent-shaped function, so we discarded this approach as too prone to data mining.

power of sentiment is small (Baker and Wurgler (2007)); and, the predictive effect of CP_{LT} is positive but small (Table 5).

IV. Discussion and interpretation

At this point we have documented several new facts regarding the comovement and predictability of bonds and bond-like stocks. We now turn to interpretation. As mentioned in the introduction, there are three basic causes of comovement between bonds and bond-like stocks: comovement in their real cash flows, comovement in their rationally required returns, or common shocks to sentiment that lead to similar mispricings in bonds and bond-like stocks.

A convincing attribution among these three driving forces is not possible, since there are no accepted models of any of them. However, the copredictability indicates that comovement in real cash flows cannot by itself be the full explanation, although it is surely an important component. Copredictability implies that some of the basic correlation patterns must reflect either time-varying, rationally required returns or periodic sentiment-induced mispricings. In this section we examine which of these two stories is more consistent with the data. To preview, it appears easier to explain the results with the sentiment channel than with time-varying, rationally required returns.

A. Determinants of rationally required returns

The time-varying, rationally required returns explanation holds that either risk factor loadings—betas—are changing over time or risk premia are changing. We can test the first possibility directly, asking whether betas on bonds and bond-like stocks increase as sentiment or fitted bond returns increase. In principle, this could induce the predictability patterns observed in the previous section.

Baker and Wurgler (2006) have already conducted this exercise in some cases of interest here. They run regressions on long-short portfolios of the form:

$$r_{p_{it}=High,t} - r_{p_{it}=Low,t} = a_p + \beta_p\left(c_p + d_p SENT_{t-1}^{\perp}\right)\left(r_{mt} - r_{ft}\right) + e_p SENT_{t-1}^{\perp} + u_{pt}\ . \qquad (5)$$

The time-varying betas interpretation of why $SENT^{\perp}$ predicts the relative returns on bond-like stocks (and bonds) implies that the composite coefficient βd be higher for bond-like stocks. However, Baker and Wurgler find that the sign of βd only rarely lines up with the sign of the return predictability. The composite coefficients are small and usually in the wrong direction. Replacing stock market returns with consumption growth gives the same conclusion. Thus, the interpretation that $SENT^{\perp}$ predicts bond returns because bond-like stocks become "riskier" has already been tested and found wanting, and we do not repeat it here.

On the other hand, how the predicted component of bond returns affects the cross-section of stock betas has yet to be examined. We run regressions of the form:

$$r_{pt} - r_{ft} = a_p + \beta_p\left(c_p + d_p CP_{LTt-1}\right)\left(r_{mt} - r_{ft}\right) + t_p CP_{LTt-1} + u_{pt}\ . \qquad (6)$$

Again, the time-varying betas interpretation of why bond predictors also predict the relative returns on bond-like stocks requires that βd be higher for bond-like stocks. Table 8 reports the βf coefficients from Eq. (6). Table 8 shows that conditional changes in betas are of the correct sign to explain, qualitatively, the earlier predictability results. For instance, when predicted bond returns are 1 percentage point higher per month and therefore predicted returns on speculative stocks are low, we find that betas on the smallest firms are lower by .20, on average, betas on the youngest firms are lower by .12, and betas on high-volatility firms are lower by .22.[5]

[5] The fact that betas on average go down in Table 8 is an artifact of equal weighting. The average value-weighted beta remains at 1.00, which is enforced by the slight increase in the largest stocks' betas.

Unfortunately, such changes in betas are far too small to explain the predictability results. There are two ways to see this. First, Table 5 shows that when predicted bond returns are 1 percentage point higher, predicted monthly returns on small, young, and high-volatility stocks are .52, .73, and .83 percentage points lower, respectively. Simply dividing the changes in predicted returns by the changes in betas in the previous paragraph implies implausibly large monthly risk premia of 2.60 to 6.08 percentage points. We extend this exercise to other portfolios by regressing the predicted excess returns in Table 5 on the changes in beta in Table 8. The implied risk premium is approximately 3.66 percentage points per month, or around 54 percentage points per year, which is again much larger than typically suggested.

Given that changes in betas conditional on Campbell-Shiller predictions are similar (unreported), and that those conditional on $SENT^{\perp}$ go in the wrong direction, we can conclude that changes in betas are at best a partial explanation. This means that if time-varying rationally required returns are driving the copredictability results, they must work primarily through a time-varying market risk premium.

Upon inspection, this explanation also encounters problems. Baker and Wurgler (2006) find that the predicted returns on certain long-short stock portfolios actually *flip sign* over time, conditional on sentiment. The same is true when conditioning on predicted bond returns. For example, when the Cochrane-Piazzesi predicted long-term bond return is below its median value, the average excess return on low volatility stocks (decile 1) is 0.37 percent per month, below the average excess return on high volatility stocks (decile 10) of 1.09 percent per month. By contrast, when the predicted excess bond return is above its mean, the average excess return on low volatility stocks, at 1.15 percent per month, actually exceeds the excess return on high volatility stocks, at 0.92 percent per month. Conditioning on more extreme fitted bond returns makes this inversion even more apparent. When the predicted bond return is in the bottom quartile, the average excess returns on low and high volatility stock deciles are 0.16 and 0.78 percent per month, respectively; when the predicted bond return is at least one standard deviation above its mean, the average returns flip to 1.31 and 0.57, respectively.

The market risk premium cannot explain such changes in sign unless the ranking of betas changes over time. As it turns out, drops of even 0.20 merely serve to narrow the gap between predicted returns on low- and high-sigma stocks, thus preserving the ranking of predicted returns over time. Given a fixed ranking of betas over time, changes in the market risk premium can only attenuate the differences in predicted returns. As long as the market risk premium is non-negative, it cannot explain how the predicted returns on long-short stock portfolios would ever flip sign. The bottom line is that the changes in betas offer mild support for a rational explanation of why bond predictors also predict the cross-section of stocks, but it is an explanation that is incomplete. There is also no obvious support for a rational explanation of why the sentiment index predicts bond returns, our other copredictability result.

On a related note, the cross-sectional results also conflict with a common interpretation of why the term spread predicts bond and stock market returns. As Fama and French (1989) point out, the term spread is countercyclical, rising in recessions and falling in booms. The term spread also predicts long-term bond and stock returns. They and others suggest that this predictability reflects rational variation in an economy-wide risk premium that drives the prices of all risky assets, including stocks and bonds.[6] One possibility is that risk aversion might be higher during recessions, so that expected returns on stocks and bonds rise. This story, however, predicts that high expected returns on bonds would be associated with particularly high expected returns on

[6] For example, Cochrane and Piazzesi (2005) write, “The slope of the term structure also forecasts stock returns, as emphasized by Fama and French (1989), and this fact is important confirmation that the bond return forecast corresponds to a risk premium and not to a bond-market fad or measurement error in bond prices” (p. 145).

the riskiest stocks. As we mentioned in the description of Table 3, our volatility sorts identify high and low risk stocks quite effectively, if risk is measured as the ex post market beta. We find, in contrast, that the predictability is concentrated in the safest, most bond-like stocks, a pattern which seems more consistent with flights to quality.

B. Plausible magnitudes of rational predictability

In a recent paper, Campbell and Thompson (2007) consider the link between an R^2 from a predictive regression and investor returns from exploiting the predictability. They show that for a mean-variance investor with a one-period horizon, the average excess return from the unconditionally optimal portfolio is equal to the squared unconditional Sharpe ratio divided by the coefficient of relative risk aversion. When the investor is given a predictive signal to exploit, the average excess return on the optimal portfolio rises to the sum of the squared unconditional Sharpe ratio and the predictive R^2 all divided by the product of the coefficient of relative risk aversion and one minus the predictive R^2.

Given the summary statistics in Table 2, the first computation implies that an investor who bets on the unconditional excess return on long-term bonds receives an average monthly return of 0.36 percentage points if she has a relative risk aversion of unity and 0.12 percentage points if her relative risk aversion is three. However, if allowed to use the Cochrane-Piazzesi forecast, which has an impressive monthly R^2 of 0.05, the investor's average monthly return rises (absurdly) to 5.64 percentage points per month with a relative risk aversion of unity and 1.88 percentage points per month with relative risk aversion of three.

One possibility is that the success of the Cochrane-Piazzesi forecast is overstated due to data mining. However, in rolling out-of-sample regressions starting in 1976, the R^2 of the fitted prediction is still above 0.01, still implying large average monthly returns of 1.37 percentage points per month for an investor with relative risk aversion of unity and 0.46 percentage points per month with relative risk aversion of three. The R^2 of the sentiment index for long-term and intermediate-term bond returns is between 0.01 and 0.02, and it was not fitted to maximize in-sample predictability, so it likewise implies large utility gains for investors who would exploit its predictive ability.

These calculations are rough, but they suggest that the apparent predictability from the best-known bond predictors is large, requiring very significant shifts in risk aversion or risk to be rationalized as compensation for ex ante expected risk. It could come from data mining, but if not, it again seems more plausible that the bond predictors capture predictability generated by behavioral flights to quality. This would naturally explain the correlation between the yield-curve-based predictors and the sentiment index, as well as their generally similar comovement and predictability properties.

C. *Mutual fund flows*

Finally, we briefly describe an analysis of mutual fund flows that also generated results consistent with a sentiment factor in bonds and bond-like stocks. Flows into mutual fund flows are an interesting complement to the previous analysis since, as for example Edwards and Zhang (1998) point out, mutual fund investors are smaller and less experienced than many other market participants, and thus more likely to be prone to sentiment-based trading. Also, we can directly observe their actions via flows. Gemmill and Thomas (2002) show that mutual fund flows are closely related to closed-end fund discounts.

Using monthly flows data from the Investment Company Institute, Baker and Wurgler (2007) analyze the pattern of flows across speculative (growth, aggressive growth, etc.) versus bond-like (income, income equity, etc.) equity mutual fund categories. Their analysis is in the spirit of Goetzmann, Massa, and Rouwenhorst (2000) and Brown, Goetzmann, Hiraki, Shiraishi, and Watanabe (2005). Baker and Wurgler find that the first principal component is a general investment into mutual funds effect, with standardized flows into each fund objective positive weights. The second principal component is consistent with a sentiment pattern in fund flows. It has positive loadings on flows into speculative stock fund categories and negative loadings into bond-like stock fund categories. Baker and Wurgler also line up this component of mutual fund flows with the cross-section of stock returns, asking whether returns on bond-like stocks are high when flows favor bond-like stock fund categories. This is indeed the case.

In unreported results, we have repeated this analysis but extended it by including government bond funds among the categories of mutual funds included in the principal components analysis. The second principal component's loading on government bond fund flows is even more negative than those of funds concentrating on bond-like stocks. This is intuitively consistent with a sentiment effect. This component again lines up well with both the cross-section of stock returns as well as bond returns in the sense that returns on bonds and bond-like stocks are higher when flows are toward funds that hold such assets.

V. Conclusion

This paper makes several new empirical connections between government bonds and stocks, two asset classes that are often treated separately. Progress comes from paying attention to the rich cross-section of stocks rather than blending stocks together into indexes. We find that government bonds covary much more strongly with bond-like stocks, i.e. stocks of large, long-listed, low-volatility, profitable, dividend-paying firms which are neither high growth nor distressed. Low return volatility appears to be the single most important bond-like characteristic.

We also find predictability evidence that represents another fundamental link between bonds and bond-like stocks. Yield curve-based variables often used to predict bond returns are also shown predict the relative returns of bond-like stocks; and, a sentiment index previously shown to predict the relative returns of bond-like stocks is found to predict bond returns. Bonds and bond-like stocks are therefore copredictable in the sense that they are predicted by the same third series.

In general, there are three potential causes of the higher comovement between bonds and bond-like stocks: common shocks to real cash flows, common shocks to rationally required returns, or common sentiment-driven mispricings. It is impossible to precisely attribute the results across these three forces, and they probably each play some role. However, several aspects of the evidence are most easily explained by the hypothesis that fluctuations in sentiment affect the demand for, and prices of, bonds and bond-like stocks relative to speculative stocks.

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Table 1. Summary statistics: Stock portfolios, 1963 to 2005. Means and standard deviations of monthly portfolio returns. For each month, we form ten portfolios according to the NYSE breakpoints of firm size (ME), age, total return risk, dividend-book ratio for dividend payers (D/BE), earnings-book ratio for profitable firms (E/BE), book-to-market ratio (BE/ME), external finance over assets (EF/A), and sales growth (GS). We also calculate portfolio returns for unprofitable firms and nonpayers. N=510.

		Decile									
	<0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Panel A. Means											
ME		1.68	1.24	1.27	1.20	1.27	1.14	1.15	1.10	1.02	0.90
AGE		1.09	1.45	1.49	1.40	1.43	1.45	1.22	1.27	1.22	1.16
σ		1.23	1.31	1.27	1.30	1.38	1.39	1.37	1.44	1.48	1.47
D/BE	1.48	1.49	1.38	1.45	1.36	1.32	1.25	1.25	1.17	1.13	1.16
E/BE	1.55	1.56	1.48	1.61	1.40	1.34	1.39	1.34	1.34	1.31	1.28
BE/ME		0.75	1.04	1.15	1.23	1.32	1.43	1.55	1.60	1.79	1.99
EF/A		1.85	1.65	1.55	1.54	1.44	1.39	1.30	1.28	1.31	0.84
GS		1.71	1.53	1.43	1.41	1.39	1.39	1.46	1.46	1.32	1.01
Panel B. Standard Deviations											
ME		6.88	6.46	6.21	5.94	5.71	5.37	5.22	5.11	4.73	4.56
AGE		7.12	6.92	6.51	6.15	5.78	5.39	4.87	4.61	4.93	4.47
σ		3.11	3.68	4.08	4.42	4.77	5.13	5.57	6.17	6.90	8.55
D/BE	7.59	5.79	5.38	5.05	4.88	4.68	4.47	4.19	3.95	3.83	4.06
E/BE	8.45	6.61	5.93	5.98	5.57	5.40	5.31	5.31	5.19	5.07	5.68
BE/ME		7.41	6.42	6.00	5.70	5.41	5.25	5.15	5.16	5.54	6.30
EF/A		6.46	5.54	5.22	5.04	4.94	4.98	5.21	5.47	5.99	7.45
GS		7.26	5.62	5.06	4.81	4.92	4.90	5.09	5.48	6.01	7.23

Table 2. Summary statistics: Stock and bond indexes, 1963 to 2005. Means, medians, standard deviations, minima, and maxima of monthly bond and stock returns. The excess return on intermediate-term bonds ($R_{IT} – R_f$) is the difference between the intermediate-term government bond return and the Treasury bill return; the excess return on long-term bonds ($R_{LT} – R_f$) is the difference between the long-term government bond return and the T-bill return; the excess return on the stock market ($R_m – R_f$) is the difference between the value-weighted CRSP stock index and the T-bill return. N=510.

	Mean	**Median**	**STD**	**Min**	**Max**
$R_{IT} – R_f$	0.13	0.09	1.56	-7.30	10.73
$R_{LT} – R_f$	0.17	0.05	2.88	-9.89	13.98
$R_m – R_f$	0.47	0.76	4.42	-23.13	16.05

Table 3. The comovement of the cross-section of stock returns with bond returns. We regress monthly excess portfolio returns on contemporaneous excess market returns and excess long-term bond returns:

$$r_{pt} - r_{ft} = a_p + \beta_p \left(r_{mt} - r_{ft}\right) + b_p \left(r_{bt} - r_{ft}\right) + u_{pt}\,.$$

We report b_p. The portfolios are formed equally-weighted within deciles on market capitalization (ME), age or years since CRSP listing (AGE), monthly volatility (σ), dividends scaled by book equity (D/BE), profits scaled by book equity (E/BE), book-to-market ratio (BE/ME), external finance scaled by assets (EF/A), and sales growth (GS). N=510. T-statistics are robust to heteroskedasticity.

		Decile									
	<0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Panel A. β_p											
ME		1.15	1.27	1.25	1.22	1.19	1.14	1.12	1.10	1.02	0.99
AGE		1.34	1.29	1.24	1.19	1.11	1.09	0.99	0.93	0.99	0.92
σ		0.52	0.70	0.81	0.89	0.96	1.03	1.10	1.21	1.31	1.53
D/BE	1.39	1.14	1.05	1.00	0.95	0.92	0.88	0.81	0.76	0.75	0.78
E/BE	1.42	1.17	1.08	1.05	1.05	1.02	1.03	1.03	1.03	1.03	1.16
BE/ME		1.47	1.31	1.22	1.14	1.08	1.03	0.99	0.96	1.01	1.05
EF/A		1.16	1.06	1.02	1.00	1.01	1.01	1.06	1.10	1.20	1.43
GS		1.25	1.05	0.98	0.95	0.98	0.98	1.03	1.12	1.22	1.42
Panel B. b_p											
ME		-0.31	-0.21	-0.18	-0.16	-0.13	-0.06	-0.02	-0.01	0.05	0.04
AGE		-0.36	-0.27	-0.19	-0.17	-0.11	-0.13	-0.05	0.02	0.00	-0.02
σ		0.17	0.10	0.03	0.00	-0.06	-0.11	-0.16	-0.23	-0.28	-0.44
D/BE	-0.38	-0.14	-0.09	-0.07	-0.03	0.01	0.04	0.08	0.11	0.13	0.06
E/BE	-0.45	-0.30	-0.17	-0.15	-0.14	-0.09	-0.08	-0.08	-0.06	-0.05	-0.13
BE/ME		-0.35	-0.24	-0.21	-0.17	-0.14	-0.09	-0.13	-0.10	-0.13	-0.23
EF/A		-0.26	-0.19	-0.13	-0.13	-0.09	-0.06	-0.10	-0.12	-0.17	-0.32
GS		-0.34	-0.19	-0.11	-0.06	-0.06	-0.07	-0.08	-0.13	-0.20	-0.33
Panel C. t(b_p)											
ME		[-4.5]	[-4.3]	[-4.0]	[-3.9]	[-4.0]	[-1.9]	[-1.0]	[-0.3]	[2.8]	[2.1]
AGE		[-6.0]	[-4.5]	[-3.9]	[-3.5]	[-2.4]	[-3.0]	[-1.4]	[0.6]	[0.1]	[-0.7]
σ		[4.6]	[3.2]	[0.8]	[0.0]	[-1.5]	[-2.8]	[-3.7]	[-4.7]	[-4.9]	[-5.6]
D/BE	[-5.6]	[-2.9]	[-2.0]	[-1.7]	[-0.8]	[0.3]	[1.2]	[2.5]	[3.8]	[5.0]	[2.0]
E/BE	[-5.5]	[-4.8]	[-3.2]	[-2.8]	[-3.0]	[-1.9]	[-2.0]	[-1.8]	[-1.6]	[-1.5]	[-3.1]
BE/ME		[-5.9]	[-5.1]	[-4.8]	[-4.0]	[-3.5]	[-2.4]	[-3.1]	[-2.4]	[-2.7]	[-3.8]
EF/A		[-4.4]	[-4.1]	[-3.2]	[-3.3]	[-2.5]	[-1.6]	[-2.8]	[-3.0]	[-4.0]	[-5.2]
GS		[-4.9]	[-3.8]	[-2.8]	[-1.5]	[-1.6]	[-1.9]	[-2.3]	[-3.4]	[-4.6]	[-5.7]

Table 4. Summary statistics: Predictor variables, 1963 to 2005. Means, medians, standard deviations, minima, maxima, and correlations of return predictors. We form Cochrane-Piazzesi (2005) predictions of intermediate-term and long-term excess bond returns using the 1-year rate and the 2- through 5-year forward rates derived from the Fama-Bliss yield curve from CRSP. The regressors are 12-month moving averages, lagged once relative to the prediction month. The predictive regressions have R^2 = 0.05, N=510 months. The fitted predictors for month *t* returns have a *t*-1 subscript as a reminder they use lagged information:

$$CP_{ITt-1} = -0.00 - 0.42 y_{1t-1} + 0.13 f_{2t-1} + 0.81 f_{3t-1} + 0.34 f_{4t-1} - 0.82 f_{5t-1}\text{, and}$$

$$CP_{LTt-1} = -0.01 - 0.90 y_{1t-1} + 0.69 f_{2t-1} + 0.70 f_{3t-1} + 0.82 f_{4t-1} - 1.27 f_{5t-1}\,.$$

We form Campbell-Shiller (1991) predictions of excess bond returns using the risk-free rate, the term spread, the credit spread, and the credit term spread. The risk-free rate is the yield on Treasury bills and the term spread is the difference between the long-term Treasury bond yield and the T-bill yield. The credit spread is the gap between the commercial paper yield and the T-bill yield. The credit term spread is the gap between Moody's Aaa bond yield and the commercial paper yield. The regressors are lagged six months relative to the prediction month. The predictive regressions have R^2 = 0.03, N=510 months for intermediate-term excess bond returns and R^2 = 0.02, N=510 months for long-term excess bond returns. The fitted predictors for month *t* returns have a *t*-1 subscript as a reminder they use lagged information:

$$CS_{ITt-1} = -0.01 + 0.06 r_{ft-6} + 0.15\left(y_{LTt-6} - r_{ft-6}\right) + 0.03\left(y_{CPt-6} - r_{ft-6}\right) + 0.30\left(y_{Aaat-6} - y_{CPt-6}\right)\text{, and}$$

$$CS_{LTt-1} = -0.01 + 0.09 r_{ft-6} + 0.33\left(y_{LTt-6} - r_{ft-6}\right) + 0.16\left(y_{CPt-6} - r_{ft-6}\right) + 0.46\left(y_{Aaat-6} - y_{CPt-6}\right).$$

We use the monthly investor sentiment index in Baker and Wurgler (2007). It is based on the first principal component of six underlying proxies for sentiment: the closed-end fund discount, the number and average first-day returns on IPOs, the dividend premium, the equity share in new issues, and NYSE share turnover. Each proxy is orthogonalized to macroeconomic conditions prior to its combination into the index. The index is lagged twelve months relative to the return prediction month. It is available from 1967, N=468 months.

						Correlations			
	Mean	**Median**	**STD**	**Min**	**Max**	CP_{IT}	CP_{LT}	CS_{IT}	CS_{LT}
CP_{IT}	0.13	0.16	0.38	-0.82	1.40	1.00			
CP_{LT}	0.17	0.17	0.66	-1.51	2.38	0.97	1.00		
CS_{IT}	0.13	0.16	0.23	-0.38	1.00	0.54	0.57	1.00	
CS_{LT}	0.17	0.21	0.50	-1.08	2.29	0.46	0.53	0.95	1.00
$SENT^{\perp}$	0.00	-0.09	1.00	-2.36	3.49	0.28	0.20	0.27	0.13

Table 5. Predicting the cross-section of stock returns with bond return forecasts: Decile portfolios. We regress monthly excess portfolio returns on excess stock market returns and the predictable component of bond returns using the Cochrane-Piazzesi forecast of excess long-term bond returns:

$$r_{pt} - r_{ft} = a_p + \beta_p \left(r_{mt} - r_{ft} \right) + t_p CP_{LTt-1} + u_{pt} \, .$$

We report t_p. The portfolios are formed equally-weighted within deciles on market capitalization (ME), age or years since CRSP listing (AGE), monthly volatility (σ), dividends scaled by book equity (D/BE), profits scaled by book equity (E/BE), book-to-market ratio (BE/ME), external finance scaled by assets (EF/A), and sales growth (GS). N=510. T-statistics are robust to heteroskedasticity.

		Decile									
	<0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Panel A. Coefficients											
ME		-0.52	-0.44	-0.45	-0.39	-0.32	-0.19	-0.21	-0.14	-0.11	0.06
AGE		-0.73	-0.50	-0.23	-0.27	-0.07	-0.25	-0.10	0.01	-0.14	-0.14
σ		0.44	0.29	0.13	-0.03	-0.06	-0.18	-0.34	-0.51	-0.69	-0.83
D/BE	-0.83	-0.37	-0.19	-0.07	-0.01	0.10	0.17	0.11	0.28	0.19	0.19
E/BE	-0.89	-0.66	-0.39	-0.36	-0.18	-0.11	-0.18	-0.19	-0.08	-0.11	-0.37
BE/ME		-0.88	-0.56	-0.36	-0.25	-0.19	-0.20	-0.21	-0.14	-0.26	-0.14
EF/A		-0.54	-0.32	-0.09	-0.12	-0.09	-0.18	-0.09	-0.14	-0.36	-0.73
GS		-0.64	-0.16	-0.08	-0.03	0.00	-0.05	-0.06	-0.26	-0.37	-0.86
Panel B. T-statistics											
ME		[-1.7]	[-2.1]	[-2.5]	[-2.4]	[-2.2]	[-1.6]	[-2.2]	[-1.6]	[-1.4]	[1.0]
AGE		[-2.9]	[-2.0]	[-1.1]	[-1.3]	[-0.4]	[-1.5]	[-0.7]	[0.1]	[-1.0]	[-1.3]
σ		[3.3]	[2.6]	[1.1]	[-0.2]	[-0.4]	[-1.2]	[-1.9]	[-2.5]	[-2.8]	[-2.6]
D/BE	[-2.8]	[-2.0]	[-1.1]	[-0.5]	[-0.1]	[0.7]	[1.3]	[0.9]	[2.4]	[1.6]	[1.5]
E/BE	[-2.4]	[-2.2]	[-1.6]	[-1.3]	[-0.9]	[-0.5]	[-1.0]	[-1.1]	[-0.5]	[-0.8]	[-2.3]
BE/ME		[-4.1]	[-3.1]	[-2.0]	[-1.4]	[-1.1]	[-1.1]	[-1.1]	[-0.7]	[-1.2]	[-0.5]
EF/A		[-2.0]	[-1.5]	[-0.5]	[-0.7]	[-0.6]	[-1.2]	[-0.6]	[-0.8]	[-1.9]	[-3.0]
GS		[-2.1]	[-0.8]	[-0.4]	[-0.2]	[0.0]	[-0.4]	[-0.4]	[-1.6]	[-2.1]	[-3.8]

Table 6. Predicting the cross-section of stock returns with bond return forecasts: Long-short portfolios. We regress monthly excess portfolio returns on contemporaneous excess market returns, HML, SMB, UMD, and the Cochrane-Piazzesi forecast of excess long-term bond returns:

$$r_{pt} - r_{ft} = a_p + \beta_p \left(r_{mt} - r_{ft}\right) + h_p HML_t + s_p SMB_t + m_p UMD_t + t_p CP_{LTt-1} + u_{pt}.$$

We do not report the constant term. The portfolios are formed equally-weighted within deciles on market capitalization (ME), age or years since CRSP listing (AGE), monthly volatility (σ), dividends scaled by book equity (D/BE), profits scaled by book equity (E/BE), book-to-market ratio (BE/ME), external finance scaled by assets (EF/A), and sales growth (GS). T-statistics are robust to heteroskedasticity.

	ME		AGE		σ		D/BE		E/BE		BE/ME		EF/A		GS	
	coef	**[t]**	**coef**	**[t]**	**coef**	**[t]**	**coef**	**[t]**	**coef**	**[t]**	**coef**	**[t]**	**coef**	**[t]**	**coef**	**[t]**
Panel A. 10-1 Portfolios																
$R_m - R_f$	-0.13	[-1.5]	0.00	[0.0]	0.53	[9.2]	-0.28	[-6.8]	0.00	[-0.1]						
HML	-0.06	[-0.4]	0.55	[6.6]	-0.38	[-3.9]	0.13	[1.7]	0.02	[0.2]						
SMB			-0.87	[-16.6]	1.26	[13.0]	-1.04	[-16.3]	-0.86	[-10.3]						
MOM	0.07	[0.6]	0.23	[2.6]	-0.23	[-2.7]	0.12	[1.7]	0.18	[2.0]						
CP_{LT}	0.59	[1.8]	0.10	[0.6]	-0.71	[-2.7]	0.63	[3.0]	0.20	[0.9]						
N		510		510		510		510		510						
R^2		0.02		0.61		0.70		0.66		0.36						
Panel B. Top 3 minus Bottom 3 or Extremes – Middle 2																
$R_m - R_f$	-0.14	[-2.3]	-0.02	[-0.6]	0.35	[9.8]	-0.24	[-10.7]	0.01	[0.2]	0.05	[2.5]	0.10	[4.5]	0.13	[4.5]
HML	0.03	[0.3]	0.36	[5.8]	-0.21	[-3.5]	-0.02	[-0.6]	-0.03	[-0.6]	-0.25	[-5.4]	-0.12	[-2.6]	-0.22	[-4.4]
SMB			-0.76	[-17.1]	0.93	[15.4]	-0.70	[-18.0]	-0.58	[-11.5]	0.25	[6.6]	0.52	[14.0]	0.55	[11.6]
MOM	0.04	[0.5]	0.14	[2.3]	-0.13	[-2.5]	0.05	[1.3]	0.12	[2.4]	-0.04	[-1.0]	-0.14	[-3.3]	-0.13	[-3.0]
CP_{LT}	0.39	[1.7]	0.02	[0.2]	-0.58	[-3.5]	0.45	[4.0]	0.26	[1.7]	-0.16	[-1.4]	-0.28	[-2.6]	-0.46	[-3.1]
N		510		509		510		510		510		510		510		510
R^2		0.04		0.65		0.75		0.75		0.39		0.38		0.57		0.54

Table 7. Predicting bond returns with investor sentiment and yield-curve-based forecasts. We regress excess intermediate-term and long-term and junk bond returns on the stock market excess return, the index of changes in investor sentiment, the predictable component of bond returns using Cochrane-Piazzesi or Campbell-Shiller forecasts of intermediate or long-term bond returns, and the index of sentiment. For example,

$$r_{bt} - r_{ft} = a + \beta\left(r_{mt} - r_{ft}\right) + \beta^{s}\Delta SENT_{t}^{\perp} + bCP_{LTt-1} + cSENT_{t-1}^{\perp} + u_{t}\ .$$

We do not report the constant term. T-statistics are robust to heteroskedasticity.

	Sentiment				Cochrane-Piazzesi		Campbell-Shiller	
	coef	**[t]**	**coef**	**[t]**	**coef**	**[t]**	**coef**	**[t]**
Panel A. Intermediate Term Bond Returns								
$R_m - R_f$	0.08	[3.5]	0.06	[3.3]	0.06	[2.9]	0.06	[3.2]
$\Delta SENT^{\perp}$	-0.20	[-2.0]						
$SENT^{\perp}$			0.22	[3.1]	0.13	[1.7]	0.17	[2.3]
CP_{IT}					0.85	[3.2]		
CS_{IT}							0.93	[2.1]
N		480		468		468		468
R^2		0.04		0.05		0.09		0.06
Panel B. Long Term Bond Returns								
$R_m - R_f$	0.18	[4.4]	0.16	[4.1]	0.15	[3.9]	0.15	[4.1]
$\Delta SENT^{\perp}$	-0.35	[-2.4]						
$SENT^{\perp}$			0.31	[2.4]	0.19	[1.5]	0.25	[1.9]
CP_{LT}					0.87	[3.5]		
CS_{LT}							1.02	[3.3]
N		480		468		468		468
R^2		0.07		0.07		0.10		0.09
Panel C. Junk Bond Returns								
$R_m - R_f$	0.22	[7.2]	0.21	[7.5]	0.21	[7.7]	0.21	[7.4]
$\Delta SENT^{\perp}$	-0.03	[-0.2]						
$SENT^{\perp}$			0.02	[0.2]	-0.03	[-0.2]	-0.07	[-0.5]
CP_{LT}					0.75	[3.2]		
CS_{LT}							0.42	[2.5]
N		254		254		254		254
R^2		0.28		0.28		0.31		0.30

Table 8. Predictable variation in bond returns and the cross-section of factor loadings. We regress monthly excess portfolio returns on the predictable component of bond returns using Cochrane-Piazzesi forecasts of long-term bond returns and the interaction between the predictable component of bond returns and excess market returns:

$$r_{pt} - r_{ft} = a_p + \beta_p \left(c_p + d_p CP_{LTt-1}\right)\left(r_{mt} - r_{ft}\right) + t_p CP_{LTt-1} + u_{pt}$$

We report $\beta_p d_p$. The portfolios are formed equally-weighted within deciles on market capitalization (ME), age or years since CRSP listing (AGE), monthly volatility (σ), dividends scaled by book equity (D/BE), profits scaled by book equity (E/BE), book-to-market ratio (BE/ME), external finance scaled by assets (EF/A), and sales growth (GS). N=510. T-statistics are robust to heteroskedasticity.

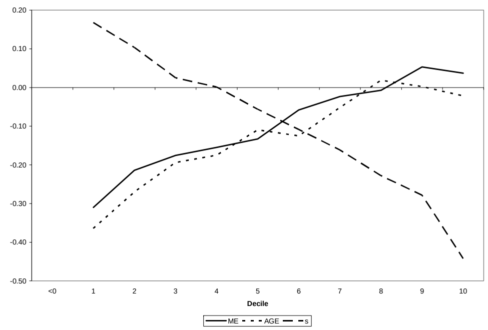
		Decile									
	<0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Panel A. Coefficients											
ME		-0.20	-0.12	-0.07	-0.05	-0.03	-0.04	-0.03	0.02	0.03	0.02
AGE		-0.12	-0.12	-0.11	-0.11	-0.06	-0.08	-0.04	-0.08	-0.09	-0.01
σ		-0.06	-0.03	-0.05	-0.07	-0.08	-0.09	-0.09	-0.15	-0.17	-0.22
D/BE	-0.23	-0.15	-0.12	-0.09	-0.07	-0.05	-0.04	-0.07	-0.07	-0.03	-0.01
E/BE	-0.22	-0.21	-0.14	-0.12	-0.11	-0.13	-0.12	-0.15	-0.13	-0.14	-0.14
BE/ME		-0.17	-0.13	-0.09	-0.07	-0.08	-0.07	-0.09	-0.11	-0.13	-0.15
EF/A		-0.18	-0.11	-0.09	-0.09	-0.08	-0.09	-0.09	-0.10	-0.13	-0.15
GS		-0.17	-0.11	-0.09	-0.07	-0.10	-0.10	-0.11	-0.13	-0.13	-0.14
Panel B. T-statistics											
ME		[-2.5]	[-2.0]	[-1.2]	[-0.9]	[-0.5]	[-1.0]	[-0.9]	[0.6]	[1.3]	[0.9]
AGE		[-1.7]	[-1.8]	[-1.6]	[-1.7]	[-1.1]	[-1.7]	[-0.9]	[-2.1]	[-2.3]	[-0.2]
σ		[-1.5]	[-0.9]	[-1.3]	[-1.6]	[-1.6]	[-1.7]	[-1.6]	[-2.5]	[-2.4]	[-2.5]
D/BE	[-2.9]	[-2.7]	[-2.3]	[-1.8]	[-1.5]	[-1.2]	[-1.0]	[-1.8]	[-1.9]	[-0.8]	[-0.2]
E/BE	[-2.2]	[-2.6]	[-2.0]	[-1.9]	[-1.9]	[-2.2]	[-2.4]	[-2.8]	[-2.6]	[-3.3]	[-3.1]
BE/ME		[-3.7]	[-2.8]	[-1.6]	[-1.2]	[-1.4]	[-1.3]	[-1.6]	[-1.7]	[-2.0]	[-1.9]
EF/A		[-2.6]	[-1.9]	[-1.8]	[-1.8]	[-1.9]	[-2.2]	[-2.0]	[-2.0]	[-2.4]	[-2.2]
GS		[-2.1]	[-1.7]	[-1.7]	[-1.5]	[-2.1]	[-2.1]	[-2.3]	[-2.7]	[-2.5]	[-2.3]

Figure 1. The comovement of the cross-section of stock returns with bond returns. We regress excess portfolio returns on contemporaneous excess market returns and excess long-term bond returns:

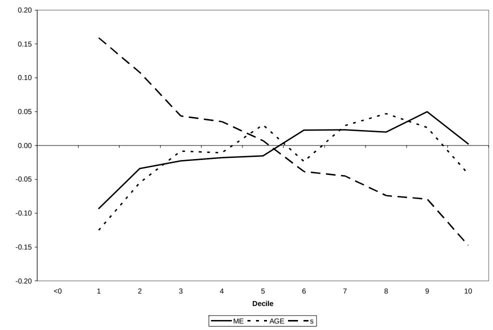
$$r_{pt} - r_{ft} = a_p + \beta_p\left(r_{mt} - r_{ft}\right) + s_p SMB_t + h_p HML_t + m_p UMD_t + b_p\left(r_{bt} - r_{ft}\right) + u_{pt}$$

We report only b_p. The portfolios are formed equally-weighted within deciles on market capitalization (ME), age or years since CRSP listing (AGE), monthly volatility (σ), dividends scaled by book equity (D/BE), profits scaled by book equity (E/BE), book-to-market ratio (BE/ME), external finance scaled by assets (EF/A), sales growth (GS). In the right panels, we perform separate regressions within each size quintile and average coefficients across the five quintiles.

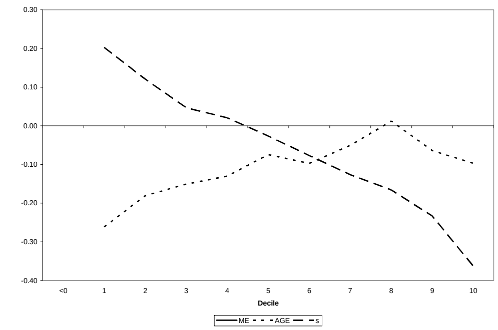
Panel A. Market model; ME, AGE, s



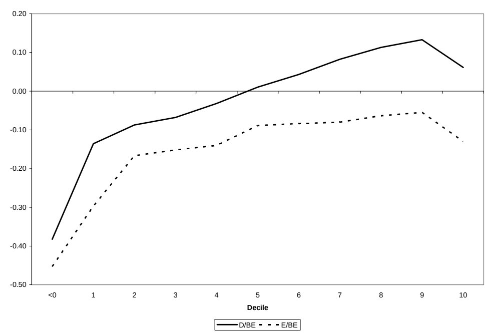
Panel D. Four factors; ME, AGE, s



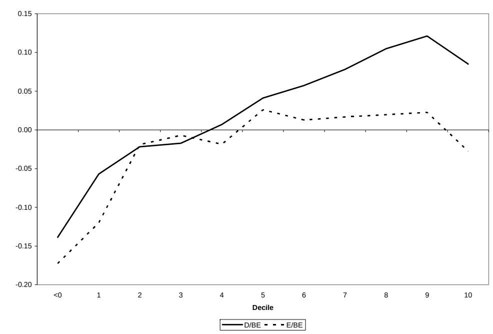
Panel G. Double sorts; AGE, s



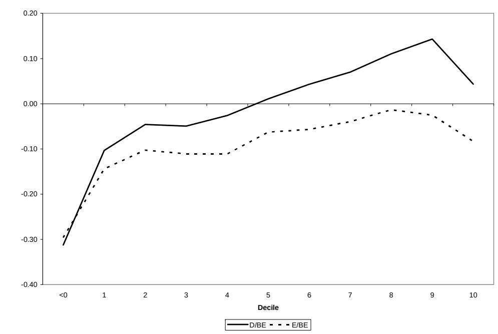
Panel B. Market model; D/BE, E/BE



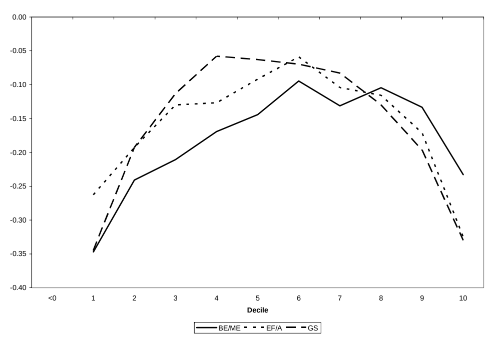
Panel E. Four factors; D/BE, E/BE



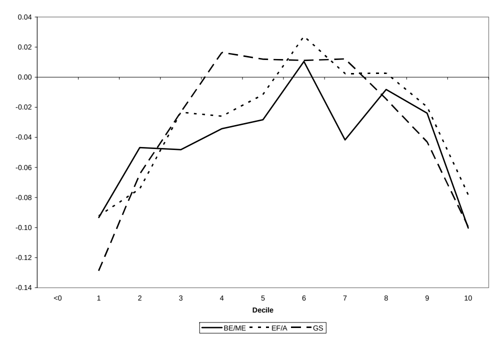
Panel H. Double sorts; D/BE, E/BE



Panel C. Market model; BE/ME, EF/A, GS



Panel F. Four factors; BE/ME, EF/A, GS



Panel I. Double sorts; BE/ME, EF/A, GS

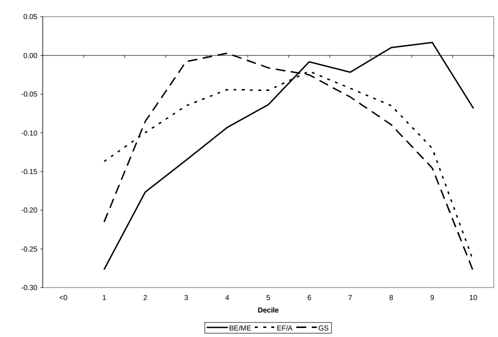


Figure 2. Investor sentiment and yield-curve-based forecasts of bond returns. The Baker-Wurgler sentiment index (dashed line), the Campbell-Shiller intermediate-term bond return predictor (thin solid line), and the Cochrane-Piazzesi long-term bond return predictor (thick solid line).

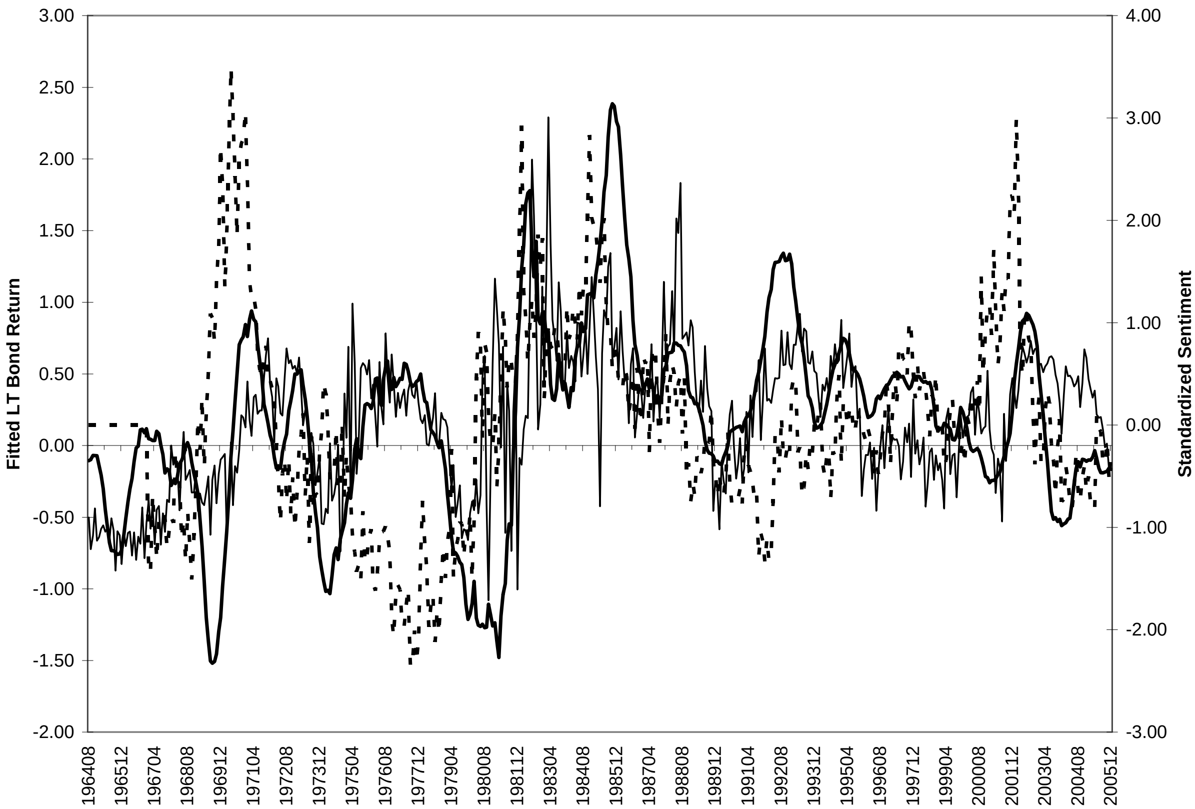
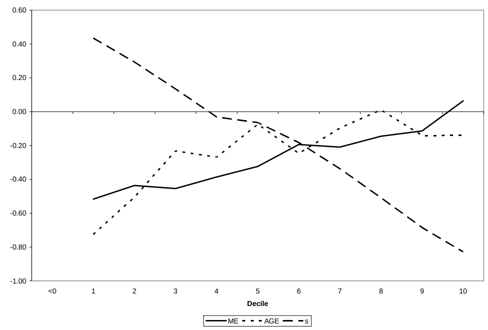


Figure 3. Predicting the cross-section of stock returns with bond return forecasts. We regress monthly excess portfolio returns on contemporaneous excess market returns, HML, SMB, UMD, and the Cochrane-Piazzesi forecast of excess long-term bond returns:

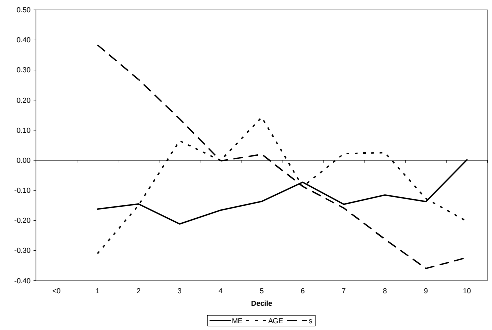
$$r_{pt} - r_{ft} = a_p + \beta_p \left(r_{mt} - r_{ft} \right) + h_p HML_t + s_p SMB_t + m_p UMD_t + t_p CP_{LTt-1} + u_{pt} .$$

We report only t_p. The portfolios are formed equally-weighted within deciles on market capitalization (ME), age or years since CRSP listing (AGE), monthly volatility (σ), dividends scaled by book equity (D/BE), profits scaled by book equity (E/BE), book-to-market ratio (BE/ME), external finance scaled by assets (EF/A), and sales growth (GS). In the right panels, we perform separate regressions within each size quintile and average coefficients across the five quintiles.

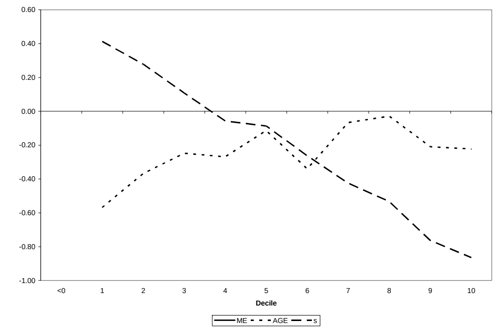
Panel A. Market model; ME, AGE, s



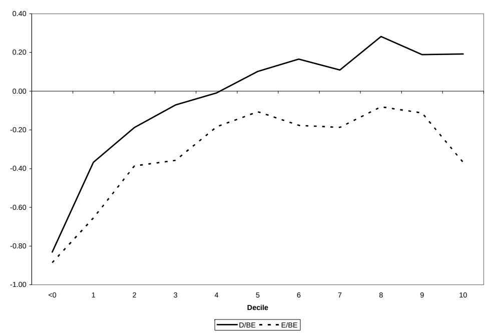
Panel D. Four factors; ME, AGE, s



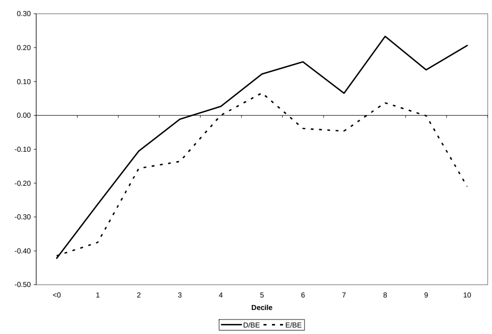
Panel G. Double sorts; AGE, s



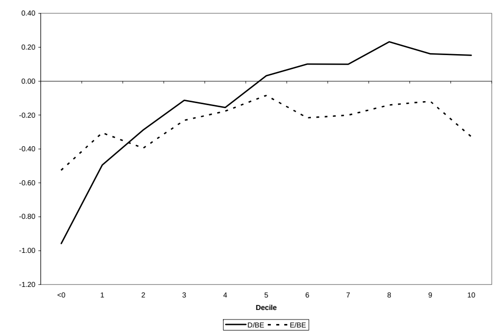
Panel B. Market model; D/BE, E/BE



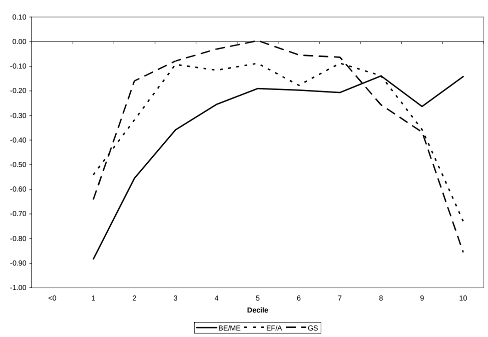
Panel E. Four factors; D/BE, E/BE



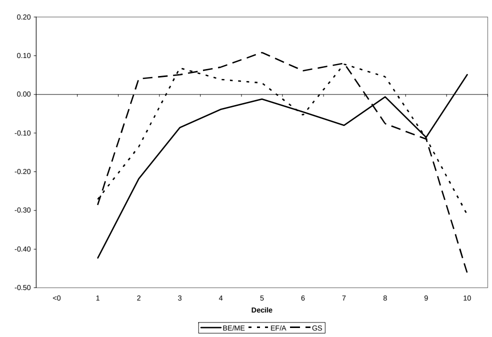
Panel H. Double sorts; D/BE, E/BE



Panel C. Market model; BE/ME, EF/A, GS



Panel F. Four factors; BE/ME, EF/A, GS



Panel I. Double sorts; BE/ME, EF/A, GS