

# Comovement and Predictability Relationships Between Bonds and the Cross-section of Stocks

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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. Variables that are derived from the yield curve that are already known to predict returns on bonds also predict returns on bond-like stocks; investor sentiment, a predictor of the cross-section of stock returns, also predicts excess bond returns. These relationships remain in place even when bonds and stocks become “decoupled” at the index level. They are 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. (*JEL* G12, G14)

## 1. 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 properties of major asset classes.

The relationships between stock and bond returns have proved difficult to pin down, however, let alone to understand. Over the past four decades, the correlation between stock index and government bond returns has been highly

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unstable. Baele, Bekaert, and Inghelbrecht (2010), for example, find that the correlation between daily returns on stock and bond indices is on average modestly positive but has ranged anywhere from +0.60 to -0.60 over the past forty years and exhibits sharp changes of 0.20 or more from month to month. In negative correlation periods, the markets are sometimes 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 decoupled as well.

In this article, 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 article 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. This control is important, because it allows us to separate stable cross-sectional relationships from time-varying aggregate correlations. 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—again, controlling for overall stock market returns. 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, there remain basic links between stocks and bonds that 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; Cochrane and Piazzesi 2005), also predict the returns on bond-like stocks relative to speculative stocks.<sup>1</sup> In the other direction, the sentiment index that Baker and Wurgler (2006) use to

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<sup>1</sup> A fuller literature review follows this introductory section.

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, nonexclusive 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 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.

Since bonds and bond-like stocks are clearly exposed to common shocks to real cash flows, we assign positive weight to the cash flow channel immediately. 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 indicate that at least one of these also must be given nonzero weight. Risk-based required returns suggest 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 that either 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, the betas do not change by nearly enough to generate the observed magnitude of predictability with a constant market risk premium of plausible magnitude. 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 consider this story from multiple angles. We observe that sentiment and flights to quality are anecdotally associated with a number of special financial market episodes, including but not limited to the stock market decline of 2008. More rigorously, periodic overreaction can explain the pattern that the riskiest stocks are, not infrequently, poised 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, there are 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 related predictability patterns, and it appears that at least three economic mechanisms are playing a role in the results.

Section 2 provides an overview of related literature. Section 3 describes the data and studies the comovement relationships between government bonds and the cross-section of stocks. Section 4 studies predictability. Section 5 discusses interpretations, and Section 6 concludes.

## 2. 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 \(2010\)](#), [Bekaert, Engstrom, and Grenadier \(2005\)](#), and [Campbell, Sunderam, and Viceira \(2009\)](#). Our methodology controls for the time-varying aggregate correlation and looks for stable correlations within the cross-section, so in that sense our results do not have immediate implications for the aggregate puzzle (but we do describe an effort to connect it to that puzzle later on).

Exceptions to an exclusive focus on stock indices include [Fama and French \(1993\)](#) and, more recently, [Kojien, Lustig, and Van Nieuwerburgh \(2010\)](#). Among other findings in their article, Fama and French document 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 covariances between yield-curve variables and various stock portfolios.

The article by [Kojien et al. \(2010\)](#) 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. On the bond market side, we use

a simpler empirical approach, and we come to different conclusions because we focus on a broader set of stock portfolios and a broader set of bond market predictors.<sup>2</sup> On the stock market side, Kojien et al. use the dividend-price ratio as an aggregate predictor of interest. Because we focus on other sorts, and the dividend-price ratio has little explanatory power for the cross-section, we focus on investor sentiment as the connection between the markets. Sentiment has been more empirically successful in the prior literature and, it turns out, in this article as well.

Our article also relates to literature that considers how shifting sentiment or flights to quality influence predictability results. 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. Lan (2008) also observes this phenomenon and uses a Campbell-Shiller (1987) decomposition to study how time-varying expectations of cash flow and risk premia may contribute to it. Beber, Brandt, and Kavajecz (2009) find traces of flights to quality and flights to liquidity in the euro-area bond market. Implicit in some of 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). Gabaix (2010) develops a model where perceptions of risks (modeled as perceptions of behavior during disasters) affect stocks and bonds systematically. He suggests a way to think quantitatively about the joint behavior of sentiment and prices.

This literature highlights another difference between our article and Fama and French (1993) and Kojien et al. (2010). These articles do not look specifically at decoupling periods, which have reemerged as an area of interest after the market meltdowns that began in the autumn of 2008. We study these patterns specifically, and find some additional links between bonds and the cross-section of stocks that do not appear in the aggregate stock-bond relationship.

### 3. 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 describe first the data and then the basic regression results.

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<sup>2</sup> Like Kojien et al. (2010), we do not find that the level of the Cochrane-Piazzesi (2005) predictor predicts the value premium unconditionally. Looking forward, we do find that it predicts volatility and real growth (sales, assets) sorted portfolios, as well as book-to-market portfolios sorted non-monotonically.

### 3.1 Data on stock and bond indices and stock portfolios

Table 1 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 (2011). Monthly excess returns on the value-weighted New York Stock Exchange (NYSE)/Amex/Nasdaq stock market are from the Center for Research in Security Prices (CRSP).<sup>3</sup>

The stock portfolio constructions follow Fama and French (1992) and Baker and Wurgler (2006). The firm-level data are from the merged CRSP-Compustat database. The sample includes all common stock (share codes 10 and 11) between 1963 and 2010. As discussed in Fama and French (1992), Compustat data prior to 1963 have major selection bias problems, being biased toward large and historically successful firms. Accounting data for fiscal year-ends in calendar year  $t - 1$  are matched to monthly returns from July  $t$  through June  $t + 1$ . We omit summary statistics on unconditional returns to save space. We are interested in conditional patterns in any event. They are similar to those reported in Baker and Wurgler (2006) for the same 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  $\sigma$ , 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,  $\sigma$  is matched to monthly returns from July of year  $t$  through June of year  $t + 1$ .

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)

**Table 1**  
Summary statistics: Stock and bond indexes, 1963 to 2010

	Mean	Median	STD	Min	Max
$r_{IT} - r_f$	0.15	0.11	1.54	-7.30	10.73
$r_{LT} - r_f$	0.19	0.07	2.99	-11.24	14.40
$r_m - r_f$	0.45	0.80	4.53	-23.14	16.05

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.  $N = 570$ .

<sup>3</sup> We do not 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 somewhat more like speculative stocks.

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.

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.

The growth and distress variables reflect several effects simultaneously. With book-to-market, high values are often associated with distress and low values with high growth opportunities. Likewise, low values of sales growth and external finance (i.e., negative numbers) can indicate distress, while high values may reflect growth opportunities. In other words, although these portfolios are often considered in a simple “high minus low” sense, a closer look suggests that the extremes include relatively more speculative stocks, in contrast to the middle deciles, which tilt toward less speculative stocks. Complicating matters further, book-to-market is a generic valuation indicator, varying with any source of mispricing or risk-based required returns. Similarly, to the extent that external finance is driven by investor demand and/or market timing, it also serves as a generic misvaluation indicator.

We use equal-weighted stock portfolios. Using value-weighted portfolios would obscure the relationships and contrasts of interest. Some of the cells would be dominated by a few large-cap stocks, reducing power, and focusing on the stocks within each group that are already more bond-like. This would move our estimates toward zero. Instead, we will control for size effects through regression and double sorts to determine that the results go beyond size alone.

### 3.2 Comovement patterns

Table 2 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):

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

The inclusion of overall stock market returns in this regression allows us to isolate cross-sectional differences in “bond beta” without confusing them with the average correlation between the aggregate stock market and bonds. The top panel shows the cross-section of stock market beta loadings  $\beta_p$ . This mainly provides some intuition about the composition of the portfolios. We focus 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 movements.

**Table 2**  
**Bond returns and the cross-section of stock returns, 1963 to 2010**

	<i>Decile</i>										
	<=0	1	2	3	4	5	6	7	8	9	10
Panel A: $\beta_p$ Coefficients											
ME		1.15	1.27	1.25	1.22	1.20	1.14	1.14	1.12	1.04	1.00
AGE		1.34	1.33	1.22	1.22	1.22	1.18	1.18	1.17	1.13	1.15
$\sigma$		0.55	0.73	0.83	0.91	0.99	1.05	1.12	1.23	1.33	1.53
D/BE	1.37	1.15	1.08	1.02	0.98	0.93	0.88	0.83	0.80	0.81	0.85
E/BE	1.41	1.13	1.03	0.98	0.99	0.99	1.00	1.05	1.11	1.17	1.22
BE/ME		1.42	1.29	1.21	1.15	1.10	1.07	1.01	0.99	1.03	1.09
EF/A		1.17	1.08	1.03	1.01	1.02	1.02	1.05	1.11	1.19	1.41
GS		1.26	1.08	1.01	0.97	0.98	0.99	1.04	1.10	1.21	1.38
Panel B: $b_p$ Coefficients											
ME		-0.31	-0.20	-0.16	-0.14	-0.14	-0.06	-0.04	-0.02	0.02	0.03
AGE		-0.34	-0.34	-0.24	-0.23	-0.23	-0.23	-0.18	-0.12	-0.11	-0.12
$\sigma$		0.13	0.07	-0.01	-0.02	-0.08	-0.12	-0.17	-0.23	-0.29	-0.41
D/BE	-0.35	-0.15	-0.10	-0.09	-0.06	-0.01	0.04	0.06	0.08	0.08	-0.01
E/BE	-0.43	-0.24	-0.12	-0.08	-0.06	-0.06	-0.05	-0.08	-0.09	-0.15	-0.16
BE/ME		-0.29	-0.22	-0.21	-0.17	-0.16	-0.13	-0.15	-0.13	-0.15	-0.26
EF/A		-0.28	-0.18	-0.15	-0.15	-0.12	-0.07	-0.11	-0.11	-0.18	-0.30
GS		-0.35	-0.21	-0.14	-0.08	-0.09	-0.09	-0.09	-0.12	-0.17	-0.30
Panel C: $t(b_p)$											
ME		[-5.1]	[-4.3]	[-3.7]	[-3.6]	[-4.0]	[-2.1]	[-1.5]	[-0.8]	[0.9]	[2.2]
AGE		[-3.8]	[-5.7]	[-4.3]	[-4.3]	[-4.6]	[-4.6]	[-3.5]	[-2.6]	[-2.6]	[-2.6]
$\sigma$		[4.0]	[2.3]	[-0.2]	[-0.7]	[-2.4]	[-3.3]	[-4.4]	[-4.9]	[-5.5]	[-6.0]
D/BE	[-6.0]	[-3.6]	[-2.3]	[-2.4]	[-1.5]	[-0.2]	[1.1]	[1.9]	[2.5]	[2.0]	[-0.2]
E/BE	[-5.9]	[-4.9]	[-3.1]	[-2.1]	[-1.8]	[-1.8]	[-1.5]	[-2.5]	[-2.9]	[-4.3]	[-3.9]
BE/ME		[-5.4]	[-5.1]	[-5.0]	[-4.3]	[-4.2]	[-3.3]	[-4.1]	[-3.0]	[-3.2]	[-4.4]
EF/A		[-5.1]	[-4.2]	[-3.9]	[-3.7]	[-3.4]	[-2.2]	[-3.2]	[-2.9]	[-4.6]	[-5.2]
GS		[-5.5]	[-4.3]	[-3.4]	[-2.1]	[-2.4]	[-2.9]	[-2.6]	[-3.5]	[-4.4]	[-5.8]

We regress monthly excess portfolio returns on contemporaneous excess market returns and excess long-term bond returns:

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

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 ( $\sigma$ ), 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).  $N = 570$ .  $t$ -statistics are robust to heteroscedasticity.

The bottom panels of Table 2 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 long-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 0.13 on the lowest-volatility stocks. In other words, a one-percentage-point-higher excess return on long-term bonds is associated with a 0.13-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.



The converse 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  $-0.41$  coefficient on the most volatile stocks.

The bottom three rows in Panel B suggest an interesting U-shaped pattern in the growth and distress variables’ coefficients. The interpretation is intuitive; 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 also suggests that simple high-minus-low portfolios can hide key aspects of the cross-section, including those in the oft-studied book-to-market portfolios.

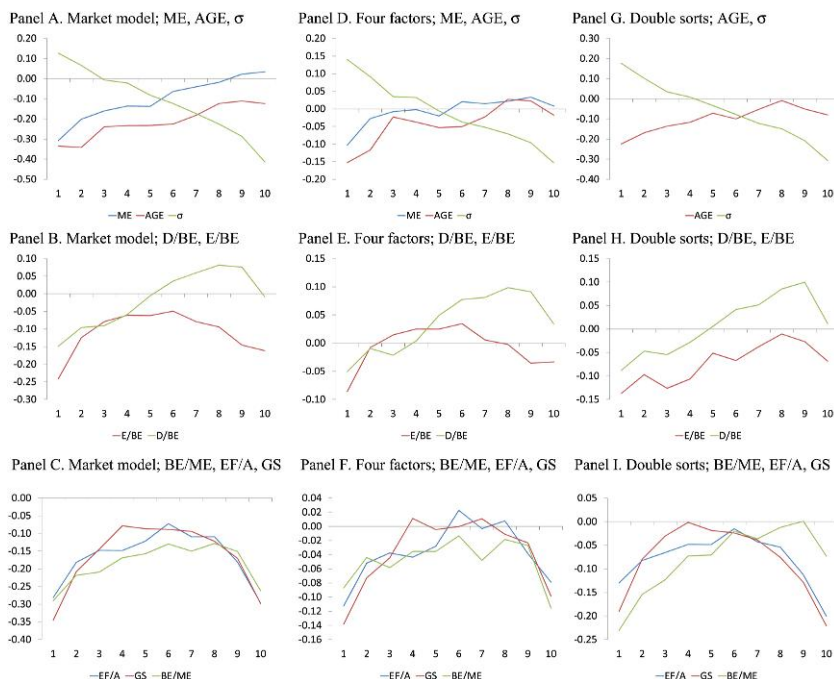
The stock characteristics examined here are correlated, so a natural question is the extent to which they embody independent effects. To examine this question, the left panels of Figure 1 plot the coefficients across stock deciles  $b_p$ , as reported in Table 2, while the middle panels plot the coefficients  $b_p$  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 Equation (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 2 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.

In unreported results, we repeat Table 2 separately for two samples, one for firms above the median profitability for the NYSE and one for firms below. This amounts to a double sort. We can ask, for example, whether a profitable growth stock (or value stock) is more bond-like than a generic growth stock. Rather than clear interactions, however, the predominant effect is simply that profitable firms have stronger comovement relationships with bonds than unprofitable firms in every characteristic-decile cell. Otherwise, the same qualitative patterns appear in both halves of the sample.

### 3.3 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,



**Figure 1**  
**Bond returns and the cross-section of stock returns, 1963 to 2010**

We regress excess portfolio returns on contemporaneous excess market returns and excess long-term bond returns:

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

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 ( $\sigma$ ), 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.  $N = 570$ .

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 sometimes said to have “decoupled.”

A number of authors have studied this 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 (2010) 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.

A natural question is whether the cross-sectional comovement patterns documented earlier exhibit similar instability. Table 3 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 2 are clearly apparent in the somewhat more common “coupling” regime in which bonds and stock indexes move in the same direction.

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, several 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 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.

### **3.4 On the relationship with aggregate stock-bond comovement**

As noted before, Equation (1) divorces our analysis from the aggregate stock-bond comovement puzzle. But our results raise the possibility that the time-varying aggregate correlation reflects a composition effect—for example, if initial public offerings (IPOs) flood the market or existing stocks become more volatile, and less bond-like, then we would expect the aggregate stock market relationship with bonds to deteriorate. To explore this, we tracked a five-year rolling average of the median total volatility across individual stocks—our strongest results are for volatility portfolios—and compared this to the five-year rolling average of the monthly covariance between stock market and bond returns. Unfortunately, outside of a window around the Internet bubble, the relationship is not as consistently negative as would seem to be required to explain the time-varying aggregate correlation via a sample composition effect.

## **4. 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 bond returns and bond-like

**Table 3**  
Bond returns and the cross-section of stock returns in index-level decoupling episodes: Long-short portfolios

	ME		AGE		$\sigma$		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, $\text{Sign}(r_m - r_f) = \text{Sign}(r_{LT} - r_f)$																
$r_m - r_f$	-0.25	[-3.1]	0.02	[0.3]	0.70	[10.9]	-0.43	[-8.6]	-0.03	[-0.7]	0.23	[6.9]	0.29	[7.6]	0.33	[8.3]
$r_{LT} - r_f$	0.32	[3.7]	0.22	[2.8]	-0.42	[-5.2]	0.32	[5.5]	0.17	[2.8]	-0.23	[-5.2]	-0.24	[-3.9]	-0.25	[-3.7]
N	323		290		323		323		323		323		323		323	
R <sup>2</sup>	0.05		0.04		0.32		0.25		0.03		0.15		0.15		0.15	
Panel B: Decoupling, $\text{Sign}(r_m - r_f) \neq \text{Sign}(r_{LT} - r_f)$																
$r_m - r_f$	-0.07	[-1.1]	-0.12	[-1.3]	0.65	[8.5]	-0.39	[-8.5]	-0.06	[-1.4]	0.21	[4.3]	0.31	[6.4]	0.41	[5.8]
$r_{LT} - r_f$	0.32	[4.0]	0.05	[0.5]	-0.34	[-4.0]	0.17	[2.2]	0.05	[0.9]	0.00	[0.0]	-0.10	[-1.7]	-0.12	[-1.7]
N	247		208		247		247		247		247		247		247	
R <sup>2</sup>	0.11		0.04		0.52		0.42		0.03		0.19		0.32		0.34	
Panel C: Decoupling, $\text{Sign}(r_m - r_f) \neq \text{Sign}(r_{LT} - r_f)$ in both current and lagged month																
$r_m - r_f$	0.04	[0.4]	-0.30	[-2.4]	0.72	[6.3]	-0.39	[-5.6]	-0.09	[-1.4]	0.24	[3.0]	0.38	[6.2]	0.53	[5.6]
$r_{LT} - r_f$	0.43	[4.2]	-0.01	[0.0]	-0.43	[-3.9]	0.29	[2.8]	0.11	[1.3]	-0.01	[-0.2]	-0.14	[-2.0]	-0.21	[-2.2]
N	110		91		110		110		110		110		110		110	
R <sup>2</sup>	0.11		0.16		0.54		0.48		0.07		0.22		0.42		0.44	

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:

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

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 ( $\sigma$ ), 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 heteroscedasticity.

stock returns 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.

#### 4.1 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 articles, 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—that is, the fitted intermediate-term excess bond return using the one-year rate and the two- through five-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 twelve-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. 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 (2011). The credit spread is the gap between the commercial paper yield and the T-bill yield. The commercial paper yield series from the National Bureau of Economic Research (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

**Table 4**  
**Summary statistics: Bond return and cross-section of stock return predictor variables, 1966 to 2010**

	N	Mean	Median	STD	Min	Max	Correlations			
							CP <sub>IT</sub>	CP <sub>LT</sub>	CS <sub>IT</sub>	CS <sub>LT</sub>
CP <sub>IT</sub>	546	0.13	0.16	0.35	-0.77	1.31	1.00			
CP <sub>LT</sub>	546	0.19	0.17	0.59	-1.26	2.21	0.93	1.00		
CS <sub>IT</sub>	546	0.18	0.20	0.19	-0.28	0.86	0.42	0.30	1.00	
CS <sub>LT</sub>	546	0.26	0.31	0.46	-1.00	2.07	0.51	0.46	0.93	1.00
SENT <sup>⊥</sup>	546	0.00	-0.01	1.00	-2.57	2.69	0.12	-0.02	0.07	-0.02
SENT <sub>lag</sub> <sup>⊥</sup>	534	0.00	-0.01	1.01	-2.57	2.69	0.33	0.19	0.31	0.24
SENT <sub>sm</sub> <sup>⊥</sup>	528	0.00	-0.06	1.01	-2.39	2.45	0.35	0.21	0.31	0.24
DSENT	545	0.00	0.00	1.00	-3.53	4.37	-0.07	-0.05	-0.01	-0.01

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 one-year rate and the two- through five-year forward rates derived from the Fama-Bliss yield curve from CRSP. The regressors are twelve-month moving averages, lagged once relative to the prediction month. The predictive regressions have  $R^2 = 0.04$ ,  $N = 570$  months. We report data from July 1965,  $N = 546$ , to match the coverage of sentiment in Table 8. The fitted predictors for month  $t$  returns have a  $t - 1$  subscript as a reminder they use lagged information:

$$\begin{aligned}
 CP_{IT,t-1} &= -0.003 - 0.19y_{1,t-1} - 0.21f_{2,t-1} + 0.50f_{3,t-1} + 0.50f_{4,t-1} - 0.55f_{5,t-1}, \text{ and} \\
 CP_{LT,t-1} &= -0.004 - 0.57y_{1,t-1} + 0.17f_{2,t-1} + 0.24f_{3,t-1} + 1.10f_{4,t-1} - 0.92f_{5,t-1}.
 \end{aligned}$$

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  $R^2 = 0.02$ ,  $N = 570$ . We report data from July 1965,  $N = 546$ , to match the coverage of sentiment in Table 7. The fitted predictors for month  $t$  returns have a  $t - 1$  subscript as a reminder they use lagged information:

$$\begin{aligned}
 CS_{IT,t-1} &= -0.01 + 0.05r_{ft-6} + 0.13(y_{LT,t-6} - r_{ft-6}) - 0.01(y_{CP,t-6} - r_{ft-6}) \\
 &\quad + 0.22(y_{Aaat-6} - y_{CP,t-6}), \text{ and} \\
 CS_{LT,t-1} &= -0.01 + 0.07r_{ft-6} + 0.30(y_{LT,t-6} - r_{ft-6}) + 0.07(y_{CP,t-6} - r_{ft-6}) \\
 &\quad + 0.32(y_{Aaat-6} - y_{CP,t-6}).
 \end{aligned}$$

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. These are described in detail in Baker and Wurgler (2007). The index 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 are twelve months old.  $SENT_{sm}^{\perp}$  averages sentiment values lagged six to eighteen months. It is available from July 1967,  $N = 528$  months.

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 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). This is the predictor that we focus on, as they

show it has predictive power across the full range of portfolios that we consider. Finally, Ghosh and Constantinides (2011) estimate a regime-switching model based on a nonlinear function of the risk-free rate and the market price-dividend ratio and derive a model-implied factor to predict conditional cross-sectional returns. Like Kojien et al. (2010), they focus on size and value portfolios.

The sentiment 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 five-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.<sup>4</sup> The sentiment index  $SENT^{\perp}$  is the first principal component of the six orthogonalized proxies. It 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. See Baker and Wurgler (2006) for further construction details and motivation.

The sentiment index is a contrarian predictor. Baker and Wurgler (2006) find that when the sentiment index takes high values, "high-sentiment-beta" stocks underperform over the next year or more. Stocks with a high sentiment beta tend to be hard to arbitrage and hard to value (speculative) stocks—for example, small, young, highly volatile, distressed, and rapid-growth stocks. These stocks are more prone to be mispriced when sentiment is highly bullish or bearish. Their difficulty of valuation permits noise traders to entertain extreme valuations, and simultaneously complicates the arbitrageurs' task of identifying fundamental value. These same stocks are also, generally speaking, more costly and risky to trade, which further discourages arbitrageurs. As a result, high-sentiment-beta stocks are prone to be (relatively) overpriced when sentiment is high and underperform going forward as prices correct, and vice versa. We hypothesize that bonds will perform more like low-sentiment-beta stocks. In a period of high sentiment, they may be relatively neglected and underpriced and perform better than average going forward, and vice versa.

Prior work tends to lag the yield curve predictors between one month, six months, and one year in part as a result of the literature's cumulative outcome of empirical searches to maximize bond return predictability. We have a similar decision here about how much to lag the sentiment index. A combination of

<sup>4</sup> The sentiment data are available at [www.stern.nyu.edu/~jwurgler](http://www.stern.nyu.edu/~jwurgler).

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.

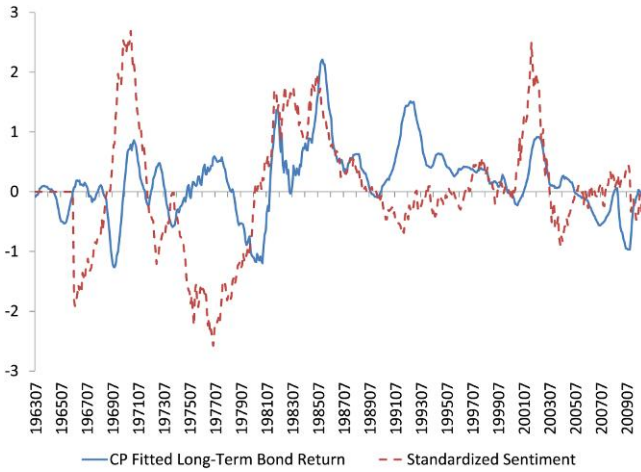
Finally, we make use of a monthly index of *changes* in sentiment,  $\Delta SENT_{\perp}$ , which is based on a similar principal components analysis of changes in the underlying sentiment proxies. Our monthly sentiment series on this variable are as used in Baker and Wurgler (2007). As this is employed only briefly as a control variable, we defer details of its construction to the header of Table 4. Baker and Wurgler find that speculative, non-bond-like stocks possess higher sentiment beta—that is, higher contemporaneous sensitivity to this index.

The predictors are summarized in Table 4 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 period of the late 1970s through mid-1980s, when bond return volatility increased.

## 4.2 Bond predictors and the cross-section of stock returns

We first test whether bond return predictors are also effective in predicting the returns to bond-like stocks relative to speculative stocks. Few articles 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





**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).

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 they do not go deeper into the cross-section of stocks, and furthermore we have more than twenty additional years of data to study.

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

$$r_{pt} - r_{ft} = a_p + \beta_p (r_{mt} - r_{ft}) + t_p CPLT_{t-1} + u_{pt}. \quad (2)$$

The specification intentionally resembles that of Equation (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 generally significantly lower than the average. While the conditional spread of returns in size portfolios—for

**Table 5**  
**Predictable variation in bond returns and the cross-section of stock returns: Decile portfolios, 1963 to 2010**

	<i>Decile</i>										
	<=0	1	2	3	4	5	6	7	8	9	10
Panel A: $t_p$ Coefficients											
ME		-0.37	-0.32	-0.40	-0.37	-0.31	-0.18	-0.20	-0.14	-0.12	0.06
AGE		-1.50	-0.78	-0.56	-0.36	-0.27	-0.22	-0.27	0.27	-0.05	-0.40
$\sigma$		0.53	0.37	0.18	0.04	0.01	-0.16	-0.30	-0.48	-0.75	-0.77
D/BE	-0.74	-0.21	-0.10	0.07	0.10	0.25	0.23	0.14	0.21	0.05	-0.05
E/BE	-0.76	-0.37	0.01	-0.01	0.04	-0.03	-0.02	-0.08	-0.20	-0.30	-0.48
BE/ME		-0.88	-0.50	-0.42	-0.27	-0.20	-0.10	-0.02	0.00	-0.04	-0.03
EF/A		-0.42	-0.14	-0.04	-0.05	-0.03	-0.03	0.02	-0.04	-0.22	-0.72
GS		-0.51	-0.02	0.02	-0.05	0.06	0.01	0.02	-0.10	-0.26	-0.76
Panel B: $t(t_p)$											
ME		[-1.2]	[-1.4]	[-2.0]	[-2.1]	[-1.9]	[-1.3]	[-1.9]	[-1.3]	[-1.2]	[0.9]
AGE		[-3.1]	[-2.5]	[-1.7]	[-1.2]	[-0.9]	[-0.8]	[-1.0]	[0.9]	[-0.2]	[-1.6]
$\sigma$		[4.0]	[3.2]	[1.4]	[0.3]	[0.0]	[-0.9]	[-1.5]	[-2.1]	[-2.7]	[-2.1]
D/BE	[-2.4]	[-1.1]	[-0.6]	[0.4]	[0.6]	[1.6]	[1.6]	[1.1]	[1.4]	[0.3]	[-0.3]
E/BE	[-1.9]	[-1.4]	[0.1]	[-0.1]	[0.3]	[-0.2]	[-0.2]	[-0.6]	[-1.3]	[-1.8]	[-2.5]
BE/ME		[-3.5]	[-2.4]	[-2.0]	[-1.4]	[-1.1]	[-0.5]	[-0.1]	[0.0]	[-0.2]	[-0.1]
EF/A		[-1.4]	[-0.6]	[-0.2]	[-0.2]	[-0.2]	[-0.2]	[0.1]	[-0.2]	[-1.1]	[-2.7]
GS		[-1.5]	[-0.1]	[0.1]	[-0.3]	[0.3]	[0.1]	[0.1]	[-0.6]	[-1.3]	[-3.2]

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:

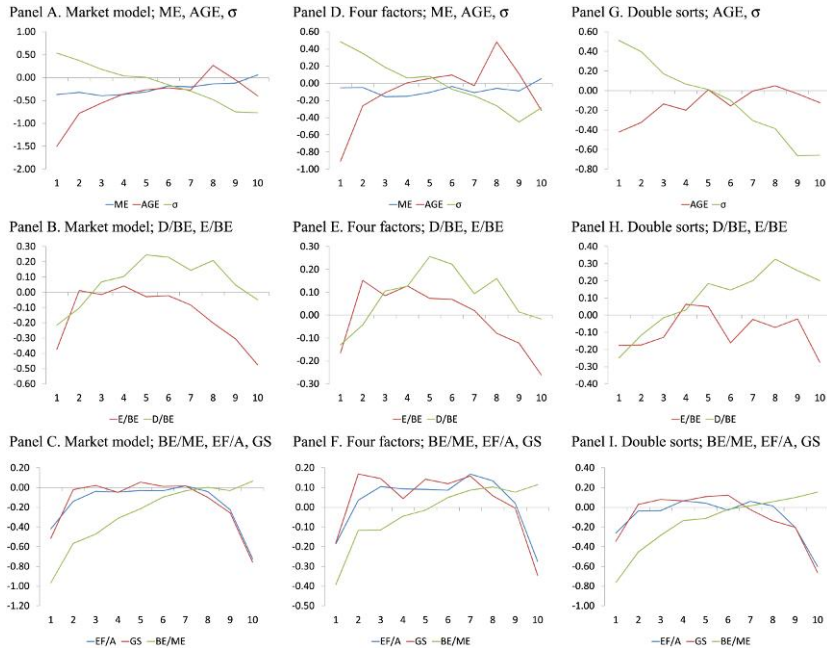
$$r_{pt} - r_{ft} = a_p + \beta_p (r_{mt} - r_{ft}) + t_p C P_{LTt-1} + u_{pt}.$$

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 ( $\sigma$ ), 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).  $N = 570$ .  $t$ -statistics are robust to heteroscedasticity.

example, as in the comovement coefficients—the total return volatility characteristic produces the greatest spread of coefficients, suggesting that it best aligns with the speculative versus bond-like differentiation. Also as before, the sales growth characteristic produces the most pronounced U-shaped pattern. Again, this is consistent with extreme-growth stocks and distressed stocks being less bond-like than firms with steady sales growth. Interestingly, the  $t_p$  coefficient estimates from Equation (2) are similar in sign but generally larger in magnitude than the  $b_p$  coefficients estimated from Equation (1). This has an interesting interpretation. Stock returns are particularly sensitive to the *predictable component* of bond returns.<sup>5</sup>

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

<sup>5</sup> Most of the  $t$ -statistics in Table 5 are not significantly different from zero. This is expected given the pattern of coefficients and is not inconsistent with theoretical predictions. For example, the sigma coefficients must pass through zero on their way from significantly positive to significantly negative. The main point is that in most portfolios, the coefficients are generally statistically significant at at least one extreme.



**Figure 3**  
**Predictable variation in bond returns and the cross-section of stock returns, 1963 to 2010**

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:

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

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 ( $\sigma$ ), 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.  $N = 570$ .

estimated after adding controls *SMB*, *HML*, and *UMD* to Equation (2). The right panels plot the coefficients from double sorts that control for firm size as described earlier. There is a quite 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 6. 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:

$$r_{pt} - r_{ft} = a_p + \beta_p (r_{mt} - r_{ft}) + h_p HML_t + s_p SMB_t + m_p MOM_t + t_p CPLT_{t-1} + u_{pt}. \tag{3}$$

Table 6  
Predictable variation in bond returns and the cross-section of stock returns: Long-short portfolios, 1963 to 2010

	ME		AGE		$\sigma$		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																
$r_m - r_f$	-0.12	[-1.8]	0.32	[4.0]	0.57	[11.1]	-0.23	[-6.1]	0.01	[0.1]						
HML	-0.07	[-0.5]	0.58	[5.0]	-0.33	[-3.6]	0.19	[2.7]	-0.10	[-1.0]						
SMB			-0.19	[-2.3]	1.23	[13.7]	-0.97	[-14.8]	-0.76	[-9.0]						
MOM	0.08	[0.9]	0.16	[1.7]	-0.23	[-3.3]	0.08	[1.3]	0.18	[2.3]						
$CP_{LTI-1}$	0.41	[1.2]	-0.12	[-0.3]	-0.77	[-2.5]	0.34	[1.5]	0.03	[0.1]						
N	570		498		570		570		570							
$R^2$	0.02		0.13		0.70		0.62		0.31							
Panel B: Top 3 minus Bottom 3 or Extremes - Middle 2																
$r_m - r_f$	-0.14	[-3.0]	0.14	[3.4]	0.38	[11.8]	-0.20	[-8.6]	0.07	[2.9]	0.06	[3.2]	0.11	[5.0]	0.14	[5.1]
HML	0.00	[0.0]	0.34	[5.3]	-0.17	[-3.1]	0.04	[1.0]	-0.16	[-3.2]	-0.21	[-5.0]	-0.13	[-2.8]	-0.24	[-4.9]
SMB			-0.17	[-3.2]	0.91	[16.2]	-0.66	[-16.1]	-0.45	[-9.9]	0.22	[6.3]	0.46	[12.7]	0.53	[11.8]
MOM	0.05	[0.7]	0.10	[1.8]	-0.14	[-3.2]	0.02	[0.8]	0.07	[1.9]	-0.05	[-1.4]	-0.13	[-3.6]	-0.13	[-3.6]
$CP_{LTI-1}$	0.27	[1.2]	0.35	[1.2]	-0.67	[-3.6]	0.23	[1.6]	-0.05	[-0.4]	-0.16	[-1.2]	-0.32	[-2.5]	-0.39	[-2.5]
N	570		498		570		570		570		570		570		570	
$R^2$	0.04		0.13		0.74		0.68		0.32		0.32		0.53		0.53	

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:

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

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 ( $\sigma$ ), 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 heteroscedasticity.

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 distress variables. We form such portfolios as the extreme three minus the middle two deciles, which intuitively should capture the contrast between speculative and bond-like stocks.

The results indicate that the Cochrane-Piazzesi factor has incremental predictive power for the top-minus-bottom portfolios formed on 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 extend directly 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.

### 4.3 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:

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

We begin with specifications that include the index of sentiment changes. We wish to investigate whether bonds have low or negative sentiment betas, as do most bond-like 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 control for contemporaneous stock market returns to determine whether sentiment can predict bonds separate from its ability to forecast stocks. We also control for the yield curve-based predictors.

Results for intermediate-term bonds are in the top panel, and long-term bonds are in the bottom panel of Table 7. 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 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  $SENT_t^\perp$  is associated with 0.16% per month higher excess returns on intermediate-term bonds and 0.26% per month higher excess returns on long-term bonds. This is a comparatively impressive degree of predictive power for several reasons. The index has a clearer interpretation than the yield curve predictors, has no mechanical connection to future returns, and was developed in a separate setting. In contrast, the bond return

**Table 7**  
Sentiment and future bond returns, 1966 to 2010

	Investor Sentiment				Cochrane-Piazzesi		Campbell-Shiller			
	coef	[t]	coef	[t]	coef	[t]	coef	[t]		
<b>Panel A: Intermediate Term Bond Returns</b>										
$r_m - r_f$	0.05	[3.0]	0.04	[2.4]	0.04	[2.3]	0.04	[2.2]	0.04	[2.2]
$\Delta SENT_t^\perp$	-0.28	[-3.3]								
$SENT_{tag,t}^\perp$			0.16	[2.4]						
$SENT_{sm,t}^\perp$					0.19	[2.8]	0.11	[1.7]	0.15	[2.2]
$CP_{LT,t-1}$							0.71	[3.0]		
$CS_{LT,t-1}$									0.69	[1.5]
$N$		545		534		528		528		528
$R^2$		0.04		0.02		0.03		0.05		0.03
<b>Panel B: Long Term Bond Returns</b>										
$r_m - r_f$	0.14	[4.1]	0.11	[3.2]	0.11	[3.1]	0.11	[3.0]	0.11	[3.0]
$\Delta SENT_t^\perp$	-0.58	[-4.1]								
$SENT_{tag,t}^\perp$			0.26	[2.1]						
$SENT_{sm,t}^\perp$					0.31	[2.5]	0.19	[1.6]	0.24	[2.0]
$CP_{LT,t-1}$							0.87	[3.4]		
$CS_{LT,t-1}$									0.77	[2.4]
$N$		545		534		528		528		528
$R^2$		0.06		0.04		0.04		0.06		0.05

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,

$$r_{bt} - r_{ft} = a + \beta (r_{mt} - r_{ft}) + \beta^s \Delta SENT_t^\perp + b SENT_{t-1}^\perp + c CP_{LT,t-1} + u_t.$$

We do not report the constant term.  $t$ -statistics are robust to heteroscedasticity. Smoothed sentiment covers only the period from July 1967 to December 2010.  $N = 528$ .

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 they may have evolved to that state over the course of many investigations in the literature.

The third pair of columns uses a smoothed version of sentiment, averaging out the values from six to eighteen months prior to the return prediction. Theory provides little 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 it 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.

## **5. Discussion and Interpretation**

This article's most concrete contribution is descriptive: bonds and bond-like stocks are connected in both comovement and predictability patterns. As mentioned in the Introduction, there are three general and nonexclusive 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. 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 role in the results. At the end, we also comment on the relationship between our results and the time-varying aggregate correlation between stocks and bonds.

### **5.1 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 an 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.

## 5.2 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.

**5.2.1 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 \(2006\)](#) conduct a time-varying betas test in some cases of interest here. They run regressions on long-short portfolios of the form

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

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  $\beta d$  be higher for bond-like stocks. They report that the sign of  $\beta d$  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, using virtually the same data as we use here (the main difference being a few extra years in our sample), so we can 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

$$r_{pt} - r_{ft} = a_p + \beta_p (c_p + d_p CP_{LT,t-1}) (r_{mt} - r_{ft}) + t_p CP_{LT,t-1} + u_{pt}. \quad (6)$$

Again, the time-varying betas interpretation of why bond predictors also predict the relative returns on bond-like stocks requires that  $\beta d$  be higher for bond-like stocks. Table 8 reports the  $\beta d$  coefficients from Equation (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 one percentage point higher per month and therefore

**Table 8**  
**Predictable variation in bond returns and the cross-section of factor loadings, 1963 to 2010**

	<i>Decile</i>										
	<0	1	2	3	4	5	6	7	8	9	10
Panel A: $\beta_p d_p$ Coefficients											
ME		-0.22	-0.16	-0.10	-0.07	-0.05	-0.06	-0.04	0.02	0.02	0.03
AGE		-0.24	-0.11	-0.13	-0.09	-0.15	-0.08	-0.14	-0.18	-0.04	-0.13
$\sigma$		-0.06	-0.05	-0.08	-0.10	-0.12	-0.13	-0.14	-0.20	-0.21	-0.24
D/BE	-0.23	-0.18	-0.16	-0.13	-0.12	-0.10	-0.07	-0.11	-0.15	-0.14	-0.09
E/BE	-0.22	-0.21	-0.15	-0.12	-0.12	-0.12	-0.11	-0.12	-0.08	-0.10	-0.12
BE/ME		-0.13	-0.09	-0.08	-0.09	-0.10	-0.13	-0.12	-0.16	-0.17	-0.25
EF/A		-0.23	-0.16	-0.13	-0.11	-0.11	-0.12	-0.10	-0.13	-0.12	-0.15
GS		-0.20	-0.17	-0.13	-0.11	-0.14	-0.12	-0.14	-0.12	-0.14	-0.12
Panel B: $t(\beta_p d_p)$											
ME		[-2.7]	[-2.4]	[-1.6]	[-1.4]	[-0.9]	[-1.5]	[-1.2]	[0.5]	[0.4]	[1.1]
AGE		[-2.1]	[-1.3]	[-1.6]	[-1.2]	[-2.0]	[-1.1]	[-1.8]	[-2.2]	[-0.6]	[-1.9]
$\sigma$		[-1.6]	[-1.3]	[-1.9]	[-2.3]	[-2.3]	[-2.3]	[-2.3]	[-3.1]	[-2.9]	[-2.9]
D/BE	[-3.1]	[-3.1]	[-2.8]	[-2.5]	[-2.1]	[-2.2]	[-1.5]	[-2.6]	[-3.2]	[-2.5]	[-1.7]
E/BE	[-2.3]	[-2.9]	[-2.6]	[-2.3]	[-2.4]	[-2.4]	[-2.4]	[-2.6]	[-1.7]	[-2.2]	[-2.2]
BE/ME		[-2.2]	[-1.8]	[-1.4]	[-1.6]	[-1.8]	[-2.2]	[-2.1]	[-2.5]	[-2.5]	[-2.8]
EF/A		[-3.0]	[-2.4]	[-2.4]	[-2.1]	[-2.2]	[-2.7]	[-2.2]	[-2.5]	[-2.1]	[-2.2]
GS		[-2.3]	[-2.5]	[-2.0]	[-1.9]	[-2.9]	[-2.7]	[-2.9]	[-2.7]	[-2.6]	[-2.1]

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:

$$r_{pt} - r_{ft} = a_p + \beta_p (c_p + d_p CP_{LT,t-1}) (r_{mt} - r_{ft}) + t_p CP_{LT,t-1} + u_{pt}.$$

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 ( $\sigma$ ), 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 heteroscedasticity.  $N = 570$ .

predicted returns on speculative stocks are low, we find that, on average, betas on high-volatility firms are lower by 0.24.<sup>6</sup>

These changes in beta are in the right direction, but they are too small to completely explain the predictability results. There are two ways to look at this. First, Table 5 shows that when predicted bond returns are one percentage point higher, predicted monthly returns on young and high-volatility stocks are 0.77 percentage points lower, respectively. Simply dividing the changes in predicted returns by the changes in betas in the previous paragraph implies an implausibly large monthly risk premium of 3.21 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 2.02 percentage points per month, or around 27 percentage points per year, which is again implausibly high. Given that changes in betas conditional on Campbell-Shiller predictions are of a similar small magnitude (unreported), and that those conditional on  $SENT^\perp$  go in the wrong direction, we conclude that changes in betas are at best a partial explanation.

**5.2.2 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 consider a sentiment-based source of predictability). Recent results, and our own results, suggest that this explanation also faces empirical challenges.

One significant challenge is the evidence in Baker and Wurgler (2006) that the predicted returns on certain long-short stock portfolios actually *flip sign* over time, conditional on sentiment. (Again, we do not need to repeat the analysis here because we are using the same predictor and portfolios.) The same is true when conditioning on predicted bond returns. For example, when the Cochrane-Piazzesi predictor forecasts that long-term bond return is below its median value, the average excess return on low-volatility stocks (decile 1) is 0.29% per month, which is below the average excess return on high-volatility stocks (decile 10) of 1.00% per month. By contrast, when the predicted excess bond return is above its mean, the average excess return on low-volatility stocks, at 1.02% per month, actually exceeds the excess return on high-volatility stocks, at 0.95% 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 narrow the gap between predicted returns on low- and high-sigma stocks, but they do not 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

<sup>6</sup> 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.

in predicted returns. As long as the market risk premium is nonnegative, the predicted returns on long-short stock portfolios cannot flip sign.

Overall, the changes in betas exercise offers some 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 modest role in terms of explaining the main results. But the magnitudes involved are small, and the theory provides no particular explanation for why the sentiment index predicts bond returns. The risk-based required returns explanation appears helpful, but it, too, is incomplete.

**5.2.3 Sentiment and flights to quality.** Investor sentiment is a third possible link between bonds and bond-like stocks. High sentiment may be indicated by periods of high demand for speculative stocks relative to demand for bond-like securities. “Flights to quality,” in contrast, may be shown by dips in sentiment in which investors shift money toward what appear to be “safe” assets without making the sophisticated trade-off between expected risks and returns that they would take under the risk-based required returns mechanism.<sup>7</sup> Under this view, bonds and bond-like stocks depart from speculative stocks as sentiment fluctuates. Predictability arises as bonds and bond-like stocks, relative to speculative stocks, correct from sentiment-driven overreactions.

Thus far, the most compelling evidence for a role for sentiment within this article is the aforementioned occasional inversion of the relationship between risk and expected return.<sup>8</sup> 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.

**5.2.4 Magnitudes of rational predictability.** Campbell and Thompson (2007) establish the relationship between the magnitude of predictability and

<sup>7</sup> 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 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, *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.

<sup>8</sup> In Baker and Wurgler (2006), it is not occasional, but rather appears in approximately half of all years between 1963 and 2005.

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 1, the first computation implies that an investor who bets on the unconditional excess return on long-term bonds receives an average monthly return of 0.40 percentage points if she has a relative risk aversion of unity and 0.13 percentage points if her relative risk aversion is three. However, if the investor is 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 4.58 percentage points per month with a relative risk aversion of unity and 1.53 percentage points per month with a relative risk aversion of three.<sup>9</sup>

These calculations are rough, but they suggest that the predictability from these bond predictors is large, requiring very significant shifts in risk aversion or risk to be rationalized as compensation for ex ante expected risk. It is at least as plausible that the bond predictors capture predictability generated by behavioral flights to quality. This could explain the correlation between the yield curve-based predictors and the sentiment index, as well as their generally similar comovement and predictability properties.

**5.2.5 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 observe their actions directly via flows. [Malkiel \(1977\)](#) and [Gemmell 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, and so on) versus bond-like (income, income equity, and so on) equity mutual fund categories. The exercise is close in spirit to those of [Goetzmann, Massa, and Rouwenhorst \(2000\)](#) and [Brown, Goetzmann, Hiraki,](#)

<sup>9</sup> 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 0.0102, implying large average monthly returns of 1.44 percentage points per month for an investor with a relative risk aversion of unity and 0.48 percentage points per month with a relative risk aversion of three.

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 receiving 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.

## 6. Conclusion

The correlation between bond and stock index returns is unstable, as documented by many authors. We find that government bonds and stocks are closely connected from a cross-sectional perspective, however. 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 that 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 some of 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 three mechanisms contribute to these patterns. Common shocks to expected real cash flows of bonds and bond-like stocks are a priori an important force. Certain evidence suggests 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 modest 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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