Are Stock and Corporate Bond Markets Integrated? Evidence from Expected Returns[*†]

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Abstract

This study explores the cross-sectional integration of stock and corporate bond markets by comparing a firm's expected stock return, as implied by corporate bond spreads, to its realized stock return. We compute expected corporate bond returns by correcting credit spreads for expected losses due to default, which are then transformed into expected stock returns. We find, surprisingly, a strong negative cross-sectional relation between these expected and realized stock returns over the period 1994-2015. This effect is stronger for firms with higher default risk, as measured by probability of default, leverage or credit rating, and cannot be explained by differences in the pricing of risk factors in stock and bond markets, limits to arbitrage or liquidity premiums.

JEL classification: G11; G12; G14

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1. Introduction

Firms can finance themselves on public capital markets in two ways: first, by issuing equity, i.e. stocks, and second by issuing debt, i.e. corporate bonds. Since both instruments are claims on the same assets, their prices and expected returns should be linked to each other. As discussed below, several studies have therefore studied the integration of stock and corporate bond markets using various empirical methods.

In this paper we add to this integration literature by directly comparing bond-implied expected equity returns to realized equity returns. For each firm, we construct the expected equity return that is implied by the credit spread on corporate bonds of this firm, following the approach of Campello, Chen and Zhang (2008). We then analyze the cross-sectional relation between these bond-implied expected equity returns and average realized equity returns for the U.S. market. Surprisingly, we find a strong negative relation. Firms with high bond-implied expected equity returns have low average equity returns and vice versa. This suggests that corporate bonds and stocks are not priced consistently. The economic significance of this result is large. When sorting firms on the bond-implied expected equity return, we find a predicted equity return gap of 1.27% per month for the highest versus lowest decile portfolio, while the realized equity return gap equals -1.79% per month.

It is important to note that our analysis of expected and realized returns provides evidence for relative mispricing of corporate bonds versus stocks. We do not aim to explain the level of bond-implied expected returns, nor the level of realized average equity returns. For such an analysis, one would need to assume a specific asset pricing model and see if these levels are in line with the model predictions. In contrast, for our main result, the negative relation between expected bond and stock returns, we do not need to assume a specific asset pricing model.

We do need to make a few other modeling assumptions. This concerns first of all the default probability, which is required to transform the credit spread to a corporate bond expected return. Second, our approach requires an estimate of the sensitivity of equity returns to corporate bond returns, which is needed to transform the corporate bond expected return to an expected equity return. Our benchmark approach uses a Merton model to estimate default probabilities, following Feldhütter and Schaefer (2016). We find the Merton model to be more adaptive than the hazard rate model of Campbell, Hilscher and Szilagyi (2008) and better able to capture the strongly increasing probability of default for low-rated debt. To estimate equity-bond sensitivities, we employ a regression approach following Campello et al. (2008). We perform a wide range of robustness checks on these two methods. We also perform robustness checks on the benchmark cross-sectional analysis, to check that results are stable over time and not concentrated in small, hard-to-arbitrage stocks. In addition, we correct for liquidity effects. We find that our key result survives all these robustness checks.

We then proceed by trying to understand this lack of integration in more detail. First, we document that the anomalous realized equity returns to some extent reflect temporary mispricing in the equity market, but substantial mispricing remains even at longer horizons. Specifically, when we focus on the realized equity returns over a period of 5 years after sorting on the predicted return, the realized return gap is -0.50% per month instead of -1.79%. Second, we analyze whether market risk or characteristics like size, book-to-market, momentum, profitability, and investment are priced differently in corporate bonds versus equities. We find some evidence that the market betas have a negative slope for average realized returns (in line with existing work on the "beta anomaly"; Frazzini and Pedersen, 2014), while the slope is positive for bond-implied returns. However, we find that these differences in pricing do not explain the negative relation between bond-implied and realized returns. In line with these results, the alpha of a portfolio that shorts stocks of firms with high bond-implied returns and buys stocks with low bond-implied returns is significantly positive, even when we control for the five factors in the Fama and French (2015) model, the Carhart (1997) momentum factor and the Quality-Minus-Junk factor of Asness, Frazzini and Pedersen (2014).

Our paper relates to various streams in the literature. Most importantly, two recent studies also focus on the cross-sectional relation between expected returns in credit markets (corporate bonds and credit default swaps) and realized equity returns: Friewald et al. (2014) and Anginer and Yildizhan (2017). Both studies conclude that there is a positive relation between the cross-section of credit risk premiums and average realized equity returns. Our results thus conflict with these studies. We now discuss both studies in more detail.

Friewald et al. (2014) and our study differ in several aspects. First, Friewald et al. (2014) use a different approach to construct credit risk premiums. Following Cochrane and Piazzesi (2005) they run predictive regressions of credit spread changes on forward credit spreads to obtain time series of the credit risk premium for each firm. Second, most of their analysis is in-sample, since they run the predictive regressions over the same period that is used to calculate realized equity returns. This is particularly important in this case. Consider a firm that has had excellent performance over the sample period with declining credit spreads and increasing equity prices. The in-sample estimation will then lead to high estimates for the credit risk premium as the credit spreads have compressed, while the average realized equity return will be high as well. Hence, the in-sample estimation biases towards finding a positive relation between credit risk premiums and equity returns[3]. In contrast, our credit risk premiums are only based on information available at the given point in time and sorting stocks on these credit risk premiums thus delivers a tradable investment strategy. Third, our sample is much more extensive, covering on average 685 firms per month for a period of more than 20 years. Friewald et al.

[3] In their out-of-sample robustness check Friewald et al. (2014) find much weaker evidence for a positive relation between credit premiums and stock returns.

(2014) use credit default swaps to obtain credit spreads, and as a result their sample period is less than 10 years and includes just 491 unique firms.

Anginer and Yildizhan (2017) use conceptually the same approach as we do to obtain the credit risk premium from credit spreads.[4] However, they do not transform the credit risk premium to an expected, corporate bond-implied, equity return. Hence, they cannot perform the quantitative comparison of expected corporate bond-implied equity returns and realized equity returns. Moreover, the focus of their paper is to analyze how systematic default risk betas relate to these expected and realized returns, while our main focus is to perform an extensive and quantitative analysis of the bond-implied equity returns and realized equity returns. Finally, Anginer and Yildizhan (2017) use a longer sample period (1980 to 2010) but have a smaller cross-section of firms: about 338 firms each month[5], compared to 685 for our sample.

Our work also relates to other studies on the integration of stock and corporate bond markets. In particular, a number of studies study integration by looking at the time-series relation between stock and corporate bond returns. Hence, these studies do not focus on pricing and expected returns, and our work thus complements this stream in the literature. Examples of studies in this literature are Collin-Dufresne, Goldstein and Martin (2001), Kapadia and Pu (2012), and Demirovic, Guermat, and Tucket (2017), who focus on the contemporaneous relation between stock and bond returns, and conclude that stock and bond markets are not perfectly integrated.[6] In addition, there is a large body of literature on lead-lag effects, concluding either that stock returns lead bond returns (Kwan, 1996; Gebhardt, Hvidkjaer and Swamanithan, 2005; Downing, Underwood and Xing, 2009; Haesen, Houweling and Van

[4] Anginer and Yildizhan (2017) employ a hazard rate model to estimate the probability of default rather than the probability of default implied by the Merton (1974) model. In the robustness section we employ the hazard rate model of Campbell et al. (2008) and obtain results that are qualitatively similar to our benchmark results.
[5] Anginer and Yildizan (2017) report 121,714 firm-month observations over the period January 1981 to December 2010, which means on average there are 338 firms in a month.
[6] Schaefer and Strebulaev (2008) find that, despite this imperfect time-series relation, the size of the exposure of corporate bonds to equity returns is similar to predictions of a Merton (1974) model.

Zundert, 2017) or vice versa (Bittlingmayer and Moser, 2014; Ben Dor and Xu, 2015), which is also indirect evidence of disintegration between the two markets as it suggests new information is not priced in in both assets at the same time. [7] Note that, even if there is an imperfect time-series relation between stock and corporate bond returns, this does not necessarily imply that long-term expected returns are different, because this imperfect time-series relation might be caused by temporary illiquidity or price pressure effects, or by exposure to factors that are not priced.

In addition, our work is related to several studies that focus on the pricing of equity market anomalies in bond markets (Chordia et al., 2017; Choi and Kim, 2017). If bond and stock markets are integrated, then well-known anomalies should be present in both stock and bond markets. Concretely, Choi and Kim (2016) study the cross-sectional pricing of known equity anomalies in the cross-section of corporate bond returns, and find that some anomalies are similarly priced (net issuance, gross profitability, idiosyncratic volatility, beta and accruals), but others are not (asset growth and momentum). Related to Choi and Kim (2016) is the work of Chordia et al. (2017), who study the predictive power of profitability, asset growth, equity market capitalization, accruals and earnings surprises. They find that, after transaction costs, bonds are efficiently priced. In our analysis, we examine whether our results can be explained by a different effect of anomalies on stock and bond markets. We control for anomalies related to beta, size, book-to-market, momentum, profitability, investment, and quality-versus-junk, and find that our main result cannot be explained by a different presence of these anomalies in stock versus corporate bond markets.

Finally, our paper is related to the literature that documents a relation between the default probability and average equity returns. They mostly document a negative relation: firms with

[7] Relatedly, there are also studies focusing on the link between credit default swaps and stocks at the firm level, such as Duarte, Longstaff and Yu (2007), Kapadia and Pu (2012), Hilscher, Pollet and Wilson (2015), Kiesel, Kolaric and Schiereck (2016).

a high default probability have low average returns. This result is often referred to as the "distress risk puzzle". We show that our main result is not simply a restatement of this distress risk puzzle. First of all, we show that the relation between our bond-implied equity return and default probabilities is not monotonic. Second, we double-sort on default probabilities and the bond-implied equity return and continue to find evidence for a negative relation between bond-implied and realized returns.

The remainder of this paper is organized as follows. In Section 2 we describe the data. Section 3 describes how we obtain expected equity returns from corporate bond credit spreads. Section 4 presents the benchmark empirical results: we analyze the relation between the bond-implied expected equity returns and realized equity returns. Section 5 provides robustness checks and Section 6 concludes.

2. Data

For our empirical analyses, we use stock data from the Center of Research in Security Prices (CRSP) at a monthly frequency over the period January 1994 to December 2015. We only include common equity (share codes 10 or 11) and exclude financials (SIC codes 6000-6999) as their financial structure is very different from corporates (see also Campbell et al., 2008).

To compute probabilities of default, we use accounting data from COMPUSTAT Quarterly. The COMPUSTAT data is linked to CRSP using the CRSP/Compustat Merged database, and all accounting data is lagged for two months to account for the reporting lag.

For the bond data we use monthly constituent data of the Bloomberg Barclays U.S. Corporate Investment Grade and Bloomberg Barclays U.S. Corporate High Yield indices, formerly known as the Lehman Brothers Fixed Income database. This dataset includes per bond the *(option adjusted) spread duration*, which is adjusted for embedded options by Bloomberg. This is necessary in case bonds are likely to be called ahead of their maturity date, as the standard modified duration would overstate the interest rate sensitivity. Using the option-adjusted spread duration, the bond is matched with the appropriate U.S. Treasury bond. The *credit spread (excess return)* is computed as the difference between the yield (return) on the corporate bond and the yield (return) on the duration-matched Treasury bond. As the embedded option-adjustment for the *spread duration* and the *credit spread* fields are not available prior to January 1994, we start at this date. Furthermore, the *credit rating*, which is the middle rating of S&P, Moody's and Fitch if all three are available, or the worst rating if only two are available, in line with Bloomberg Barclays index methodology, is included.

We link the bond data to the stock/accounting data using CUSIPs and if not possible, hand-match the data, while taking M&A activity into account. See Appendix A for details. A single stock can have multiple bonds associated. To make the selected bonds as comparable as possible between stocks, we always pick a senior unsecured bond. If multiple senior unsecured bonds exist, we pick the one with the spread duration closest to 5 years in order to reduce the dispersion across maturities.

Finally, we obtain the 1-month T-bill rate, the five Fama-French (2015) factors and the Carhart (1997) Momentum factor return series from the website of Kenneth French.[8] The Quality-Minus-Junk factor is from the website of AQR.[9]

3. Methodology

Our empirical framework is based on the idea that the equity and bond risk premium of a firm are linked to each other as both are contingent claims on the same firm assets (Merton, 1974). In the Merton (1974) model, the bond and equity value are dependent on the firm value, the

[8] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[9] https://www.aqr.com/library/data-sets/quality-minus-junk-10-qualitysorted-portfolios-monthly

interest rate and the asset volatility. To arrive at a parsimonious model, we assume, following Campello et al. (2008)[10], the interest rate term structure to be flat and deterministic, and the asset volatility to be at most a function of asset value. This leaves the firm value as the sole driver of expected bond and equity returns.

3.1 Obtaining expected equity returns

In this framework, the expected return of the equity of firm j can be written as a function of the expected return on the bond:

$$E_t\left(r_j^E\right) = y_{g,t} + \left(\frac{\delta E}{E} \Big/ \frac{\delta B}{B}\right) \cdot \left(E_t\left(r_j^B\right) - y_{g,t}\right) \tag{1}$$

where $y_{g,t}$ is the yield of the duration matched Treasury $y_{g,t}$,[11] $\left(\frac{\delta E}{E} / \frac{\delta B}{B}\right)$ the elasticity of equity returns to bond returns and $E_t\left(r_j^B\right) - y_{g,t}$ the expected return of the bond of firm j over the duration matched Treasury bond. To implement this equation, we need to have estimates for the elasticity and the expected bond return.

We follow Campello et al. (2008), Bongaerts, De Jong and Driessen (2017), and others for computing the expected bond return over Treasuries. Specifically, we assume defaults occur at maturity only and approximate the coupon-paying bonds by zero-coupon bonds with maturity equal to the duration of the original bonds. Then, an investment of \$1 in the zero-coupon corporate bond pays off $\left(1 + y_{g,t} + s_{j,t}\right)^{T_{j,t}}\left(1 - L \cdot \pi_{j,t}\right)$ by expectation at maturity $T_{j,t}$. Here, $s_{j,t}$ is the credit spread, $\pi_{j,t}$ the cumulative probability of default to maturity, L is the loss rate in case of default, and $T_{j,t}$ the time to maturity, which we set equal to the duration of the bond.

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[10] Campello et al. (2008) also include a convexity effect. As we estimate the expected return to maturity, convexity effects are not relevant in our setting.

[11] Under our assumption of a flat interest rate term structure, we can pick any maturity for the risk-free rate. Empirically, the term structure is not flat. We accommodate this by picking the duration-matched Treasury bond yield, which is the relevant rate for the chosen corporate bond. This also allows us to use the (option-adjusted) credit spreads as supplied by Bloomberg-Barclays to compute the expected bond return.

It then follows that the annualized expected bond return in excess of a maturity-matched Treasury bond is given by

$$E_t\left(r_j^B\right) - y_{g,t} = \left(1 + y_{g,t} + s_{j,t}\right)\left(1 - L \cdot \pi_{j,t}\right)^{\frac{1}{T_{j,t}}} - \left(1 + y_{g,t}\right) \tag{2}$$

Given the observed credit spread and Treasury bond yield, only an estimate of the loss rate and default probability are needed to obtain a forward-looking expected return. The loss rate L is set to 60% following Bongaerts et al. (2017).[12] In the next section we discuss the estimation of default probabilities.

3.2 Estimating default probabilities

There are several existing approaches to estimate default probabilities. A first popular approach is to use structural models such as the Merton model, calibrated to equity data, to obtain default probabilities. Besides academic work (Vassalou and Xing, 2004; Duffie, Saita and Wang, 2007), this is also a common approach in practice. For example, Moody's-KMV use this approach. Second, several articles model default events as a function of various financial and accounting measures and estimate logit or hazard rate models to explain default occurrences (Campbell et al., 2008; Bharath and Shumway, 2008). Third, one can simply focus on credit ratings to measure default risk, using the historical default rates per credit rating (see for example Elton, Gruber, Agrawal and Mann, 2001 and Campello et al., 2008).

Since the default probability is a key input variable for the expected equity return, we use all three approaches in this paper and find that our empirical results are largely similar across these three methods. For our benchmark analysis we choose to use the structural Merton model to

[12] A loss rate of 60% (recovery rate of 40%) is a reasonable assumption, as the recovery rates for senior unsecured bonds with credit ratings between AA and C vary between 37.2% and 44.5% for the period 1985-2014 (Moody's, 2015, exhibit 21, assuming default occurs within two to five years). Setting it to 50% or 70% does not alter our conclusions. Results are available upon request.

estimate default probabilities. As we show below, this approach is able to generate substantial cross-sectional and time-series variation in default probabilities. The other two approaches generate much less variation. This is directly clear for the ratings-based approach, since credit ratings are quite stable over time while default rates spike around crisis periods. In Appendix B we provide more details on the accuracy of hazard rate models. We find that the hazard rate model is unable to model the strong increase in default probabilities when credit ratings deteriorate, in contrast to the Merton model. For instance, the historically observed average 5-year cumulative default rate for B-rated bonds equals 20.54%. The Merton model predicts an average probability of 19.6% for all B-rated bonds in our sample, while the hazard-rate model predicts a mere 5.4%.

We now discuss the implementation of the Merton model in more detail. In the Merton model, the probability of default is given by (subscripts *j* and *t* have been removed for brevity):

$$\pi = N\left(-\frac{\log\left(\frac{V}{D}\right) + (\mu - \delta - 0.5\sigma^2)T}{\sigma\sqrt{T}}\right) \tag{3}$$

where *N(.)* is the normal cumulative distribution function, *V* the value of the firm's assets and *D* the default barrier at maturity. The value of the firm is set to the market value of equity plus the book value of total liabilities, where book value of liabilities approximates the market value of liabilities. The default barrier is set to the book value of total liabilities. The term $\mu - \delta$ represents the net growth rate of the firm's assets over time, where the drift rate μ represents the earnings generated by the firm's assets and the payout rate δ represents the amount distributed to all stakeholders of the firm. This growth rate holds over the specific horizon *T*, and is unobservable ex-ante. Therefore, we set the drift rate μ equal to the risk-free rate over this horizon, the duration-matched Treasury yield $y_{g,t}$, plus a term to reflect the risk of the firm's assets. We set the risk premium equal to a constant price of risk (θ) times the volatility of the firm's assets σ, using θ=0.22 for all firm-month observations following Feldhütter and Schaefer (2016) and Chen, Collin-Dufresne and Goldstein (2009). The procedure to compute the volatility of the firm's assets is described below. The payout rate δ consists of all cash distributed to or collected from debt (interest) and equity holders (dividends and stock issuance/repurchase). We compute the past year's payout ratio and assume it remains at this level over the horizon *T*.

To compute the firm's assets volatility σ over the coming *T* years, we need to predict the volatility of equity and debt over *T* years. In most implementations of the Merton (1974) model, the asset volatility is derived from the equity volatility, which is assumed to be constant and equal to historically observed volatility levels. Empirically, however, equity volatility mean reverts to a long-run mean to a large extent within five years, which is the typical maturity of corporate bonds in our sample. For instance, the VIX, a measure of implied equity index volatility for the S&P500 index, reached in November 2008 a high of 80.86, whereafter it quickly fell to a level lower than the long run average of approximately 20 in January 2010.[13] In the fall of 2008, we would overstate the expected volatility over the coming five years substantially by using the equity volatility level at that time. Therefore we estimate the expected average stock return variance over the horizon by incorporating the mean-reversion, and then transform it into an asset variance. The expected average variance can replace the constant variance in an option pricing model (like the Merton model) under some assumptions (Hull and White, 1987). In Appendix C we discuss in detail how we obtain, for each firm and at each point in time, an estimate of the expected average equity variance over the maturity of the given bond.

[13] Numbers obtained from http://www.cboe.com/micro/vix/vixintro.aspx.

To transform the resulting equity volatility (σ_E) estimate into an asset volatility σ_A, we follow Feldhütter and Schaefer (2016). Their starting point is that, given that the assets of the firm (*V*) are the sum of equity (*E*) and debt (*B*) values, asset volatility is a weighted average of equity and debt volatility: $\sigma_A^2 = \left(\frac{E}{V}\right)^2 \sigma_E^2 + \left(\frac{B}{V}\right)^2 \sigma_B^2 + 2\frac{E}{V}\frac{B}{V}\sigma_{BE}$. To avoid estimation of the debt return variance σ_B and equity-debt covariance σ_{BE}, they propose an approximation. Specifically, their asset volatility is given by $\left(\frac{E}{V}\right)\sigma_E c$, where c is a factor depending on the leverage ratio *B/V* (=*1-E/V*) to account for Treasury bond volatility. The factor *c* is 1 if *B/V* < 0.25, 1.05 if 0.25 < *B/V* ≤ 0.35, 1.10 if 0.35 < B/V ≤ 0.45, 1.20 if 0.45 < *B/V* ≤ 0.55, 1.40 if 0.55 < *B/V* ≤ 0.75, and 1.80 if *B/V* > 0.75.

Table 1 shows the average value for each of the inputs of the probability of default estimation, both on average as well as per credit rating. The results show that as the credit rating deteriorates, the asset volatility, leverage and payout ratio increase, which all three lead (ceteris paribus) to a higher probability of default in Equation (3). The time-to-maturity is shorter when the credit rating is lower, reflecting shorter-dated issuance by high yield firms.

3.3 Estimating the elasticity

We then turn to estimation of the equity-bond elasticity $\left(\frac{\delta E}{E} / \frac{\delta B}{B}\right)$. We follow Campello et al. (2008) and use the fitted values of a regression model for the realized elasticities. We now describe this approach in detail.

For each firm and each month, we determine the change in market value of equity (*E*) and market value of debt (*B*) over the month. The market value of debt is estimated by the book value of total liabilities multiplied by the ratio of the corporate bond price and its nominal value ($100 usually). In this way, the monthly change in the market value of debt reflects the change in corporate bond market prices, which is important to capture the elasticity properly. If we would take book values, there would be many months with zero debt return as book values are not updated on a monthly basis.

We calculate the realized elasticity, $\frac{\delta E}{E} / \frac{\delta B}{B}$, for each month and each firm. Then we perform a panel regression of these realized elasticities on the variables of which the elasticity is a function in the Merton (1974) model: leverage, volatility, the (duration-matched) risk-free rate and the time-to-maturity. This results in the following panel regression for the elasticity for each month and each firm:

$$\frac{\delta E}{E} \Big/ \frac{\delta B}{B} = c + \beta_{LEV} LEV + \beta_{VOL} VOL + \beta_{y_g} y_g + \beta_T T + \varepsilon \qquad (4)$$

where all right hand variables are known as of the beginning of the month, and the elasticity is measured over the coming month. *LEV* is the leverage ratio *B/V*, *VOL* is the past 1-month annualized stock return volatility in fractions, y_g the duration matched Treasury yield in fractions and *T* the time-to-maturity in years. When estimating Equation (4), we remove the top and bottom 5% of elasticity observations, since bond returns close to zero can deliver extreme elasticities, and the top 5% of equity volatility observations. See Appendix D for more discussion and robustness checks on this winsorization.[14]

The results are reported in Table 2. We find that the coefficients for leverage (significantly positive), volatility (significantly positive) and the risk-free rate (negative but insignificant) have the signs as predicted by the Merton (1974) model (Schaefer and Strebulaev, 2008, p. 7). The effect for time-to-maturity is ambiguous in theory; we find a significantly negative coefficient of -0.09 for this sample.

[14] We differ from Campello et al. (2008) in a few minor aspects: 1) leverage is *B/V* instead of *E/B*, as leverage appears as *B/V* in the Merton model, 2) equity volatility is based on past 1-month returns instead of past 180 days, 3) we use the duration-matched Treasury yield instead of the 1-month rate as an independent variable following the Merton model and 4) we add time-to-maturity, as it is a driver of elasticity as well in the Merton model.

Figure 1 reports the distribution of the fitted elasticities, which shows there is substantial variation between firm-month observations. The average value is 0.98, but values as low as 0.25 or as high as 2 are not uncommon. This shows that we cannot simply assume the elasticity to be identical across firms and time.

We use the fitted values of the regression model in (4) to construct, for each firm and each month, the expected elasticity given the values of the explanatory variables. These fitted elasticities are then used to construct expected equity returns based on equation (2). In Section 5 we find that our empirical results are robust to the exact specification of elasticity. In particular, using a 12-month historical elasticity or no elasticity at all (i.e., sort directly on expected bond returns) leads to similar results.[15]

3.4 Aggregate expected returns over time

Before we turn to our main focus, the cross-sectional patterns in expected returns, we report in Figure 2 the market value weighted average of the expected bond and equity returns per month as estimated following the approach discussed in the previous sections. We find that there is substantial variation over time. Whereas in spring 2007 expected monthly equity returns (over 1-month T-bill) are close to zero, they are equal about 60 basis points at the beginning of November 2008. The average level is 18 basis points per month, or 2.19% per annum. Expected corporate bond returns (over duration-matched Treasury) tend to show lower variation through time compared to equities, with an average annualized level of 0.83%.

[15] We could also have used the Merton (1974) model, as it implies an explicit expression for the elasticity of equity returns to bond returns: $\frac{N(d1)}{1-N(d1)} \times \frac{B}{E}$, where *N(d1)* is the usual call-option delta. However, this expression is very sensitive to the parameter inputs, as the delta is typically close to 1, potentially leading to extreme values for the elasticity.

4. Benchmark results

In this section we compare our corporate bond-implied expected equity return with realized equity returns. Section 4.1 contains the results of portfolio sorts on expected returns. Section 4.2 tests whether the results can be explained by mispricing.

4.1 Cross-sectional results

If corporate bond and equity markets are integrated, the expected equity returns inferred from the corporate bond spreads should equal the realized equity return on average. At a minimum, stocks with high expected returns as implied from corporate bonds should have high realized returns as well and vice versa. We test this by creating each month equal-weighted decile portfolios based on the expected equity returns as implied from corporate bond spreads. The monthly rebalancing means that we implicitly test whether the bond-implied expected returns, which have an average horizon of 5 years, are consistent with realized 1-month returns. Hence we implicitly assume that the term-structure of expected returns is flat. In the next subsection, we evaluate this assumption. In the robustness checks, we verify that our results are robust to the sampling period, to value weighting of the portfolios and various methods to construct expected equity returns from corporate bond spreads.

Table 3 reports the full-sample results. The first row shows the expected return we sort on, sorting from high to low expected returns. It declines from 1.14% per month for the first decile (D1) to -0.14% per month for D10. However, for the realized stock returns, we observe a generally increasing pattern, with D1 (high expected return) having a strong negative average return of -0.87% per month, and then it increases until around D5. From D6 to D10 the returns are relatively similar, at a level of 0.8% to 1.0% per month. The last column reports the D1-D10 long-short portfolio, which has a realized return of -1.79% per month, with a corresponding robust *t*-statistic of -3.35, while the bond-implied expected return for the long-short portfolio is 1.27% per month.

These striking results show that the hypothesis that higher bond-implied expected returns imply higher equity returns is clearly rejected. The evidence points towards the opposite conclusion: the higher the expected return implied by the corporate bond, the lower the realized equity return is. A stricter test focuses on whether realized returns are (on average) equal to expected returns. We test this for each portfolio in lines 4 and 5 of Table 3. For 8 out of the 11 portfolios this hypothesis is rejected. In particular, for the long-short portfolio D1-D10, the difference between realized and expected returns amounts to -3.07% per month (-36.8% per annum), which is highly economically and statistically significant (*t*-statistic of -5.57). We thus conclude from this empirical evidence that there is major mispricing in the cross-section of equity versus corporate bond markets. This is the key finding of our paper. In Section 5 we therefore conduct a wide range of robustness checks on this result.

Rows 6 to 10 of Table 3 show the volatility of the realized returns, the average corporate bond spread, the expected bond return, the elasticity and the estimated probability of default. From all measures, it is clear that the high (default) risk firms are concentrated in D1, D2 and D10. This is important, as it shows that the puzzle we document is not simply a restatement of the low-volatility anomaly (Haugen and Heins, 1972), which states that low-volatility stocks have high risk-adjusted returns, or the traditional distress risk anomaly (Dichev, 1998; Griffin and Lemmon, 2002; Campbell et al., 2008), which states that stocks with high default probabilities have low returns. We formally control for these anomalies in Section 5.

4.2 Understanding the mispricing

In this subsection, we aim to better understand the negative relation between bond-implied expected and realized equity returns. We first analyze realized bond and equity returns over various horizons. Second, we test whether the negative relationship between expected and realized equity returns can be related to well-known proxies of mispricing, and third, we link the expected and realized equity returns to standard asset pricing models.

Before we discuss these analyses in detail, it is important to note that our analysis of expected and realized returns provides evidence for relative mispricing of corporate bonds versus stocks. We do not aim to explain the level of bond-implied expected returns, nor the level of realized average equity returns. For such an analysis, one would need to assume a specific asset pricing model and see if these levels are in line with the model predictions. As mentioned earlier, our analysis of relative mispricing does not require assumptions on an asset pricing model.

Horizon effects for bonds

To understand our key finding better, we first study the horizon effects in more detail. In the previous section we assumed that the term structure of expected returns is flat in order to compare 5-year ahead expected returns with 1-month realized returns. It could however be that this term structure of expected returns is not flat. In the extreme case that bonds with a high (low) 5-year expected return have a low (high) expected return for the coming month, which is more than reversed in the remainder of the 5-year period, the realized 1-month equity returns would not be anomalous at all.

We thus start by analyzing the 1-month realized returns on the corporate bonds. We create each month ten portfolios based on the expected bond return. For each portfolio, we compute the 1-month realized return.[16] Table 4, Panel A, reports the results. We find a monotonically increasing pattern in realized returns from the low expected return portfolio (-0.09%) to the high expected return portfolio (0.29%). Moreover, we observe that the 1-month realized returns, except for D1, match the 5-year expected returns in magnitude quite well. Hence we

[16] The return is the excess return of the bond over the duration matched Treasury bond, in line with the computation of the credit spread. The excess return is provided by Barclays and corrected for embedded options.

do not find evidence against a flat term structure of expected returns for bonds. Importantly, we can thus conclude that the mismatch in horizon between the expected and realized returns is not driving the empirical negative relation between expected and realized equity returns.

Panel A of Table 4 also presents realized bond returns over a 5-year horizon.[17] We pick 5 years, as the bonds used to calculate expected returns tend to have an average maturity of about 5 years. If our estimate of the probability of default is unbiased, these 5-year realized bond returns should by construction be equal to the bond-implied expected returns (on average).[18] This is because, corrected for expected default losses, the corporate bond yield exactly equals the return of holding the bond to maturity. Hence, analyzing 5-year bond returns provides an important check on the validity of our default probability estimates. Table 4 shows that, for these 5-year returns, expected and realized returns line up quite well. Realized returns depend positively on expected returns except for D9 and D10, but D9 and D10 (which have low expected returns) still have realized returns well below D1 and D2. Although the cross-sectional spread in 5-year realized returns is smaller in magnitude compared to the 1-month realized returns, implying that the effect is stronger on the short horizon, there is no evidence of a reversal after 1 month. This gives us confidence that we predict the probability of default reasonably well. If we would have strongly over (under) estimated the probabilities of default, the expected bond returns would be too low (high) compared to realized returns.

In sum, the main findings of this horizon analysis for bonds are: 1) both on a 1-month as well as a 5-year horizon, we find a positive relationship between expected and realized corporate bond returns, 2) this relation is strongest for the 1-month horizon, in the longer run it remains,

[17] The 5-year return is computed using the overlapping portfolio approach of Jegadeesh and Titman (1993).
[18] In Appendix B we directly compare our estimated probabilities of default to historical default rates and find that they match well.

though somewhat diminished and 3) the 1-month realized returns match the (5-year) expected returns well in magnitude.

Horizon effects for stocks

We then turn to horizon effects for equities. Our main goal is to analyze how persistent the effects for 1-month realized returns are. If bond-implied expected returns and realized equity returns are more in line with each other on a longer horizon, this would suggest that equities are temporarily mispriced relative to bonds.

Panel B of Table 4 reports the results for equities. The expected and 1-month realized returns are identical to the numbers in Table 3, Panel A, and are only included for reference purposes. The 5-year returns, like for bonds, differ less across the portfolios, but still reveal a negative relationship. In particular, D1-D10 has an economically sizeable negative return of -0.50% per month, which does not differ significantly from zero (*t*-statistic of -1.47). However, it does differ significantly from the bond-implied expected return of 1.27% for D1-D10 (*t*-statistic of -5.20). Given that the average return on D1-D10 equals -1.79% in the first month, these results indeed provide evidence for temporary mispricing of equities, which is partially but not fully resolved over a longer horizon.

Which stocks are mispriced most?

A common concern for research that documents anomalies is that these anomalies might only be present in small, hard-to-arbitrage stocks. In such a case, the economic relevance of the anomaly might be limited. We analyze whether this issue applies to our setting using Fama-MacBeth (1973) regressions at the firm level. As proxies for the "economic relevance" and arbitrage costs we use the number of analysts following the stock (obtained from I/B/E/S; see for instance Hong, Lim and Stein, 2000), the turnover of the stock over the past month (Amihud and Mendelson, 1986) and the market capitalization of the equity (Merton, 1987; Grossman and Miller, 1988).[19]

Table 5 reports the results. In the first specification, the 1-month realized return is only regressed on the bond-implied expected return. If the expected and realized returns would match, we should find a slope equal to one and a R-squared of 100%. However, we find a strongly negative coefficient of -2.64 with a *t*-statistic of -5.30 and a R-squared of only 2.7%, confirming the results of the portfolio sorts in Table 3. If the mispricing is concentrated in small, hard-to-arbitrage stocks, we would expect this coefficient to be more negative for such stocks. For all three proxies, we therefore split the stock universe each month in three equal-sized groups and create dummies per group, which we interact with the bond-implied expected return. The base level is the group for which the number of analysts is high, the stock turnover high and the market capitalization large, i.e. the group of large stocks with low arbitrage costs. If mispricing is concentrated in small, hard-to-arbitrage stocks, the interaction terms should be significantly negative. However, columns 2 to 5 in Table 5 show that this is not the case. In specification 3, we even find a statistically positive coefficient (at the 10% level) for the middle stock turnover group. The coefficient for the base group in the specification with all three proxies included is -2.31 (*t*-statistic of -2.74), not far from the unconditional coefficient of -2.64 found in the first regression specification. The group with the least negative slope (high number of analysts following the stock, low turnover, large market capitalization) has a slope of -2.31+0.81=-1.50, still far below the a priori expected level of +1. In sum, even for the stocks

[19] To obtain the number of analysts following a stock, the number of estimates for the item earnings-per-share (EPS) for fiscal year 1 (FY1) is taken from the I/B/E/S database. The I/B/E/S data is linked to CRSP by matching the CUSIP on the historical CUSIP (NCUSIP) field in CRSP.

which are least likely to be mispriced we find a strong negative relationship between the expected and realized equity returns.

Pricing of risk factors across markets

A large number of studies in the asset pricing literature focuses on explaining differences in expected returns using factors, the prime example being the Fama and French (1992) three-factor model. In this paper we compute expected equity returns and compare those directly with realized equity returns. As mentioned earlier, this analysis does not require any assumptions on a specific asset pricing model. In other words, it does not matter which factors or characteristics drive the returns and whether they can fully explain the variation in returns. Any factor or characteristic that drives expected returns should affect both the bond-implied expected equity return and the realized equity return equally. But if equities are mispriced relative to bonds, it might be because, for some reason, some risk factor exposure or characteristic is priced differently in stock versus bond markets. Choi and Kim (2016) provide evidence this might be the case for asset growth and momentum.

To investigate this, we perform the usual Fama-MacBeth regressions where we regress the cross-section of realized (or expected) equity returns on the equity market beta and various characteristics. We focus on characteristics like size rather than exposure to the SMB factor to avoid estimating many risk factor exposures. We use the standard Fama-French (1992) characteristics (size and value, specification 1) and an extended version including the momentum, operating profitability and investments characteristics (specification 2). The construction of these variables follows standard practice, see Appendix A.IV for details. Table 6 reports the results.

When we use the realized return as left-hand-side variable, we find that the equity risk premium is not priced (specification 1) or even negatively priced (specification 2). This result is in line with an extensive literature on the slope of the Capital Asset Pricing Model being too flat or even negative (Black, Jensen and Scholes, 1972). For size and value we also find effects contrary to expectations. This could be driven by the large cap bias in our universe as we require companies to have bonds outstanding meeting the minimum amount outstanding criteria of the Bloomberg-Barclays indices. However, for the expected equity returns, we find effects as expected: market beta, size (specification 1 only) and book-to-market are priced. For momentum, we find it to be strongly negatively priced.

When we use the expected return as left-hand-side variable, our results are similar to Campello et al. (2008)[20]. For operating profitability we do not find significant results. For the investments variable, we find that companies with high investments have actually higher expected returns than companies with low investments in our sample. The final two columns of Table 6 show the statistics for regressions where the left-hand-side variable is the difference between the realized and expected return. Only in the full model (specification 2) do we find statistically significant pricing differences between realized and expected returns: especially the pricing of the market beta, size and momentum differ substantially between the equity and corporate bond market (*t*-statistics of -2.20, 1.91 and 1.60 respectively), suggesting that these are not well integrated.

It could thus be that we find a negative relationship between the expected and realized returns due to different pricing of risk factors or characteristics. Therefore, we remove the risk exposures and effects of characteristics from both the expected and realized returns by using the 6-factor coefficients in Table 6 (columns 2 and 4; FF6) to compute “excess” expected and realized returns. Subsequently, we regress these excess realized returns on excess expected

[20] An important distinction between the approach of Campello et al. (2008) and ours is that we do not use historical default rates per credit rating but rather use the Merton model directly to estimate the probability of default, leading to more adaptive probabilities of default through time. Appendix B provides more details on the accuracy of our method.

returns in the same way as in Table 5, specification 1. The slope coefficient of -2.64 for the total return (Table 5) becomes -4.15 (t-statistic of -4.68) when using these “excess” returns, implying that the different pricing of risk factors and characteristics across equity and bond markets does not drive our findings. In fact, the relation between expected and realized returns becomes even more negative.

5. Robustness

This section describes the results of our robustness checks. We find that the results are robust through time, not dependent on implementation details of the portfolios and expected return calculations, and are not driven by default risk or liquidity.

Results are robust through time

In Table 7, panels A and B, the results are shown per sub period, where the first period covers January 1994 to December 2004 and the latter January 2005 to December 2015. We find that the results are comparable to the full sample results. Most importantly, for D1-D10, the hypothesis that realized returns are equal to expected returns is rejected. For the period January 1994 - December 2004 we reject the hypothesis that the return is equal to zero as well, as it is strongly negative; in the recent period the D1-D10 return is -128bps a month on average, but not statistically significant different from zero.

To provide more insight into the results in Table 3 through time, Figure 3 shows the cumulative (log) bond-implied expected equity return as well as the realized equity return. As the portfolio is constructed by going long high expected return and short low expected return, the bond-implied expected return is steadily trending upwards by construction. During crisis periods, such as the dot-com bubble and the Great Financial Crisis, the dispersion in expected equity returns is larger and as a result the line trends upwards at a higher rate during those periods. The realized equity return, on the other hand, is steadily declining. There is some variation through time, but except for the calendar years 2003 and 2009 the realized return is always negative.

Results are robust to choices in portfolio construction and expected return calculation

We first conduct robustness checks on the construction of the decile portfolios. We test market-value weighted portfolios instead of equal-weighted portfolios. The results for the long-short portfolio are in Table 8, column 2. We find that the realized D1-D10 equity returns are still negative, but the effect is statistically weaker with a *t*-statistic of -1.68. Compared to the expected returns, the realized returns are significantly lower (*t*-statistic of -2.89).

For the robustness to the estimation of the elasticity we test two alternatives: 1) using the past 12-month observed elasticity and 2) exclude the elasticity altogether (i.e. assume it is one for every stock). The results are in Table 8, columns 3 and 4. We find that the results for both choices are very similar to the base case results, with all four tests (versus zero and versus expected return) having *t*-statistics of -2.17 and lower.

For the probability of default, we test two alternatives, namely using the hazard rate model of Campbell et al. (2008), and using average default rates per credit rating. The hazard rate model of Campbell et al. (2008) includes the following accounting and market-related explanatory variables: past 12-month net income to total assets (NIMTAAVG), total liabilities to total assets (TLMTA), past 12-month stock excess return over the S&P500 (EXRET), past 3-month daily stock return volatility (SIGMA), relative size of the stock in comparison the S&P500 total market capitalization (RSIZE), cash and cash equivalents to total assets (CASHMTA), market to book ratio (MB) and the log of the stock price winsorized at $15 (PRICE). We transform these variables to a probability of default using the estimated parameters for the 12-month horizon (Campbell et al., 2008, Table IV). For details on the construction of these variables, see Appendix A.III. In Appendix B we analyze the differences with the probabilities of default as estimated by the Merton model. In particular, we find that the Merton model is better able to match the high probabilities of default for lower credit ratings. The portfolio return results when using the hazard rate model are in Table 8, column 5. We find that the realized returns D1-D10 are again negative at -0.24% per month, but no longer statistically different from zero. However, compared to the expected return, the returns are substantially lower with a *t*-statistic of -2.60.

The second alternative to estimate the probabilities of default is to use credit ratings. We obtain long-run average cumulative default rates provided by Moody's (2015, exhibit 34) for the period 1920 to 2014. For each bond and each month, we use the credit rating and maturity to infer the cumulative default rate.[21] We find that the results, reported in column 6, are very similar to those of specification 1. In particular, the realized returns are still significantly different from the expected returns with a *t*-statistic of -4.72.

Finally, if we assume that 1) the expected credit return of a bond is a fixed proportion of the total credit spread, 2) the credit spread, and thus the expected return, is constant over maturities (flat term structure) and 3) firms do not differ in their elasticity, then expected equity returns are proportional to the credit spread. The assumption that expected equity returns are proportional to credit spreads is very strong. For instance, the expected return measure used in our benchmark analysis is not increasing in the credit spread. Rather, in the group with the 10% lowest expected returns, some of highest credit spreads can be found (see Table 3; D10 has a credit spread of 24bps per month, which is only exceeded by D1, D2 and D3). Still, we find that the results for sorting directly on the credit spread (column 7) are quite similar to those for the base case (column 1), with strongly negative *t*-statistics of -2.16 and -3.24 for the tests versus zero and the expected equity return respectively.

[21] As the maturity is usually not equal to a round number, we use linear interpolation between the two maturities nearest by. For example, a BB-rated bond with 4.5 years' time-to-maturity will have a default probability of 9.35% (average of 8.24% for 4-year horizon and 10.46% for 5-year horizon).

Interaction with default risk

In the portfolio sorts reported in Section 4.1 an interaction of expected equity returns with physical default risk is visible, but the relationship is not monotonic, as D1, D2 and D10 have higher risk than other groups. This suggests that our results are not simply a mirror image of the traditional distress risk puzzle. To further analyze this, we construct a double sort based on five (default) risk measures, namely 1) the credit spread of the bond, 2) probability of default as measured with the Merton (1974) model implementation, 3) the credit rating of the bond, 4) past 1-month equity return volatility and 5) past 36-month equity market beta. First we split the universe each month in five equal sized groups based on the default risk measure. Second, within each risk group, we sort on the bond-implied expected return and create a top 20% minus bottom 20% long-short portfolio. The mean realized returns and associated *t*-statistics of the top-bottom portfolios are reported in Table 9. We see that the negative returns on the top-bottom expected return portfolios are concentrated in the 40% highest risk groups, with highly significant negative returns for the 20% highest risk group for all default risk measures. For the 20% lowest risk group, we observe positive returns on the top-bottom expected return portfolios for all risk measures (except for the equity beta), but not significantly positive. Thus we conclude that also after correcting for the interaction with default risk, no evidence exists for a positive relation between expected and realized equity returns.

Bond liquidity

So far we assumed that the part of the credit spread that cannot be attributed to physical default risk probability is a risk premium for the credit risk. In various other studies part of the credit spread is attributed to an illiquidity premium (Bao, Pan and Wang, 2011; Dick-Nielsen, Feldhütter and Lando, 2012; Bongaerts, de Jong and Driessen, 2017). Hence our expected return measure might be biased due to these liquidity effects. We therefore use data from the TRACE database to construct an estimate of the illiquidity premium. TRACE is a transaction report database covering almost all trading in USD-denominated corporate bonds. We use Enhanced TRACE from 2002 to Q3 2014, and standard TRACE afterwards, as Enhanced TRACE is only available after 18 months. To filter the data for cancellations, reversals and errors, we follow Dick-Nielsen (2009) and Dick-Nielsen (2014) for the non-enhanced and enhanced version respectively. The TRACE data is linked to the bond data using the CUSIPs.

We first compute the monthly turnover of all bonds per expected return portfolio, which is equal to the total dollar amount traded in a given month divided by the total dollar notional amount outstanding at the beginning of the month. Second, we follow the procedure of Feldhütter (2012) and compute realized bid-ask spreads by identifying pairs of transactions on a given day for the same bond and transaction size. The absolute value of the price difference of the two transactions, divided by the average of the two prices, is a good measure of the percentage bid-ask spread as the two transactions likely involve a dealer intermediating a bond transfer from a seller (or buyer) to a buyer (or seller). See Feldhütter (2012) for more details.[22] Finally, we compute the product of turnover and the realized bid-ask spread as a proxy for the illiquidity premium, which is what the Amihud and Mendelson (1986) model with homogenous investors predicts. Bongaerts, de Jong and Driessen (2017) estimate liquidity premiums for corporate bonds and find that their estimates are close to these Amihud and Mendelson (1986) predictions.

Table 10 reports the results. We observe that the bonds of companies with the highest expected returns, D1, experience the highest turnover on average (14.3% per month, or 172% per annum), but also have the highest round-trip costs. This results in an average bond liquidity premium of 5.2 basis points per month (or 62 basis points per annum), substantially larger than the average liquidity premium of 2.3 basis point per month across all portfolios. Thus, our

[22] In our data set, buy and sell indicators are available, allowing us to more precisely define roundtrips compared to Feldhütter (2012).

expected return measure is indeed tilted to companies with less liquid bonds. To correct the expected equity return for this liquidity premium, we multiply the bond liquidity premium with the average bond-equity elasticity; the results are reported in the third row of Table 10. We find that the expected equity returns are biased upwards by 8.2 basis points for D1, and somewhat less for other deciles. Still, the magnitude of this bias is small compared to the total expected return. Specifically, Table 10 reports all liquidity-corrected expected returns and we see that the effect of liquidity is minor. For instance, D1 has an expected equity return of 114 basis points (row 4). Deducting 8.2 basis points monthly liquidity premium results in 106 basis points expected equity return after correction (row 5), which is still much higher than 38 basis points for D2. It thus seems unlikely that the presence of a liquidity premium is substantially affecting our sorting, and therefore our results.

Risk factors

In Section 4.2 we show that the difference between expected and realized returns cannot be explained by different pricing of risk factors in bond versus equity markets. Although we construct expected returns independent of a particular asset pricing model, a comparison with leading asset pricing models is still of interest. In particular, we find a statistically and economically sizeable monthly return of -179bps for our D1-D10 portfolio sorted on expected returns (Table 3).

Before we turn to the asset pricing models, we show in Figure 4 the relation between the monthly D1-D10 portfolio returns and the monthly market returns. We find that there is a clear positive relationship, with a correlation of 0.42. Thus the high expected return stocks outperform the low expected return stocks during positive states of the world. Given the higher volatility, credit spreads and probability of default of D1 in comparison to D10, this is not a surprising result. Next we show that this market beta cannot explain the negative return of D1-D10. In Table 11 we regress these D1-D10 realized equity portfolio returns on the five Fama-

French (2015) equity risk-factors, the Carhart (1997) momentum factor and the Asness, Frazzini & Pedersen (2014) Quality-Minus-Junk factor for various factor model specifications. Regardless of the specification, we find large and statistically significant alphas, ranging from -130bps a month to -236bps a month (*t*-statistics of -3.66 to -5.85). The coefficients reveal sizeable positive loadings on the market premium (Mkt-RF) and size (SMB), and negative loadings on momentum (MOM) and profitability (RMW). Hence, our sort on expected returns implies an equity trading strategy with a considerable alpha, and this trading strategy does not simply mirror existing risk factors or anomalies.

6. Conclusions

We perform a direct test of the cross-sectional integration of corporate bond and stock market pricing. The test does not rely on a specific asset pricing model. As the stock and bond of a firm are contingent claims on the same assets, we can use the risk premium on the bond to infer a risk premium on the stock. We find empirically that bond-implied expected stock returns relate negatively to realized stock returns, suggesting stock and corporate bond markets are not integrated and that relative mispricing between stocks and corporate bonds exists.

This negative relation cannot be explained by methodological choices. First, to transform corporate bond spreads to expected bond returns, we deduct the expected loss from the corporate bond credit spread using an estimate of the probability of default. We model the probability of default using an implementation of the Merton (1974) model, but find similar results when employing a hazard rate model or using historical default rates as a function of credit rating instead. Second, to transform expected bond returns to equity returns, we measure the bond-equity sensitivity using a regression approach as in Campello et al. (2008). Even when the sensitivity is set to one for all stocks, the results remain similar. Third, our main analyses compares 5-year ahead bond-implied stock returns with one-month realized stock returns. Also when using 5-year realized stock returns, we find a negative relationship.

We find differences in the pricing of systematic risk factors, especially momentum, between bond-implied stock returns and realized stock returns. These differences cannot, however, explain our key result. Our findings can also not be attributed to the portfolio weighting scheme, specific time periods, limits to arbitrage nor a potential illiquidity premium in the corporate bond spread. Finally, our results point towards temporary mispricing in equity markets, which is only partially corrected over longer horizons.

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Table 1: Parameter estimates equity volatility and average characteristics

For each column (rating group), per month, the asset volatility, leverage, payout ratio and time to maturity are averaged, and subsequently averaged over time. The column "All" denotes the average across all credit ratings. The data sample runs from January 1994 to December 2015.

Rating	All	AAA/AA	A	BBB	BB	B	CCC-C
Avg number of observations per month	685	31	150	207	103	155	39
Asset volatility (σ)	24.31%	20.16%	19.79%	21.11%	25.04%	30.43%	37.44%
Leverage (*B/V*)	0.54	0.43	0.48	0.51	0.55	0.61	0.71
Payout ratio (δ)	2.76%	2.17%	2.31%	2.59%	2.83%	3.27%	3.77%
Time-to-maturity (*T, in years*)	4.88	5.19	5.24	5.26	4.70	4.29	4.07
Equity market capitalization (bln USD)	12.34	96.47	24.29	9.20	3.61	1.58	0.99
Book-to-market ratio	0.75	0.50	0.55	0.68	0.83	0.84	1.63

Table 2: Determinants of bond-equity return elasticity

This table shows the results of the full sample pooled panel regression estimated using Ordinary Least Squares

$$\frac{\delta E}{E} \Big/ \frac{\delta B}{B} = c + \beta_{LEV} LEV + \beta_{VOL} VOL + \beta_{y_g} y_g + \beta_{TTM} T + \varepsilon$$

Where LEV is defined as the ratio of the book value of total liabilities to book value total liabilities + market value equity, VOL is the past 1-month annualized equity volatility, y_g is the duration matched Treasury yield, and T is the time-to-maturity of the bond. The table shows the coefficients and associated t-statistics. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Standard errors are calculated using two-way firm-month clustered standard errors (Petersen, 2009). The data sample runs from January 1994 to December 2015.

	constant	LEV	VOL	y_g	T	Adj R2	# obs
coefficient	0.63**	1.00***	1.09***	-3.54	-0.09***	0.15%	153527
t-stat	*(2.08)*	*(4.85)*	*(2.44)*	*(-0.71)*	*(-3.24)*		

Table 3: Decile portfolios based on expected equity return

This table shows the returns and other characteristics of decile portfolios based on expected equity returns, where D1 contains the 10% highest expected equity returns and D10 the lowest 10% expected equity returns. D1-D10 is long the D1 portfolio and short the D10 portfolio. Expected equity returns are constructed as described in Section 3. The portfolios are monthly rebalanced and equal weighted. For each portfolio, the expected return, the realized return, realized minus expected return, the volatility of realized returns, the spread, expected bond return, elasticity and probability of default are shown. All returns and the credit spread are monthly and in percentages. The *t*-statistics use Newey and West (1987) robust standard errors with lag selection following Newey and West (1994). Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Data sample is from January 1994 to December 2015.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10
Expected return	1.14	0.41	0.32	0.27	0.24	0.21	0.19	0.17	0.14	-0.14	1.27
Realized return	-0.87	0.66	0.83*	0.84**	0.90***	0.99***	0.88***	0.87***	0.78***	0.92**	-1.79***
	(-1.06)	(1.22)	(1.86)	(2.18)	(2.76)	(3.21)	(2.99)	(3.25)	(2.87)	(2.29)	(-3.35)
realized minus expected return	-2.01**	0.25	0.52	0.57	0.66**	0.78**	0.69**	0.70***	0.64**	1.06***	-3.07***
	(-2.37)	(0.46)	(1.15)	(1.47)	(2.02)	(2.50)	(2.33)	(2.60)	(2.35)	(2.65)	(-5.57)
Volatility realized returns	11.33	8.07	6.39	5.61	4.88	4.71	4.40	4.08	4.00	5.78	7.52
Credit spread	0.70	0.36	0.26	0.21	0.18	0.15	0.13	0.12	0.12	0.24	0.46
Expected return bond	0.50	0.22	0.17	0.14	0.11	0.09	0.08	0.06	0.04	-0.12	0.62
Elasticity	1.57	1.11	0.96	0.89	0.84	0.79	0.77	0.77	0.83	1.28	0.29
Probability of default (in %)	17.90	11.34	8.59	7.16	6.20	5.40	4.84	4.64	5.96	20.87	-2.97

Table 4: Expected versus realized returns over short and long horizon

In panel A (B) the expected and realized returns for bonds (equities) are shown of decile portfolios sorted on the expected return of the bond (equity). All figures are monthly and in percentages. The *t*-statistics use Newey and West (1987) robust standard errors with lag selection following Newey and West (1994). Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Data sample is from January 1994 to December 2015.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10
Panel A: Bonds											
Expected bond return	0.52	0.23	0.17	0.14	0.11	0.09	0.08	0.06	0.03	-0.13	0.65
Realized return 1-month	0.29	0.33	0.23	0.13	0.13	0.09	0.04	0.03	-0.01	-0.09	0.38
	(0.70)	(1.51)	(1.52)	(0.98)	(1.25)	(0.93)	(0.51)	(0.40)	(-0.16)	(-0.76)	(1.16)
Realized 1-month minus expected	-0.23	0.10	0.06	-0.01	0.02	-0.00	-0.03	-0.03	-0.04	0.04	-0.27
	(-0.56)	(0.45)	(0.40)	(-0.07)	(0.19)	(-0.02)	(-0.37)	(-0.43)	(-0.58)	(0.32)	(-0.84)
Realized return 5-years	0.23	0.21	0.16	0.15	0.13	0.12	0.10	0.09	0.10	0.14	0.09
	(0.79)	(1.03)	(1.01)	(1.11)	(1.14)	(1.17)	(1.17)	(1.15)	(1.03)	(1.03)	(0.53)
Realized 5-year minus expected	-0.29	-0.02	-0.01	0.01	0.02	0.03	0.02	0.03	0.07	0.27**	-0.56***
	(-1.00)	(-0.10)	(-0.06)	(0.07)	(0.18)	(0.29)	(0.23)	(0.38)	(0.72)	(1.99)	(-3.30)
Panel B: Equities											
Expected equity return	1.14	0.41	0.32	0.27	0.24	0.21	0.19	0.17	0.14	-0.14	1.27
Realized return 1-month	-0.87	0.66	0.83*	0.84**	0.90***	0.99***	0.88***	0.87***	0.78***	0.92**	-1.79***
	(-1.06)	(1.22)	(1.86)	(2.18)	(2.76)	(3.21)	(2.99)	(3.25)	(2.87)	(2.29)	(-3.35)
realized 1-month minus expected	-2.01**	0.25	0.52	0.57	0.66**	0.78**	0.69**	0.70***	0.64**	1.06***	-3.07***
	(-2.37)	(0.46)	(1.15)	(1.47)	(2.02)	(2.50)	(2.33)	(2.60)	(2.35)	(2.65)	(-5.57)
Realized return 5-years	0.30	0.60	0.73*	0.83**	0.88***	0.84***	0.83***	0.78***	0.80***	0.80**	-0.50
	(0.46)	(1.19)	(1.72)	(2.25)	(2.69)	(2.71)	(2.71)	(2.58)	(2.80)	(2.13)	(-1.47)
Realized 5-year minus expected	-0.84	0.19	0.41	0.56	0.64**	0.63**	0.64**	0.61**	0.66**	0.94***	-1.77***
	(-1.29)	(0.38)	(0.97)	(1.52)	(1.96)	(2.03)	(2.09)	(2.02)	(2.31)	(2.50)	(-5.20)

Table 5: Fama-MacBeth analysis

Each month, a cross-sectional regression of realized equity return on the corporate bond implied equity return ("expected equity return") and one or more interaction terms is conducted. Equity return and expected equity return are monthly and in percentages. Specifications 2 to 5 include interaction terms of ExpReturnEquity (ex-ante expected equity return) with dummies proxying the likelihood of mispricing. The dummies are constructed by each month splitting the universe in three equal sized buckets based on number of analysts following the stock, the turnover of the stock and the equity market cap. The base case is a stock with high number of analysts, high stock turnover and large equity market cap (i.e. least likely mispriced). The *t*-statistics use Newey and West (1987) robust standard errors with lag selection following Newey and West (1994). Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Sample period January 1994 to December 2015.

	1	2	3	4	5
constant	1.21***	1.22	1.21	1.23	1.23***
	(3.91)	(4.02)	(4.15)	(3.68)	(3.68)
expected equity return	-2.64***	-2.09***	-3.23***	-1.97***	-2.31***
	(-5.30)	(-3.13)	(-4.23)	(-2.37)	(-2.74)
[expected equity return] x [#analysts mid]		-0.70			-0.57
		(-1.22)			(-1.15)
[expected equity return] x [#analysts low]		-0.77			-0.58
		(-1.23)			(-1.03)
[expected equity return] x [stock turnover mid]			0.98*		0.80
			(1.83)		(1.63)
[expected equity return] x [stock turnover low]			0.93		0.81
			(1.44)		(1.30)
[expected equity return] x [equity mcap mid]				-0.44	-0.01
				(-0.55)	(-0.02)
[expected equity return] x [equity mcap low]				-0.90	-0.40
				(-0.89)	(-0.40)
Adj R2	2.7%	3.5%	3.7%	3.7%	5.2%
Number observations per month	685	685	685	685	685

Table 6: Fama-MacBeth regressions on factor characteristics

Each month, a cross-sectional regression of the monthly realized equity return (monthly bond-implied expected return) on various characteristics (winsorized at 1 and 99% percentile each month) is conducted:

1. FF3: 36-month beta to RMRF, log of equity market cap in millions USD, log of book to market ratio
2. FF6: FF3 + 12 minus 1-month momentum, operating profitability, investments

Equity return and expected equity return are monthly, in excess of the risk-free rate and in percentages. The *t*-statistics use Newey and West (1987) robust standard errors with lag selection following Newey and West (1994). Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Sample period January 1994 to December 2015.

Dependent variable	Realized equity returns		Expected equity returns		Realized minus expected returns	
Factor model	FF3	FF6	FF3	FF6	FF3	FF6
constant	0.52	-1.79	0.64***	0.15	-0.12	-1.94
	(0.61)	(-1.06)	(7.72)	(1.40)	(-0.14)	(-1.10)
Beta Mkt_RF	0.03	-0.60**	0.04***	0.05***	-0.01	-0.65**
	(0.25)	(-2.01)	(4.83)	(2.59)	(-0.07)	(-2.20)
Log(Mcap)	0.01	0.30**	-0.05***	0.00	0.05	0.30*
	(0.08)	(2.01)	(-5.82)	(0.27)	(0.69)	(1.91)
Log(Book-to-Market)	-0.14	-0.34	0.05***	0.04**	-0.19	-0.37
	(-1.20)	(-1.12)	(5.25)	(2.20)	(-1.62)	(-1.21)
Mom12_1M		1.56		-0.21***		1.77
		(1.45)		(-3.27)		(1.60)
Oper. Prof.		-0.79		0.20		-1.00
		(-0.68)		(1.19)		(-0.76)
Investments		0.06		0.03***		0.03
		(0.13)		(2.52)		(0.07)
Adj. R2	0.05	0.12	0.09	0.11	0.05	0.12
Nobs	627	530	627	530	627	530

Table 7: Decile portfolios based on expected equity return for sub periods

This table shows the returns and other characteristics of decile portfolios based on expected equity returns, where D1 contains the 10% highest expected equity returns and D10 the lowest 10% expected equity returns. D1-D10 is long the D1 portfolio and short the D10 portfolio. Expected equity returns are constructed as described in Section 3. The portfolios are monthly rebalanced and equal weighted. For each portfolio, the expected return, the realized return, realized minus expected return, the volatility of realized returns, the spread, expected bond return, elasticity and probability of default are shown. All returns and the credit spread are monthly and in percentages. The *t*-statistics use Newey and West (1987) robust standard errors with lag selection following Newey and West (1994). Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Panel A reports the first 11 years and Panel C the final 11 years of the sample

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10
Panel A: Jan 1994 – Dec 2004											
Expected return	1.37	0.40	0.30	0.26	0.23	0.21	0.19	0.18	0.15	-0.07	1.43
Realized return	-1.25	0.69	0.93**	0.87**	0.88**	0.99***	0.91**	0.92***	0.78**	1.06**	-2.31***
t-stat vs 0	(-1.24)	(1.15)	(2.07)	(2.20)	(2.19)	(2.90)	(2.47)	(2.71)	(2.18)	(2.34)	(-3.32)
realized minus expected return	-2.61**	0.29	0.63	0.61	0.65	0.78**	0.71*	0.75**	0.63*	1.13**	-3.74***
t-stat vs expected return equity	(-2.45)	(0.48)	(1.39)	(1.53)	(1.60)	(2.25)	(1.92)	(2.18)	(1.75)	(2.47)	(-4.90)
Panel B: Jan 2005 – Dec 2015											
Expected return	0.90	0.42	0.33	0.28	0.24	0.21	0.19	0.16	0.12	-0.21	1.11
Realized return	-0.50	0.63	0.73	0.80	0.92*	0.99*	0.86*	0.82**	0.78*	0.78	-1.28
t-stat vs 0	(-0.38)	(0.70)	(0.94)	(1.22)	(1.78)	(1.92)	(1.85)	(1.97)	(1.91)	(1.17)	(-1.60)
realized minus expected return	-1.41	0.21	0.40	0.52	0.67	0.77	0.67	0.66	0.66	0.98	-2.39***
t-stat vs expected return equity	(-1.08)	(0.23)	(0.51)	(0.79)	(1.30)	(1.50)	(1.44)	(1.57)	(1.59)	(1.50)	(-3.11)

Table 8: Robustness top-bottom decile portfolio results

This table shows the returns of decile portfolios based on expected equity returns. There are six specifications:

1. Base case (as in Table 3)
2. Market value weighted stock positions (instead of equal weighted)
3. Sort on expected bond returns
4. Elasticity is based on past 12-month OLS of realized equity returns on realized credit returns (instead of pooled panel regression)
5. Probability of default estimated using the Campbell, Hilscher and Szilagyi (2008; CHS) model rather than implementation of Merton's (1974) model
6. Probability of default using long-term cumulative default rates per credit rating over the period 1920-2014 (Moody's, 2015, Exh. 32).
7. Sort on credit spread

For each portfolio, the expected return, the realized return, realized minus expected return, the volatility of realized returns, the spread, expected bond return, elasticity and probability of default are shown. The expected returns are computed as described in Section 4.1, except for specifications 4, 5, 6, where the expected equity return follows the modification. All returns are monthly and in percentages. The *t*-statistics use Newey and West (1987) robust standard errors with lag selection following Newey and West (1994). Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Sample runs from January 1994 to December 2015.

Specification	1	2	3	4	5	6	7
Expected return	1.27	0.76	0.98	1.87	1.61	1.35	0.80
Realized return	-1.79***	-1.10*	-1.03**	-0.85**	-0.24	-1.87***	-1.48**
t-stat vs 0	(-3.35)	(-1.68)	(-2.21)	(-2.17)	(-0.34)	(-2.81)	(-2.16)
realized minus expected return	-3.07***	-1.86***	-2.01***	-2.72***	-1.84***	-3.22***	-2.29***
t-stat vs expected return equity	(-5.57)	(-2.89)	(-4.10)	(-6.50)	(-2.60)	(-4.72)	(-3.24)

Table 9: Expected equity return top-bottom portfolios within risk groups

Each month, the universe is split in five groups according to a risk measure. The risk measures are (1) the credit spread of the bond, (2) the probability of default as described in Section 3.2, (3) the credit rating, (4) the past 1-month daily return equity volatility and (5) the equity market beta which is computed by regressing the past 36 month stock returns on the RMRF factor provided by Kenneth French. Within each group, an equal weighted long-short portfolio is constructed by going long (short) the 20% highest (lowest) expected equity returns stocks. The table reports the mean monthly realized return in percentages and the associated *t*-statistic which uses Newey and West (1987) robust standard errors with lag selection following Newey and West (1994). Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Sample runs from January 1994 to December 2015.

	High risk	2	3	4	5 (low risk)
Credit spread	-2.79***	-0.67***	-0.21	0.11	0.06
	(-4.91)	(-3.01)	(-1.02)	(0.63)	(0.44)
Probability of default	-2.89***	-1.35***	-0.07	-0.29	0.47
	(-4.56)	(-3.05)	(-0.23)	(-1.27)	(1.40)
Credit rating	-3.50***	-0.49	-0.07	0.15	0.15
	(-5.05)	(-1.54)	(-0.22)	(0.66)	(0.84)
Equity volatility	-2.93***	-0.35	-0.53**	-0.23	0.14
	(-5.16)	(-0.87)	(-2.16)	(-1.40)	(0.88)
Equity RMRF beta	-1.59***	-0.63*	-0.84***	-0.46	-1.55***
	(-2.99)	(-1.88)	(-2.62)	(-1.30)	(-2.90)

Table 10: Liquidity of the expected return portfolios

This table shows liquidity characteristics for the ten decile portfolios sorted on expected equity returns as in Table 3, where D1 contains the 10% highest expected equity returns and D10 the lowest 10% expected equity returns. The *monthly turnover* is computed per month and per portfolio as the total trading volume in TRACE divided by the total notional amount outstanding of the bonds, and subsequently averaged over time. The *round-trip cost* is computed per bond per month as the average bid-ask spread of all customer-to-customer round trips that occur within 24 hours, and then averaged over all bonds in the portfolio and subsequently over time. The *bond liquidity premium per month* is the product of the monthly turnover and the average round-trip cost. The last row shows the implied liquidity premium in the expected bond return by multiplying the bond liquidity premium with the average elasticity. The data runs from January 2005 to December 2015.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Monthly turnover	14.3%	9.9%	8.7%	7.9%	7.4%	7.3%	7.3%	8.7%	8.4%	9.6%
Round-trip cost	0.37%	0.28%	0.24%	0.24%	0.23%	0.22%	0.21%	0.20%	0.23%	0.24%
Bond liquidity premium per month	0.052%	0.028%	0.021%	0.019%	0.017%	0.016%	0.016%	0.017%	0.020%	0.023%
Liquidity premium in expected equity return	0.082%	0.031%	0.020%	0.017%	0.014%	0.013%	0.012%	0.013%	0.016%	0.029%
Expected equity return before liquidity premium	1.14	0.41	0.32	0.27	0.24	0.21	0.19	0.17	0.14	-0.14
Expected equity return after liquidity premium	1.06	0.38	0.30	0.25	0.23	0.20	0.18	0.16	0.12	-0.17

Table 11: Expected equity return top-bottom portfolio factor regressions

The D1-D10 expected equity return portfolio is constructed as described in Table 3. The realized returns of this portfolio (R) are regressed on one or more factors denoted by F: $R = \alpha + \beta \boldsymbol{F} + \varepsilon$. For $\boldsymbol{F}$ we use the following specifications:

1. RMRF
2. RMRF, SMB, HML
3. RMRF, SMB, HML, MOM
4. RMRF, SMB, HML, RMW, CMA
5. RMRF, SMB, HML, RMW, CMA, MOM
6. RMRF, SMB, HML, MOM, QMJ
7. RMRF, SMB, HML, MOM, RMW, CMA, QMJ

The factor series are obtained from the website of Kenneth French, except for QMJ which is obtained from the website of AQR (Quality Minus Junk, Asness, Frazzini and Pedersen, 2014). The table reports the monthly alpha in percentages, the coefficients β and all associated robust *t*-statistics following Newey and West (1987, 1994). Sample period is January 1994 to December 2015.

	1 (CAPM)	2 (FF3)	3 (FF3-Carhart)	4 (FF5)	5 (FF5-Carhart)	6 (FF3-Carhart - QMJ)	7 (FF5-Carhart-QMJ)
Alpha realized	-2.30***	-2.36***	-1.78***	-1.65***	-1.30***	-1.13***	-1.09***
	(-5.49)	(-5.87)	(-5.06)	(-3.70)	(-3.66)	(-3.14)	(-2.88)
Mkt_RF	0.83***	0.74***	0.44***	0.45***	0.26**	0.18	0.17
	(6.07)	(5.62)	(4.90)	(3.84)	(2.57)	(1.56)	(1.31)
SMB		0.63***	0.72***	0.33**	0.45***	0.31*	0.32**
		(5.26)	(4.78)	(2.18)	(3.33)	(1.93)	(2.19)
HML		0.04	-0.24	0.69***	0.21	-0.24	0.06
		(0.17)	(-1.16)	(2.58)	(1.23)	(-1.34)	(0.35)
MOM			-0.74***		-0.69***	-0.64***	-0.65***
			(-6.26)		(-6.36)	(-5.95)	(-6.37)
RMW				-1.12***	-0.91***		-0.55**
				(-4.79)	(-4.14)		(-2.43)
CMA				-0.72	-0.38		-0.29
				(-1.42)	(-1.19)		(-0.97)
QMJ						-0.52***	-0.31**
						(-3.70)	(-2.03)
Adj. R2	0.23	0.30	0.52	0.38	0.57	0.57	0.57

Figure 1: Distribution fitted elasticities

The following pooled panel OLS regression is estimated:

$$\frac{\delta E}{E}\Big/\frac{\delta B}{B} = c + \beta_{LEV}LEV + \beta_{VOL}VOL + \beta_{y_g}y_g + \beta_T T + \varepsilon$$

where $\frac{\delta E}{E}/\frac{\delta B}{B}$ is the observed elasticity measured over the month (winsorized top and bottom 5%); all right hand variables are known as of the beginning of the month: *LEV* is the leverage ratio *B/V*, *VOL* is the past 1-month annualized stock return volatility (winsorized top 5%), y_g the duration matched Treasury yield and *T* the time-to-maturity. The figure reports the distribution of the fitted elasticities, winsorized at the 0.5% and 0.995% quantiles.

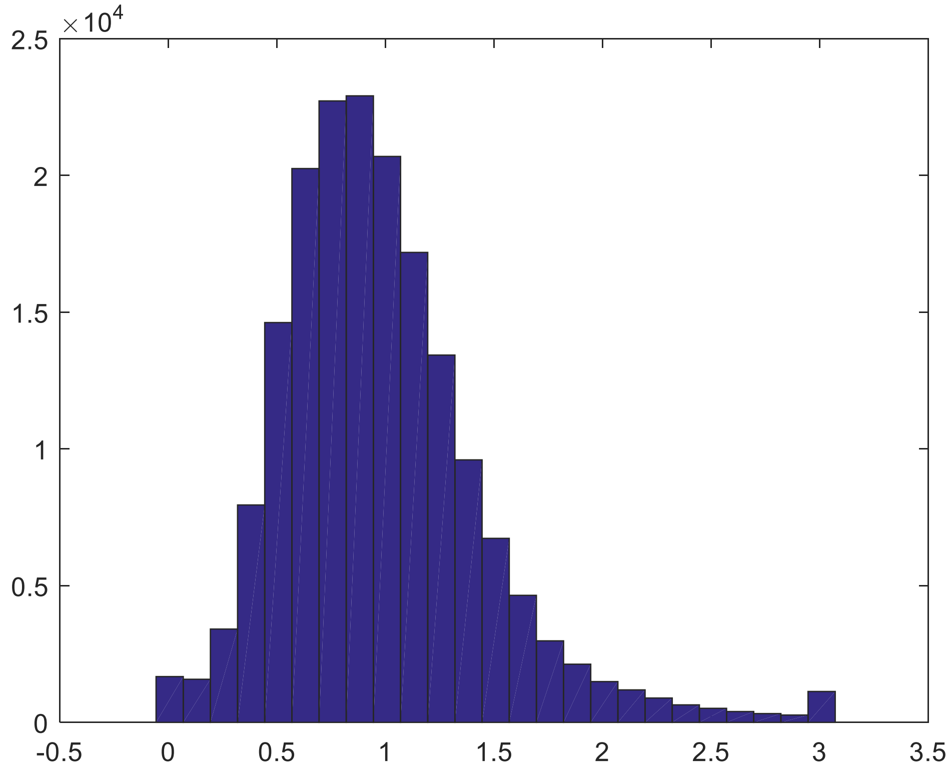


Figure 2: Average expected bond and equity returns through time

This figure reports the monthly expected bond return over duration matched Treasuries and the expected equity return over the 1-month T-bill following the methodology in Section 3. Sample from January 1994 to December 2015.

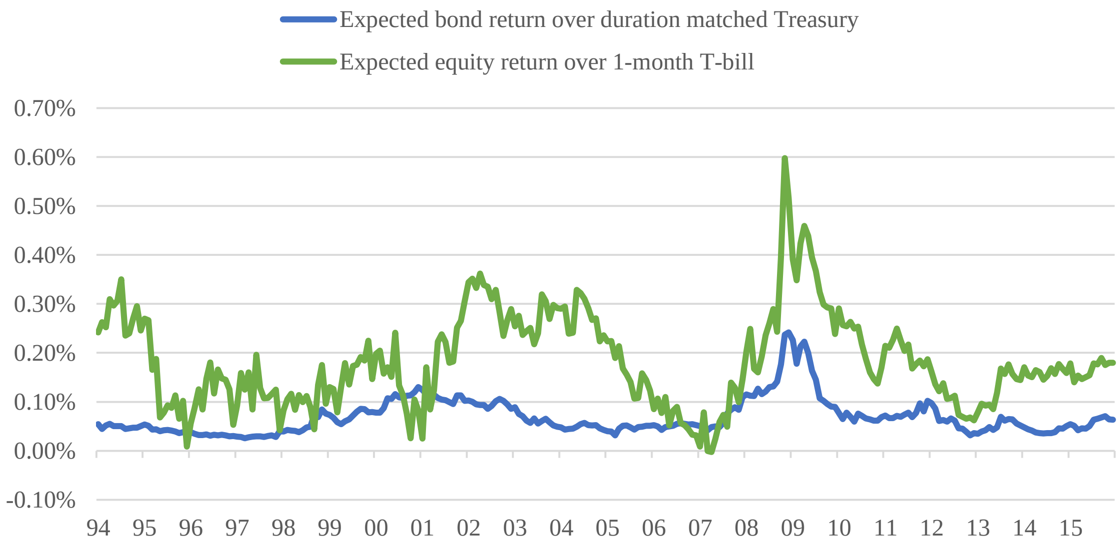


Figure 3: Cumulative log realized and bond-implied expected equity returns of the D1-D10 bond-implied expected equity return portfolio.

The D1-D10 expected equity return portfolio is constructed as described in Table 3. Sample from January 1994 to December 2015.

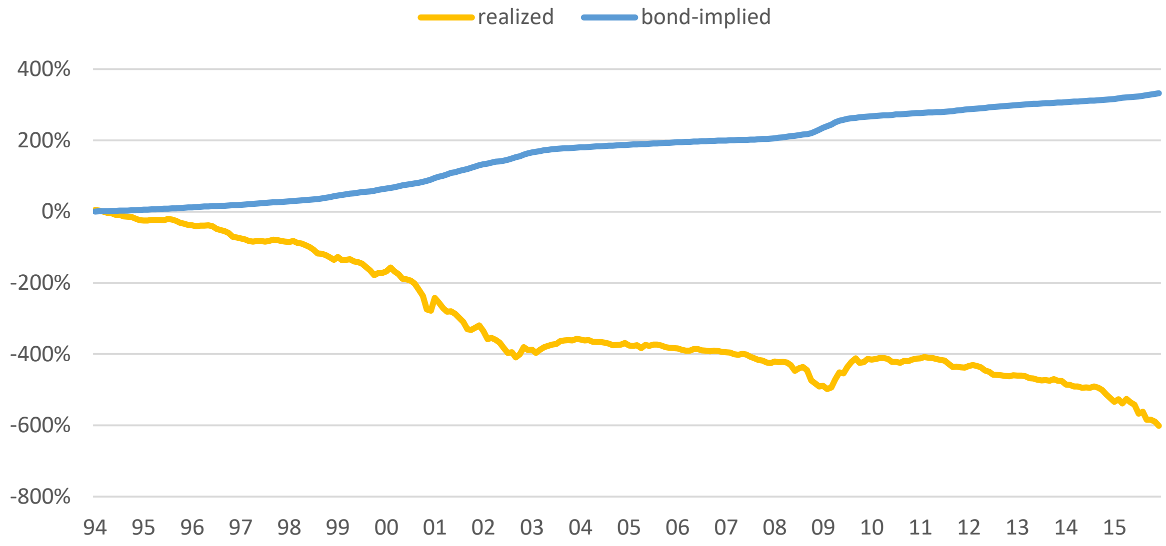
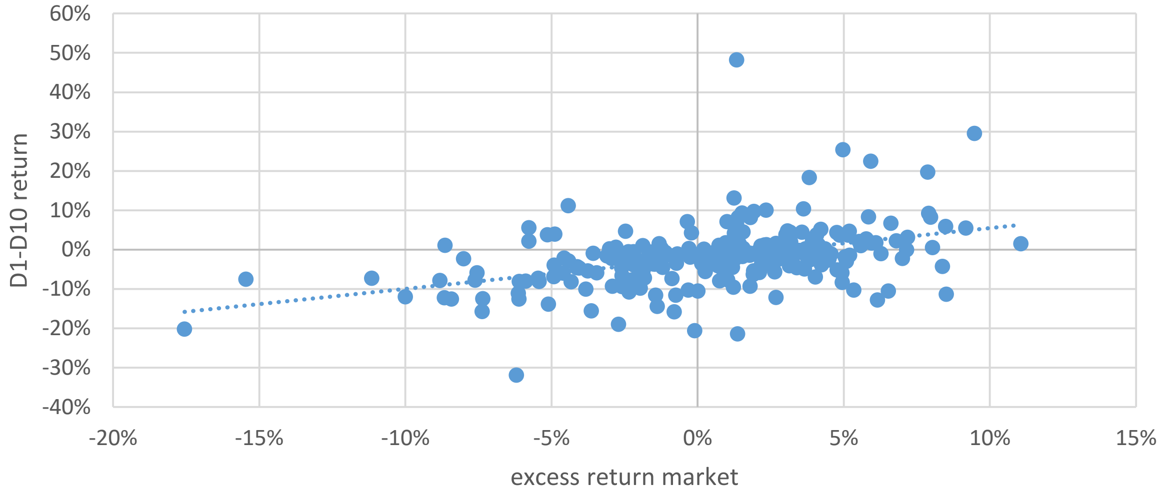


Figure 4: Relation D1-D10 expected equity return portfolio with stock market return

This figure plots the monthly realized equity return of the stock market over the 1-month T-bill to the D1-D10 expected equity return portfolio monthly realized returns following the methodology in Section 3. Sample from January 1994 to December 2015.



Appendix A – Data

A.I - Linking bond to stock data

In principle, linking bonds to stocks is straightforward. At bond issuance, the first six digits of the bond CUSIP should match the first six digits of issuer's historical CUSIP. The seventh and eight digit of the CUSIP identify the specific security of the issuer; the last digit is a check digit. Hence one could match on the first six digits of the CUSIP. However, due to mergers, acquisitions, bankruptcies and other delisting reasons this might not work. Therefore, we match a bond to a company at issuance, and then follow it through time. Example:

Feb 16, 1993, MOBIL CORP issues MOBIL CORP 02/23/2033 (CUSIP: 607059AZ). Matching on the first six digits with CRSP's NCUSIP field leads to a match with PERMCO 21211 (CUSIP: 6075910), company name MOBIL CORP in CRSP. For this bond, from issuance we assign this PERMCO until it does not exist anymore. This happens in November 1999, when EXXON and MOBIL merge into EXXON MOBIL. CRSP has an ACPERM field which indicates that the stock has been taken over by PERMNO 11850, which belongs to the combined EXXON MOBIL entity (PERMCO 11850). From December 1999 onwards, the bond is assigned to PERMCO 11850, and the process is repeated until the bond expires.

Note that a single company (PERMCO) might have multiple stock listings (PERMNO). We always assign a bond to a PERMCO, hence a bond can be assigned to multiple stock listings (PERMNO) at the same time.

Our procedure thus consists of two steps:

1. For each bond, identify the issuing company in CRSP. If no match is found using the first six digits of the CUSIP, try to hand-match data using the company names in the bond and stock data sets. If still no match is found, the bond is not linked to any stock in CRSP.

2. If a PERMCO has been found at issuance, follow it in CRSP from the moment of bond issuance until either
    a. The bond matures.
    b. The stock is delisted. In this case verify why it is delisted. If an acquiring company is known (ACPERM), continue by following this company and repeat. Otherwise the link stops.

A.II – Inputs for Merton (1974) probability of default

In this section the exact definitions of the variables using CRSP and COMPUSTAT fields are given. All fields are from COMPUSTAT except SHROUT, PRC and RET. All COMPUSTAT data is lagged two months to account for the reporting lag.

- Value of the firm (V) = market value equity + book value total liabilities
    - Market value equity: SHROUT * |PRC| / 1000 (in millions USD)
    - Book value total liabilities: LTQ
- Default barrier (D): LTQ
    - Feldhütter and Schaefer (2016) find that this choice for the default barrier fits historical probabilities of default well.
- Drift rate (μ) = $y_{g,t}$ + θ σ,
    - $y_{g,t}$: duration matched Treasury yield from Barclays
    - θ = 0.22 following Feldhütter and Schaefer (2016) and Chen, Collin-Dufresne and Goldstein (2009)
    - σ: asset volatility; see below.
- Payout ratio (δ) = (Interest payments - Net stock repurchases + dividends) / V.
    - The ratio is capped at 0.13 following Feldhütter and Schaefer (2016).
    - Interest payments: previous fiscal year's fourth quarter INTPNY
    - Dividends: DVPSXQ x SHROUT / 1000

- Net stock repurchases: previous fiscal year's fourth quarter PRSTKCY

- Time to maturity (T) = option adjusted duration of the corporate bond
- Asset volatility (σ) = (1-D/V) x σ^E x c
    - *D* and *V* as given above
    - σ^E : based on past 1-month daily stock return (RET) volatility; extrapolated using the method as described in Section 3
    - c: coefficient to adjust for bond volatility following Feldhütter and Schaefer (2016), ranging from 1 to 1.8.

A.III – Inputs for the hazard rate model

In this section the exact definitions of the variables using CRSP and COMPUSTAT fields are given. All fields are from COMPUSTAT except SHROUT, PRC and RET. All COMPUSTAT data is lagged two months to account for the reporting lag.

- market value total assets: book value total liabilities (LTQ) plus market cap equity (SHROUT * |PRC| / 1000)
- NIMTAAVG: weighted average over the past four fiscal quarters of NIMTA, where a weight of 1 is assigned the most recent quarter, 0.5 to the quarter before, 0.25 to the third most recent quarter and 0.125 for the first quarter.
- NIMTA: net income (NIQ) to market value of total assets
- TLMTA: total liabilities (LTQ) to market value of total assets
- EXRET: past 12-month stock return (RET) over the S&P500 (obtained from Bloomberg)
- SIGMA: past 3-month stock return (RET) volatility
- RSIZE: log of the ratio of the market cap of the stock (SHROUT * |PRC| / 1000) to the market cap of the S&P500 (obtained from Bloomberg)
- CASHMTA: cash and cash equivalents (CHEQ) to market value of total assets

- MB: ratio of market value of total assets to book value of assets (ATQ), where for the latter 10% of the difference between the market value of equity and book value of common equity (CEQQ) is added. In case book value of equity is negative, we divide by $1+book value liabilities (LTQ) instead (i.e., the book value of equity cannot be below $1).
- PRICE: log of the stock price, where the price is winsorized at $15.

A.IV – Construction risk characteristics

In this section the exact definitions of the variables using CRSP and COMPUSTAT fields are given. All fields are from COMPUSTAT except SHROUT, PRC and RET. All COMPUSTAT data is lagged two months to account for the reporting lag.

- Beta Mkt_Rf: the beta is obtained by regressing the past 36-month equity returns from CRSP on the RMRF factor provided by Kenneth French. If less than 18 out of the 36 months are available, no beta is estimated.
- Log(Mcap): log of total market capitalization of all common stocks outstanding (SHROUT * |PRC| / 1000).
- Log(Book-to-Market): log of the ratio of book value equity (including deferred taxes; CEQQ + TXDBQ) to market value equity (SHROUT * |PRC| / 1000). If book and/or market value are zero, no value is computed.
- Mom12_1M: the stock return (RET) over the past 12 months, skipping the most recent month to account for short-term reversals.
- Oper. Prof: revenues (SALEQ) minus cost of goods sold (COGSQ) minus selling, general and administrative expenses (XSGAQ) minus interest expense (INTPNY) over the quarter, divided by the book value of equity.
- Investments: book value of assets (ATQ) as of now minus the book value of assets 12 months ago divided by the book value of assets 12 months ago.

Appendix B – Estimating the probability of default

To assess the accuracy of our estimated probabilities of default, we compare the 5-year probabilities from the Merton (1974) and Campbell et al. (2008) hazard rate model (hereafter: CHS) through time and in the cross section with realized default data from Moody's (2015). We use a 5-year horizon, as this is the average time-to-maturity of the bonds in our sample. As noted by Feldhütter and Schaefer (2016), default models should be calibrated to long-run averages of default rates, not to realizations over a short period of time. For instance, if we would compare the 5-year expectations of the models with 5-year realized default rates at January 2005, we would find a severe underestimation, because the realized rates will include the Great Financial Crisis in 2008/2009. It is unlikely market participants anticipated this event at the start of 2005.

Figure B.1 reports the average 5-year cumulative probabilities of default through time, and compared with the long-run average based on 1920-2014 Moody's (2015) data ("average 1920-2014").[23] Both models show substantial variation in probability of default levels through time, with clear increases visible for the dot-com bubble (1999-2003) and the great financial crisis (2008-2009). We find that the average level is higher for the Merton model, and better matches the historical average. In contrast, the CHS model is consistently below the historic average.

Table B1 reports the average levels through time per credit rating for the 5-year horizon. We find that the Merton model (10.03%) matches the long-run average of 9.44% probability of default well. Moreover, the model is able to capture the strong increase in default rates when credit ratings deteriorate, although estimated probabilities are a bit too high for AAA to BBB

[23] The default rates are constant through time per credit rating; the average probability of default fluctuates due to changes in the credit rating composition of the universe.

rated firms. The CHS model, on the other hand, underestimates default rates considerably for BB and lower rated bonds, leading to an overall substantial underestimation (3.61% versus 9.44%).

Figure B.1: Average 5-year cumulative probability of default through time

Average 5-year probability of default for the Merton (1974) model implementation and the Cambell, Hilscher and Szilagyi (2008; CHS) hazard rate model; equal weighted. *Average 1920-2014* is the average cumulative 5-year default rate for a bond given its credit rating using data from Moody's (2015). Fluctuations in this series are caused by a changing credit rating composition of the universe. Sample period January 1994 to December 2015.

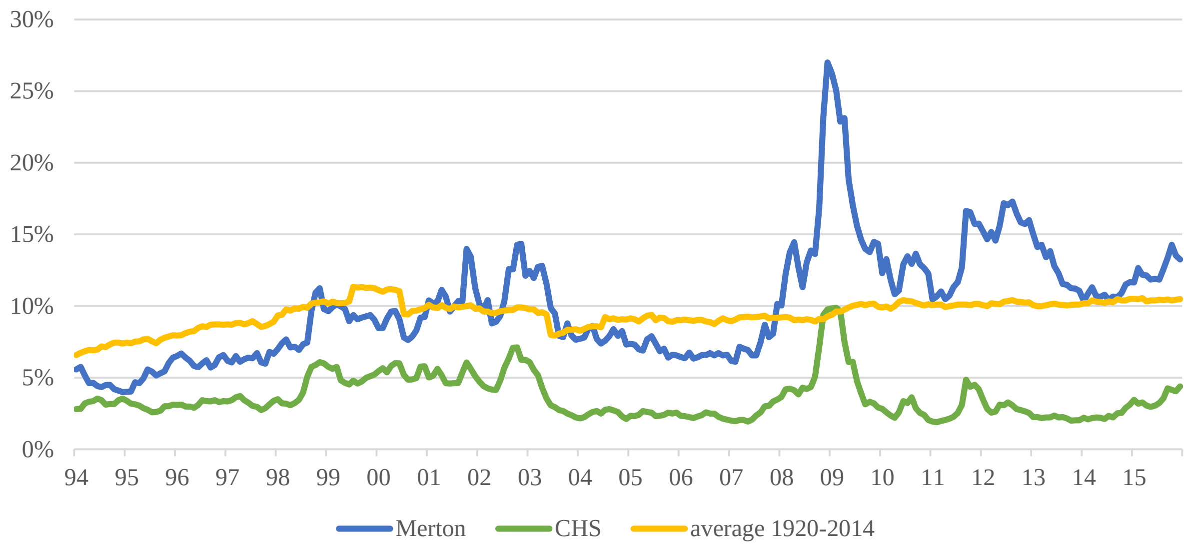


Table B.1: Cumulative 5-year probability of default per credit rating

Long-run average: 1920-2014 based on data of Moody's (2015, exhibit 32).

model	Avg.	AAA/AA	A	BBB	BB	B	CCC/CC/C
Merton	10.03%	2.14%	2.83%	4.69%	9.39%	19.61%	35.81%
CHS	3.61%	1.86%	2.09%	2.45%	3.36%	5.38%	10.38%
Long-run average	9.44%	0.70%	1.37%	2.87%	9.34%	20.54%	39.77%

Appendix C – Estimating volatility over long horizons

To estimate the degree of mean reversion of stock return variance, we estimate per firm an AR(1) time series model:

$$\sigma_E{}^2{}_t - \gamma = \theta(\sigma_E{}^2{}_{t-12} - \gamma) + \varepsilon_t \tag{C.1}$$

where $\sigma_E{}^2{}_t$ is the squared stock return volatility over month t using daily stock returns from CRSP, γ the long run average parameter and θ the mean reversion parameter. We estimate this equation using standard Ordinary Least Squares. We use as explanatory variable the volatility 12 months ago, not the most recent month, to capture the long-run dynamics of volatility, as our typical horizon is five years due to choosing bonds closest to the 5-year point.

Per firm, we estimate Equation C.1 for each of the 12 calendar months, with the restriction that at least 10 observations are required. As this effectively requires at least 10 years of stock return data, not all firms have an estimate for theta. Therefore, we average all thetas across all twelve calendar months per firm, and then over all firms. This results in an average $\hat{\theta}$ of 0.8735. Figure C.1 shows the distribution of the thetas across the firms, showing that most firms have thetas in the 0.80 to 0.95 range. Thus, the average of 0.8735 is a close approximation for most firms in our data set. For the long run mean γ, we take into account that some firms are riskier than others by using the average stock return variance of all observations with the same credit rating.[24] Per credit rating, we compute per month the median variance (not mean, to prevent outliers affecting our results) of all stocks with this rating, and then average over time to obtain the long-run mean. Table C.1 shows the long-run mean parameter per credit rating. It increases from 0.1078 to 1.0214 when moving from rating AAA/AA to CCC-C.

[24] The credit rating is of the selected (senior unsecured) bond.

The expected equity volatility over the horizon T is then given by:

$$\widehat{\sigma_{E,t,t+T}} = \frac{1}{12T}\sqrt{\sum_{k=1}^{12T}\widehat{\sigma_E{}^2{}_{t+k}}} = \frac{1}{12T}\sqrt{\sum_{k=1}^{12T}\hat{\gamma} + \hat{\theta}^{k/12}(\sigma_E{}^2{}_t - \hat{\gamma})} \tag{C.2}$$

where $\sigma_E{}^2{}_t$ is the past 1-month daily equity return variance and $\hat{\gamma}$ and $\hat{\theta}$ are the parameter estimates.

Table C.1: Long-term average variance parameter

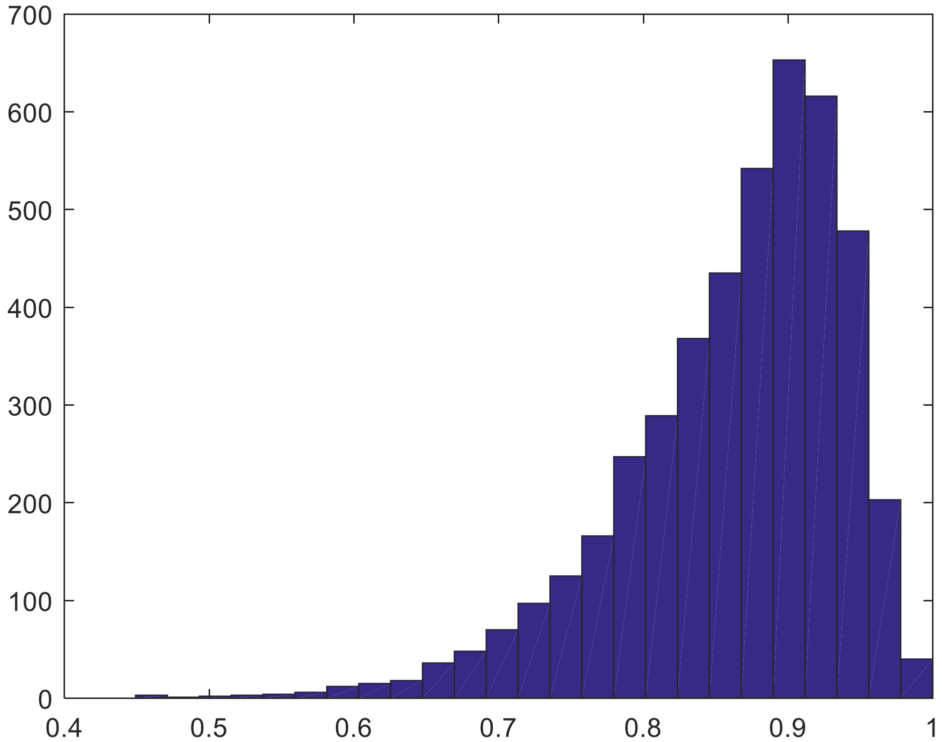
Rating	AAA/AA	A	BBB	BB	B	CCC-C
gamma	0.1078	0.1162	0.1349	0.2113	0.3938	1.0214

Figure C.1: Distribution mean-reversion parameter equity return variance

Per stock, we estimate for each calendar month the following regression using OLS:

$$\sigma_E{}^2{}_t - \gamma = \theta(\sigma_E{}^2{}_{t-12} - \gamma) + \varepsilon_t$$

where $\sigma_E{}^2{}_t$ is the squared stock volatility over month t using daily stock returns from CRSP, γ the long run average parameter and θ the mean reversion parameter. For each stock, we take the average over the 12 θ's. The figure shows the distribution of thetas, where thetas below zero or above 1 are excluded.



Appendix D – Equity-bond elasticity

For each firm and each month, we determine the change in market value of equity (E) and market value of debt (B) over the month. The market value of debt is estimated by the book value of total liabilities multiplied by the ratio of the corporate bond price and its nominal value (100 usually). In this way, the monthly change in the market value of debt reflects the change in corporate bond market prices, which is important to capture the elasticity properly. If we would take book values, there would be many months with zero debt return.

We can calculate the realized elasticity, $\frac{\delta E}{E} / \frac{\delta B}{B}$, for each month and each firm. We find that this is very noisy, and as bond returns can be zero (which happens for 3.68% of all observations) or close to zero, there can be extreme values as the distribution in Table D.1 shows. Instead of directly plugging in the most recently observed, potentially extreme, elasticity we follow Campello et al. (2008) by regressing these realized elasticities on variables suggested by the Merton (1974) model using Ordinary Least Squares. To prevent the outliers from distorting the fit, we exclude those observations which have an elasticity in the top or bottom 5% (i.e., bond return is close to zero, hence hard to infer the elasticity between the bond and the equity), or an equity volatility in the top 5% (which corresponds with a volatility of 90.63% per annum). Together, this removes 14.41% of all observations from the estimation of the coefficients. To check for the robustness of the estimation, we run four separate estimations, using either 2.5%, 5% (the base case), 7.5% or 10% as the threshold; see Table D.2. We find that the coefficients differ not much from one estimation to another.

We have also considered various alternative regression specifications. In particular, Kronmal (1993) suggests for regressions involving ratio's on the left-hand side to move the denominator to the right hand side, and use a Weighted Least Squares approach where the weight is the inverse of the denominator to correct for the change in definition of the error term. However, in our setting the bond return is the denominator, and negative and zero values are perfectly valid. Hence this is not an option, as it would result in observations with infinite weight.

Taking all considerations into account, the OLS fit seems the best option available. To ensure our conclusions are not driven by this particular choice, we have also included results for two alternative equity-bond elasticity:

1. Use the past 12-month observed bond-equity elasticity,
2. Assume the elasticity to be one for all firms.

Neither these alternatives changes our conclusion that there is a distress risk puzzle.

Table D.1: Percentiles observed equity-bond elasticity full panel

Percentile	<1.5	2	2.5	3	4	5	95	96	97	97.5	98	>98.5
Elasticity	-inf	-361.24	-137.52	-85.84	-50.35	-35.62	42.12	59.81	105.83	192.42	1,732.96	+inf

Table D.2: Coefficients panel OLS regression for various thresholds

threshold		constant	LEV	VOL	y_g	T	Adj R2	# obs
2.5%	coefficient	1.20***	0.79**	0.76	-2.61	-0.10*	0.02%	166311
	t-stat	(2.59)	(2.00)	(1.27)	(-0.35)	(-1.88)		
5%	coefficient	0.63**	1.00***	1.09***	-3.54	-0.09***	0.15%	153527
	t-stat	*(2.08)*	*(4.85)*	*(2.44)*	*(-0.71)*	*(-3.24)*		
7.5%	coefficient	0.48*	0.85***	1.10***	-2.79	-0.07***	0.22%	141173
	t-stat	*(1.92)*	*(5.40)*	*(2.77)*	*(-0.67)*	*(-3.47)*		
10%	coefficient	0.35*	0.80***	1.01***	-1.83	-0.05***	0.26%	129216
	t-stat	*(1.68)*	*(6.16)*	*(2.85)*	*(-0.55)*	*(-3.24)*		

References

Kronmal, R. A., 1993. Spurious correlation and the fallacy of the ratio standard revisited. Journal of the Royal Statistical Society. Series A (Statistics in Society), 379-392.