Is There Froth in the Corporate Bond Market?

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Abstract

Using the variance decomposition approach and the novel data on payoffs of corporate bonds, I extract long-run risk premiums on the corporate bond market portfolio which vary every month, and are easy to compare with the predictions from an asset pricing model. The expected cash flows from corporate bonds, identified based on the data on default and exercise of embedded call options, are slow-moving and predict a decline in economic growth over the long horizon, while risk premiums are subject to high-frequency fluctuation and negatively predicts economic growth over the short horizon. To determine if credit spreads are too low before recessions, I compare time-varying risk premiums on the corporate bond market portfolio with the CAPM benchmark with time-varying risk exposure, and find that their variation is largely consistent with each other.

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1 Introduction

Are corporate bond prices too high before recessions, perhaps fueled by excessive lending activities? In good times, investors may be complacent, underestimate default risks, and overprice defaultable bonds. Such overpricing in turn could cause firms to take excessive risks, leading to subsequent recessions or, in an extreme case, financial crises (Krishnamurthy and Muir (2016)). However, there is no widely accepted definition of mispricing or an identification strategy for it. One can identify mispricing using deviation from the prediction of structural (e.g., Huang and Huang (2012)) or reduced-form models of debt (Driessen (2005)), or analyzing the behavior of returns on bonds (Greenwood and Hanson (2013) and Lopez-Salido, Stein and Zakrajsek (2015)). However, a model-based approach depends on assumptions on dynamics of firm asset values and other risk factors, while estimating risk premiums based on past returns may suffer from potential survivorship bias in the data. In this paper, I follow Campbell and Shiller (1988a, b) and define mispricing as variation in risk premiums, rather than asset prices, which is unjustified based on a benchmark economic model.

I apply the variance decomposition to the market portfolio of corporate bonds and stocks, and jointly estimate the long-run risk premiums and risk exposures to see if the variation in risk premiums is consistent with each other. The variance decomposition allows me to separate the expected returns from cash flows in asset prices, and analyze if the bond risk premiums are much lower during good times than the stock market (i.e. the CAPM) benchmark with time-varying risk exposures.

Though stock data is readily available to researchers, applying variance decomposition to bonds requires the proper identification of cash flow shocks to corporate bonds, both empirically and theoretically. Empirically, I merge panel data of corporate bonds from 1973 to 2014 to the default data from *Moody's Default and Recovery Database* and to the early repayment data from *Mergent FISD*. This dataset allows me to keep track of an eventual outcome for the life of each bond in sample; namely, a corporate bond is either i) paid in full at maturity, ii) defaults and iii) paid before maturity due to an exercise of call options. For each bond, the database shows the history of coupon and principal payments which I use to identify cash flow from the bond. As I explicitly account for default and early redemption due to call exercise, my return measure corrects for survivorship bias, in the same way *CRSP* corrects for the bias by computing delisting returns on stocks. Using this database, I form a value-weighted market portfolio of corporate bonds, construct a time-series of returns with and without payouts, and compute measures of credit spreads and credit loss, or the growth rate in repayments from corporate bonds relative to Treasury bonds.

Theoretically, I show that credit spreads, excess returns and credit loss are tightly linked by a simple loglinear identity, and that a credit spread can be decomposed into long-run credit loss and long-run risk premiums. A credit spread is a function of long-run risk premiums rather than one-period risk premiums, and it is credit spreads rather than one-period expected returns which affect firms' behavior and macroeconomic activities (Gilchrist and Zakrajsek (2012)). Thus, I estimate conditional expectations based on a VAR using credit loss and excess returns, and infer the long-run expectations for cash flows and excess returns from the VAR dynamics.

As I am interested in evaluating bond risk premiums using equity risk premiums as a benchmark, I estimate a VAR involving both credit spreads on the bond market portfolio and the dividend price ratio on the stock market portfolio. In addition, I include distance-to-default of Merton (1974), slope of Treasury yield curve, lagged returns on corporate bonds, Treasury bonds and stocks in the vector of state variables. I also tested if the ratio of high yield bond issues to the total bond issue (motivated by Greenwood and Hanson (2013)) helps predict bond returns, as the ratio works as a measure of potential mispricing in credit spreads. I find that once I control for stock dividend price ratio, the ratio does not help forecast bond returns in my sample.

The estimated VAR-implied long-run expectations for credit loss and excess returns are consistent with the previous literature (e.g., Cochrane (2011) for stocks, Collin-Dufresne, Goldstein and Martin (2001) and Nozawa (2016) for bonds). Namely, for both bond and stock portfolios, risk premium variation accounts for significant portion of price variation, while cash flow variance is relatively small.

The risk premiums and expected growth in cash flows on the corporate bond market portfolio fluctuate differently over time. The correlation between the two components is negative, and the expected credit loss is cyclical and slow-moving while the risk premiums are counter-cyclical and subject to high-frequency fluctuation. In good times, investors become less risk-averse while anticipating that the default in the future will be higher. Thus, before recessions, risk premiums fall and expected credit loss rises. During recessions, risk premiums jump up while expected growth in default becomes lower, since the current level of default is high. Such difference in time-series behavior between the two components of credit spreads affects their predictive power for economic growth. Risk premiums on the corporate bond market portfolio predicts a slowdown in economy over the short horizon, while expected credit loss predicts a decline in economic growth better in the longer horizon.

I apply the same decomposition to three Euro area countries (Germany, France and Italy) as well as to UK. The risk premiums are correlated across countries, and the time-series variation is similar to the risk premiums in US.

The flexibility of the VAR approach allows me to include other variables that previous research finds as important determinants of corporate bond risk premiums in the analysis. Hence, I test if such variables affect bond risk premiums in a multivariate setup, controlling for other key variables such as credit spreads. For example, a strand of literature finds that illiquidity is a key in understanding the variation in credit spreads (Edwards, Harris and Piwowar (2007), Chen, Lesmond and Wei (2007), Bao, Pan and Wang (2011), Lin, Wang and Wu (2011) and Feldfutter (2012)). Building on to Hu, Pan and Wang (2013), I include $Noise$ as a measure of market-wide illiquidity in the VAR and find that, after controlling for other state variables, illiquidity does not help predict excess returns on corporate bonds, a result consistent with Culp, Nozawa and Veronesi (2016).

I use estimated time-varying long-run risk premiums on bonds and stocks to examine if bond risk premiums are too low during booms and too high during recessions. To this end, I estimate the long-run CAPM risk exposure, or covariance between stock and bond returns, that varies over time. To estimate the variation in risk exposure, I use the dynamic conditional correlation model of Engle (2002). In this model, I let both the variance and correlation matrix vary every month. Based on the model, I also let the risk exposure to vary across horizon, so that the covariance of one period returns is different from the covariance of long-run returns.

I find that long-run risk premiums and long-run CAPM risk exposure have similar volatility, and show very similar variation over time. They are both low during booms, and go up during recessions. I compare the risk premiums and exposures averaged separately during booms and recessions, and find that the difference is economically small, and statistically insignificant. The low credit spreads during booms reflect lower market risk exposure, implying that there is no evidence for pronounced mispricing then. Furthermore, I did not find a strong evidence for mispricing in the portfolio of high-yield bonds. This finding is surprising, as high-yield bonds are less liquid than investment grade bonds, and one would expect stronger evidence of mispricing in the high-yield bond market.

The VAR approach allows me to measure risk premiums month by month rather than the averaged values during booms and recessions. I take advantage of this data availability and compare the corporate bond risk premiums with stock risk premiums separately for the period of credit expansions and contractions. Such analysis is important because the period of credit expansion does not necessarily coincide with economic booms. In addition, credit expansion combined with low bond risk premiums, rather than low bond risk premiums themselves, are claimed to cause a serious recession (Krishnamurty and Muir (2016)). I find that risk premiums on the corporate bond market portfolio and the CAPM benchmark are similar to each other both during the period of credit expansions and recessions.

To evaluate the economic significance of the part of risk premiums unexplained by the CAPM, I forecast macroeconomic variables such as GDP growth using the CAPM-implied risk premiums and the remaining mispricing component in bond risk premiums. A shock to the CAPM-based risk premiums has a persistent impact on future economic activities, consistent with the argument that a forward-looking agent foresees a contraction in economy and becomes risk-averse. In contrast, a shock to the mispricing on the corporate bond market portfolio has a small effect on the economic activities. Thus, the difference between the bond risk premiums and the CAPM benchmark is economically small.

As I evaluate the bond risk premiums relative to stock risk premiums, this article sheds light on the questions as to if there are credit-market specific frictions such as credit crunch that cause bond risk premiums to vary too much. Institutional investors have greater shares of the corporate bond market compared with the stock market, and thus the effect of regulations on financial institutions and distorted managerial incentives may cause the bond market-specific mispricing, which may not exist in the stock market where individual investors have greater share. In my analysis, I do not find compelling evidence for bond-market specific mispricing before the recent recessions.

There is a strand of literature which investigates the relationship between bond and equity risk premiums. Elkamhi and Ericsson (2008) use the Leland and Toft (1996) model to estimate risk premiums on corporate bonds, and find that bond and stock risk premiums are highly correlated. In contrast to Elkamhi and Ericsson (2008), I jointly estimate the long-run risk premiums using a VAR over the long horizon, and document their cyclical behavior over a long sample. Though my goal is similar to Elkamhi and Ericsson (2008), the approach is very different, and this article is complementary to Elkamhi and Ericsson (2008). Chen, Cui, He and Milbradt (2016) develop a structural model to decompose credit spreads into default and liquidity components, while Elton, Gruber, Agrawal and Mann (2001), Bongaerts (2010) and Nozawa (2016) employ more reduced-form approach and empirically decompose credit spreads. The focus of this paper is different, as I study on the variance decomposition on the market portfolio, allowing time-varying expected returns.

An increasing number of papers study the relationship between corporate bond prices and the dynamics in macro economy. Gilchrist and Zakrajsek (2012) find the deviation of credit spreads from the Merton model benchmark predict macro variables, and Lopez-Salido, Stein and Zakrajsek (2015) argue that a mispricing in the corporate bond market causes real economic activities to contract. Furthermore, Krishnamurthy and Muir (2016) find that credit spreads appear to be 'too low' before financial crises. In contrast to these papers, Culp, Nozawa and Veronesi (2016) use option prices and find that credit spreads were not too low before the financial crisis relative to the option-based benchmark.

Lastly, there is large literature on structural models of debt, which connects stock values with bond values by extending the Merton (1974) model. While some papers focus on matching average credit spreads given average stock risk premiums and default rates (e.g., Huang and Huang (2012)), others try to explain the time variation in risk premiums, separately for booms and recessions (e.g., Chen, Collin-Dufresne and Goldstein (2009), Bahmra, Kuehn and Strebulaev (2010), Chen (2010) and Gourio (2012)). In addition, Feldhutter and Schaefer (2016) show that the Merton model works fine in pricing corporate bonds, using proper estimation methodology. In this paper, I estimate time-varying risk premiums at the monthly frequency, and decompose spreads into cash flows and risk premiums with no unexplained residuals. Also, with the variance decomposition approach, I do not take a stand on how firms optimally choose to default, refinance, and set leverage, or whether they strategically default, a point emphasized in Anderson and Sundaresan (1996), in estimating risk premiums.

The rest of the paper is organized as follows: Section 2 shows the variance decomposition framework applied to corporate bonds, and Section 3 describes the data and estimate a VAR and implied long-run risk premiums on bonds and stocks. Section 4 evaluates if bond risk premiums deviate from the CAPM benchmark, Section 5 investigates if two components of credit spreads predict macro economic growth over various horizons, and Section 6 concludes.

2 Variance Decomposition of the Bond and Stock Market Portfolio

In this section, I define a return on a corporate bond with and without distribution, which is used to compute credit spreads and credit loss on the bond. Using these variables, I decompose a credit spread on the market portfolio of corporate bond, and show that the spread can be decomposed into long-run expected credit loss and long-run risk premiums.

2.1 Adjusting Corporate Bond Returns for Distribution

If an investor buys and holds a corporate bond, either of the following eventually occurs: i) a bond matures and the investor receives the principal, ii) a bond is called early, and the investor receives the principal at the call price and iii) a bond defaults, and the investor receives the residual value by selling the bond upon default. In either cases, the outstanding face value of bond, F_t, changes upon the events above. Let f_t be the ratio of the outstanding face value at t to $t-1$, so $f_t = F_t/F_{t-1}$. Furthermore, let P_t be a dirty price of a bond (i.e. a price including accrued interest), and P_t^D be the value upon redemption. When a bond matures at t, $P_t^D = 100$, and when a bond defaults or is called at t, P_t^D is the market price upon default or exercise price of the call option.

A return including distributions is

$$\begin{aligned} R_{t+1} &= \frac{P_{t+1}f_{t+1} + P_{t+1}^D\left(1 - f_{t+1}\right) + C_{t+1}}{P_t}, \\ &= \frac{P_{t+1}f_{t+1} + D_{t+1}}{P_t}, \end{aligned} \tag{1}$$

where C_{t+1} is coupon payment and $D_{t+1} \equiv P_{t+1}^D\left(1 - f_{t+1}\right) + C_{t+1}$ is the amount of distribution. A return without distribution is

$$RND_{t+1} = \frac{P_{t+1}f_{t+1}}{P_t}. \tag{2}$$

If $P_t^D = P_t$, the definition of a return in (1) yields numerically the same value as the conventional measure of a return on a corporate bond, $\left(P_{t+1} + C_{t+1}\right)/P_t$, (see e.g., Gebhardt, Hvidkjaer and Swaminathan (2005)). However, by explicitly accounting for distribution and reduction in amount outstanding, returns in (1) on the value-weight market portfolio of corporate bonds accurately accounts for the loss accrued to an investor due to the acceleration of the principal repayment, and these returns are consistent with the time-varying market value of the portfolio.

Using bond-level data of returns with and without distribution, I construct time-series data of the value-weighted bond market portfolio. Using annualized market returns, I construct the ratio of distribution to the price and the growth rate of distribution by comparing R_t and RND_t.

$$\frac{D_t}{P_t} = \frac{R_t}{RND_t} - 1, \tag{3}$$

$$\frac{D_{t+1}}{D_t} = (R_{t+1} - RND_{t+1}) \left(\frac{R_t}{RND_t} - 1 \right)^{-1}. \tag{4}$$

As I compute annual returns using monthly price and distribution data, I have to take a stand on how an investor reinvest the cash flows that occur during the year. In the main analysis below, I assume that the investor does not reinvest the distribution and consume away, rather than reinvesting in the corporate bond. This assumption is realistic as the cost of purchasing a small fraction of a corporate bond is high due to bonds' illiquidity, and this assumption helps avoid inducing mechanical persistence in (3). Furthermore, this assumption on reinvestment helps avoid the criticism of Chen (2009) on the variance decomposition on stocks.

In the sections below, I derive credit spreads from (3) and (4), and apply these equations to the data to compute credit spreads and loss given default.

2.2 Decomposition of Credit Spreads

In this subsection, I show how a credit spread relates to investors' expectations for future payoffs and excess returns on corporate bond investment. I assume that an investor takes a long position in a corporate bond and a short position in the matching Treasury bond which has the same cash flow schedule as the corporate bond. If the corporate bond defaults, then the investor sells the corporate bond and uses the proceeds to buy Treasury bond with the same remaining time to maturity. I further assume that the loss given default (measured as a price of the defaulted corporate bond relative to the price of the matching Treasury bond) is the same for principal and coupons.

Under these assumptions, I can log-linearize excess returns using credit spreads, s_t, and credit loss, l_t, as

$$r^e_{t+1} \equiv \log R_{t+1} - \log R_{f,t+1} \approx -\rho s_{t+1} + s_t - l_{t+1}, \tag{5}$$

where

$$s_t \equiv \log \left(\frac{P_{f,t}}{D_{f,t}} \frac{D_t}{P_t} \right) = \begin{cases} 0 & \text{if the bond matures or defaults at time } t, \\ \log \left(\frac{P_{f,t}}{P^*_t} \right) & \text{if the bond is called at time } t, \\ \log \left(\frac{P_{f,t}}{P_t} \right) & \text{otherwise,} \end{cases} \tag{6}$$

where P^*_t is a call-adjusted price, such that $P^*_t \equiv P_t D^*_t$ and $D^*_t = (P_{f,t}(1 - f_t) + C_t) / (P_{D,t}(1 - f_t) + C_t)$. A call-adjusted price of corporate bonds tends to the price of the matching Treasury bonds (and thus s_t tends to zero) as a larger fraction of the bond is called early. Thus, s_t is a relative price of a corporate bond to Treasury bonds, conditional on no payment acceleration.

My credit spread measure, s_t, is price spreads rather than commonly used yield spreads. For coupon-bearing bonds, yield spreads can be defined only implicitly, and computed only numerically, making it difficult to relate it to returns and defaults. Therefore, I decompose price spreads, s_t, rather than yield spreads in the paper. Nonetheless, price spreads and yield spreads are closely tied together, as price changes can be approximated by yield changes multiplied by duration. The top panel of Figure 1 plots credit spreads scaled by average duration for the market portfolio, s_t/τ, and the conventional measure of credit spreads (yield spreads) averaged across corporate bonds. These two series keeps track of each other quite closely, and correlation is 0.91. Thus, the analysis on the information contained in s_t is useful in understanding the information in yield spreads.

The figure also shows excess returns on the corporate bond market portfolio, r^e_{t+1}. Credit spreads and excess returns one year later are positively related, and I analyze this correlation more formally in the section below.

The value of a constant, ρ, is set at 0.889 in order to maximize the correlation between r^e_{t+1} and $\tilde{r}^e_{t+1} = -\rho s_{t+1} + s_t - l_{t+1}$. Appendix A shows that the variation of r^e_{t+1} and $\tilde{r}^e_{t+1}$ is effectively identical, and the approximation error in (5) is negligible.

Credit loss is defined as a relative growth rate in distributions,

$$l_t \equiv \log\left(\frac{D_{f,t}}{D_{f,t-1}}\frac{D_{t-1}}{D_t}\right). \tag{7}$$

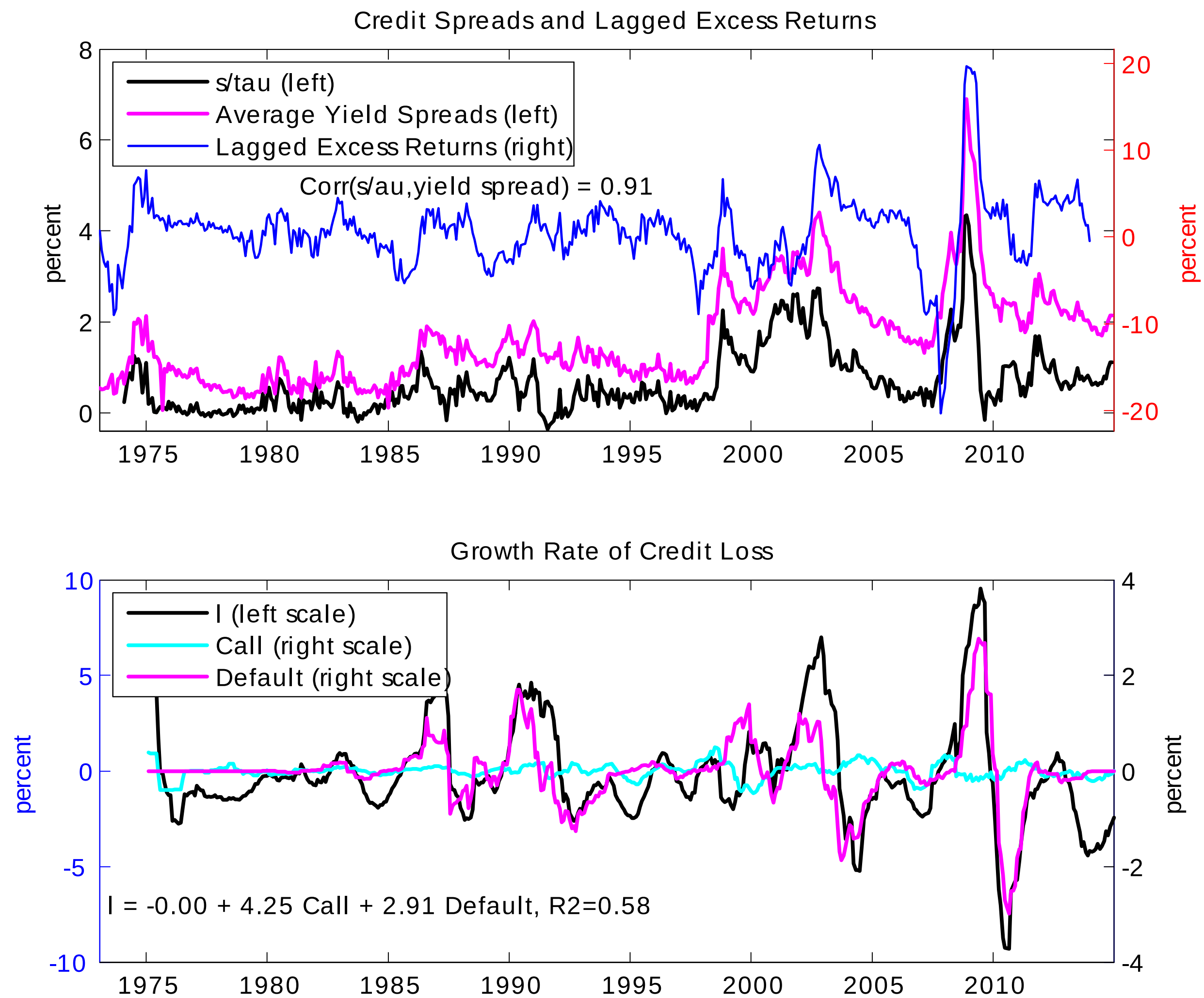
To get more intuition of the credit loss variable, I derive the values of l_t under the four scenarios, assuming that there is no acceleration of payment in time $t-1$,

$$l_t = \begin{cases} 0 & \text{if the bond matures at time } t, \\ \log\left(\frac{P_{f,t}}{P_t}\right) & \text{if the bond defaults at time } t, \\ \log\left(D^*_t\right) & \text{if the bond is called at time } t, \\ 0 & \text{otherwise.} \end{cases} \tag{8}$$

Thus, l_t becomes larger if the bond defaults or called at a price lower than the price for the matching Treasury bond. Scheduled coupon and principal payments from the corporate bond cancel with those from the matching Treasury bonds, and thus $l_t = 0$ holds if there is no acceleration of payments at time t. Therefore, l_t is growth rate of credit loss accrued to corporate bond investors due to deviation from the scheduled repayment.

The bottom panel of Figure 1 plots credit loss, l_t, along with annual changes in loss due to default and exercise of embedded call options. To compute more intuitive measures of default loss and loss due to exercise of calls, I computed average of the relative price upon calls and default, $P^D_{i,t}/P_{f,t}$, weighted by amount outstanding every month and accumulated it over a year. The figure shows that variation in loss due to exercise of call is less volatile, and credit loss, l_t, tracks changes

Figure 1: Credit Spreads, Excess Returns and Credit Loss



The top panel plots credit spreads divided by duration, s_t/τ_t, yield spreads averaged across bonds and lagged one year excess returns on the corporate bond market portfolio, r^e_{t+1}. The bottom panel plots credit loss, l_t, along with annual changes in default loss and loss due to the exercise of embedded call options. Specifically, loss due to default and call for month m is computed by

$$Loss_m = \left(\sum_{i \in N_D} \frac{P^D_{i,m}}{P_{f,m}} F_{i,m} \right) / \left(\sum_{i \in N_m} F_{i,m} \right),$$

where N_D is the set of bonds that are in default or called in month m. I accumulate $Loss_m$ over one year separately for default and calls, and plot changes in the bottom panel.

in default loss fairly closely. Hence, I call l_t credit loss though this variable captures any deviation in payments of a corporate bond from the matching Treasury bond.

Equation (5) is a difference equation for a credit spread. I iterate (5) up to infinity to obtain

$$s_t \approx \sum_{j=1}^{\infty} \rho^{j-1} r^e_{t+j} + \sum_{j=1}^{\infty} \rho^{j-1} l_{t+j} + const. \tag{9}$$

assuming $\rho^j s_{t+j} \to 0$ as $j \to \infty$.

In iterating the equation, I assume that investors will replace the maturing bonds with newly issued bonds as they historically do. This is the same assumption implicitly made in decomposing the stock market portfolio. In the distant future, most of the current stocks will be delisted and disappear, and yet the difference equation for the dividend-price ratio is iterated up to infinity.

As (9) holds for any paths, it holds under time$-t$ conditional expectations,

$$\begin{aligned} s_t &\approx E\left[\sum_{j=1}^{\infty} \rho^{j-1} r^e_{t+j} \middle| \mathcal{F}_t\right] + E\left[\sum_{j=1}^{\infty} \rho^{j-1} l_{t+j} \middle| \mathcal{F}_t\right] + const, \\ &= s^r_t + s^l_t + const. \end{aligned} \tag{10}$$

where $\mathcal{F}_t$ is an investors' information set.

The present value formula in (10) shows that a price of a corporate bond relative to the matching Treasury bond is relative cash flows discounted by relative returns, and that movements in credit spreads can be decomposed into long-run expected excess returns and credit losses with no unexplained residuals.

Next, I decompose stock prices following Campbell and Shiller (1988). The log stock return is approximated with a log dividend-price ratio, dp_t, and the dividend growth rate, g_t,

$$r_{s,t+1} \approx -\rho_s dp_{t+1} + dp_t + g_{t+1} + const. \tag{11}$$

where ρ_s is set at 0.976 in order to maximize the correlation between $r_{s,t+1}$ and $-\rho_s dp_{t+1} + dp_t + g_{t+1}$ in the empirical exercise below.

Iterating (11) yields the decomposition of a dividend yield into risk premiums and expected cash flow components,

$$\begin{aligned} dp_t &\approx E\left[\sum_{j=1}^{\infty} \rho_s^{j-1} r_{s,t+j} \middle| \mathcal{F}_t\right] + E\left[\sum_{j=1}^{\infty} \rho_s^{j-1} g_{t+j} \middle| \mathcal{F}_t\right] + const, \\ &= dp^r_t + dp^g_t + const. \end{aligned} \tag{12}$$

The question about mispricing in the bond market can be addressed by analyzing bond risk premiums, s_t^r, in relation to stock risk premiums, dp_t^r. To this end, I estimate corporate bond risk premiums, s_t^r, and stock risk premiums, dp_t^r, jointly based on the same set of state variables in $\mathcal{F}_t$ in the next section.

3 Data and VAR-Based Decomposition of Credit Spreads and Stock Prices

In this section, I estimate the long-run expected returns and cash flows on the bond and stock market portfolio in (10) and (12) using VARs. I relate the estimated cash flow and risk premium component to the future macroeconomic activities, and examine the relationship between these two components with the liquidity conditions in financial markets.

3.1 Data

I construct the panel data of U.S. corporate bond prices from January 1973 to December 2014 combining the *Lehman Brothers Fixed Income Database*, the *Mergent FISD/NAIC Database*, *TRACE*, *DataStream and Merrill Lynch*. In Appendix B, I provide a detailed description of these databases, and compare prices across databases using the overlapping observations. Overall, prices are reasonably close to each other, and I do not see any trends in gaps in historical data across databases.

When there are overlaps among the five databases, I prioritize in the following order: the *Lehman Brothers Fixed Income Database*, *TRACE*, *Mergent FISD/NAIC*, *DataStream and Merrill Lynch*. I confirm that the main result is robust to the change in orders, and report the results in Appendix B. If the observation for a defaulted bond is missing in the databases above, I use Moody's *Default Risk Service* to complement the price upon default. For exercise of calls and call prices, I use *Mergent FISD*, and for bonds that are in *Lehman Brothers Fixed Income Database* but not in *Mergent FISD*, I use the changes in amount outstanding to identify exercise of calls, and assume that call price is the market price. I remove junior bonds, bonds with floating rates and with option features other than callable bonds.

As I compute returns on value-weighted market portfolios, I make sure that bond prices do not disappear except for the cases of maturity, default and exercise of calls. If a bond have missing observations which last more than 12 months, I drop the bond from the sample. If a bond have missing observations less than 12 months, I fill missing observations assuming constant a credit spread.

I apply three filters to remove the observations that are likely to be subject to erroneous recording. First, I remove the price observations that are higher than matching Treasury bond prices. Second, I drop the price observations below one cent per dollar. Third, I remove the return observations that show a large bounceback. Specifically, I compute the product of the adjacent return observations and remove both observations if the product is less than -0.04. After applying the filters, the resulting sample is an unbalanced panel data of 1,688,220 bond month observations for 27,808 bonds over 504 months.

CRSP and *Compustat* provide the stock prices and accounting information. I obtain economic activity data from *FRED*.

In order to compute excess returns and credit spreads, I construct the prices of the synthetic Treasury bonds that match the corporate bonds using the *Federal Reserve*'s constant-maturity yields data. The methodology is detailed in Appendix B.

I obtained quarterly price and characteristics data for corporate bonds in UK, Germany, France and Italy from International Data Corporation, and respective government bond yield data from Global Financial Data.

3.2 Effect of Distribution on Corporate Bond Returns

Before decomposing credit spreads on the market portfolio, I show how explicitly accounting for cash distribution changes returns on corporate bonds. For this analysis, I use individual bond-level gross returns, and compare returns before a distribution event and upon the event. Specifically, I picked bonds which I can identify the eventual redemption outcome. (There are other bonds which remain in sample without the final redemption at the end of December 2014.) Then I classify these bonds based on what happened in the last observation for the bond, namely i) matured, ii) defaulted and iii) entirely called. For each bond, I compare a gross return upon the final redemption event and the average returns before redemption.

Columns 3 and 4 in Table 1 reports annual gross returns upon redemption and average annual gross returns before redemption, averaged across bonds within each redemption category. The bonds that mature and repay in full have a similar return upon repayment (8.02%) to the average returns before repayment (7.32%). In contrast, the bonds that eventually default have very low returns even before default (0.25%). However, their returns upon default are even lower at -32.8%, and the difference between returns upon default and before default is large. Finally, the bonds that are entirely called have somewhat lower returns upon call (7.43%) compared with the average returns before call (8.97%). This difference arises as bonds are more likely to be called at a favorable price for the issuer, which pushes down returns for investors.

The last two columns in Table 1 report the time to maturity at issuance and realized time to maturity, which is the final redemption date minus the issue date. Default and early redemption from call options have large effect on effective time to maturity for corporate bonds. The bonds that eventually default are entirely called have maturity much shorter than anticipated at issuance. Thus, an early redemption affects bond returns and maturity significantly, and missing the last observations is likely to lead to mismeasurement of risk premiums.

Table 1: Gross Annual Returns on Corporate Bonds By Types of Redemption

Event	N	$\bar{R}_{T-1}$	R_T	Time to Maturity	
				At issuance	Realized
		(%)	(%)	(years)	(years)
Matured	9164	8.02	7.32	7.6	7.6
Defaulted	1179	0.25	-32.80	11.7	4.4
Entirely Called	3168	8.97	7.43	9.7	2.9

For bonds I can identify the eventual redemption, I classify into three types of redemption. N is the number of bonds in each category. $\bar{R}_{T-1}$ is gross annual returns for the bond averaged from issuance to one year before redemption events. R_T is a gross annual return upon redemption events. Time to maturity at issuance is the difference between maturity dates and issue dates, while realized time to maturity is the difference between redemption event dates and issue dates.

3.3 Estimation by a VAR

I estimate the conditional expectations in (10) and (12), and measure their volatilities based on a VAR. In the basic setup, I use a vector of state variables,

$$X_t = \begin{pmatrix} r_{b,t} & r^f_{b,t} & s_t & slope_t & DD_t & r_{s,t} & dp_t \end{pmatrix}', \tag{13}$$

where $r_{b,t}$ is log returns on the bond market portfolio, $r^f_{b,t}$ is log returns on matching Treasury bond portfolio (so that $r^e_t = r_{b,t} - r^f_{b,t}$), $slope_t$ is the difference in yield between 1- and 10-year Treasury bonds, DD_t is distance-to-default of Merton (1974) averaged across bonds, $r_{s,t}$ is a log return on the CRSP stock market portfolio, dp_t is log dividend price ratio.

The dynamics of the state variables is given by

$$X_{t+1} = A_0 + AX_t + B_t W_{t+1}. \tag{14}$$

I assume that W_t is uncorrelated over time, but do not make assumptions about the probability distribution at this point.

Let $e_i, i = 1, \ldots, 7,$ be unit vectors whose $i-$th entry is one and the other entries are zero.

Then, the long-run expected loss and excess returns on bonds and stocks implied by the VAR is

$$
\begin{aligned}
s_t^l &= E\left[\left.\sum_{j=1}^{\infty}\rho^{j-1}l_{t+j}\right|X_t\right] = e_L G X_t - (e_1 - e_2)\,G_0, && (15)\\
s_t^r &= E\left[\left.\sum_{j=1}^{\infty}\rho^{j-1}r^e_{b,t+j}\right|X_t\right] = (e_1 - e_2)\,G X_t + (e_1 - e_2)\,G_0, && (16)\\
dp_t^g &= E\left[\left.\sum_{j=1}^{\infty}\rho_s^{j-1}g_{t+j}\right|X_t\right] = e_g G X_t - e_6 G_0, && (17)\\
dp_t^r &= E\left[\left.\sum_{j=1}^{\infty}\rho_s^{j-1}r_{s,t+j}\right|X_t\right] = e_6 G X_t + e_6 G_0, && (18)
\end{aligned}
$$

where $G \equiv A\,(I-\rho A)^{-1}$, $G_0 \equiv \sum_{j=1}^{\infty}\rho^{j-1}\left(I-A^j\right)(I-A)^{-1}A_0$, $e_L = -\rho e_3 + e_3 A^{-1} - (e_1 - e_2)$ and $e_g = -\rho e_7 + e_7 A^{-1} - e_6$.[1]

Since we condition on $X_t \subseteq \mathcal{F}_t$, the estimated volatilities based on the VAR, $\sigma\left(s_t^l\right)$ and $\sigma\left(s_t^r\right)$, give the lower bound for the true volatility based on the agent's information set.

Panel A of Table 2 shows the summary statistics of the state variables, as well as credit loss, l_t. The log-linear identity (5) holds well in sample and a correlation coefficient between r^e_{t+1} and $-\rho s_{t+1} + s_t - l_{t+1}$ is greater than 0.999. Since the identity ties credit loss, excess returns and credit spreads linearly, whether forecasting excess returns or credit loss does not affect the decomposition results.

Before showing the main results, I analyze how adding more variables changes the bond return predictability. The first row of Panel B of Table 2 shows the regression of one-year bond excess returns on lagged excess returns and credit spreads. Credit spreads, s_t, forecasts one-year excess returns positively, with adjusted R-squared of 0.09.

The second row adds another set of variables to forecast bond excess returns. y_t is zero coupon yield on 1-year Treasury bonds and $\log HYR$ is the log ratio of high yield bond issues to all bond issues, motivated by the findings of Greenwood and Hanson (2013). My construction of HYR_t differs slightly from Greenwood and Hanson (2013), as they compute the ratio for debt issue instead of bond issues. For the period from 1973 to 2008 (when their sample ends), the correlation between my measure and theirs is 0.91. Consistent with Greenwood and Hanson (2013), I find that the increased ratio of high-yield issue predicts excess returns negatively. On the other hand, one-year

[1] To obtain (15), I use the one-period identity in (5). Solving for l_{t+1} and taking the conditional expectation, we have

$$
\begin{aligned}
E\left[l_{t+j}|\,X_t\right] &= E\left[-\rho e_3 X_{t+j} + e_3 X_{t+j-1} - (e_1 - e_2)\,X_{t+j}|\,X_t\right],\\
&= e_L A^j X_t.
\end{aligned}
$$

Plugging $E\left[l_{t+j}|\,X_{i,t}\right]$ into $E\left[\sum \rho^{j-1} l_{t+j}\right|X_t\left.\right]$ yields (15).

Table 2: Summary Statistics and Bond Return Forecasting Regressions: 1973-2014

Panel A: Summary statistics

	Mean	Std	Percentiles				
			1	10	50	90	99
$r_{b,t}$	7.34	5.94	-5.31	0.27	6.86	14.28	25.80
$r^f_{b,t}$	6.84	6.37	-6.67	-0.61	6.39	13.64	25.22
s_t	3.53	3.67	-0.82	0.09	2.36	8.77	15.76
$slope_t$	1.32	1.29	-1.81	-0.26	1.41	3.12	3.62
DD_t	7.34	1.94	3.03	4.54	7.43	9.69	11.97
$r_{s,t}$	10.17	17.18	-48.52	-13.75	13.57	27.43	42.31
dp_t	-359.78	42.84	-448.06	-419.37	-364.30	-303.33	-291.42
l_t	-0.18	2.65	-6.80	-2.58	-0.55	3.82	8.63

Panel B: One-period bond excess return forecasting regressions

	$r^e_{b,t}$	s_t	$\log HYR_t$	y_t	$slope_t$	DD_t	$r_{s,t}$	dp_t	$\bar{R}^2$
(1)	0.02	0.36							0.09
	(0.15)	(0.16)							
(2)	-0.03	0.33	-1.13	-0.09	0.83				0.21
	(0.17)	(0.18)	(0.39)	(0.14)	(0.49)				
(3)	0.16	0.58	-0.14		0.80	-0.17	-0.04	0.04	0.30
	(0.19)	(0.24)	(0.38)		(0.52)	(0.32)	(0.03)	(0.01)	

Panel A shows the summary statistics of variables. $r_{b,t}$ is a log return on corporate bonds, $r^f_{b,t}$ is a log return on the matching Treasury bonds, s_t is a credit spread, $\log HYR_t$ is a log ratio of high yield issues to the entire issue amount over the past one year, y_t is one-year Treasury zero coupon yield, $slope_t$ is the difference between 10- and 1-year yield, DD_t is distance-to-default averaged across firms, $r_{s,t}$ is a log stock market return, dp_t is log dividend yield, l_t is credit loss. Panel B shows the estimates for a one-year bond excess return forecasting regression of the form,

$$r^e_{b,t+1} = b_0 + b_1 X_t + \varepsilon_{b,t+1},$$

and $\bar{R}^2$ is adjusted R-squared. Standard errors corrected for overlapping observations using Hodrick (1992) are reported in parentheses. The sample is monthly overlapping series of annual returns from 1973 to 2014.

yield does not predict returns, while the yield slope predicts return positively.

The last row shows the regression with all variables, including stock variables, such as stock returns and dividend-price ratio, and distance to default. All else equal, higher dividend-price ratio predicts an increase in excess returns next period, while the high-yield issue ratio becomes insignificant. This loss of significance for the log high-yield issue ratio is primarily due to high correlation with dividend yield (-0.67) in my sample. Both log high-yield ratio and dividend yield move across business cycles, and it is hard to tell whether the return predictability by the high yield ratio is due to investor optimism or time-varying risk premiums. Thus, in the results that follows, I drop $\log HYR$ from the regression. Finally, adding stock volatility as a proxy for default risk (Atkeson, Eisfeldt and Weill (2014)) or yield volatility (one-year rolling standard deviation of daily changes in 10-year Treasury yield) does not change the results, and hence I omit them here.

3.4 Empirical Results

Now I estimate a VAR in (14) and implied long-run expectations. Panel A of Table 3 shows the estimated VAR coefficients. Even under the null that VAR is correctly specified, the use of overlapping data induces serial correlation in error terms. Thus, I correct the standard errors following Hodrick (1992).

Panel A shows that once controlling for other state variables, credit spreads are not as persistent as dividend yield, and predictable by lagged dividend yield. Stock returns are predictable by lagged stock returns and dividend yield, but not by bond variables.

Panel B shows the VAR-implied long-run forecasting coefficients for credit loss, bond excess returns, dividend growth rate and stock returns in equations (15) to (18). In the long-run, credit spreads become the dominant predictor of excess returns and credit loss on the corporate bond portfolio. When credit spreads go up by 1 percentage point, all else equal, long-run credit loss increases by 0.18 percentage point while long-run risk premiums increase by 0.82 percentage point. Thus, at the market level, greater variation of credit spreads is associated with bond risk premiums rather than expected credit loss. As a result, standard deviation of long-run risk premiums is estimated at 3.26 percent, greater than standard deviation of long-run credit loss (2.28 percent). The ratio of the risk premium volatility to the credit spread volatility is 0.88, while the ratio of the credit loss volatility to the credit spread volatility is lower. Moreover, Panel C shows that correlation between credit spreads and long-run credit loss is only 0.49, while correlation between credit spreads and risk premiums is highly significant at 0.79. Overall, these findings support the observation that time-series variation of the credit spread of the aggregate bond portfolio is associated more closely with risk premiums than with expected cash flows from default and exercise of calls, consistent with Nozawa (2016).

Figure 2 shows the time-series of credit spreads scaled by duration (to turn it effectively into yield spreads rather than price spreads), compared with the expected credit loss and excess return

Table 3: VAR Estimates and Implied Long-Run Expectations: 1973-2014

Panel A: VAR estimates

	$r_{b,t}$	$r_{b,t}^{f}$	s_t	$slope_t$	DD_t	$r_{s,t}$	dp_t	R^2	$\sigma(E[\cdot])$
$r_{b,t+1}$	0.09	-0.10	-0.23	0.61	-0.93	-0.10	0.04	0.27	3.03
	(0.26)	(0.20)	(0.24)	(0.82)	(0.39)	(0.05)	(0.01)		
$r_{b,t+1}^{f}$	0.05	0.05	-0.79	-0.41	-0.68	-0.08	-0.01	0.13	2.30
	(0.27)	(0.21)	(0.26)	(0.87)	(0.42)	(0.06)	(0.01)		
s_{t+1}	0.02	0.00	0.19	-0.39	-0.03	0.02	-0.05	0.48	2.55
	(0.26)	(0.20)	(0.23)	(0.62)	(0.34)	(0.04)	(0.01)		
$slope_{t+1}$	0.05	0.01	0.06	0.38	-0.04	-0.02	0.00	0.48	0.88
	(0.05)	(0.04)	(0.05)	(0.19)	(0.09)	(0.01)	(0.00)		
DD_{t+1}	0.24	-0.22	0.06	0.29	0.59	-0.03	0.01	0.56	1.46
	(0.05)	(0.04)	(0.05)	(0.11)	(0.07)	(0.01)	(0.00)		
$r_{s,t+1}$	0.90	-0.65	-0.47	-0.06	0.25	-0.31	0.09	0.16	6.52
	(0.91)	(0.72)	(0.87)	(2.04)	(1.42)	(0.17)	(0.04)		
dp_{t+1}	0.12	-0.42	1.11	-0.53	1.46	-0.25	1.00	0.92	41.25
	(0.25)	(0.22)	(0.31)	(0.64)	(0.48)	(0.05)	(0.01)		

Panel B: Long-run regression coefficients, $e_k G$

	$r_{b,t}$	$r_{b,t}^{f}$	s_t	$slope_t$	DD_t	$r_{s,t}$	dp_t	R^2	$\sigma(E[\cdot])$
$\sum_{j=1}^{\infty} \rho^{j-1} l_{t+j}$	0.00	0.06	0.18	-0.95	0.44	0.01	-0.04		2.28
	(0.11)	(0.10)	(0.16)	(0.35)	(0.28)	(0.02)	(0.03)		
$\sum_{j=1}^{\infty} \rho^{j-1} r_{b,t+j}^{e}$	0.00	-0.06	0.82	0.95	-0.44	-0.01	0.04		3.26
	(0.11)	(0.10)	(0.16)	(0.35)	(0.28)	(0.02)	(0.03)		
$\sum_{j=1}^{\infty} \rho^{j-1} g_{t+j}$	-1.41	1.56	-2.40	-1.28	-2.82	0.48	-0.01		11.43
	(0.67)	(0.64)	(1.08)	(1.91)	(1.94)	(0.12)	(0.26)		
$\sum_{j=1}^{\infty} \rho^{j-1} r_{s,t+j}$	1.41	-1.56	2.40	1.28	2.82	-0.48	1.01		39.32
	(0.67)	(0.64)	(1.08)	(1.91)	(1.94)	(0.12)	(0.26)		

Panel C: Variation of VAR-implied conditional expectations

$\frac{\sigma(s^l)}{\sigma(s)}$	$\frac{\sigma(s^r)}{\sigma(s)}$	$\frac{\sigma(dp^g)}{\sigma(dp)}$	$\frac{\sigma(dp^r)}{\sigma(dp)}$	$\varrho(s^l, s)$	$\varrho(s^r, s)$	$\varrho(s^l, s^r)$	$\varrho(dp^g, dp)$	$\varrho(dp^r, dp)$	$\varrho(dp^g, dp^r)$
0.62	0.88	0.26	0.91	0.49	0.79	-0.15	0.46	0.97	0.21
(0.25)	(0.13)	(0.11)	(0.25)	(0.22)	(0.18)	(0.17)	(0.80)	(0.02)	(0.84)

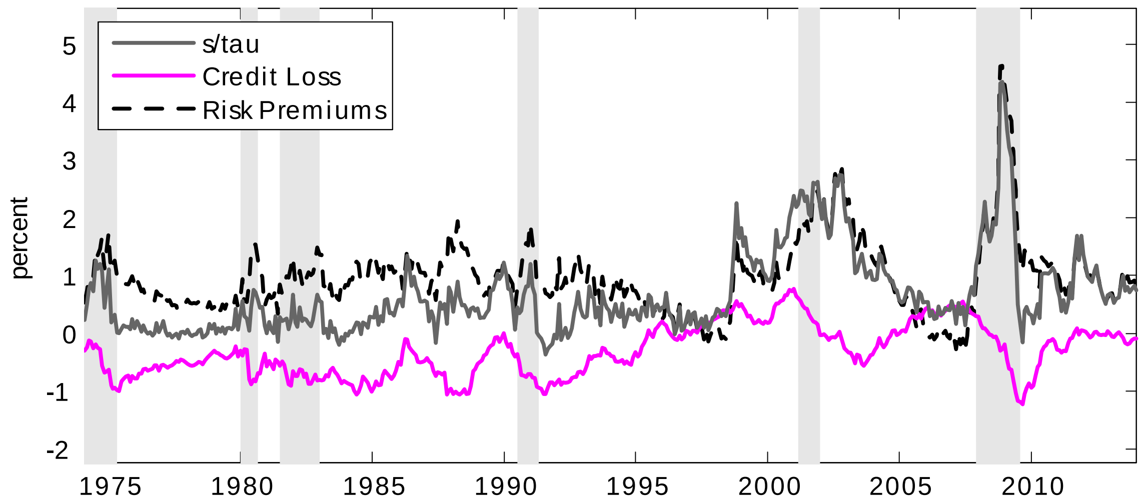
Panel D: Variation of VAR-implied conditional expectations (VAR(2))

$\frac{\sigma(s^l)}{\sigma(s)}$	$\frac{\sigma(s^r)}{\sigma(s)}$	$\frac{\sigma(dp^g)}{\sigma(dp)}$	$\frac{\sigma(dp^r)}{\sigma(dp)}$	$\varrho(s^l, s)$	$\varrho(s^r, s)$	$\varrho(s^l, s^r)$	$\varrho(dp^g, dp)$	$\varrho(dp^r, dp)$	$\varrho(dp^g, dp^r)$
0.66	1.18	0.32	0.93	0.03	0.83	-0.54	0.36	0.95	0.04
(0.18)	(0.22)	(0.16)	(0.31)	(0.41)	(0.12)	(0.23)	(0.87)	(0.05)	(0.82)

Panel A shows the estimated VAR coefficients. $\sigma(E[\cdot])$ shows standard deviation of the estimated conditional expectations for each variable. Panel B shows the long-run forecasting coefficients implied from one-period VAR based on (15), (16), (17) and (18). Panel C shows volatility and correlation, $\varrho(\cdot,\cdot)$, for long-run conditional expectations. Standard errors corrected for overlapping observations using Hodrick (1992) are reported in parentheses.

components, both of which are also scaled by duration. Risk premiums are almost as volatile as credit spreads, and highly counter-cyclical. On the other hand, expected long-run credit loss is slow-moving and somewhat pro-cyclical.

Figure 2: Variance Decomposition of Credit Spreads: 1973-2014



The figure plots the credit spread (scaled by duration), s_t/τ_t, expected credit loss, s_t^l/τ_t, and risk premium components, s_t^r/τ_t. The shaded area corresponds to NBER recessions.

The pro-cyclicality of expected credit loss arises since it measures growth, rather than levels, in payoffs due to default and prepayment. Before recession, the current level of default is low, and investors anticipates default to rise in the future, leading to higher expected credit loss. Once the economy enters into a recession, the current default rises while investors anticipate relatively lower default in the future, pushing down expected credit loss.

Another interesting difference between two components of credit spreads is their persistence. The autocorrelation coefficient for one-year lag is 0.64 for expected credit loss and 0.35 for risk premiums. Risk premiums accounts mostly for the high-frequency variation in credit spreads, while the cash flow component varies more slowly.

One-period risk premiums and long-run risk premiums on the bond market portfolio are very different from each other, and what affects firms' investment decision is a price of the bond, of which the long-run risk premiums is the key driver, not the one-period risk premium studied in the literature (e.g., Lopez-Salido, Stein and Zakrajsek (2015)). I find that standard deviation of long-run bond risk premiums is about twice as large as the one-period risk premiums. The correlation between credit spreads and one-period period risk premium is only 0.50 (not reported in the table), lower than the correlation between credit spreads and long-run premiums. With the variance decomposition approach, I can measure variation of long-run risk premiums and examine their behavior in relation to the overall economy.

Panel B also shows the variance decomposition of dividend yield for the stock market portfolio. Consistent with the previous findings (e.g., Campbell and Shiller (1988a, b) and Cochrane (2011)), dividend yield is mostly associated with expected stock returns rather than dividend growth. One percentage point change in dividend yield is associated with a 1.01 percentage point rise in expected returns, and a 0.01 percentage point decrease in cash flows. Bond variables, such as lagged bond returns, credit spreads, help forecast stock returns in the long run. The volatility ratio for stock expected returns, reported in Panel C, is as high as 0.91, and supports the view that much of the variation in stock prices corresponds to time-varying expected returns.

Panel D of Table 3 shows the behavior of the long-run expectations when I estimate VAR(2) instead of VAR(1). The long-run expectations are just as volatile and behave similarly whether I use VAR(1) or VAR(2), and adding extra lags do not change the main results.

3.5 Components of Credit Spreads and Macroeconomy

Credit spreads on corporate bonds are known to predict future macroeconomic activities (e.g. Gilchrist and Zakrajsek (2012)). However, the channel through which credit spreads are linked to real economy is not clear. If investors foresee corporate profitability to decline due to adverse state of macroeconomy, corporate bond prices should fall today, reflecting higher expected credit loss. If investors risk aversion rises due to an exogenous shock, rising risk premiums can depress future firm investments and hence macroeconomic activities.

Forecasting macro variables using the two components of credit spreads in the variance decomposition sheds light on this question about the channel. I predict changes in economic activities using components of the credit spread by

$$\nabla^h Y_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i \nabla Y_{t-i} + \gamma_1 s_t + \gamma_2 TS_t + \gamma_3 RFF_t + \varepsilon_{t+h}, \tag{19}$$

where $\nabla^h Y_{t+h} = \ln(Y_{t+h}/Y_t)$ and $h(= 3, 12, 36)$ is the forecast horizon. For macro variable Y_t, I use log non-farm payroll employment, unemployment rate, log industrial production at the monthly frequency, and log GDP at the quarterly frequency. I determine lags p based on the Akaike Information Criterion. Since I use overlapping observations, I correct standard errors using Hodrick (1992). I use term spread, TS_t, (the difference in yields between 10-year Treasury note and 3-month T-bill), and real federal funds rate, RFF_t, as control variables.

The first three columns of Table 4 reports the estimated coefficients γ_1 and adjusted R-squared for the three-month horizon. Bond risk premiums, s_t^r, predicts significantly negative economic growth. Higher risk premiums are correlated with lower payroll growth, industrial production, GDP growth and with higher unemployment three month later. In contrast, the signs of the coefficients

Table 4: Forecasts of Marco Variables Using Expected Credit Loss and Risk Premiums

	3 Months Horizon			12 Months Horizon			36 Months Horizon		
	s_t^r	s_t^l	$\bar{R}^2$	s_t^r	s_t^l	$\bar{R}^2$	s_t^r	s_t^l	$\bar{R}^2$
	Payroll growth								
(1)	-0.05		0.63	-0.24		0.54	-0.29		0.35
	(-8.44)			(-14.19)			(-8.09)		
(2)		-0.01	0.57		-0.15	0.46		-0.78	0.45
		(-1.08)			(-3.70)			(-6.92)	
(3)	-0.05	-0.01	0.63	-0.23	-0.14	0.56	-0.27	-0.77	0.48
	(-8.39)	(-0.98)		(-14.12)	(-3.68)		(-7.78)	(-7.26)	
	Unemployment rate								
(1)	4.00		0.38	14.92		0.43	5.82		0.44
	(5.33)			(6.45)			(1.18)		
(2)		-0.18	0.30		1.85	0.31		12.63	0.45
		(-0.14)			(0.41)			(1.03)	
(3)	4.06	-0.82	0.38	14.94	-0.30	0.43	4.73	11.78	0.45
	(5.29)	(-0.66)		(6.34)	(-0.07)		(0.97)	(0.99)	
	Industrial production								
(1)	-0.25		0.35	-0.69		0.32	-0.25		0.27
	(-6.03)			(-6.37)			(-1.21)		
(2)		-0.01	0.23		-0.23	0.21		-1.13	0.33
		(-0.09)			(-1.11)			(-1.95)	
(3)	-0.25	0.02	0.35	-0.68	-0.19	0.33	-0.22	-1.12	0.33
	(-5.99)	(0.27)		(-6.30)	(-0.96)		(-1.02)	(-2.05)	
	GDP growth rate								
(1)	-0.09		0.19	-0.25		0.26	-0.14		0.23
	(-4.47)			(-4.57)			(-1.15)		
(2)		-0.02	0.09		-0.13	0.16		-0.44	0.27
		(-0.69)			(-0.93)			(-1.14)	
(3)	-0.09	-0.02	0.18	-0.25	-0.12	0.27	-0.13	-0.43	0.27
	(-4.51)	(-0.61)		(-4.56)	(-0.90)		(-1.07)	(-1.19)	

The table reports the estimated slope coefficients for the regressions of 3, 12 and 36 month log changes in macro variables in the future on risk premium measures at the monthly frequency for payroll growth rate, unemployment and industrial production and at the quarterly frequency for GDP growth rate. For unemployment rate, I forecast changes rather than log changes. s_t^r is the long-run risk premiums on the corporate bond market portfolio and s_t^l is the long-run expected credit loss. $\bar{R}^2$ is adjusted R-squared. The regression includes lagged monthly growth rate, in which the number of lags are determined by the Akaike Information Criterion. In addition, the regressors include real risk-free rate and term spreads as control variables. The values in parentheses are t-statistics corrected for overlapping observations using Hodrick (1992). The sample is from 1974 to 2014.

on expected credit loss are not consistent with each other, and not statistically significant. Hence, the short-term predictability of economic growth using credit spreads comes mostly from the risk premium component. The regression for the twelve-month horizon, reported in the next three columns, show that the qualitatively similar results hold.

The last three columns of Table 4 shows the estimates for the same predicting regression for the three-year horizon. For all four variables, the loading on expected credit loss is greater in magnitude than that on risk premiums, and adjusted R-squared is higher for expected credit loss than risk premiums. Hence, expected credit loss rises long before a decline in growth, while risk premiums rises just before the contraction. The R-squared for the regression using expected credit loss rises with horizon except payroll growth, while there is no such increasing pattern in R-squared for risk premiums. This is expected, as expected credit loss is more persistent than risk premiums, and tends to rise before a recession begins.

3.6 Effect of Corporate Bond Liquidity

As corporate bonds are traded in over-the-counter market, trade occurs infrequently, and investors may demand liquidity premiums (Edwards, Harris and Piwowar (2007), Chen, Lesmond and Wei (2007), Bao, Pan and Wang (2011), Lin, Wang and Wu (2011) and Feldfutter (2012)). If the liquidity premium affects the market-wide variation in corporate bond prices, then it would show up as risk premiums in my estimates. To tell the difference between a reward for holding risky securities and a reward for holding illiquid securities, I extend the VAR including a measure for liquidity.

In the recent article, Hu, Pan and Wang (2013) show that fitting error of a yield curve model to Treasury securities ("$Noise$") works as a proxy for the constraints on arbitrage capital in the economy, and thus provides a measure of illiquidity across various financial markets. In contrast to other liquidity measures of corporate bonds which depend on the availability of high-frequency data of corporate bond prices, $Noise$ goes further back in history as it depends only on Treasury bond prices, making it a suitable proxy for illiquidity in this exercise. To be specific, I extend the sample of $Noise$ back to 1973, so the market-wide liquidity measure is available throughout my sample of corporate bonds. Following Fu, Pan and Wang (2013), $Noise$ is computed every day using cross-section of Treasury yields from 1 to 10 years. I take average within a month to obtain the monthly series of $Noise$. Then I include $Noise$ as an additional state variable in a VAR in (13) and (14).

If time-varying risk premiums partly reflect variation in liquidity premium, then the loading of long-run excess bond returns, $\sum \rho^{j-1} r^e_{t+j}$, on $Noise$ should be significantly positive. In addition, if $Noise$ carries the information not contained in other state variables, the volatility of bond risk premiums should go up when including $Noise$ in the VAR.

I leave the detailed estimation results in Appendix C, and present the abbreviated results here.

The loading of $\sum \rho^{j-1} r^e_{t+j}$ on $Noise$ is positive, but only one standard error away from zero. By including $Noise$ in the VAR, the standard deviation of $\sum \rho^{j-1} r^e_{t+j}$ is estimated at 3.29 percent, about unchanged from the main results in Table 3. The correlation between credit spreads and risk premiums is also similar to the main results, estimated at 0.89. Thus, including $Noise$ in this framework does not change the main results in this article, and I do not find evidence that illiquidity is the significant driver for the time-varying bond risk premiums.

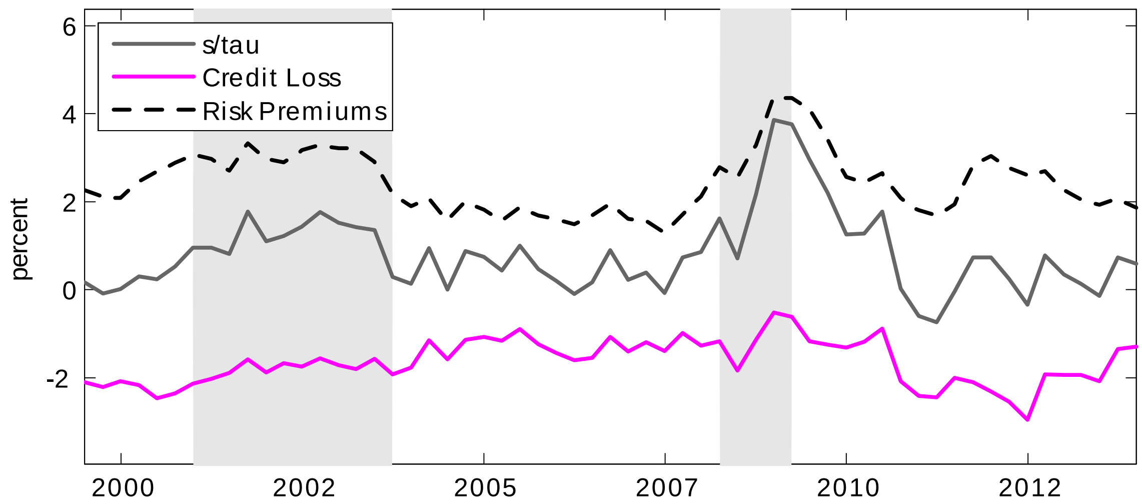
In conclusion, this section shows that a VAR jointly estimated using both bond and stock variables yields a decomposition of risk premiums and cash flows which is consistent with the previous literature. However, this analysis does not tell if bond risk premiums are anomalously low during the boom from the perspective of the equity market, and this is the question I turn to next.

3.7 Decomposition Outside the United States

Since the number of business cycles in the US in my sample is limited, the analysis on the corporate bond prices outside of the US is useful. Using the quarterly corporate bond price data from International Data Corporation, I run the same VAR as (13) and (14) for three Euro area countries (Germany, France and Italy) and United Kingdom, except that I drop stock returns and the dividend price ratio. Since the sample period is short (1999-2014), the risk premiums are not estimated statistically precisely, but we can still see that the similar pattern emerges.

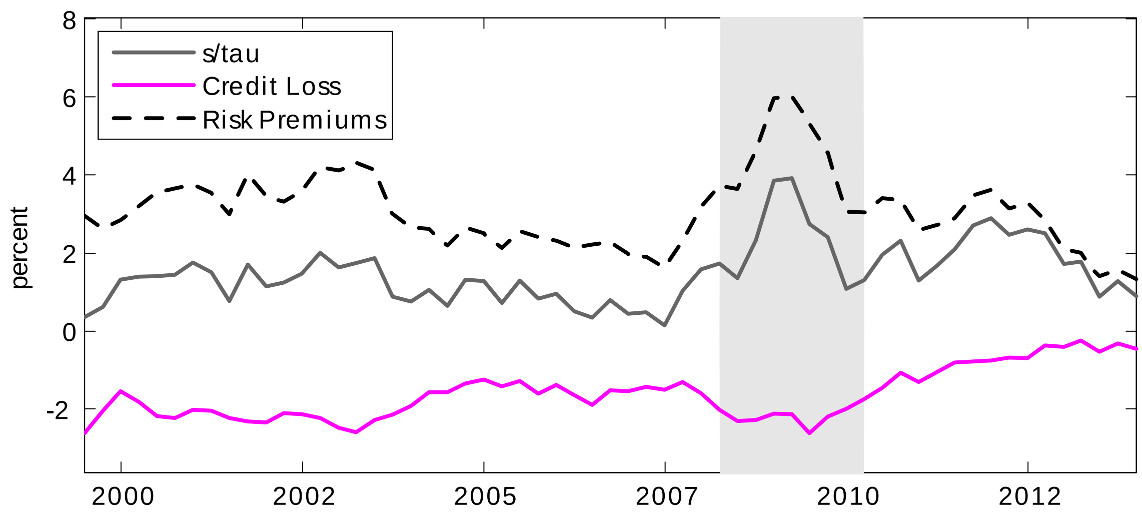
Figure 3 shows the decomposition results for the market portfolio of Euro area countries, and Figure 4 shows those for UK. In either cases, the risk premiums fall until 2007, and increases during the 2008 recessions. The expected credit loss is higher before the 2008 recessions, and fall once the economy enters recession. The credit spread rises in 2011 due to the sovereign crisis in the Euro area, but this rise seems to correspond mostly to risk premiums rather than expected credit loss in Germany, France and Italy. The expected credit loss in UK rises after the 2008 recession. Overall, the figures show that there is a good deal of market integration in risk premiums across countries, and the time-series variation in risk premiums are similar to each other.

Figure 3: Variance Decomposition of Credit Spreads in Germany, France and Italy: 1999-2014



The figure plots the credit spread (scaled by duration), s_t/τ_t, expected credit loss, s_t^l/τ_t, and risk premium components, s_t^r/τ_t. The shaded area corresponds to recessions in Germany.

Figure 4: Variance Decomposition of Credit Spreads in United Kingdam: 1999-2014



The figure plots the credit spread (scaled by duration), s_t/τ_t, expected credit loss, s_t^l/τ_t, and risk premium components, s_t^r/τ_t. The shaded area corresponds to recessions in UK.

4 VAR and Long-Run Euler Equation

4.1 Estimating Time-Varying Risk Exposure

The risk premiums estimated in the previous section may reflect variety of factors, including changes in risk, risk aversion, investors' sentiments and other frictions in the market. In order to separate rational reward for taking risks from mispricing, one needs to take a stand on an asset pricing model. Therefore, I extend the CAPM allowing the risk exposure of the bond portfolio to vary over time and analyze if corporate bond risk premiums are too high or too low. To make the analysis tractable, in this section, I assume that corporate bonds, matching Treasury bonds and stocks are conditionally log-normally distributed. Then, the CAPM implies that the long-run corporate bond risk premiums obey[2],

$$E\left[\sum_{j=1}^{\infty}\rho^{j-1}r^e_{b,t+j}\middle| X_t\right] = b\sum_{j=1}^{\infty}\rho^{j-1}Cov\left(r^e_{b,t+j}, r_{s,t+j}\middle| X_t\right) + C, \tag{21}$$

where $C = -0.5\sum_{j=1}^{\infty}\rho^{j-1}\left(\sigma^2\left(r_{b,t+j}\right) - \sigma^2\left(r_{f,t+j}\right)\right)$.

As the corporate bond risk premiums vary every month, I estimate time-varying risk exposure $Cov\left(r^e_{b,t+j}, r_{s,t+j}\middle| X_t\right)$ using the dynamic conditional correlation (DCC) model of Engle (2002). In doing so, I ensure that the variation in risk exposure is consistently estimated both over time and across horizon.

In order to estimate covariance matrix accurately, I work with monthly non-overlapping returns. Specifically, I first estimate the VAR in (14) replacing all annual return variables with corresponding monthly returns, and extract the monthly fitting errors. Suppose that the error terms for bond returns, matching Treasury returns and stock returns have covariance matrix,

$$E_{t-1}\left(\varepsilon_{r,t}\varepsilon'_{r,t}\right) \equiv H_t = D_t U_t D_t,$$

where $D_t = diag\left\{\sqrt{h_{i,t}}\right\}$ and U_t is correlation matrix which varies over time. Let $u_t = \varepsilon_{r,t}/h_t$. Then, following Engle (2002), I model the dynamics of the variance for each variable to follow a

[2] To see this, let the stochastic discount factor be

$$M_t = \exp\left(-a - br_{s,t+1}\right).$$

Then the Euler equation for the bond return at $t+1$ implies

$$\begin{aligned} E\left[r_{b,t+1}\middle| X_t\right] + \frac{1}{2}\sigma^2\left[r_{b,t+1}\middle| X_t\right] - r_{f,t} &= Cov\left(r_{b,t+1}, r_{s,t+1}\middle| X_t\right)b, \\ E\left[r_{f,t+1}\middle| X_t\right] + \frac{1}{2}\sigma^2\left[r_{f,t+1}\middle| X_t\right] - r_{f,t} &= Cov\left(r_{f,t+1}, r_{s,t+1}\middle| X_t\right)b. \end{aligned}$$

Therefore,

$$E\left[r^e_{b,t+1}\middle| X_t\right] + \frac{1}{2}\sigma^2\left[r_{b,t+1}\middle| X_t\right] - \frac{1}{2}\sigma^2\left[r_{f,t+1}\middle| X_t\right] = Cov\left(r^e_{b,t+1}, \tilde{r}_{s,t+1}\middle| X_t\right)b. \tag{20}$$

Adding (20) over the long run leads to (21).

Table 5: DCC Model Parameters: Monthly 1973-2014

Panel A: Variance Dynamics

	$\bar{h}$	α_i	β_i
$\varepsilon_{b,t}$	0.19	0.13	0.77
	(0.10)	(0.05)	(0.08)
$\varepsilon_{f,t}$	0.10	0.10	0.84
	(0.05)	(0.03)	(0.04)
$\varepsilon_{s,t}$	0.58	0.09	0.88
	(0.47)	(0.03)	(0.03)

Panel B: Correlation Dynamics

Unconditional correlation, $\bar{U}$

	$\varepsilon_{f,t}$	$\varepsilon_{s,t}$
$\varepsilon_{b,t}$	0.63	0.42
	(0.08)	(0.07)
$\varepsilon_{f,t}$		0.09
		(0.06)

α_q	β_q
0.05	0.93
(0.02)	(0.04)

Panel A shows the estimated parameters for GARCH(1,1) model for residuals of VAR in (14), replacing annual returns with monthly returns. $\varepsilon_{b,t}$ is a residual for bond returns, $\varepsilon_{f,t}$ is a residual for matching Treasury returns, and $\varepsilon_{s,t}$ is a residual for stock returns. Panel B shows unconditional correlation among residuals, and parameters that govern the dynamics of the correlation matrix. Values in parentheses show standard errors.

univariate GARCH(1,1) process,

$$h_{i,t} = \bar{h}_i \left(1 - \alpha_i - \beta_i\right) + \alpha_i \varepsilon^2_{r,i,t-1} + \beta_i h_{i,t-1}.$$

Furthermore, the correlation follows a common autoregressive process,

$$Q_t = \bar{U}\left(1 - \alpha_q - \beta_q\right) + \alpha_q \left(u_{t-1} u'_{t-1}\right) + \beta_q Q_{t-1},$$

and correlation matrix is obtained by $U_t = diag\left\{Q_t\right\}^{-1} Q_t diag\left\{Q_t\right\}^{-1}$, and $\bar{U}$ is an unconditional correlation matrix. Matrix Q_t is positive definite since it is a weighted average of positive definite and positive semidefinite matrices.

The advantage of the DCC model is that, by assuming that scaler parameters α_q and β_q are common among all elements in the correlation matrix, the number of parameters in the dynamics is relatively small, which leads to robust estimates of conditional covariance. In this application, the number of variables is 3, and I need to estimate 14 parameters.

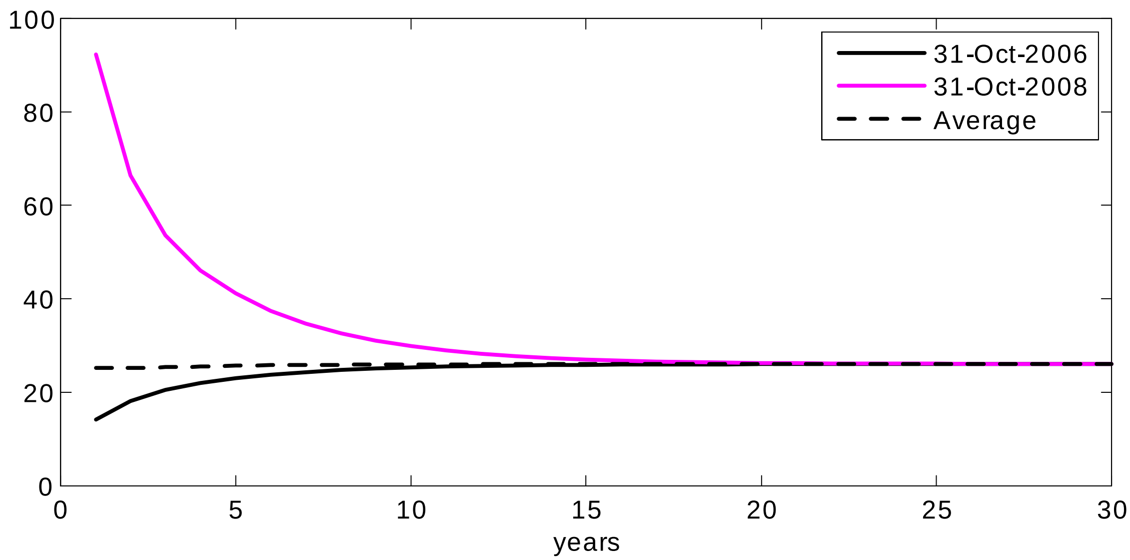
Table 5 shows the estimated parameters of the DCC model using Maximum Likelihood. At the monthly frequency, the correlation matrix slowly varies over time, with persistence parameter β_q estimated at 0.93, which is far from zero in the data. The estimated DCC model suggests that the covariance between bond and stock returns varies substantially over time, and accounting for time-varying risk exposure is essential in understanding time-varying risk premiums.

Based on these estimates, I compute conditional covariance matrix for annual returns as

$$Cov\left(r^e_{b,t+j}, r_{s,t+j} \middle| X_t\right) = \left(e_1 - e_2\right)\left(\sum_{k=0}^{11} H_{t+j-k}\right) e'_s.$$

Figure 5 shows the estimated CAPM risk exposure, $Cov\left(r^{e}_{b,t+j}, r_{s,t+j} \middle| X_t\right)$, for different horizon j in a month before the financial crisis (October 2006) and a month during the crisis (October 2008). For the short horizon, the risk exposure varies considerably over time. In October 2006, the risk exposure is increasing in horizon, and short-term risk is relatively low. In contrast, during the financial crisis, the short-term risk exposure shoots up dramatically, and it mean-reverts slowly across horizon.

Figure 5: CAPM Betas Over Different Horizon



The figure plots the CAPM risk exposure for one-year excess returns on the corporate bond market portfolio, $Cov\left(r^{e}_{b,t+j}, r_{s,t+j} \middle| X_t\right)$, for different time in the future, j, observed in different months. Average is the time-series average of the covariance.

To find the reward for risk parameter, b in (21), I minimize the sum of squared distance between the left-hand side and right-hand side of equation (21). The optimal value for the corporate bond market portfolio is estimated at $b^{*} = 0.055$. As I fix b, a testable implication of equation (21) is that the monthly variation in long-run mean excess returns must match the time-variation in long-run CAPM risk exposure. This is not a trivial restriction, as there is no mechanical link between the first and second moment in returns.

I do not estimate b using expected returns on stocks, as stock returns are far from normally distributed, invalidating the relationship in (21). For example, in my sample, an error term corresponding to $r_{b,t}$ has skewness of -0.35 and excess kurtosis of 0.34, while an error corresponding to $r_{s,t}$ has skewness of -0.74 and excess kurtosis of 1.17.

The proper application of the CAPM requires one to use a return on the wealth portfolio as a pricing factor rather than the return on the stock market portfolio, as I do here. I use the stock market portfolio, as the issue of market integration between corporate bonds and stocks is interesting on its own, even if the stock market portfolio is not the same as the wealth portfolio. In particular, since both corporate bonds and stocks depend on the firm value of issuers, the stock market portfolio is a natural proxy for the wealth portfolio in pricing corporate bonds.

4.2 Evaluating Corporate Bond Risk Premiums Using the CAPM

To examine if bond risk premiums are too low in good times, I need to define precisely what good times for the bond market mean. Aside from the NBER-defined booms and recessions, the key description of the credit market condition is whether credit supply is increasing or not. Thus, I measure credit conditions by one-year changes in debt securities and loans in nonfinancial business sector reported in Flow of Funds' Table 104. I define credit expansion as the period in which one-year changes exceed the past ten-year averages. Credit contraction occurs when changes in credit are below the ten-year moving averages.

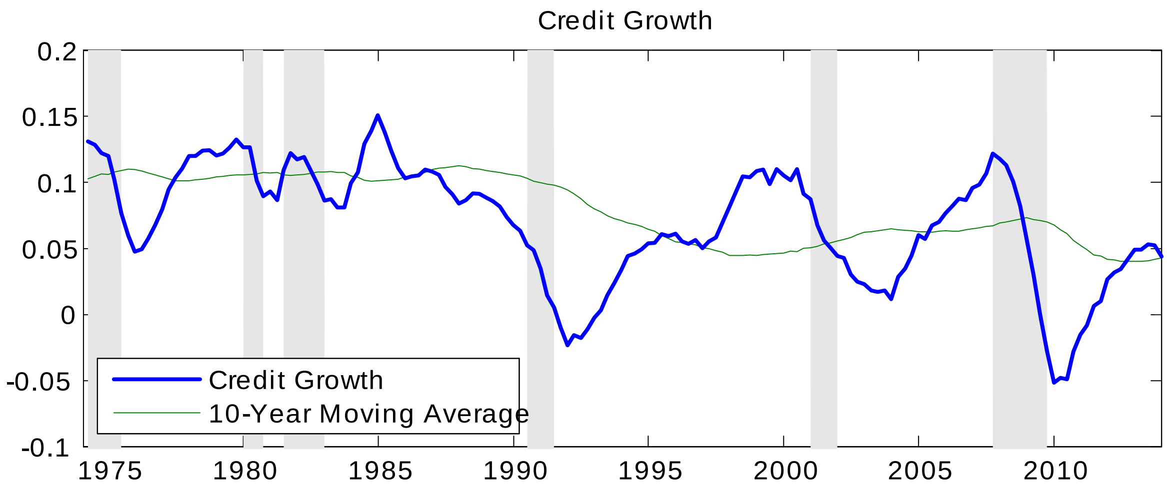
The top panel of Figure 6 shows one-year changes and ten-year moving averages. The figure shows that credit growth is procyclical, but there are some difference between business and credit cycles. For example, the recession in the mid-1980s does not involve sizable credit contraction, and credit expands rapidly afterwards. In contrast, after the recession in the early 1990s, the recovery in credit cycle is slow and credit growth exceeds the trend only after several years have passed since the end of the recession.

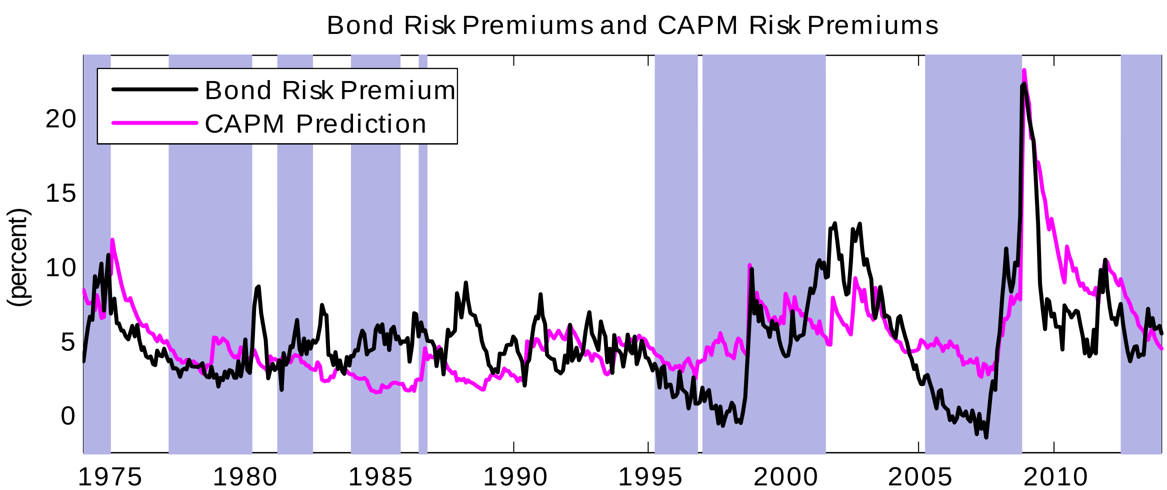
The bottom panel of Figure 6 shows the long-run bond risk premiums and CAPM-implied risk premiums, or the left-hand side and right-hand side of (21). The shaded area in the plot shows the period of credit expansions. Both bond risk premiums and CAPM risk premiums are countercyclical and comove reasonably well together, with a correlation coefficient of 0.62. In addition, volatility of long-run bond risk premiums (3.26 percent) is close to the CAPM-based counterpart (3.15 percent).

The fact that correlation between long-run bond risk premiums and the CAPM benchmark is below one may not be surprising, given the well-known limitation of the CAPM (e.g., Fama and French (1992)) and the one-factor Merton model (e.g., Collin-Dufresne, Goldstein and Martin (2001)). A more interesting question is whether there is any systematic pattern in mispricing or not. In particular, if there is froth in corporate bond market, the long-run bond risk premiums would be too low relative to the CAPM benchmark during the period with credit expansion. If such frothy conditions lead to too much risk-taking by firms and eventual recessions, then the bond risk premiums would be too high during the recession.

The bottom panel of Figure 6 presents weak evidence for the existence of froth. The long-run bond risk premiums are fairly close to the CAPM benchmark during the 2001 and 2008 recessions. Moreover, there is little evidence that the bond risk premiums are too low prior to recessions. In particular, prior to the recession in 1990 and 2001, bond risk premiums are about the same as the CAPM benchmark, and from this perspective, there is no froth specific to the corporate bond

Figure 6: Credit Cycles, Corporate Bond and CAPM Risk Premiums





The top panel plots credit growth, a one-year change in debt of the nonfinancial corporate sector, as well as the trailing ten-year average of the credit growth. The shaded area corresponds to NBER recessions. The bottom panel plots the long-run bond risk premiums based on the VAR, $E\left[\sum_{j=1}^{\infty}\rho^{j-1}r^{e}_{b,t+j}\middle| X_t\right]=(e_1-e_2)(G_0+GX_t)$ and the CAPM-implied bond risk premiums, $b\sum_{j=1}^{\infty}\rho^{j-1}Cov\left(r^{e}_{b,t+j},\tilde{r}_{s,t+j}\middle| X_t\right)+C$. The shaded area corresponds to the period with credit expansion.

Table 6: Bond and CAPM Risk Premiums

	Bond	CAPM	Difference	t(Difference)
Full Sample				
Boom	4.41	4.95	-0.54	(-0.06)
Recession	8.44	7.18	1.26	(0.14)
High Credit Growth	3.94	4.73	-0.79	(-0.09)
Low Credit Growth	5.97	5.79	0.19	(0.02)
-1989				
Boom	4.43	3.56	0.87	(0.11)
Recession	6.07	5.41	0.66	(0.09)
1990-				
Boom	4.40	5.80	-1.40	(-0.14)
Recession	10.94	9.04	1.90	(0.19)

Table shows the long-run bond risk premiums based on the VAR, $E\left[\sum_{j=1}^{\infty}\rho^{j-1}r_{b,t+j}^{e}\middle|X_t\right]=(e_1-e_2)(G_0+GX_t)$ and the CAPM-implied bond risk premiums, $b\sum_{j=1}^{\infty}\rho^{j-1}Cov\left(r_{b,t+j}^{e},\tilde{r}_{s,t+j}\middle|X_t\right)+C$. Values in parentheses are t-statistics.

market. If bonds are mispriced prior to recessions and bond risk premiums are too low, then such arguments applies both to bond and stock markets. In contrast, the bond risk premiums appear somewhat lower before the Great Recession in 2008, but such difference does not appear to be large relative to standard errors, shown in Table 6.

Table 6 shows the average values of bond risk premiums and the CAPM benchmark, averaged over different time periods. If I use the full sample and compute the average just for NBER booms or the period with credit expansions, long-run bond risk premiums are lower than the CAPM benchmark by 0.54 and 0.79 percentage points, respectively. However, such gaps are economically small compared with the overall variation in long-run bond risk premiums (whose standard deviation is 3.26 percent), and the difference is statistically insignificant. During NBER recessions and the period of credit expansions, bond risk premiums are higher than the CAPM benchmark by 1.26 and 0.19 percentage points, respectively. Again, the difference is economically and statistically insignificant.

The bottom panel of Figure 6 shows that the volatility of bond risk premiums appears to increase over time. Thus, I show the difference in risk premiums before and after 1990. Though the bond risk premiums during recessions increase in the second half of the sample, so does the CAPM benchmark, and there is little change in difference between the two over time.

4.3 Term Structure of Risk Premiums

Furthermore, I examine the term structure of bond risk premiums implied by the VAR and the CAPM counterparts. Figure 7 shows the slope of risk premiums, or the difference between ten-year and two-year expected returns on the corporate bond market portfolio, $E\left[r_{b,t+10}^{e}\middle|X_t\right]-$

Figure 7: Slope of Risk Premiums: 10-Year Horizon Minus 2-Year Horizon

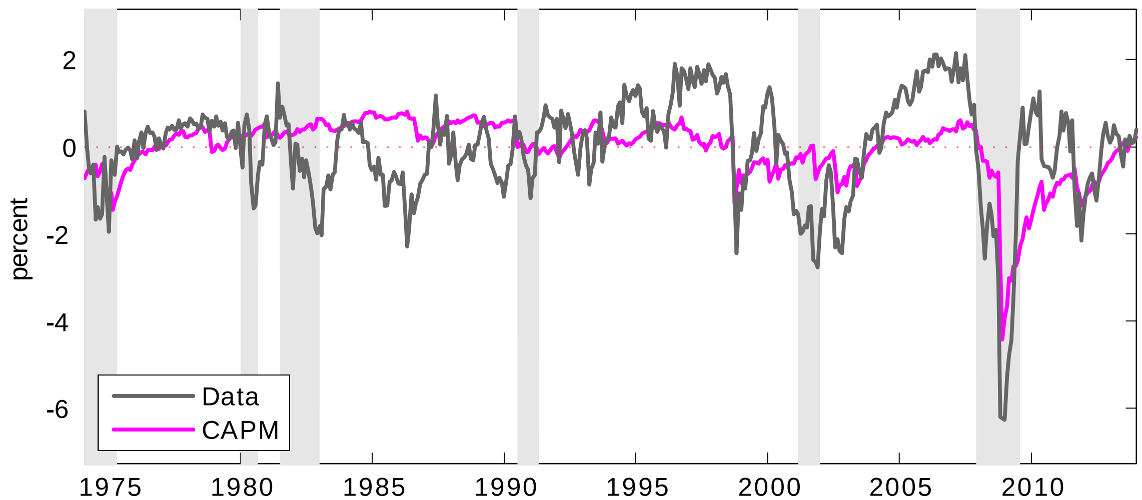


Figure plots the difference in bond risk premiums for ten-year returns and two-year returns, $E\left[r^e_{b,t+10}\middle| X_t\right] - E\left[r^e_{b,t+2}\middle| X_t\right]$, and the CAPM-implied counterparts The shaded area corresponds to the NBER recessions.

$E\left[r^e_{b,t+2}\middle| X_t\right]$. In the data, the term structure tends to be downward sloping during recessions (i.e. the slope is negative), while it is upward sloping during booms. The CAPM-based slope tracks the slope in the data, and tends to decrease during recessions. The CAPM-based term structure turns strongly downward sloping during the financial crisis, which is consistent with the data. However, the CAPM-based slope is stable and remain positive in the 1980s, when the slope in the data fluctuate with changing signs.

One may argue that mispricing should be more pronounced for high-yield bonds than investment grade bonds. As high-yield bonds are less liquid (e.g., Bao, Pan and Wang (2011)), mispricing is less likely to be arbitraged away for those bonds, compared with investment grade bonds. To address this concern, in Appendix D, I show the similar results hold for subportfolios of corporate bonds sorted on credit ratings (portfolios of investment grade bonds and high-yield bonds). In fact, for high-yield bonds, the CAPM benchmark overpredicts bond risk premiums during recessions, and underpredicts during booms, a pattern opposite to what one should expect from the existence of "froth".

4.4 Economic Significance

In order to evaluate the economic significance of the deviation of the corporate bond risk premiums from the CAPM benchmark, I study the information content in the risk premiums. As shown in the previous section, rising corporate bond risk premiums predict a contraction in economic activities. In this subsection, I examine which of the two components of risk premiums - the component explained by the CAPM and the other unexplained component - drive the predictability. If the deviation of the bond risk premiums from the benchmark is economically significant, it should be the primary source of predictability for the economic activity.

To evaluate the contribution of the mispricing to future economic activities, I run a VAR involving macro variables and a component of bond risk premiums, following Gilchrist and Zakrajsek (2012). The set of state variables is identical to those of Gilchrist and Zakrajsek (2012), except that I use each of the two components of the bond risk premiums instead of their measure of mispricing ("excess bond premiums"). Specifically, I include variables in the following order: (i) log growth of real personal consumption expenditure, (ii) log growth in real nonresidential investment, (iii) log GDP growth rate, (iv) log changes in GDP deflator, (v) the component of corporate bond risk premiums, (vi) returns on the CRSP value-weight stock market portfolio in excess of Treasury bills, (vii) yields on 10-year Treasury bond and (viii) nominal Federal Funds Rate. I use the one-year forecasting horizon, and determine the order of VAR lags using the Akaike Information Criterion.

Figure 8 shows the response of endogenous variables to a one standard deviation shock to the CAPM-based bond risk premiums, or the right-hand side of (21). As the CAPM-based risk premiums rise, the growth rates for consumption, investment and output fall. This is not surprising, as the worsening future growth prospect leads to an increase in risk premiums across the financial markets. In contrast, the response of stock returns and risk-free rates are statistically insignificant.

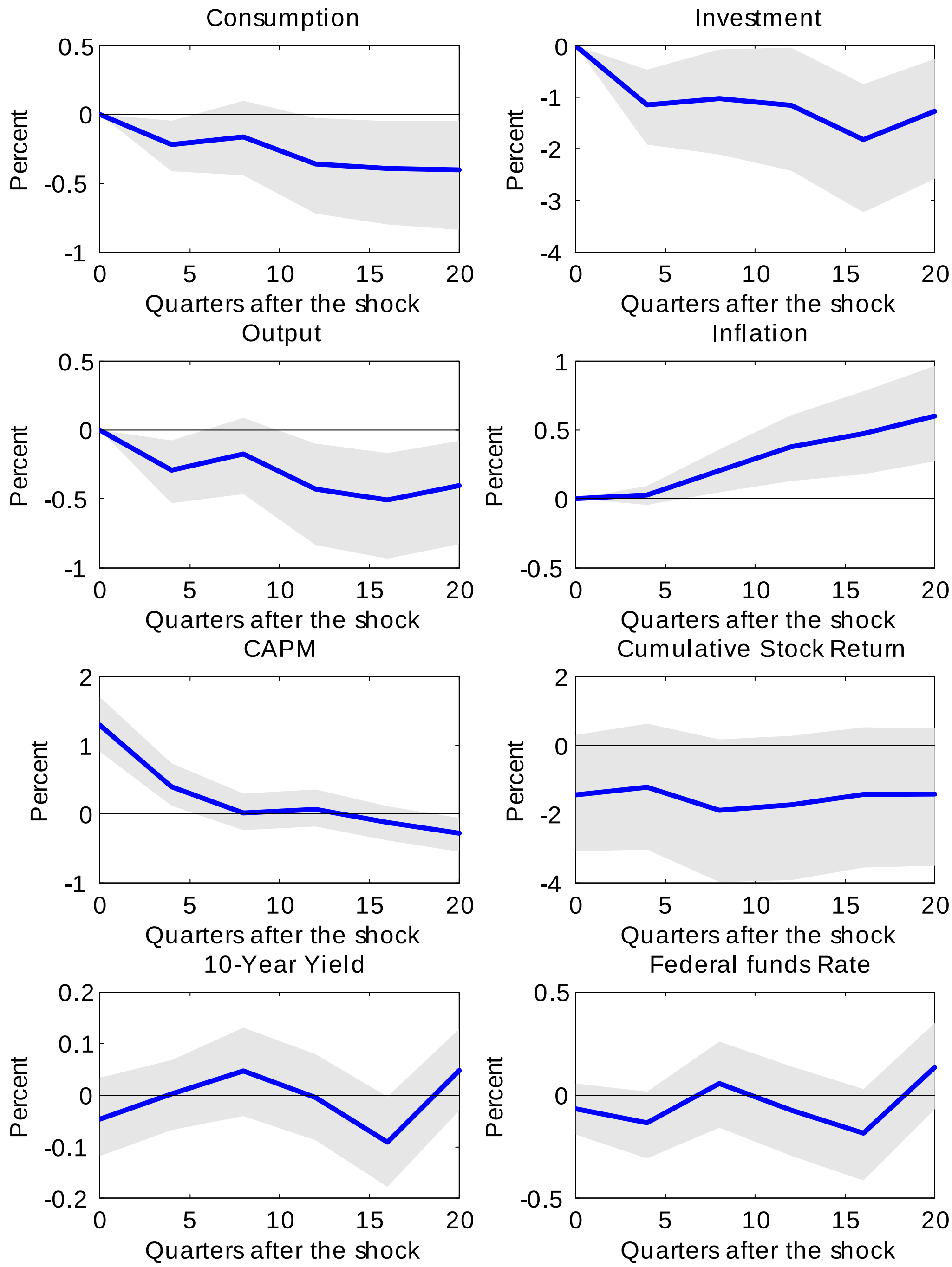
Figure 9 shows the response of endogenous variables to a one standard deviation shock to the mispricing component, which is the difference between the bond risk premiums and the CAPM benchmark. The response of macro variables are short-lived and mostly disappear in two years after the shock. Except for the first year, the negative responses of these variables are statistically insignificant, and turn positive three years after the shock. The financial variables, including stock and Treasury yields, show muted response to the mispricing shock. Thus, the economic significance of the difference between the bond risk premiums and CAPM prediction is limited.

To support these results, I extend the analysis and decompose the excess bond premium of Gilchrist and Zakrajsek (2012) using my measure of risk premiums, and examine the information content in the excess bond premium. The results, reported in Appendix E, are largely consistent with the interpretation above.

5 Conclusion

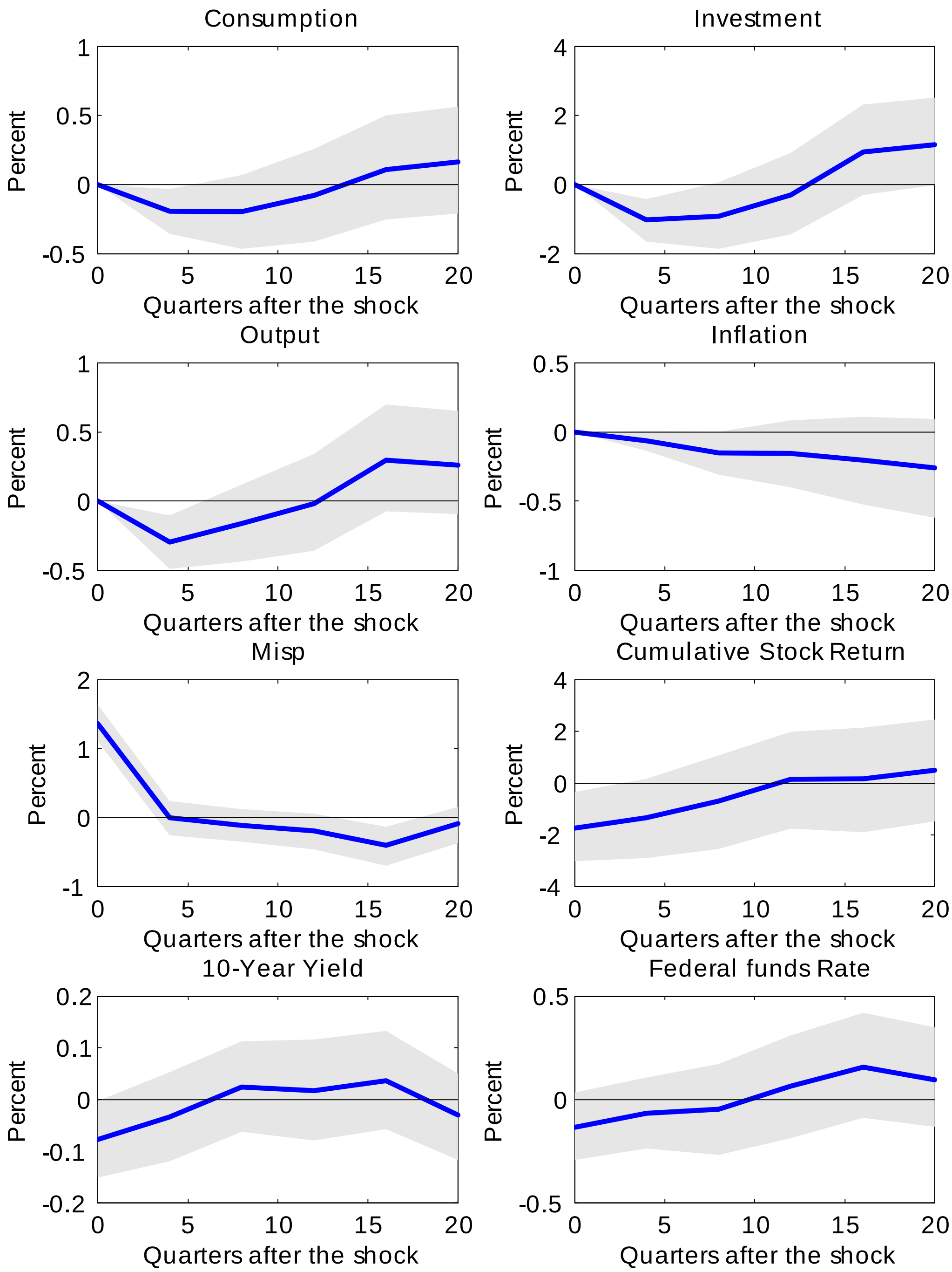
This paper applies the variance decomposition approach of Campbell and Schiller (1988a, b) to the market portfolio of corporate bonds and stocks, and jointly estimates the long-run risk premiums for each portfolio. To identify the cash flow shocks to corporate bonds, I construct the extensive data of corporate bond prices and payouts which keep track of the eventual repayment outcome, such as maturity, default and prepayment from an exercise of call options. Using the data, I

Figure 8: Response to the CAPM-Implied Risk Premiums



The response of endogenous variables to a one standard deviation shock to the CAPM-implied bond risk premiums. The variables are ordered as consumption, investment, output (GDP growth), inflation, the CAPM-based bond risk premiums, stock returns (cummulative), 10-year yield and Federal Funds Rate. The sample is from 1973-2014.

Figure 9: Response to the CAPM-Implied Risk Premiums



The response of endogenous variables to a one standard deviation shock to the mispricing in bond risk premiums (the difference between the risk premiums and the CAPM-implied counterpart). The variables are ordered as consumption, investment, output (GDP growth), inflation, the CAPM-based bond risk premiums, stock returns (cummulative), 10-year yield and Federal Funds Rate. The sample is from 1973-2014.

construct the market portfolio of corporate bonds, and relate credit spreads to expected excess returns and credit loss over the long-run.

I find that, consistent with the previous literature, much of the variation in credit spreads over time corresponds to the variation in risk premiums rather than expected cash flows. However, without an asset pricing model, it is impossible to tell if changing risk premiums reflects changes in fair reward to bear risks, or time-varying mispricing due to overly optimistic/pessimistic investors providing too much/little credit to the borrowers. I use the CAPM and evaluate the long-run risk premiums on the bond market portfolio using the time-varying expected returns on the stock market portfolio as a benchmark.

Comparing long-run risk premiums on the bond market portfolio with the stock market benchmark, I find that bond risk premiums are not unusually low compared with the stock market benchmark prior to the recessions. Averaging through the sample period, bond risk premiums are indeed slightly lower than the benchmark, but the difference does not seem large relative to the overall variation in bond risk premiums. To complement the analysis, I also decompose EBP of Gilchrist and Zakrajsek (2012) into the component correlated with risk premiums and the orthogonal component. Though the risk premium component is important in explaining the predictive power of EBP, there is a significant orthogonal component as well.

Taken together the evidence thus far, it seems premature to conclude that low credit spreads prior to recessions are solely due to mispricing of bonds caused by over-supply of credit. If credit over-supply is the leading cause for the low corporate bond risk premiums, it is not clear why such credit market friction also affects stock risk premiums at the same time. Instead, explanation for the low credit spreads before recessions should be consistent with the high price-dividend ratio for stocks.

However, more can be done to understand the seemingly frothy financial market before recessions. In particular, this article does not explain why stocks' price-dividend ratio seems high during booms and low during recessions. To obtain deeper insight in understanding both bonds and stocks jointly, one needs to write down the stochastic process for consumption and investors' risk preference, but this is outside of the scope of this paper. In addition, an evidence outside of U.S. needs to be studied.

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A Loglinear Approximation

In this section, I show that the loglinear approximation of an excess return on the market portfolio in (5) work well, and the approximation error at the optimal value of ρ is negligible. To find the optimal value, I regress $\tilde{s}_{t+1} \equiv s_t - l_{t+1} - r^e_{t+1}$ on s_{t+1} and a constant. The estimated results are,

$$\tilde{s}_{t+1} = \underset{(0.007)}{-0.060} + \underset{(0.002)}{0.889} s_{t+1} + \varepsilon_{t+1}, \qquad R^2 = 0.999,$$

where the values in parentheses show standard errors. Though a constant is statistically significant, the variance decomposition focuses on variation, and thus adding a constant does not change the results.

Table 7: Analysis on Approximation Errors

	r^e_t	$\tilde{r}^e_t$
Mean	0.501	0.563
Std	4.325	4.325
Corr	1.000	

Sample is monthly from 1973 to 2014. r^e_t is an annualized excess return on the bond market portfolio, and $\tilde{r}^e_t$ is an approximated excess return defined by $\tilde{r}^e_t \equiv -\rho s_t + s_{t-1} - l_t$, where s_t is a credit spread and l_t is credit loss.

Table 7 compares the excess return in the data, r^e_t, and the excess return based on loglinear approximation, $\tilde{r}^e_t \equiv -\rho s_t + s_{t-1} - l_t$. Standard deviation is the same for r^e_t and $\tilde{r}^e_t$, estimated at 4.325 percent, and correlation is greater than 0.999. Thus, the approximation error in (5) is very small, and whether one predicts returns or credit loss does not affect the decomposition results .

B Data

B.1 Corporate Bond Database

In this section, I provide a more detailed description of the panel data of corporate bond prices. I obtain monthly price observations of senior unsecured corporate bonds from the following four data sources. First, for the period from 1973 to 1997, I use the *Lehman Brothers Fixed Income Database*, which provides month-end bid prices. Since Lehman Brothers used these prices to construct the Lehman Brothers bond index while simultaneously trading it, the traders at Lehman Brothers had an incentive to provide correct quotes. Thus, although the prices in the *Lehman Brothers Fixed Income Database* are quote-based, they are considered reliable.

In the *Lehman Brothers Fixed Income Database*, some observations are dealers' quotes while others are matrix prices. Matrix prices are set using algorithms based on the quoted prices of other bonds with similar characteristics. Though matrix prices are less reliable than actual dealer quotes (Warga and Welch (1993)), I choose to include matrix prices in my main result to maximize the power of the test. However, I also repeat the main exercise in the online appendix and show that the results are robust to the exclusion of matrix prices.

Second, for the period from 1994 to 2014, I use the *Mergent FISD/NAIC Database*. This database consists of actual transaction prices reported by insurance companies. Third, for the period from 2002 to 2014, I use *TRACE* data, which provides actual transaction prices. *TRACE* covers more than 99% of the OTC activities in U.S. corporate bond markets after 2005. The data from *Mergent FISD/NAIC* and *TRACE* are transaction-based data, and therefore the observations are not exactly at the end of months. Thus, I use only the observations that are in the last five days of each month. If there are multiple observations in the last five days, I use the latest one and treat it as a month-end observation. Fourth, I use the *DataStream* database, which provides month-end price quotes from 1990 to 2011. Lastly, I use *Merrill Lynch* database which provides month-end quotes from 1998 to 2014.

TRACE includes some observations from the trades that are eventually cancelled or corrected. I drop all cancelled observations, and use the corrected prices for the trades that are corrected. I also drop all the price observations that include dealer commissions, as the commission is not reflecting the value of the bond, and these prices are not comparable to the prices without commissions.

Since there are some overlaps among the four databases, I prioritize in the following order: the *Lehman Brothers Fixed Income Database*, *TRACE*, *Mergent FISD/NAIC* , *DataStream* and *Merrill Lynch*. To check the data consistency, I examine the effect of priority ordering by reversing the priority, and the effect of the price difference on the empirical result in the online appendix.

To classify the bonds based on credit ratings, I use the ratings of Standard & Poor's when available, and use Moody's ratings when Standard & Poor's rating is not available.

To identify defaults in the data, I use *Moody's Default and Recovery Database*, which provides a historical record of bond defaults from 1970 onwards. The same source also provides the secondary-market value of the defaulted bond one month after the incident. If the price observation in the month when a bond defaults is missing in the corporate bond database, I add the Moody's secondary-market price to my data set in order to include all default observations in the sample.

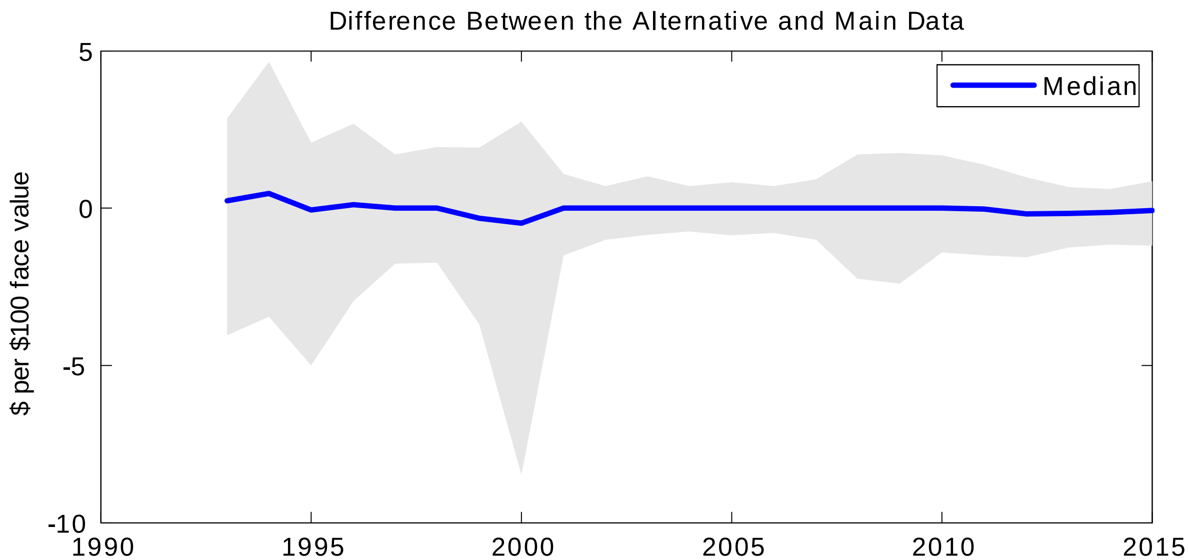
B.2 Comparing Overlapping Data Sources

As I merge various databases to construct the datasets, it is fair to be concerned about the consistency across databases, and the sensitivity of the analysis to the priority ordering given to these five databases. The fraction of overlapping observations is not large, and the most overlaps are found between *TRACE* and *DataStream* (11% of the total bond-month observations), followed by *DataStream* and *Merrill Lynch* (6%).

To evaluate the discrepancy among databases, I plot the 10th, 50th and 90th percentiles of the price difference between alternative databases (with a lower priority) and main databases used in the analysis every year in Figure 10. The price difference is in dollars per 100-dollar face value, so if a bond has a price of 101 dollars per 100-dollar face value in the main datasets, while the alternative data says 100, then the difference is -1.

Figure 10 shows that the median difference is close to 0 throughout the period, with greater dispersions in before 2000. This is because the number of overlaps increases over time, and there are fewer overlapping observations before 2000, leading to noisier shape of distributions. Since *TRACE* is introduced in 2002, the number of overlapping observations increases and the distribution of gaps becomes tight and stable over time, suggesting that *TRACE* helps improve the price transparency.

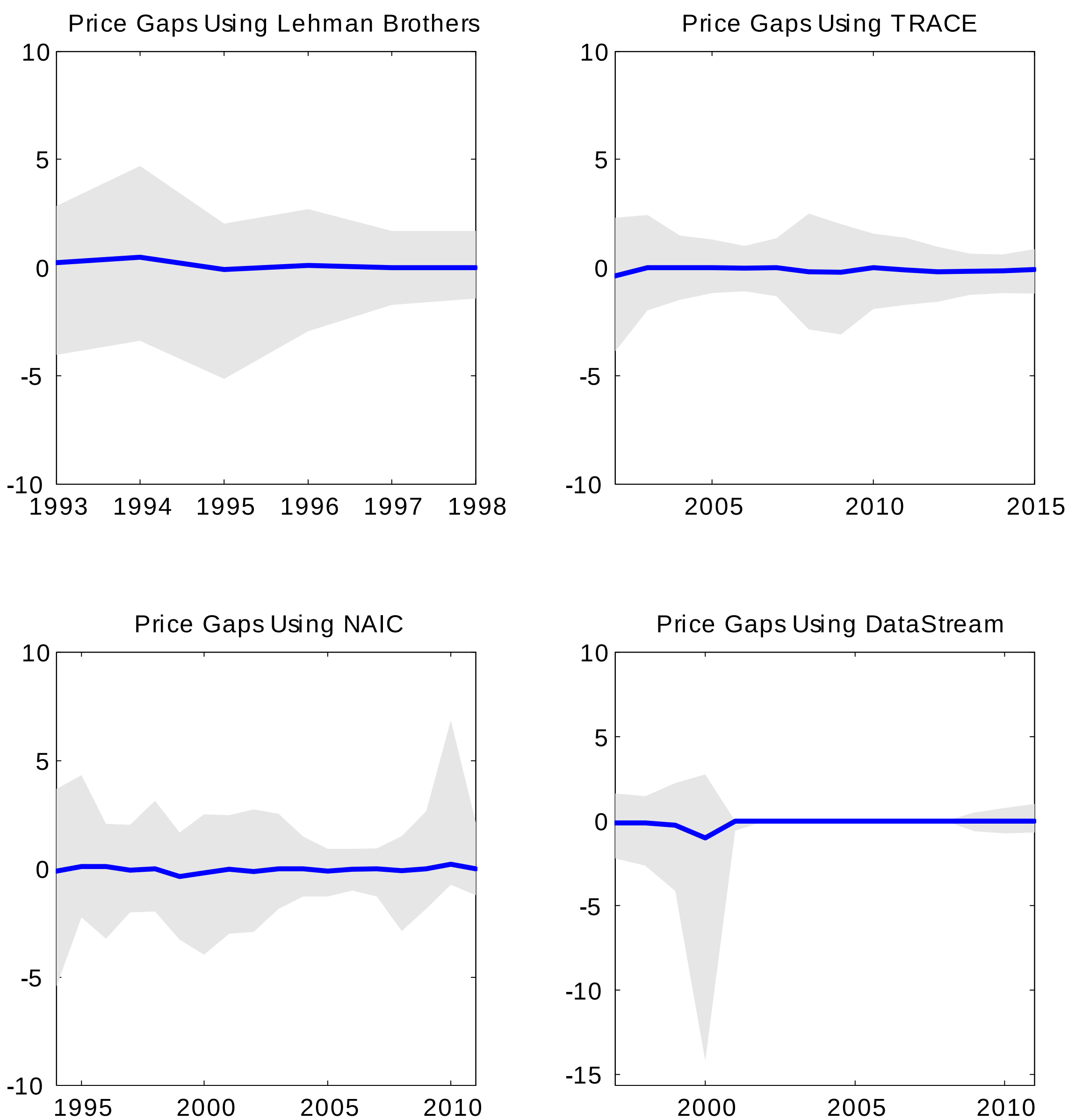
Figure 10: The Dollar Price Difference Between Alternative Data and the Main Data



The figure plots the difference in dollar bond prices between alternative databases (which has a lower priority than the main data) and main databases. In each year I find overlaps in databases, I compute the 10th, 50th and 90th percentiles for the difference, and plot the median using the solid line and the 10th and 90th percentiles as the shaded area.

Figure 11 shows the breakdown by the main database. The figure in general confirms a somewhat improving trend of price gaps over time. In the earlier sample, there is some suspicious stale pricing in *DataStream*, which led to a larger difference from *Merrill Lynch*. However, such observations are eventually filtered out in the main analysis as I remove (clean) price that do not change for more than 3 months.

Figure 11: The Dollar Price Difference Between Alternative Data and the Main Data: By Main Data Source



The figures plot the difference in dollar bond prices between alternative databases (which has a lower priority than the main data) and main databases. In each year I find overlaps in databases, I compute the 10th, 50th and 90th percentiles for the difference, and plot the median using the solid line and the 10th and 90th percentiles as the shaded area. Each panel corresponds to a different main database.

Next, I construct an alternative datasets by reversing the priority order to *Merrill Lynch*, *DataStream*, *Mergent FISD/NAIC*, *TRACE* and the *Lehman Brothers Fixed Income Database*.

Table 8: VAR Estimates and Implied Long-Run Expectations: Alterntative Data with Reverse Priority Order

Panel A: VAR estimates

	$r_{b,t}$	$r^f_{b,t}$	s_t	$slope_t$	DD_t	$r_{s,t}$	dp_t	R^2	$\sigma(E[\cdot])$
$r_{b,t+1}$	0.08	-0.10	-0.16	0.61	-0.93	-0.10	0.04	0.27	3.07
	(0.25)	(0.19)	(0.24)	(0.82)	(0.41)	(0.05)	(0.01)		
r^f_{t+1}	0.08	0.02	-0.63	-0.54	-0.68	-0.07	-0.01	0.11	2.11
	(0.26)	(0.20)	(0.25)	(0.87)	(0.43)	(0.05)	(0.01)		
s_{t+1}	0.05	-0.02	0.24	-0.51	-0.08	0.03	-0.05	0.51	2.80
	(0.26)	(0.20)	(0.23)	(0.66)	(0.35)	(0.04)	(0.01)		
$slope_{t+1}$	0.05	0.02	0.06	0.38	-0.03	-0.02	0.00	0.48	0.88
	(0.05)	(0.04)	(0.05)	(0.19)	(0.09)	(0.01)	(0.00)		
DD_{t+1}	0.21	-0.21	0.04	0.32	0.58	-0.03	0.01	0.56	1.45
	(0.04)	(0.04)	(0.05)	(0.11)	(0.08)	(0.01)	(0.00)		
$r_{s,t+1}$	0.74	-0.52	-0.67	-0.02	0.13	-0.31	0.08	0.16	6.55
	(0.88)	(0.70)	(0.85)	(2.04)	(1.41)	(0.17)	(0.04)		
dp_{t+1}	0.22	-0.50	1.23	-0.47	1.59	-0.26	1.01	0.92	41.26
	(0.24)	(0.21)	(0.30)	(0.66)	(0.50)	(0.05)	(0.01)		

Panel B: Long-run regression coefficients, $e_k G$

$\sum_{j=1}^{\infty}\rho^{j-1}l_{t+j}$	0.02	0.05	0.24	-1.02	0.46	0.01	-0.05		2.76
	(0.12)	(0.11)	(0.17)	(0.40)	(0.30)	(0.02)	(0.03)		
$\sum_{j=1}^{\infty}\rho^{j-1}r^e_{b,t+j}$	-0.02	-0.05	0.76	1.02	-0.46	-0.01	0.05		3.25
	(0.12)	(0.11)	(0.17)	(0.40)	(0.30)	(0.02)	(0.03)		
$\sum_{j=1}^{\infty}\rho^{j-1}g_{t+j}$	-1.35	1.53	-2.31	-1.39	-2.84	0.48	-0.03		10.93
	(0.66)	(0.64)	(1.06)	(1.93)	(1.97)	(0.12)	(0.27)		
$\sum_{j=1}^{\infty}\rho^{j-1}r_{s,t+j}$	1.35	-1.53	2.31	1.39	2.84	-0.48	1.03		39.99
	(0.66)	(0.64)	(1.06)	(1.93)	(1.97)	(0.12)	(0.27)		

Panel C: Variation of VAR-implied conditional expectations

$\frac{\sigma(s^l)}{\sigma(s)}$	$\frac{\sigma(s^r)}{\sigma(s)}$	$\frac{\sigma(dp^g)}{\sigma(dp)}$	$\frac{\sigma(dp^r)}{\sigma(dp)}$	$\varrho(s^l,s)$	$\varrho(s^r,s)$	$\varrho(s^l,s^r)$	$\varrho(dp^g,dp)$	$\varrho(dp^r,dp)$	$\varrho(dp^g,dp^r)$
0.71	0.83	0.25	0.93	0.57	0.72	-0.16	0.41	0.97	0.17
(0.28)	(0.10)	(0.10)	(0.26)	(0.16)	(0.24)	(0.23)	(0.89)	(0.02)	(0.92)

Panel A shows the estimated VAR coefficients. $\sigma(E[\cdot])$ shows standard deviation of the estimated conditional expectations for each variable. Panel B shows the long-run forecasting coefficients implied from one-period VAR based on $(15), (16), (17)$ and (18). Panel C shows volatility and correlation, $\varrho(\cdot,\cdot)$, for long-run conditional expectations. Standard errors corrected for overlapping observations using Hodrick (1992) are reported in parentheses.

Then I estimate the main VAR in Table 3 using the bond market portfolio based on the alternative datasets, and report the results in Table 8. Panels in Table 8 show that the variance decomposition results are very similar to Table 3. Thus, the results in this paper is not driven by a particular priority order among the databases.

B.3 Construction of Matching Treasury Bonds

In this section, I explain the methodology to construct prices of the matching Treasury bonds. First, I interpolate the Treasury yield curve using cubic splines and construct Treasury zero-coupon curves by bootstrapping. At each month and for each corporate bond in the data set, I construct the future cash flow schedule for the coupon and principal payments. Then I multiply each cash flow by the zero-coupon Treasury bond price with the corresponding time to maturity. I add all of the discounted cash flows to obtain the synthetic Treasury bond price that matches the corporate bond. I do this process for all corporate bonds at each month to obtain the panel data of matching Treasury bond prices. With this method, the credit spread measure is, in principle, unaffected by changes in the Treasury yield curve.

C Effect of Liquidity

In this section, I show the estimated risk premiums when I include $Noise$ as a liquidity measure in a VAR. I estimate VAR(1) by adding $Noise$ to a state vector, and compute implied long-run risk premiums. Table 9 shows the estimated dynamics of long-run risk premiums. Though $Noise$ predicts one-period bond returns negatively, it also predicts matching Treasury returns negatively, and thus the effects cancel out for excess returns. In the long-run, $Noise$ does not predict excess returns or credit loss, and thus the dynamics of long-run bond risk premiums does not change when I add the liquidity variable in the VAR.

D Robustness: Subsample by Credit Rating

In this section, I examine if the mispricing of the corporate bond market is prevalent across different credit rating category. To this end, I form two subportfolios of corporate bonds, one consists with investment grade (IG) bonds, and the other with high-yield (HY) bonds. A bond with a certain credit rating at time$-t$ is included in portfolios to compute the return from t to $t+1$, so the bonds dropping out of portfolio due to rating change at $t+1$ are still included in the computation of time$-t+1$ returns. This is important, as a bond which is downgraded from IG to HY should earn low returns, and the investor who invests only on IG bonds suffers from such an outcome.

Using returns with and without payouts on the rating-based portfolios, I run the same VAR as (14), and decompose credit spreads into long-run cash flow and risk premium components.

Table 9: VAR Estimates Including Noise as a Liquidity Measure: 1973-2014

Panel A: VAR estimates

	$r_{b,t}$	$r^f_{b,t}$	s_t	$slope_t$	DD_t	$Noise_t$	$r_{s,t}$	dp_t	R^2	$\sigma(E[\cdot])$
$r_{b,t+1}$	-0.04	-0.08	-0.52	1.30	-0.53	0.47	-0.10	-0.02	0.39	3.62
	(0.25)	(0.20)	(0.24)	(0.69)	(0.38)	(0.15)	(0.05)	(0.01)		
r^f_{t+1}	-0.10	0.08	-1.12	0.38	-0.21	0.55	-0.08	-0.08	0.26	3.25
	(0.27)	(0.21)	(0.26)	(0.74)	(0.41)	(0.17)	(0.06)	(0.01)		
s_{t+1}	0.00	0.01	0.15	-0.30	0.02	0.06	0.02	-0.06	0.48	2.56
	(0.26)	(0.20)	(0.24)	(0.65)	(0.33)	(0.09)	(0.04)	(0.01)		
$slope_{t+1}$	0.04	0.01	0.05	0.39	-0.03	0.01	-0.02	0.00	0.48	0.88
	(0.05)	(0.04)	(0.05)	(0.15)	(0.09)	(0.04)	(0.01)	(0.00)		
DD_{t+1}	0.25	-0.23	0.09	0.21	0.54	-0.06	-0.03	0.02	0.58	1.47
	(0.05)	(0.04)	(0.05)	(0.11)	(0.07)	(0.02)	(0.01)	(0.00)		
$Noise_{t+1}$	-0.20	-0.08	-0.06	-0.84	-0.11	0.67	0.04	0.02	0.74	5.73
	(0.26)	(0.18)	(0.18)	(0.59)	(0.34)	(0.20)	(0.06)	(0.01)		
$r_{s,t+1}$	0.94	-0.66	-0.37	-0.32	0.09	-0.18	-0.31	0.11	0.16	6.56
	(0.91)	(0.73)	(0.88)	(2.09)	(1.41)	(0.34)	(0.17)	(0.04)		
dp_{t+1}	0.10	-0.41	1.06	-0.39	1.55	0.10	-0.25	0.99	0.92	41.25
	(0.25)	(0.22)	(0.31)	(0.66)	(0.48)	(0.13)	(0.05)	(0.01)		

Panel B: Long-run regression coefficients, $e_k G$

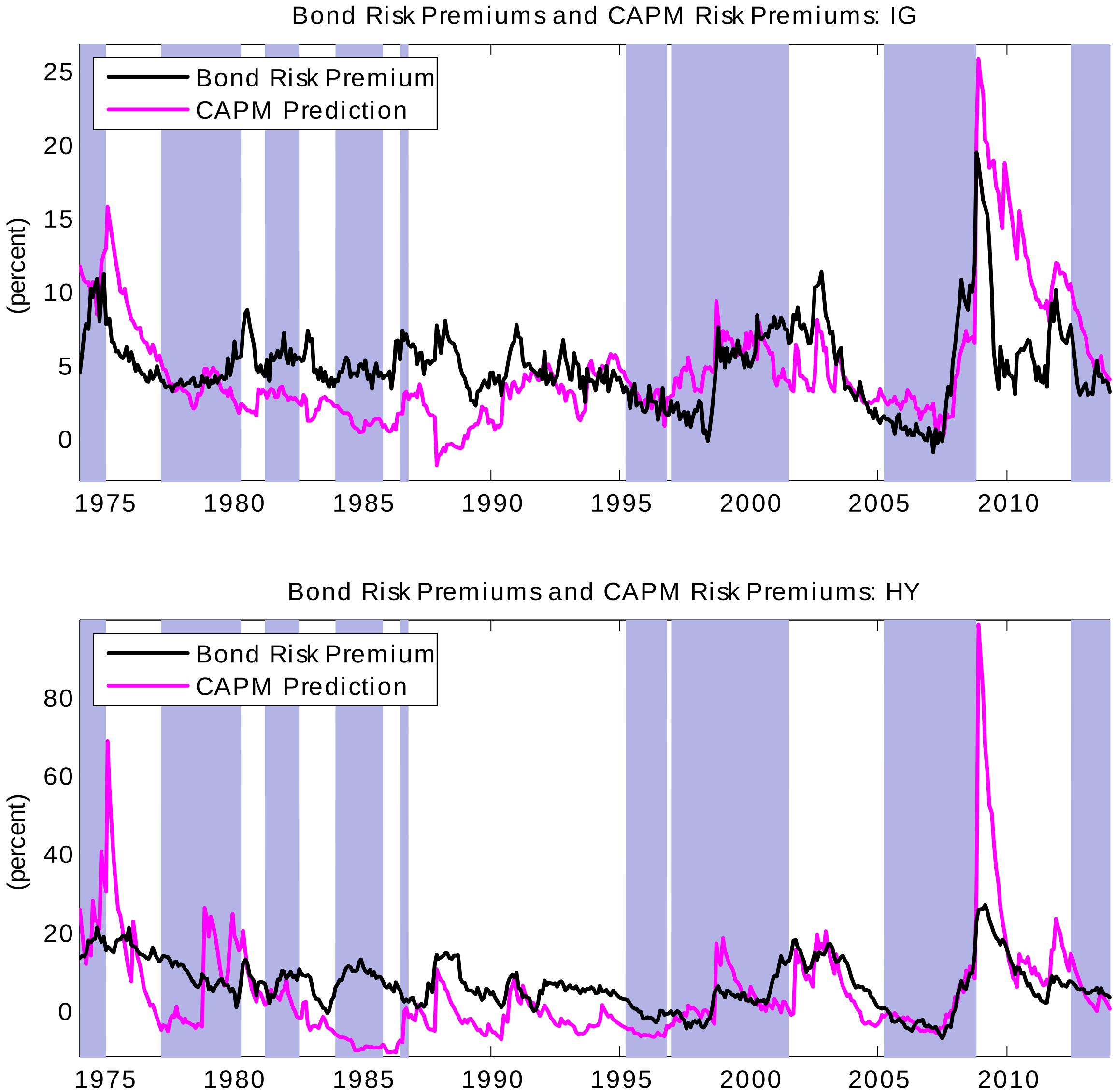
	$r_{b,t}$	$r^f_{b,t}$	s_t	$slope_t$	DD_t	$Noise_t$	$r_{s,t}$	dp_t	$\sigma(E[\cdot])$
$\sum_{j=1}^{\infty} \rho^{j-1} l_{t+j}$	0.00	0.05	0.17	-0.94	0.47	0.04	0.01	-0.05	2.28
	(0.11)	(0.11)	(0.17)	(0.35)	(0.27)	(0.07)	(0.02)	(0.03)	
$\sum_{j=1}^{\infty} \rho^{j-1} r^e_{b,t+j}$	0.00	-0.05	0.83	0.94	-0.47	-0.04	-0.01	0.05	3.29
	(0.11)	(0.11)	(0.17)	(0.35)	(0.27)	(0.07)	(0.02)	(0.03)	
$\sum_{j=1}^{\infty} \rho^{j-1} g_{t+j}$	-1.43	1.48	-2.44	-1.26	-2.56	0.31	0.50	-0.02	11.87
	(0.69)	(0.71)	(1.27)	(1.96)	(1.97)	(0.43)	(0.12)	(0.32)	
$\sum_{j=1}^{\infty} \rho^{j-1} r_{s,t+j}$	1.43	-1.48	2.44	1.26	2.56	-0.31	-0.50	1.02	38.70
	(0.69)	(0.71)	(1.27)	(1.96)	(1.97)	(0.43)	(0.12)	(0.32)	

Panel C: Variation of VAR-implied conditional expectations

$\frac{\sigma(s^l)}{\sigma(s)}$	$\frac{\sigma(s^r)}{\sigma(s)}$	$\frac{\sigma(dp^g)}{\sigma(dp)}$	$\frac{\sigma(dp^r)}{\sigma(dp)}$	$\varrho(s^l, s)$	$\varrho(s^r, s)$	$\varrho(s^l, s^r)$	$\varrho(dp^g, dp)$	$\varrho(dp^r, dp)$	$\varrho(dp^g, dp^r)$
0.62	0.89	0.28	0.90	0.47	0.79	-0.16	0.49	0.96	0.25
(0.28)	(0.12)	(0.14)	(0.31)	(0.23)	(0.20)	(0.18)	(0.90)	(0.02)	(0.96)

Panel A shows the estimated VAR coefficients. $\sigma(E[\cdot])$ shows standard deviation of the estimated conditional expectations for each variable. Panel B shows the long-run forecasting coefficients implied from one-period VAR based on (15), (16), (17) and (18). Panel C shows volatility and correlation, $\varrho(\cdot,\cdot)$, for long-run conditional expectations. Standard errors corrected for overlapping observations using Hodrick (1992) are reported in parentheses.

Figure 12: Credit Cycles, Corporate Bond and CAPM Risk Premiums



The top panel the long-run bond risk premiums based on the VAR, $E\left[\sum_{j=1}^{\infty}\rho^{j-1}r^{e}_{b,t+j}\middle| X_t\right] = e_1GX_t$ and the CAPM-implied bond risk premiums, $\sum_{j=1}^{\infty}\rho^{j-1}\frac{Cov\left(r^{e}_{b,t+j},\tilde{r}_{s,t+j}|X_t\right)}{\sigma^2\left(r_{s,t+j}|X_t\right)}E\left[r^{e}_{s,t+j}\middle| X_t\right]$ for the IG corporate bond portfolio. The bottom panel plots the same variables for the HY corporate bond portfolio. Both series are demeaned. The shaded area corresponds to the period with credit expansion.

Figure 12 shows the estimated long-run risk premiums on the rating-based bond portfolios and the CAPM-implied risk premiums. The CAPM betas are estimated at around 0.10 for IG bonds and 0.24 for HY bonds, which vary little over horizon. Figure 12 shows the similar behavior in risk

Table 10: Bond and CAPM Risk Premiums: By Credit Rating

	Bond	CAPM	Difference	t(Difference)	Bond	CAPM	Difference	t(Difference)
	IG Bonds				*HY Bonds*			
Boom	4.33	4.35	-0.02	(0.00)	5.73	1.98	3.74	(0.28)
Recession	8.20	7.29	0.91	(0.10)	12.13	16.88	-4.75	(-0.35)
High Credit Growth	4.29	4.13	0.17	(0.02)	4.50	2.15	2.35	(0.17)
Low Credit Growth	5.49	5.40	0.09	(0.01)	8.62	6.18	2.44	(0.18)
-1989								
Boom	4.77	2.94	1.83	(0.22)	8.59	1.08	7.51	(0.66)
Recession	6.99	5.94	1.04	(0.13)	11.42	14.82	-3.40	(-0.29)
1990-								
Boom	4.07	5.22	-1.15	(-0.11)	3.98	2.53	1.45	(0.10)
Recession	9.48	8.70	0.77	(0.07)	12.88	19.04	-6.16	(-0.39)

Table shows the long-run bond risk premiums based on the VAR, $E\left[\sum_{j=1}^{\infty}\rho^{j-1}r^e_{b,t+j}\middle| X_t\right]=e_1GX_t$ and the CAPM-implied bond risk premiums, $\sum_{j=1}^{\infty}\rho^{j-1}\frac{Cov\left(r^e_{b,t+j},\tilde{r}_{s,t+j}\middle|X_t\right)}{\sigma^2\left(r_{s,t+j}\middle|X_t\right)}E\left[r^e_{s,t+j}\middle| X_t\right]$. Both series are demeaned, and taken average across various subperiods. The left panel shows the values for the IG bond portfolio, while the right panel shows the estimates for the HY bonds.

premiums for both IG and HY bonds over credit cycles, with the greater variation in magnitude for HY bonds than IG bonds.

Table 10 shows the risk premiums estimated from the VAR for different subsamples. As in the aggregate corporate bond market portfolio, bond risk premiums are lower during the first half of the sample, and become more elevated in the second half. In addition, bond risk premiums are slightly lower than the CAPM benchmark during booms and the period with high credit growth, though the effects are statistically significant only for HY bonds. Thus, the potential mispricing of the aggregate corporate bond market portfolio, if any, comes from mispricing in HY bonds rather than IG bonds.

E Excess Bond Premium as a Sign of Froth

To measure mispricing, Gilchrist and Zakrajsek (2012) construct excess bond premium (EBP) as a difference between corporate credit spreads and the spreads predicted by the Merton model. Gilchrist and Zakrajsek (2012) interpret EBP as a measure of credit crunch, in which expanding/shrinking credit supply pushes corporate bond prices away from their fundamental values. Since EBP depends on the specific asset pricing model, it is not clear if EBP reflects risk premiums that a rational investor demands in taking risks or deviation from the security's fundamental values.

To understand the information content in EBP, I show that the estimated risk premiums using VARs are just as good as EBP in predicting future economic activities. Then using the estimated bond and stock risk premiums, I decompose EBP into two components; risk premiums and residuals.

Lines (1) and (2) in each panel of Tables 11 and 12 show the estimated slope coefficient γ_1 in (19). Long-run bond risk premiums, s_t^r, predict economic growth negatively, regardless of forecasting horizon and variables I forecast. Investors foresee a decline in economic activities, and require higher returns to take risks. However, stock risk premiums, dp_t^r, do not predict economic activities well, which is consistent with Philippon (2009) who claims stock prices partly reflect growth options and are not as good proxy to Tobin's q as bond prices. However, when I use both s_t^r and dp_t^r in a multivariate regression, dp_t^r predicts economic activities negatively (though in some cases insignificantly).

Line (4) in each panel of Tables 11 and 12 show the predictive regressions using EBP instead of risk premiums. Confirming Gilchrist and Zakrajsek (2012), EBP predicts future economic activities negatively. However, comparing the adjusted R-squared between Lines (1) and (4), they are about the same for all variables and for each forecasting horizon. Long-run bond risk premiums, which rationally predict returns on bond investment, also predict economic activities as well as EBP does.

Next, I decompose EBP using risk premium component, and residuals by contemporaneously regressing EBP on s_t^r and dp_t^r, which is estimated at

$$EBP_t = \underset{(6.68)}{5.04} s_t^r + \underset{(5.41)}{0.37} dp_t^r + eEBP_t, \tag{22}$$

with R-squared of 0.22. Let $\widehat{EBP}_t$ be the fitted value of the regression (22). I use the risk premium component of EBP, $\widehat{EBP}_t$, and residuals, $eEBP_t$, to forecast future economic activities.

Lines (5) to (7) in Tables 11 and 12 show the estimated forecasting regressions. In the univariate regressions (lines (5) and (6)), both the risk premium and residual components significantly

Table 11: Forecasts of Marco Variables Using Risk Premium Measures

	3 Months Horizon						12 Months Horizon					
	s_t^r	dp_t^r	EBP	$\widehat{EBP}_t$	$eEBP_t$	$\bar{R}^2$	s_t^r	dp_t^r	EBP	$\widehat{EBP}_t$	$eEBP_t$	$\bar{R}^2$
	Payroll growth											
(1)	-0.04					0.62	-0.18					0.54
	(-6.10)						(-9.83)					
(2)		0.00				0.57		0.01				0.45
		(0.65)						(3.04)				
(3)	-0.05	0.00				0.63	-0.19	0.00				0.54
	(-7.24)	(-2.78)					(-12.43)	(-0.97)				
(4)			-0.29			0.62			-1.13			0.50
			(-7.41)						(-10.63)			
(5)				-0.73		0.62				-2.62		0.49
				(-6.30)						(-9.21)		
(6)					-0.26	0.60					-1.09	0.48
					(-5.79)						(-8.06)	
(7)				-0.19	-0.62	0.63				-0.84	-2.13	0.51
				(-4.52)	(-5.37)					(-6.26)	(-7.19)	
	Unemployment rate											
(1)	2.03					0.34	7.94					0.38
	(3.19)						(3.80)					
(2)		0.04				0.30		-0.05				0.31
		(0.64)						(-0.23)				
(3)	3.08	0.18				0.37	10.52	0.45				0.40
	(4.45)	(2.90)					(5.04)	(2.00)				
(4)			24.99			0.39			83.12			0.42
			(5.83)						(6.83)			
(5)				57.84		0.36				184.04		0.39
				(4.46)						(4.71)		
(6)					24.66	0.36					84.08	0.39
					(4.72)						(5.58)	
(7)				19.01	45.99	0.40				66.71	141.54	0.43
				(3.88)	(3.52)					(4.31)	(3.42)	

The table reports the estimated slope coefficients for the regressions of 3 or 12 month log changes in macro variables in the future on risk premium measures at the monthly frequency for payroll growth rate, unemployment and industrial production and at the quarterly frequency for GDP growth rate. For unemployment rate, I forecast changes rather than log changes. s_t^r is the long-run risk premiums on the corporate bond market portfolio, dp_t^r is the long-run risk premiums on the stock market portfolio, EBP is excess bond premium of Gilchrist and Zakrajsek (2012), $\widehat{EBP}_t$ is EBP predicted by contemporaneous bond and stock risk premiums, and $eEBP_t$ is EBP orthogonal to $\widehat{EBP}_t$. $\bar{R}^2$ is adjusted R-squared. The regression includes lagged monthly growth rate, in which the number of lags are determined by the Akaike Information Criterion. In addition, the regressors include real risk-free rate and term spreads as control variables. The values in parentheses are t-statistics corrected for overlapping observations using Hodrick (1992). The sample is from 1974 to 2014.

Table 12: Forecasts of Marco Variables Using Risk Premium Measures, Continued

	3 Months Horizon						12 Months Horizon					
	s_t^r	dp_t^r	EBP	$\widehat{EBP}_t$	$eEBP_t$	$\bar{R}^2$	s_t^r	dp_t^r	EBP	$\widehat{EBP}_t$	$eEBP_t$	$\bar{R}^2$
	Industrial production											
(1)	-0.14					0.31	-0.46					0.30
	(-4.42)						(-4.64)					
(2)		0.00				0.23		0.00				0.20
		(-0.73)						(0.45)				
(3)	-0.22	-0.01				0.36	-0.60	-0.02				0.32
	(-5.58)	(-3.84)					(-6.02)	(-2.37)				
(4)			-1.35			0.33			-2.94			0.27
			(-5.64)						(-4.65)			
(5)				-4.01		0.35				-10.12		0.30
				(-5.50)						(-5.68)		
(6)					-1.16	0.28					-2.39	0.23
					(-4.57)						(-3.29)	
(7)				-0.77	-3.55	0.37				-1.21	-9.27	0.31
				(-3.47)	(-4.98)					(-1.79)	(-5.34)	
	GDP growth rate											
(1)	-0.05					0.14	-0.17					0.24
	(-2.40)						(-2.61)					
(2)		0.00				0.08		0.00				0.15
		(-0.35)						(0.50)				
(3)	-0.07	0.00				0.16	-0.20	-0.01				0.24
	(-3.53)	(-2.37)					(-3.64)	(-0.95)				
(4)			-0.59			0.20			-1.18			0.22
			(-4.44)						(-3.83)			
(5)				-1.22		0.16				-3.22		0.22
				(-3.82)						(-3.63)		
(6)					-0.63	0.17				-1.10		0.19
					(-3.46)					(-2.79)		
(7)				-0.50	-0.87	0.20				-0.67	-2.74	0.23
				(-2.71)	(-2.72)					(-1.63)	(-3.05)	

negatively forecast economic activities. In multivariate regressions in line (7), both components are significant except that $\widehat{EBP}_t$ is significant at the 10% level for industrial production and GDP growth rates over the 12 month horizon.

The decomposition of EBP suggests that the risk premium component in EBP is important for its forecasting power, while there is a component that is orthogonal to risk premiums, which is about as important as risk premiums.