Comovement and Predictability Relationships Between Bonds and the Cross-Section of Stocks[*]

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Abstract

In contrast to the well-known unstable relationship between the returns on government bonds and stock indices, we find that bonds are robustly related to the cross-section of stock returns in both comovement and predictability patterns. Government bonds comove more strongly with bond-like stocks: stocks of large, mature, low-volatility, profitable, dividend-paying firms that are neither high growth nor distressed. Time-series variables already known to predict returns on bonds also predict returns on bond-like stocks, and vice-versa. These relationships remain in place even when bonds and stocks become "decoupled" at the index level. They are likely driven by a combination of effects including correlations between real cash flows on bonds and bond-like stocks, correlations between their risk-based return premia, and periodic flights to quality.

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I. Introduction

The empirical relationships between the stock and bond markets are of considerable interest to economists, policymakers, and investors. Economists are interested in understanding the mechanisms that link these markets. Through such understanding, financial market regulators aim to improve the markets' information aggregation and capital allocation functions and their robustness to shocks to the financial system. Investors want to know the return and diversification propeties of major asset classes.

The relationships between stock and bond returns have proved difficult to pin down, however, let alone understand. Over the last four decades, the correlation between stock index and government bond returns has been highly unstable. Baele, Bekaert, and Inghelbrecht (2009), for example, find that the daily correlation between stock and bond indices is on average modestly positive but has ranged anywhere from +0.60 to -0.60 over the last forty years and exhibits sharp changes of 0.20 or more. In negative correlation periods the markets are said to have "decoupled." Many attempts have been made to explain this time variation, but no consensus exists, and the literatures on stock and bond pricing remain rather separate.

In this paper we look at these two markets from a different perspective. We document and discuss the links between government bonds and the *cross-section* of stocks. Prior research has focused almost exclusively on index-level time-series relationships. The cross-sectional perspective complements this research, and it uncovers new and robust facts about the connections between stocks and bonds.

The paper has three parts. The first studies the contemporaneous comovement patterns between bonds and the (time-series of) the cross-section. The second part studies the predictability patterns common to excess government bond returns and the cross-section. The third part considers explanations for the patterns that we document. It concludes that at least three mechanisms play a nonzero role.

The main comovement pattern between government bonds and the cross-section of stocks is quite intuitive: bonds comove more strongly with “bond-like” stocks. 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, younger firms, highly volatile stocks, and stocks of firms with extremely strong growth opportunities *or* those in distress, display a considerably weaker link to bonds. These patterns remain even when bonds and stock *indices* are moving in opposite directions. Thus, while so-called decoupling episodes are dramatic and undoubtedly worthy of attention, it is important to understand that basic links between stocks and bonds are unaffected even in such extreme periods.

Bonds and bond-like stocks also exhibit similar predictability characteristics. The same yield curve variables often used to predict returns on government bonds, such as the term spread and combinations of forward rates (Fama and French (1989), Campbell and Shiller (1991), and Cochrane and Piazzesi (2005)), also predict the returns on bond-like stocks relative to speculative stocks.[1] In the other direction, the sentiment index that Baker and Wurgler (2006) use to predict the returns on bond-like relative to speculative stocks also predicts the returns on government bonds. This cross-sectional focus complements Fama and French's stock-index-level tests and delivers strong evidence that the expected returns of stocks and bonds are firmly linked.

We offer a preliminary assessment of the drivers of these patterns. We consider three general, non-exclusive reasons why bonds would be more closely linked to some stocks than others. They involve cash flows, risk-based required returns, and flights to quality or investor

[1] A fuller literature review follows this introductory section.

sentiment. These have all been suggested and studied before but not in the cross-sectional context, which provides some additional power to assess their relevance. We believe that it is simply not possible to provide a complete, unambiguous attribution across these forces, because so many untestable structural assumptions would need to be made. We therefore pursue a more realistic goal, asking whether each should be given zero or nonzero weight in the results.

For reasons described in the text involving business cycles, we assign positive weight to the cash flow channel immediately. It is self-evident that bonds and bond-like stocks are exposed to common shocks to real cash flows. More interesting and difficult is the task of disentangling and assessing the risk-based required returns and investor sentiment channels. The bond-cross-section predictability connections indicates that at least one of these also must be given nonzero weight. Tisk-based required returns suggests a degree of predictability, as does any predictable correction of periodic flights to quality or drifts away from quality in which investors reallocate without a sophisticated eye toward risks and expected returns.

There is evidence that both of these mechanisms play a role. The risk-based required returns channel explains the stylized facts as the result of bonds and bond-like stocks (relative to speculative stocks) being subject to common, risk-based discount rate shocks. This implies either that betas or market risk premia vary over time with the bond and stock predictors. 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, calibrations suggest that betas do not change by nearly enough to generate the observed magnitude of predictability with a constant market risk premium. The time-varying risk premium is also unable to provide a complete explanation, particularly for the fact that higher beta or other categories of speculative firms are often predicted to have *lower* returns than presumably lower-risk stocks.

The investor sentiment channel explains the comovement evidence as sentiment affecting bonds and bond-like stocks less intensively than it does speculative stocks, and the predictability evidence as the somewhat forecastable correction of overreaction. We approach this story from several angles. We note that sentiment and flights to quality are anecdotally associated with a number of special financial market episodes, including but not limited to the catastrophic stock market decline of 2008, facts difficult to ignore. We also observe that the support for the risk-based required returns channel is modest in light of the strong predictability connections; perfect tests are impossible, but process of elimination alone suggests a role for investor sentiment.

More rigorously, time-varying overreaction can explain the pattern that the riskiest stocks are, not infrequently, positioned to deliver the lowest expected returns. In addition, we conduct a calibration in the spirit of Campbell and Thompson (2007) that suggests that bond returns are simply too predictable to be consistent with fully efficient markets. Finally, we factor analyze mutual fund flows across fund categories as in Goetzmann, Massa, and Rouwenhorst (2000) and uncover an important factor consistent with flights to quality.

To summarize, the important findings of the paper are that there are strong and intuitive cross-sectional differences in the comovement of government bonds and stocks; these patterns are stable even when index-level comovement relationships break down; bonds and bond-like stocks also exhibit similar predictability patterns; and it appears that at least three economic mechanisms are playing a role in the results.

Section II provides an overview of related literature. Section III describes the data and studies the comovement relationships between government bonds and the cross-section of stocks. Section IV studies predictability patterns. Section V discusses alternative interpretations of the results, and Section VI concludes.

II. Related literature

There is a substantial prior literature that studies stocks and government bonds. As mentioned above, it commonly focuses on stock indices. Fama and Schwert (1977), Keim and Stambaugh (1986), and Campbell and Shiller (1987) started a literature that used dividend yields and interest rates to forecast stock and bond index returns. Using the term spread, the default spread, and the dividend yield, for example, Fama and French (1989) find common predictable components in bond and stock indices. 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. Recent contributions include Baele, Bekaert, and Inghelbrecht (2009), Bekaert, Engstrom, and Grenadier (2005), and Campbell, Sunderam, and Viceira (2009).

Exceptions to an exclusive focus on stock indices include Fama and French (1993) and, more recently, Koijen, Lustig, and Van Nieuwerburgh (2010). Among the 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. They do not develop or interpret the cross-sectional differences in the relationships, however, as their emphasis is on documenting covariances between yield-curve variables and various stock portfolios. Koijen et al. is also complementary. They develop a no-arbitrage model that prices stocks and bonds, with a cross-sectional focus on size and book-to-market portfolios. Another substantial difference is that these papers do not look specifically at decoupling periods, where we uncover additional robust patterns, and which have reemerged as an area of interest after the market meltdowns that began in the autumn of 2008.

Our paper also relates to the developing strand of literature that considers how shifting sentiment or flights to quality influence predictability results, as opposed to leaving the source of return predictability unspecified or assumed. Connolly, Stivers, and Sun (2005) show that bond returns tend to be high relative to stock index returns when the implied volatility of equity index options increases. Gulko (2002) was among the first to document the decoupling phenomenon in showing that the unconditional positive correlation between stocks and bonds switches sign in stock market crashes. Beber, Brandt, and Kavajecz (2009) find traces of flights to quality and flights to liquidity in the Euro-Area bond market. Implicit in these results is the notion of mispricing in the bond market, such as is argued for by the predictability associated with relatively exogenous government bond supply shocks in Greenwood and Vayanos (2010a,b). Finally, Gabaix (2010) develops a model where perceptions of risks (modeled as perceptions of behavior during disasters) affect stocks and bonds systematically, and proposes a way to think quantitatively about the joint behavior of sentiment and prices.

The stock-bond literature is larger than we can summarize here, and it is deservedly large. We view our results, as a whole, as contributing a relatively large new playing field of robust empirical facts for future work in this area, and contributing a degree of progress toward the interpretation of these facts.

III. 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 those formed 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 indices*

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 1963 and 2008. 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 are often associated with distress and low values with high growth opportunities. Also, as a scaled-price variable, book-to-market is a generic valuation indicator, varying with any source of mispricing or risk-based required returns. Likewise, low values of sales growth and external finance (i.e., negative numbers) can 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 (2008). Monthly excess returns on the value-weighted NYSE/Amex/Nasdaq stock market are from CRSP.[2]

B. Comovement patterns

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 (portfolio market beta):

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

The top panel shows the cross-section of stock market beta loadings β_p. This mainly provides some intuition about the composition of the portfolios. We focus on the coefficient b_p,

[2] We don't consider corporate bonds because they are spanned by government bonds and the wide cross-section of stocks in the comovement characteristics that we study. High-grade corporate bonds behave more like government bonds, while junk bonds behave somewehat more like speculative stocks.

which tells us the relationship between stock portfolio *p* and government bonds that arises over and above their relationship through general stock market movements. In this way, we can document cross-sectional differences in comovement with bonds.

The bottom panels of Table 3 reveal a novel but intuitive comovement pattern. Generally speaking, portfolios of "bond-like" stocks—stocks with the characteristics of safety as opposed to risk and opportunity—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 Panel B is the 0.14 on the lowest-volatility stocks. In other words, a one percentage point higher excess return on long-term bonds is associated with a 0.14 percentage point higher monthly excess return on low-volatility stocks, all controlling for general stock market returns. The second-largest coefficients involve stocks paying high dividends relative to book equity. The relationship is not monotonic across the top deciles, however, possibly because some stocks with very low equity may actually be in distress.

Of course, another way to view this pattern is that stocks that are relatively more "speculative" are relatively less connected to bonds. 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 -0.43 is on the unprofitable stocks portfolio; a one percentage point higher excess return on long-term bonds is associated with a 0.43 percentage point lower excess return on unprofitable stocks, controlling for general stock market returns. The second-lowest coefficient in the table is the -0.42 coefficient on the most volatile stocks.

The bottom three rows in Panel B indicate an interesting 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. Note that the pattern also suggests that traditional high-minus-low portfolios can hide key aspects of the cross-section, including those in the oft-studied book-to-market portfolios.

The stock characteristics examined here are correlated, so a natural question is the extent to which they embody common effects versus 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 (but not reported in a table) after adding Fama and French's (1993) factors *SMB* and *HML* and the momentum factor *UMD* to Eq. (1). As expected, the patterns are attenuated by the inclusion of the additional stock portfolios, but remain qualitatively identical in every portfolio.

Another way of examining the degree of independence of the effects in Table 3 is through a double sort methodology. In particular, many of the characteristics we examine are correlated with firm size, so 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 similar.

C. Comovement in "decoupling" episodes

As mentioned in the Introduction, the correlation between government bonds and stock indices is well-known to be highly unstable. For example, Baele, Bekaert, and Inghelbrecht (2010) show that within our own sample period the correlation between indices has ranged from over +0.60 to below -0.60. Where the correlation switches from positive to negative it is typically said to have "decoupled."

A number of authors have studied this time variation. Gulko (2002) finds that decoupling is associated with steep stock market declines, and, relatedly, Connolly, Stivers, and Sun (2005) find that the correlation falls when the implied volatility of equity index options rises, which also happens during market declines. Baele, Bekaert, and Inghelbrecht conclude that time variation is driven more by liquidity and flight-to-quality factors than by changing macroeconomic fundamentals, and Bansal, Connolly, and Stivers (2009) also find links to liquidity. Campbell, Sunderam, and Viceira (2009) propose an explanation that includes an associated time-varying covariance between inflation and real shocks.

An important and obvious question is whether the cross-sectional comovement patterns documented earlier exhibit similar instability. Table 4 explores this question under definitions of “decoupling” suited to our monthly data. We use long-short portfolios rather than deciles to save space. In Panel A, we confirm that the bond-cross-section patterns from Table 3 are clearly apparent in the somewhat more common “coupling” regime in which bonds and stock indexes move in the same direction.

Strikingly, Panel B shows that not a single one of these patterns reverses when bonds and stock indexes move in opposite directions. Most remain statistically significant, including those that are also of relatively high magnitude in the coupling regime: volatility, size, and dividends. Panel C imposes an even stricter definition of decoupling, requiring that bonds and stocks move in opposite directions in each of the two prior months. Here, too, none of the patterns reverse. Indeed, they actually become stronger in economic and statistical significance than under the looser definition of decoupling, and despite a much smaller sample size.

To summarize, this section documents a simple and very robust stylized fact about comovement between bonds and stocks: relative to speculative stocks, bond-like stocks comove more closely with bonds. Our evidence suggests that the stock characteristics most closely associated with bonds are low volatility, large size, seasoned age of listing, and high dividends. Connections also exist between bonds and stocks with high profitability and neither high growth nor distress. These cross-sectional relationships remain highly stable even when the correlation between bonds and stock indices inverts.

IV. Predictability of bonds and the cross-section of stocks

The comovement patterns provide us with new stylized facts, but shed no light on their drivers. In this section, we study whether bonds and bond-like stocks are predictable using the same variables. The analysis adds more new facts that are interesting in their own right. It also allows us to begin to assess the causes of the comovement patterns.

Specifically, this sort of "overlapping" predictability is implied by only two of the three categories of potential causes of comovement: time-variation in risk-based required returns, if the predictor captures a state variable related to risk premia; and, the correction of sentiment-driven mispricings, if the predictor captures the state of sentiment. In other words, the absence of overlapping predictability would, in a crude sense, rule out both of these channels, while the presence of overlapping predictability would rule in at least one of them.

A. Data on predictors

We construct two types of time-series predictors: those that have been used primarily to forecast bond returns, and those that have been used to forecast the time series of the cross-section of stock returns. This involves several predictors drawn from several papers so the full data description is not short.

Starting first with variables previously used to forecast excess bond returns, Fama and Bliss (1987) and Cochrane and Piazzesi (2005) develop predictors based on forward rates. Cochrane and Piazzesi find that a tent-shaped function of one- to five-year forward rates forecasts 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 5, confirming the established tent-shaped function of forward rates. The Cochrane-Piazzesi variables are perhaps the strongest known predictors of bond returns.

Fama and French (1989) and Campbell and Shiller (1991) find that a large term spread predicts higher excess bond returns. 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 (2008). The credit spread is the gap between the commercial paper yield and the T-bill yield. The commercial paper yield series from the NBER website is based on Federal Reserve Board data. The credit term spread is the difference between Moody's Aaa bond yields, also as reported by the 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 5, confirming known results such as the positive coefficients on the short-term rate and the term spread.

There is a much smaller literature on predicting the time-series of the cross-section of stock returns. One predictor is the investor sentiment index proposed 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.[3]

The sentiment index $SENT^{\perp}$ is the first principal component of the six orthogonalized proxies for investor sentiment, which has the expected pattern of positive loadings on the equity issuance and turnover variables and negative loadings on the closed-end fund discount and the dividend premium. As reported in Baker and Wurgler (2006), when the sentiment index takes high values, the future return on hard to arbitrage, hard to value, speculative, "high sentiment beta" stocks is low relative to the return of bond-like (low sentiment beta) stocks over the next twelve months or more.

[3] The sentiment data have been updated through the end of 2007 and are available at: www.stern.nyu.edu/~jwurgler.

Prior work tends to lag the yield curve predictors between one month, six months, and one year in part as a the literature's cumulative outcome of empirical searches to maximize bond return predictability. We have a similar decision here of how much to lag the sentiment index. We prefer not to conduct an empirical search. A combination of ex ante and Occam's razor considerations suggests one course of action. As in the case of the cross-sectional variable momentum, there is a tension in the dynamics of sentiment between short-term positive autocorrelation and long-term reversal. We aim to focus on the latter to match the spirit of the yield curve predictors and the style of predictability found in Baker and Wurgler (2006). We also prefer a round number that matches how the majority of yield curve variables are handled. We therefore lag the index one year. We denote this $SENT_{lag}^{\perp}$.

An index that is simply lagged one year still has one undesirable property, namely that it possesses significant monthly variation based on events that occurred between months *t*-11 and *t*-12, for example sharp monthly changes in the number of IPOs and their market reception. This is noise for the purposes of predictability from months *t* onward. To eliminate this but maintain the index centered on *t*-12, we construct the moving average of $SENT^{\perp}$ monthly values from *t*-6 to *t*-18. We denote this $SENT_{sm}^{\perp}$. This balances several considerations and thus is the preferred predictor based on investor sentiment. To facilitate interpretation all sentiment indices are standardized after their construction.

Finally, we make use of 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 on this variable are as used in Baker and Wurgler (2007). As this is employed only briefly as a control variable, we defer details of its construction to the header of Table 5. In the Baker and Wurgler paper, it is used to document that speculative, non-bond-like stocks possess higher sentiment beta, or in other words higher contemporaneous sensitivity to this index.

The predictors are summarized in Table 5 and plotted in Figure 2. By construction, the means of the fitted bond-return predictors match the means of the bond returns and the sentiment indices have 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. Several predictors are positively correlated at the 1% level, although this is overstated because all of the series are persistent. Nonetheless, these positive correlations already suggest that the predictors may possess overlapping predictive ability. Suggesting correct lagging treatment of the sentiment index, the lagged index is much more correlated with the yield curve predictors than the contemporaneous index. Figure 2 indicates that the bond return predictors and the sentiment index are most 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 firsts test whether bond return predictors are also effective in predicting the returns to bond-like stocks relative to speculative stocks. Few papers have investigated this 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 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 indices, but do not go deeper into the cross-section of stocks, and further we have 20 years more data to study.

In Table 6 we regress excess stock portfolio returns on contemporaneous excess market returns and the Cochrane-Piazzesi forecast of long-term excess bond returns:

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

The specification intentionally resembles that of Eq. (1). It tests whether the Cochrane-Piazzesi predictor extends to portfolio *p* with a differentially higher or lower predictive coefficient for stock portfolio *p* than for the value-weighted average market return. Varying *p* thereby tests for cross-sectional differences in forecasting ability. Coefficient t_p measures the percentage increase in returns associated with a one-percentage-point increase in the predicted long-term bond return, controlling for the value-weighted stock return.

Predictors of excess bond returns do indeed nicely apply to the cross-section of stock returns in the hypothesized directions. When predicted bond returns are high, the returns on bond-like stocks (large, established, low-volatility firms) are also higher than the value-weighted average stock return; the returns of speculative stocks (small, young, nonpaying, unprofitable, high-volatility, and high-growth and distressed) are significantly lower than the average. As in the comovement coefficients, the total return volatility characteristic produces the greatest spread of coefficients, suggesting that it best aligns with the speculative-vs.-bond-like differentiation. 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). This has an interesting interpretation. Stock returns are particularly sensitive to the *predictable component* of bond returns.

The predictive coefficients t_p are plotted in Figure 3. The left panels plot t_p across stock deciles. The middle panels plot the coefficients that are estimated after adding controls *SMB*, *HML*, and *UMD* to Eq. (2). The right panels plot the coefficients from double sorts that 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. At least some of the comovement patterns shown earlier derive from shared predictable components.

We use the bond predictors to forecast long-short portfolios in Table 7. We also control for the *SMB*, *HML*, and *UMD* portfolios to study special predictive power for portfolio *p*. We consider regressions that are variants of this general form:

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

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 reduce noise by forming long-short portfolios as the top three minus the bottom three deciles for these characteristics. We also form portfolios that may detect the U-shaped patterns in comovement coefficients for growth and destress variables. We form such portfolios as the extreme three minus the middle two deciles.

The results indicate that the Cochrane-Piazzesi factor has incremental predictive power for the top minus bottom portfolios formed on size, volatility and dividends, even controlling for future SMB and therefore the predictable component of SMB. Contrasting the top three and bottom three deciles tends to strengthen these effects; it brings profitability up to a marginally significant coefficient. The middle minus extreme portfolios also generate the U-shaped pattern that is identical to the pattern of comovement. When predicted bond returns are high, so are predicted returns on steady, slow growing stocks relative to the more speculative high growth and/or distressed 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. The takeaway here is that variables known to predict bond returns directly extend to the cross-section of stocks. As a descriptive matter, this substantially enlarges the known sources of predictable variation of the time-series of the cross-section of stock returns. It is also intuitively consistent with the connection between the bond predictors and the sentiment index in Figure 2, as high values of the sentiment index are known to predict high returns on bond-like stocks relative to other stocks.

C. Bond-like stock predictors and bond returns

We now reverse the analysis. We study whether the investor sentiment index *SENT*, which is known to predict the relative return on bond-like stocks and speculative stocks, also predicts bond returns. We run versions of this predictive regression:

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

We begin with specifications that include the index of sentiment changes. We wish to investigate that bonds have low or negative "sentiment betas," following the evidence that so do most bond-like stocks in the stock portfolios studied in Baker and Wurgler (2007). This is not a test of predictability, but is expected if sentiment is a driver of bond returns, which in turn may lead to predictability using levels of sentiment. We also control for contemporaneous stock market returns to determine whether sentiment can predict bonds separate from its ability to forecast stocks. We also control the yield curve-based predictors to see whether any predictive power of sentiment overlaps closely or is somewhat independent.

Results for intermediate-term bonds are in the top panel and long-term bonds are in the bottom panel of Table 8. The first specification includes only contemporaneous stock returns and the index of contemporaneous changes in sentiment. As expected, bonds exhibit negative sentiment betas, similar to, for example, low-volatility stocks as reported in Baker and Wurgler (2007). This is another novel but rather intuitive connection between bonds and bond-like stocks.

The remaining columns show predictive regressions. The second includes the sentiment index. It has a statistically and economically significant ability to predict intermediate-term and long-term excess bond returns. A one-standard-deviation higher value of $SENT^{\perp}$ is associated with 0.16 percent per month higher excess returns on intermediate-term bonds and 0.26 percent per month higher excess returns on long-term bonds. We view this as a reasonably impressive degree of predictive power, in light of the fact that the index has a perhaps clearer interpretation than the yield curve predictors, has no mechanical connection to future returns, and was developed in an entirely separate setting. In contrast, the better-known bond return predictors might be criticized as ad hoc combinations of yields that have had their lag structures and other features explicitly tuned to maximize in-sample predictability, or may have essentially evolved to that state over the course of many investigations of the expectations hypothesis.

The third pair of columns uses a smoothed version of sentiment, averaging out the values from six to 18 months prior to the return prediction. There is no precise guidance to the lag structure of the relationship between sentiment and future bond returns. We expect bond returns to rise as sentiment falls from a high level back to average, but the speed of this mean reversion is unclear. Another advantage of smoothing is that it irons out idiosyncratic jumps in the underlying components of investor sentiment. Consistent with expectations, smoothing improves the statistical and economic significance somewhat.

The last two sets of columns in each panel explore the independent predictive power of the sentiment index and other bond return predictors. The overall message is that sentiment loses predictive power when included alongside the strong Cochrane-Piazzesi predictor, although remains marginally statistically significant, and is less affected by the Campbell-Shiller type predictors. The inclusion of the sentiment index also tends to reduce the coefficient on the bond predictors (below unity) and vice-versa. This is not a proper horse race, as the bond predictors are overfit, having been pre-fitted over the same sample to maximize predictability, unlike the sentiment index. However, for our analysis the interesting point is not that a particular variable wins a horse race, but precisely the opposite—that the predictors do overlap to some degree. This is consistent with the positive but moderate correlation in these series in Figure 2.

V. Discussion and interpretation

This paper's most concrete contribution is descriptive: bonds and bond-like stocks are closely connected in both comovement and predictability patterns. As mentioned in the Introduction, there are three general and non-exclusive causes of comovement between bonds and bond-like stocks: comovement in their real cash flows, comovement in their risk-based required returns, and common shocks to sentiment that affect bonds and bond-like stocks similarly. As also mentioned before, a convincing quantitative attribution to these three causes is not possible, given the required structural assumptions, and an approximate attribution is a sizeable endeavor best left for future work. In this section we pursue the first step in that agenda. We try to assess whether one, two, or all three mechanisms play a nonzero role in the results.

A. Shocks to real cash flows

Bonds and bond-like stocks are linked through common shocks to real cash flows. Most obviously, a business cycle contraction is often associated with lower inflation and rising bond prices, and will generally have less of an impact on the cash flows of stable, mature firms versus more speculative growth firms or already-distressed firms. For example, Chen, Roll, and Ross (1986), find that a equal-weighted stock index is almost uniformly more affected by a range of macroeconomic shocks, including to inflation, than a value-weighted index. Such effects would contribute to the relatively stronger comovement between bonds and bond-like stocks. Subsequent studies in the spirit of the arbitrage pricing theory and intertemporal CAPM have indicated similar cross-sectional sensitivities to inflation shocks, such as Ferson and Harvey (1991) again for size portfolios. Therefore, we acknowledge the considerable importance of a mechanism working through shocks to real cash flows, and turn to the more difficult cases

B. Shocks to risk-based required returns

Comovement in real cash flows, while certainly important, cannot by itself be the full explanation for our results, because it does not give rise to predictability. A traditional discount rate channel, in which bonds and bond-like stocks experience similar shocks to risk-based discount rates, implies both predictability and comovement. For example, 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. Alternatively, 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.

B.1. Time-varying betas

We can test the first possibility directly, asking whether market betas on bonds and bond-like stocks increase as sentiment or fitted bond returns increase. If so, such a pattern would be consistent with the predictability patterns observed in the previous section, and of course also consistent with the comovement evidence. We mention at the outset that Ferson and Harvey (1991) find little evidence that time-varying betas in size portfolios can explain their own results.

Baker and Wurgler (2006) have already conducted a time-varying betas test in some cases of interest here. They run regressions on long-short portfolios of the form:

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

The time-varying betas interpretation of why $SENT^{\perp}$ predicts the relative returns on bond-like stocks (and the excess return on bonds) implies that the composite coefficient βd be higher for bond-like stocks. They report that the sign of βd generally does not line 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 view that the sentiment index predicts bond returns because bond-like stocks become "riskier" has already been tested, so we build on that evidence rather than repeat it here.

How the predicted component of bond returns affects the cross-section of stock betas has to our knowledge not been 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 9 reports the βd coefficients from Eq. (6). Table 9 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, on average, betas on the youngest firms are lower by 0.14, and betas on high-volatility firms are lower by 0.24.[4]

These changes in beta are in the right direction, but are too small to completely explain the predictability results. There are two ways to look at this. First, Table 6 shows that when predicted bond returns are 1 percentage point higher, predicted monthly returns on young and high-volatility stocks are 0.53, and 0.54 percentage points lower, respectively. Simply dividing

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[4] The fact that betas on average go down in Table 9 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.

the changes in predicted returns by the changes in betas in the previous paragraph implies implausibly large monthly risk premia of 2.25 to 3.79 percentage points. We extend this exercise to other portfolios by regressing the predicted excess returns in Table 6 on the changes in beta in Table 9. The implied risk premium is approximately 2.18 percentage points per month, or around 30 percentage points per year, which is again much larger than typically suggested. Given that changes in betas conditional on Campbell-Shiller predictions are of similar small magnitude (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.

B.2. Time-varying risk premia

Apparently, if shocks to risk-based discount rates are driving the predictability results, they must work primarily through a time-varying market risk premium. This is the explanation that Ferson and Harvey (1991) favor for their own results (they do not attempt to examine a sentiment-based source of predictability). Recent results, and our own results, suggest that this explanation also faces empirical challenges.

Perhaps the most significant challenge is that 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 0.13 percent per month, which is below the average excess return on high volatility stocks (decile 10) of 0.50 percent per month. By contrast, when the predicted excess bond return is above its mean, the average excess return on low volatility stocks, at 1.11 percent per month, actually exceeds the excess return on high volatility stocks, at 1.08 percent per month.

The market risk premium cannot explain such changes in sign unless the ranking of betas changes over time. It turns out that drops of beta of even 0.20 only narrow the gap between predicted returns on low- and high-sigma stocks, they don't change the ranking of predicted returns. 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, the predicted returns on long-short stock portfolios cannot flip sign.

Overall, the changes in betas exercise offers moderate support for a risk-based required returns explanation of why bond predictors also predict the cross-section of stocks. We cannot rule out that better tests using ICAPM or CCAPM models may strengthen the results, however, so we conservatively assign this explanation a nonzero weight in terms of explaining the main results. But the magnitudes involved are small, and there is also no clear explanation for why the sentiment index predicts bond returns. The risk-based required returns explanation appears helpful, but it, too, is clearly incomplete.

C. Sentiment and Flights to Quality

Investor sentiment is a third possible link between bonds and bond-like stocks. High sentiment may be periods of high demand for speculative stocks relative to demand for bond-like securities. "Flights to quality," on the other hand, may be dips in sentiment in which investors shift money toward what appear to be "safe" assets without making the sophisticated tradeoff between expected risks and returns that they would take under the risk-based required returns mechanism.[5] Under this view, bonds and bond-like stocks depart from speculative stocks as

[5] The anecdotes are presumably familiar. 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

sentiment fluctuates. Predictability arises as bonds and bond-like stocks, relative to speculative stocks, correct from sentiment-driven overreactions.

Thus far, the clearest and most significant evidence for a role for sentiment within this paper is again the aforementioned occasional inversion of the relationship between risk and expected return.[6] That is, when the sentiment index is high, the "riskiest" stocks deliver the lowest returns. We augment this with two additional tests that also suggest the relevance of sentiment as a tie between bonds and bond-like stocks. One exercise asks whether the degree of predictability we observe is consistent with rationality or not. The other exercise involves an analysis of mutual fund flows.

C.1. Magnitudes of Rational Predictability

Campbell and Thompson (2007) establish the relationship between the magnitude of predictability and the investor returns from optimally exploiting it. For a mean-variance investor with a one-period horizon, the average excess return from the unconditionally optimal portfolio equals the squared unconditional Sharpe ratio divided by the coefficient of relative risk aversion. When the investor is given a predictive signal, 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 0.51 percentage points if she has a relative risk aversion of unity and 0.17 percentage

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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). Pundits and economists alike have commented on what they perceived to be an unprecedented flight to quality at the outset of the current global financial crisis.

[6] In Baker and Wurgler (2006), it is not occasional, but rather appears in approximately half of all years between 1963 and 2005.

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 0.04, the investor's average monthly return rises (absurdly) to 4.51 percentage points per month with a relative risk aversion of unity and 1.50 percentage points per month with relative risk aversion of three.[7]

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 seems at least as 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.2. Mutual Fund Flows

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. Furthermore, we can directly observe their actions via flows. Gemmill and Thomas (2002) find that mutual fund flows are closely related to closed-end fund discounts, another asset class that is disproportionately held by individuals.

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. The exercise is close in

[7] 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 0.0092, implying large average monthly returns of 1.45 percentage points per month for an investor with relative risk aversion of unity and 0.48 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.

spirit to those of Goetzmann, Massa, and Rouwenhorst (2000) and Brown, Goetzmann, Hiraki, Shiraishi, and Watanabe (2005). They find that the first principal component is simply a general investment-into-mutual-funds effect, with standardized flows into each fund objective positive weights. The second principal component is also clearly interpretable as a sentiment pattern in fund flows. The loadings on flows into speculative stock fund categories are opposite to those of flows 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. They find that returns on bond-like stocks are high when flows favor bond-like stock fund categories.

In unreported results, we have extended this analysis by including government bond funds among the categories of mutual funds involved in the principal components analysis. In this case, 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 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.

VI. Conclusion

It is well-known that the correlation between bond and stock index returns is highly unstable, switching from highly positive to negative over within a few months. The apparent lack of robust integration between bond and stock markets has significant implications both for our understanding of the financial markets, and for practical regulation and asset allocation.

We find that government bonds and stocks are, in fact, robustly connected from a cross-sectional perspective. The relationships are intuitive. Government bonds covary more closely with “bond-like” stocks: stocks of large, long-listed, low return volatility, profitable, dividend-paying firms which are neither high growth nor distressed. Importantly, this relationship remains stable even when the index-level correlation between bonds and stocks breaks down. Furthermore, excess returns on government bonds, and relative returns on bond-like stocks over speculative stocks, are predictable by the same time series variables. These findings suggest that empirical finance researchers might more profitably merge two playing fields, bonds and the cross-section of stocks, that they often study in isolation.

A conservative interpretation of these results, based on our own investigation, a priori considerations, other findings in the literature, and anecdotal evidence, is that at least three mechanisms contribute to these patterns. Common shocks to expected real real cash flows of bonds and bond-like stocks is ex ante an important force. Several aspects of the evidence suggest that fluctuations in investor sentiment, for example flights to quality, play a role in generating comovement and, as a consequence of price overreaction, predictability. There is also some support for a time-varying required returns channel. Reaching more precise estimates of the relative importance of these mechanisms is an important task for future research.

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Table 1. Summary statistics: Stock portfolios, 1963 to 2008. 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 in years since initial CRSP listing, monthly volatility (σ), earnings-book ratio for profitable firms (E/BE), dividend-book ratio for dividend payers (D/BE), fixed assets (PPE/A), research and development (RD/A), 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=546.

		Decile									
	<=0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Panel A. Means											
ME		1.47	1.09	1.14	1.11	1.13	1.02	1.01	0.96	0.89	0.79
AGE		0.88	1.25	1.30	1.23	1.20	1.30	1.07	1.13	1.11	1.07
σ		1.08	1.18	1.13	1.14	1.22	1.25	1.23	1.29	1.33	1.25
D/BE	1.31	1.31	1.24	1.25	1.22	1.18	1.15	1.12	1.04	0.98	1.09
E/BE	1.30	1.34	1.21	1.44	1.28	1.17	1.23	1.20	1.21	1.19	1.16
BE/ME		0.62	0.87	0.98	1.09	1.16	1.24	1.39	1.40	1.57	1.74
EF/A		1.66	1.41	1.39	1.31	1.28	1.23	1.14	1.12	1.07	0.62
GS		1.45	1.29	1.22	1.25	1.24	1.23	1.31	1.23	1.16	0.79
Panel B. Standard Deviations											
ME		6.80	6.46	6.21	5.93	5.73	5.39	5.28	5.18	4.80	4.59
AGE		7.06	6.86	6.50	6.16	5.76	5.44	4.94	4.69	4.95	4.50
σ		3.17	3.73	4.13	4.48	4.84	5.17	5.60	6.18	6.93	8.47
D/BE	7.54	5.83	5.45	5.07	4.91	4.69	4.48	4.19	3.99	3.93	4.19
E/BE	8.48	6.47	5.84	6.04	5.52	5.38	5.28	5.33	5.16	5.06	5.65
BE/ME		7.36	6.49	6.02	5.74	5.46	5.33	5.17	5.19	5.55	6.25
EF/A		6.45	5.56	5.23	5.04	4.99	5.03	5.20	5.47	5.95	7.38
GS		7.23	5.69	5.10	4.85	4.89	4.88	5.19	5.45	6.03	7.10

Table 2. Summary statistics: Stock and bond indexes, 1963 to 2008. 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 market ($R_m – R_f$) is the difference between the value-weighted CRSP stock index and the T-bill return. N=546.

	Mean	**Median**	**STD**	**Min**	**Max**
$R_{IT} – R_f$	0.15	0.10	1.55	-7.30	10.73
$R_{LT} – R_f$	0.21	0.06	2.93	-9.89	14.40
$R_m – R_f$	0.38	0.75	4.45	-23.14	16.05

Table 3. Bond returns and the cross-section of stock returns, 1963 to 2008. 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 in 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=546. 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	1.25	1.24	1.21	1.19	1.13	1.13	1.11	1.03	0.99
AGE		1.32	1.29	1.23	1.19	1.11	1.10	1.00	0.95	0.99	0.92
σ		0.54	0.71	0.82	0.90	0.97	1.04	1.11	1.21	1.32	1.52
D/BE	1.38	1.14	1.06	1.00	0.96	0.92	0.87	0.80	0.76	0.77	0.82
E/BE	1.42	1.16	1.07	1.03	1.04	1.03	1.02	1.04	1.02	1.02	1.15
BE/ME		1.44	1.30	1.22	1.15	1.09	1.05	1.00	0.97	1.02	1.06
EF/A		1.15	1.06	1.01	0.99	1.01	1.01	1.05	1.10	1.20	1.41
GS		1.25	1.05	0.98	0.95	0.97	0.98	1.04	1.10	1.22	1.39
Panel A. b_p											
ME		-0.31	-0.20	-0.15	-0.13	-0.13	-0.05	-0.03	0.00	0.05	0.04
AGE		-0.33	-0.25	-0.18	-0.17	-0.12	-0.14	-0.07	0.00	-0.01	-0.02
σ		0.14	0.09	0.01	-0.01	-0.06	-0.11	-0.16	-0.22	-0.27	-0.42
D/BE	-0.35	-0.14	-0.09	-0.07	-0.04	-0.01	0.03	0.06	0.09	0.11	0.02
E/BE	-0.43	-0.26	-0.15	-0.15	-0.15	-0.09	-0.09	-0.10	-0.06	-0.05	-0.12
BE/ME		-0.30	-0.22	-0.20	-0.15	-0.14	-0.11	-0.14	-0.12	-0.14	-0.24
EF/A		-0.27	-0.16	-0.13	-0.13	-0.11	-0.07	-0.10	-0.11	-0.18	-0.29
GS		-0.33	-0.20	-0.12	-0.06	-0.08	-0.07	-0.08	-0.13	-0.18	-0.30
Panel B. t(b_p)											
ME		[-4.9]	[-4.3]	[-3.6]	[-3.6]	[-4.0]	[-1.7]	[-1.2]	[-0.1]	[2.5]	[2.5]
AGE		[-5.9]	[-4.7]	[-4.1]	[-3.6]	[-2.8]	[-3.5]	[-1.8]	[-0.1]	[-0.5]	[-0.7]
σ		[4.0]	[2.7]	[0.3]	[-0.3]	[-1.8]	[-3.2]	[-4.0]	[-4.8]	[-5.3]	[-5.9]
D/BE	[-5.8]	[-3.3]	[-2.2]	[-2.0]	[-1.2]	[-0.1]	[1.0]	[2.1]	[3.0]	[3.2]	[0.5]
E/BE	[-5.7]	[-4.8]	[-3.1]	[-2.8]	[-3.2]	[-2.3]	[-2.0]	[-2.4]	[-1.7]	[-1.4]	[-3.2]
BE/ME		[-5.4]	[-5.0]	[-4.8]	[-3.8]	[-3.7]	[-2.7]	[-3.5]	[-2.8]	[-3.0]	[-4.2]
EF/A		[-4.8]	[-3.9]	[-3.4]	[-3.3]	[-3.0]	[-1.9]	[-2.8]	[-2.9]	[-4.5]	[-5.2]
GS		[-5.2]	[-4.1]	[-2.9]	[-1.6]	[-2.1]	[-2.2]	[-2.3]	[-3.4]	[-4.5]	[-5.8]

Table 4. Bond returns and the cross-section of stock returns in index-level decoupline episodes: Long-short portfolios. We regress monthly excess portfolio returns on contemporaneous excess market returns and excess long-term bond returns under index-level non-decoupling and decoupling episodes:

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

We do not report the constant term. The portfolios are formed equally-weighted within deciles on market capitalization (ME), age in 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). The dependent variable is the difference between the top three and bottom three decile portfolios or the difference between the middle two and the extreme portfolios, for the last three pairs of columns. 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. Stocks and Bonds Move Together, Sign ($R_m - R_f$) = Sign($R_{LT} - R_f$)																
$R_m - R_f$	-0.26	[-3.1]	-0.30	[-5.4]	0.70	[10.5]	-0.47	[-10.1]	-0.16	[-2.7]	0.24	[7.1]	0.28	[7.2]	0.33	[8.0]
$R_{LT} - R_f$	0.35	[3.8]	0.25	[3.4]	-0.44	[-5.2]	0.35	[6.3]	0.24	[3.3]	-0.25	[-5.5]	-0.22	[-4.0]	-0.23	[-3.7]
N		312		312		312		312		312		312		312		312
R^2		0.06		0.09		0.32		0.29		0.04		0.16		0.15		0.15
Panel B. Decoupling, Sign ($R_m - R_f$) ≠ Sign($R_{LT} - R_f$)																
$R_m - R_f$	-0.07	[-1.0]	-0.39	[-5.2]	0.65	[7.9]	-0.41	[-8.9]	-0.23	[-4.0]	0.22	[4.2]	0.32	[6.1]	0.42	[5.6]
$R_{LT} - R_f$	0.31	[3.7]	0.12	[1.5]	-0.35	[-3.9]	0.20	[2.3]	0.06	[0.8]	-0.02	[-0.3]	-0.11	[-1.7]	-0.13	[-1.8]
N		234		233		234		234		234		234		234		234
R^2		0.10		0.25		0.49		0.44		0.15		0.20		0.31		0.34
Panel C. Decoupling, Sign ($R_m - R_f$) ≠ Sign($R_{LT} - R_f$) in both current and lagged month																
$R_m - R_f$	0.04	[0.4]	-0.43	[-3.8]	0.75	[6.0]	-0.42	[-6.0]	-0.32	[-4.2]	0.27	[3.3]	0.39	[6.2]	0.57	[5.8]
$R_{LT} - R_f$	0.44	[4.3]	0.26	[2.8]	-0.46	[-4.1]	0.31	[3.1]	0.07	[0.9]	-0.04	[-0.6]	-0.14	[-2.1]	-0.23	[-2.4]
N		102		101		102		102		102		102		102		102
R^2		0.11		0.35		0.54		0.51		0.29		0.28		0.42		0.46

Table 5. Summary statistics: Bond return and cross-section of stock return predictor variables, 1966 to 2008. 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 = 0.04, N=546 months. We report data from July 1965, N=522, to match the coverage of current and lagged sentiment in Table 8. The fitted predictors for month *t* returns have a *t*-1 subscript as a reminder they use lagged information:

$$CP_{ITt-1} = -0.002 - 0.25 y_{1t-1} - 0.10 f_{2t-1} + 0.59 f_{3t-1} + 0.52 f_{4t-1} - 0.73 f_{5t-1}, \text{ and}$$

$$CP_{LTt-1} = -0.004 - 0.56 y_{1t-1} + 0.19 f_{2t-1} + 0.31 f_{3t-1} + 1.12 f_{4t-1} - 1.01 f_{5t-1}.$$

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 = 0.02, N=546 months for intermediate-term excess bond returns and R^2 = 0.03, N=546 months for long-term excess bond returns. We report data from July 1965, N=522, to match the coverage of current and lagged sentiment in Table 8. The fitted predictors for month *t* returns have a *t*-1 subscript as a reminder they use lagged information:

$$CS_{ITt-1} = -0.01 + 0.05 r_{ft-6} + 0.13\left(y_{LTt-6} - r_{ft-6}\right) + 0.01\left(y_{CPt-6} - r_{ft-6}\right) + 0.30\left(y_{Aaat-6} - y_{CPt-6}\right), \text{ and}$$

$$CS_{LTt-1} = -0.01 + 0.07 r_{ft-6} + 0.31\left(y_{LTt-6} - r_{ft-6}\right) + 0.11\left(y_{CPt-6} - r_{ft-6}\right) + 0.51\left(y_{Aaat-6} - y_{CPt-6}\right).$$

We use the monthly investor sentiment index in Baker and Wurgler (2007). It is 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:

$$SENT_{t-1}^{\perp} = -0.19 CEFD_{t-1} + 0.21 TURN_{t-13} + 0.25 NIPO_{t-1} + 0.26 RIPO_{t-13} - 0.28 PDND_{t-13} + 0.19 S_t$$

These are described in detail in Baker and Wurgler (2007). It is available from July 1966, N=510. Each proxy is orthogonalized to macroeconomic conditions prior to its combination into the index $SENT^{\perp}$. We also produce a lagged $SENT_{lag}^{\perp}$, smoothed $SENT_{sm}^{\perp}$, and first differenced version of sentiment DSENT. $SENT_{lag}^{\perp}$ uses data that is 12 months old. $SENT_{sm}^{\perp}$ averages sentiment values lagged six to 18 months. It is available from July 1967, N=498 months.

							Correlations			
	N	**Mean**	**Median**	**STD**	**Min**	**Max**	CP_{IT}	CP_{LT}	CS_{IT}	CS_{LT}
CP_{IT}	522	0.16	0.18	0.33	-0.67	1.31	0.55	0.45	1.00	
CP_{LT}	522	0.22	0.20	0.58	-1.26	2.21	0.60	0.56	0.94	1.00
CS_{IT}	522	0.17	0.19	0.19	-0.28	0.86	1.00			
CS_{LT}	522	0.24	0.25	0.46	-1.00	2.07	0.93	1.00		
$SENT^{\perp}$	510	0.00	-0.05	1.00	-2.39	2.93	0.11	-0.03	0.00	-0.09
$SENT_{lag}^{\perp}$	510	0.00	-0.05	1.00	-2.39	2.93	0.32	0.17	0.31	0.21
$SENT_{sm}^{\perp}$	498	0.00	-0.10	1.00	-2.23	2.48	0.34	0.19	0.32	0.21
DSENT	509	0.00	0.01	1.00	-3.59	3.40	-0.10	-0.07	-0.03	-0.03

Table 6. Predictable variation in bond returns and the cross-section of stock returns: Decile portfolios, 1963 to 2008. 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 in 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=546. T-statistics are robust to heteroskedasticity.

		Decile									
	<=0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Panel A. Coefficients											
ME		-0.24	-0.30	-0.39	-0.34	-0.27	-0.13	-0.15	-0.07	-0.06	0.08
AGE		-0.53	-0.32	-0.04	-0.04	0.06	-0.11	0.09	0.15	-0.13	-0.13
σ		0.56	0.41	0.23	0.09	0.04	-0.10	-0.23	-0.36	-0.58	-0.54
D/BE	-0.68	-0.20	-0.09	0.09	0.10	0.23	0.22	0.19	0.35	0.28	0.20
E/BE	-0.59	-0.44	-0.14	-0.22	0.01	0.06	-0.08	0.04	0.02	-0.03	-0.30
BE/ME		-0.86	-0.45	-0.36	-0.18	-0.13	0.00	0.01	0.10	0.06	0.23
EF/A		-0.23	0.03	0.11	0.05	0.05	0.02	0.08	0.00	-0.20	-0.59
GS		-0.34	0.12	0.19	0.07	0.11	0.11	0.05	-0.10	-0.21	-0.69
Panel B. T-statistics											
ME		[-0.7]	[-1.3]	[-2.0]	[-1.9]	[-1.7]	[-1.0]	[-1.5]	[-0.7]	[-0.6]	[1.1]
AGE		[-1.9]	[-1.2]	[-0.2]	[-0.2]	[0.3]	[-0.6]	[0.6]	[1.0]	[-0.9]	[-1.1]
σ		[3.9]	[3.3]	[1.8]	[0.6]	[0.3]	[-0.6]	[-1.2]	[-1.6]	[-2.1]	[-1.5]
D/BE	[-2.1]	[-1.0]	[-0.5]	[0.5]	[0.6]	[1.5]	[1.6]	[1.4]	[2.7]	[2.2]	[1.4]
E/BE	[-1.5]	[-1.5]	[-0.5]	[-0.7]	[0.0]	[0.3]	[-0.4]	[0.2]	[0.1]	[-0.2]	[-1.7]
BE/ME		[-3.3]	[-2.1]	[-1.8]	[-0.9]	[-0.7]	[0.0]	[0.0]	[0.5]	[0.2]	[0.7]
EF/A		[-0.8]	[0.1]	[0.6]	[0.3]	[0.3]	[0.1]	[0.5]	[0.0]	[-1.0]	[-2.2]
GS		[-1.0]	[0.5]	[0.9]	[0.4]	[0.6]	[0.7]	[0.3]	[-0.6]	[-1.1]	[-2.8]

Table 7. Predictable variation in bond returns and the cross-section of stock returns: Long-short portfolios, 1963 to 2008. 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 in 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	[-1.7]	-0.01	[-0.4]	0.54	[9.9]	-0.26	[-6.6]	-0.03	[-0.7]						
HML	-0.08	[-0.5]	0.51	[6.2]	-0.38	[-4.0]	0.14	[1.9]	-0.03	[-0.3]						
SMB			-0.85	[-16.5]	1.23	[13.0]	-1.00	[-15.2]	-0.86	[-10.2]						
MOM	0.07	[0.6]	0.23	[2.7]	-0.20	[-2.5]	0.11	[1.6]	0.19	[2.2]						
CP_{LT}	0.34	[0.9]	-0.06	[-0.3]	-0.59	[-2.0]	0.53	[2.3]	0.05	[0.2]						
N		546		546		546		546		546						
R^2		0.01		0.58		0.70		0.64		0.36						
Panel B. Top 3 minus Bottom 3 or Extremes – Middle 2																
$R_m - R_f$	-0.13	[-2.5]	-0.03	[-0.9]	0.36	[10.6]	-0.24	[-10.9]	-0.01	[-0.5]	0.06	[2.7]	0.11	[5.2]	0.14	[4.9]
HML	0.02	[0.2]	0.34	[5.6]	-0.20	[-3.6]	-0.01	[-0.4]	-0.06	[-1.0]	-0.23	[-5.2]	-0.12	[-2.7]	-0.24	[-4.9]
SMB			-0.73	[-17.1]	0.91	[15.5]	-0.68	[-17.0]	-0.55	[-11.0]	0.22	[6.2]	0.47	[12.9]	0.52	[11.5]
MOM	0.04	[0.6]	0.14	[2.4]	-0.11	[-2.2]	0.04	[1.0]	0.13	[2.7]	-0.03	[-0.9]	-0.13	[-3.2]	-0.13	[-2.9]
CP_{LT}	0.28	[1.2]	-0.09	[-0.6]	-0.55	[-3.0]	0.42	[3.3]	0.15	[0.9]	-0.09	[-0.7]	-0.26	[-2.0]	-0.37	[-2.3]
N		546		545		546		546		546		546		546		546
R^2		0.03		0.64		0.74		0.73		0.38		0.34		0.54		0.53

Table 8. Sentiment and future bond returns, 1966 to 2008. We regress excess intermediate-term and long-term 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,

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

We do not report the constant term. T-statistics are robust to heteroskedasticity. Smoothed sentiment only covers the period from July 1967 to 2008, N=498.

	Investor Sentiment						Cochrane-Piazzesi		Campbell-Shiller	
	coef	**[t]**	**coef**	**[t]**	**coef**	**[t]**	**coef**	**[t]**	**coef**	**[t]**
Panel A. Intermediate Term Bond Returns										
$R_m - R_f$	0.07	[3.6]	0.04	[2.5]	0.05	[2.9]	0.05	[2.6]	0.05	[2.8]
$\Delta SENT^{\perp}$	-0.25	[-3.0]								
$SENT_{lag}^{\perp}$			0.16	[2.4]						
$SENT_{sm}^{\perp}$					0.20	[2.9]	0.10	[1.5]	0.15	[2.1]
CP_{IT}							0.92	[3.2]		
CS_{IT}									0.81	[1.7]
N		509		510		498		498		498
R^2		0.05		0.03		0.04		0.07		0.04
Panel B. Long Term Bond Returns										
$R_m - R_f$	0.18	[4.8]	0.13	[3.6]	0.14	[3.9]	0.13	[3.7]	0.14	[3.8]
$\Delta SENT^{\perp}$	-0.54	[-4.3]								
$SENT_{lag}^{\perp}$			0.26	[2.1]						
$SENT_{sm}^{\perp}$					0.32	[2.5]	0.21	[1.7]	0.24	[2.0]
CP_{LT}							0.91	[3.5]		
CS_{LT}									0.92	[2.9]
N		509		510		498		498		498
R^2		0.08		0.05		0.06		0.09		0.08

Table 9. Predictable variation in bond returns and the cross-section of factor loadings, 1963 to 2008. 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 in 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. N=546.

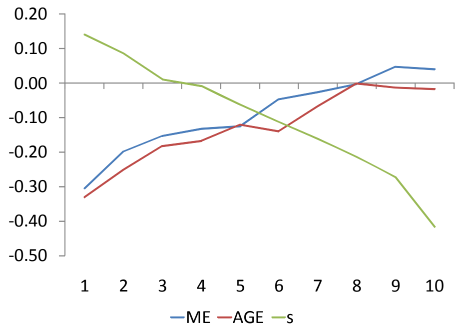
		Decile									
	<0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Panel A. Coefficients											
ME		-0.23	-0.14	-0.08	-0.05	-0.02	-0.04	-0.03	0.04	0.05	0.04
AGE		-0.14	-0.14	-0.13	-0.12	-0.06	-0.10	-0.04	-0.09	-0.09	0.00
σ		-0.06	-0.03	-0.06	-0.08	-0.09	-0.11	-0.11	-0.18	-0.19	-0.24
D/BE	-0.27	-0.18	-0.15	-0.10	-0.09	-0.08	-0.03	-0.08	-0.07	-0.04	-0.01
E/BE	-0.24	-0.25	-0.18	-0.13	-0.13	-0.16	-0.14	-0.17	-0.17	-0.15	-0.15
BE/ME		-0.19	-0.12	-0.09	-0.07	-0.08	-0.09	-0.11	-0.11	-0.14	-0.18
EF/A		-0.21	-0.11	-0.10	-0.08	-0.09	-0.11	-0.10	-0.12	-0.12	-0.16
GS		-0.17	-0.13	-0.08	-0.06	-0.12	-0.11	-0.14	-0.13	-0.14	-0.15
Panel B. T-statistics											
ME		[-2.6]	[-2.0]	[-1.2]	[-0.9]	[-0.5]	[-1.1]	[-0.9]	[1.1]	[1.8]	[1.6]
AGE		[-1.8]	[-1.8]	[-1.8]	[-1.7]	[-1.1]	[-1.9]	[-0.9]	[-1.9]	[-2.1]	[0.1]
σ		[-1.3]	[-0.8]	[-1.3]	[-1.6]	[-1.7]	[-2.0]	[-1.9]	[-2.7]	[-2.6]	[-2.6]
D/BE	[-3.3]	[-2.8]	[-2.4]	[-1.9]	[-1.6]	[-1.5]	[-0.6]	[-1.7]	[-1.8]	[-0.9]	[-0.3]
E/BE	[-2.3]	[-2.9]	[-2.3]	[-1.7]	[-2.0]	[-2.5]	[-2.3]	[-2.8]	[-3.1]	[-3.2]	[-3.0]
BE/ME		[-3.4]	[-2.3]	[-1.6]	[-1.3]	[-1.4]	[-1.5]	[-1.7]	[-1.7]	[-1.9]	[-2.1]
EF/A		[-2.7]	[-1.7]	[-1.7]	[-1.4]	[-1.8]	[-2.3]	[-1.9]	[-2.2]	[-2.2]	[-2.3]
GS		[-1.9]	[-1.8]	[-1.3]	[-1.1]	[-2.3]	[-2.1]	[-2.7]	[-2.7]	[-2.6]	[-2.4]

Figure 1. Bond returns and the cross-section of stock returns, 1963 to 2008. We regress excess portfolio returns on contemporaneous excess market returns and excess long-term bond returns:

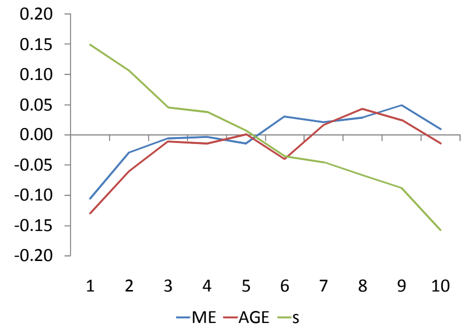
$$r_{pt} - r_{ft} = a_p + \beta_p \left(r_{mt} - r_{ft}\right) + s_p SMB_t + h_p HML_t + m_p UMD_t + b_p \left(r_{bt} - r_{ft}\right) + u_{pt}$$

We report only b_p. The portfolios are formed equally-weighted within deciles on market capitalization (ME), age in 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. N=546.

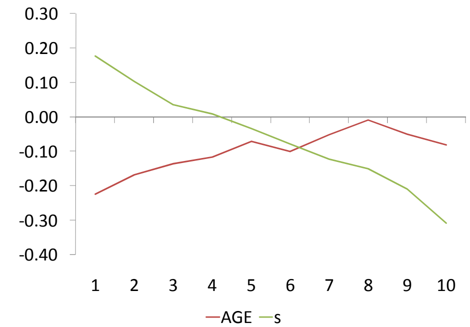
Panel A. Market model; ME, AGE, σ



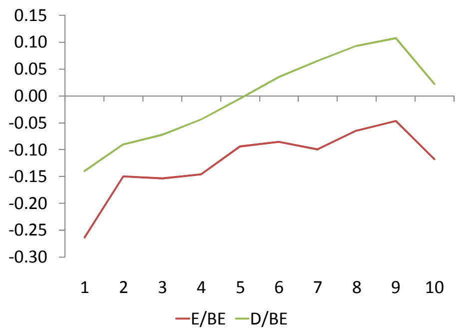
Panel D. Four factors; ME, AGE, σ



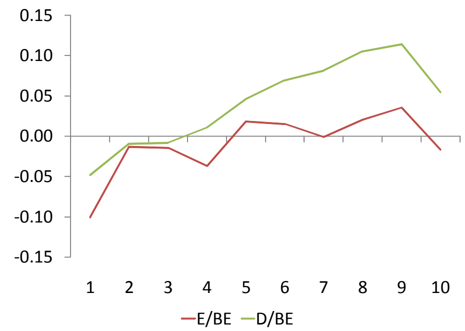
Panel G. Double sorts; AGE, σ



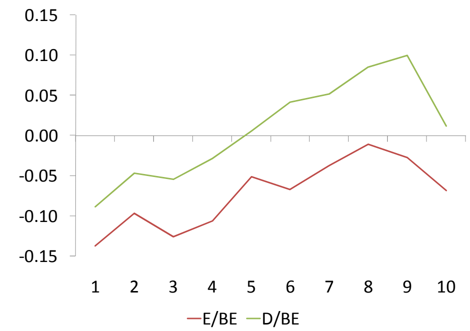
Panel B. Market model; D/BE, E/BE



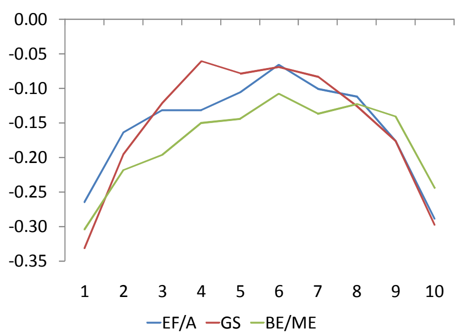
Panel E. Four factors; D/BE, E/BE



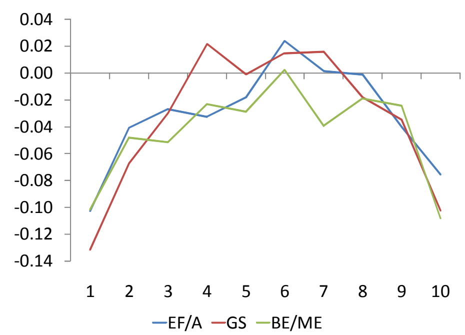
Panel H. Double sorts; D/BE, E/BE



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

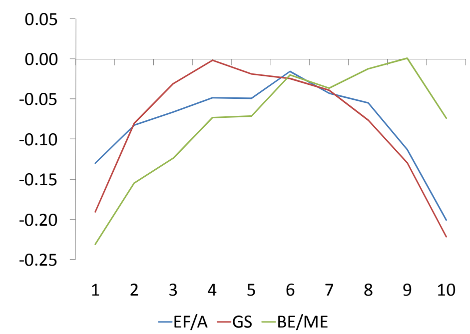


Figure 2. Predictable variation in bond returns and sentiment. The lagged sentiment index (dashed line) and the Cochrane-Piazzesi long-term bond return predictor (solid line).

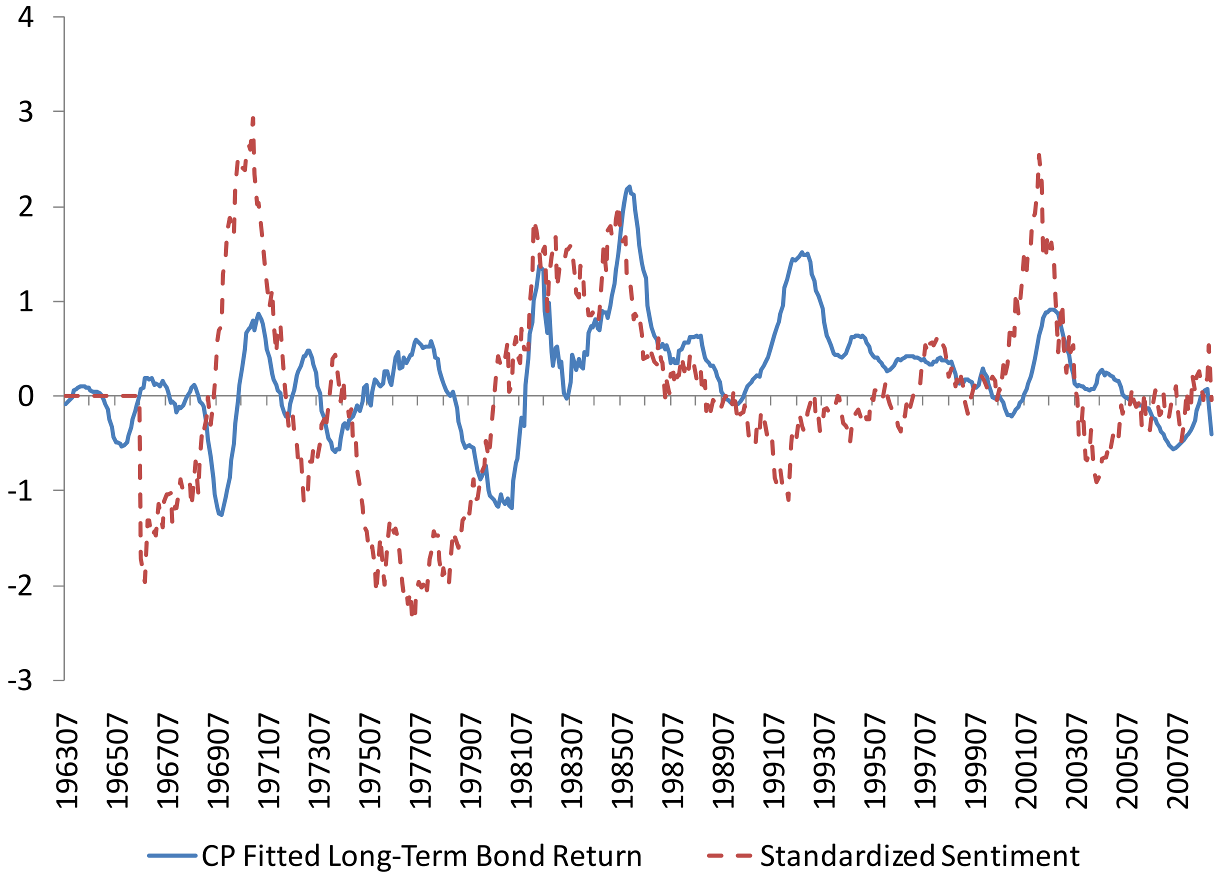
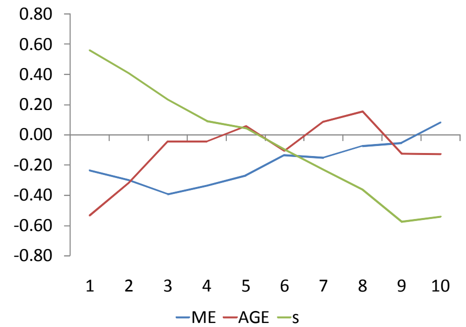


Figure 3. Predictable variation in bond returns and the cross-section of stock returns, 1963 to 2008. We regress monthly excess portfolio returns on contemporaneous excess market returns, HML, SMB, UMD, and the Cochrane-Piazzesi forecast of excess long-term bond returns:

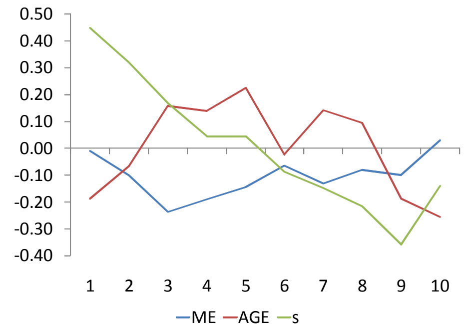
$$r_{pt} - r_{ft} = a_p + \beta_p \left(r_{mt} - r_{ft} \right) + h_p HML_t + s_p SMB_t + m_p UMD_t + t_p CP_{LTt-1} + u_{pt} .$$

We report only t_p. The portfolios are formed equally-weighted within deciles on market capitalization (ME), age in 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. N=546.

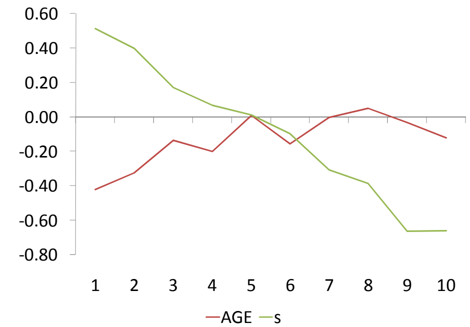
Panel A. Market model; ME, AGE, σ



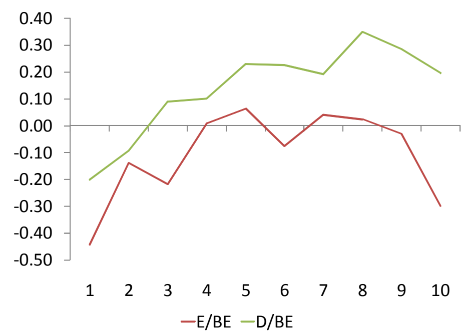
Panel D. Four factors; ME, AGE, σ



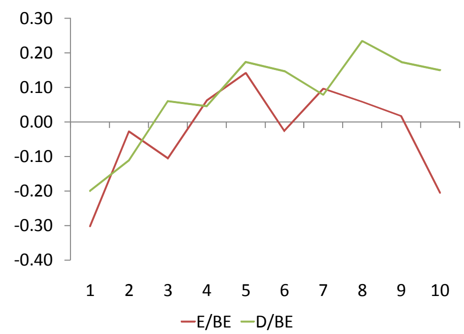
Panel G. Double sorts; AGE, σ



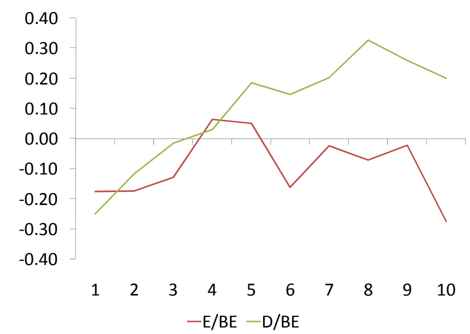
Panel B. Market model; D/BE, E/BE



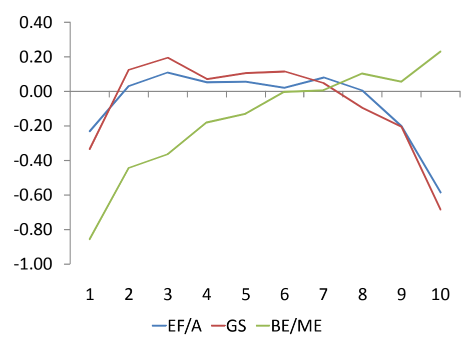
Panel E. Four factors; D/BE, E/BE



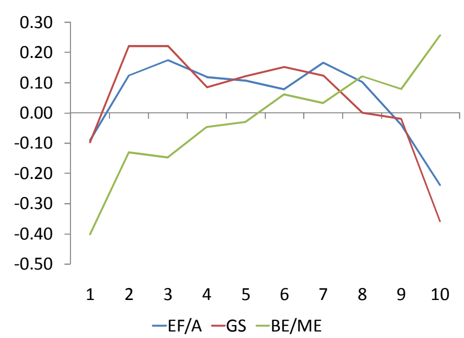
Panel H. Double sorts; D/BE, E/BE



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