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The q-factors and expected bond returns[☆]

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ABSTRACT

This study provides new insight into the recent debate on profitability and investment patterns in the cross-section of expected returns. Relying on implied risk premia of U.S. corporate bonds, we document a strong negative relation between exposure to the profitability factor and cost of debt. We do not observe a robust relation between exposure to the investment factor and cost of debt. Our findings are consistent with profitability being a risk factor, but suggest that high profitability implies lower (and not higher) risk. Because the market portfolio consists of all risky assets including corporate bonds, our findings challenge a risk-based explanation for the profitability and investment patterns in stock returns.

1. Introduction

A substantial amount of empirical research shows that measures of firm profitability and investment have explanatory power for the cross-section of future stock returns.[1] High profit firms tend to outperform low profit firms and high investment firms tend to underperform low investment firms. Fama and French (2015) and Hou et al. (2015b) point out that these profitability and investment patterns in stock returns can arise under rational pricing, i.e., they may reflect some priced risk factors. As a consequence, Fama and French (2015) enrich their traditional three-factor model with two additional factors for profitability and investment. Hou et al. (2015b) design a q-factor model containing a size, a profitability, and an investment factor, which they show is able to explain a significant portion of other remaining stock market anomalies. However, to what extent the return predictability associated with profitability and investment is indeed consistent with market efficiency is heavily debated.[2] In this respect, Hou et al. (2015b, p. 685) highlight "the importance of understanding the driving forces behind the q-factors and their broad empirical power in the cross section."

We rely on a sample of U.S. corporate bonds from 1995 to 2011 and examine how exposure to the q-factors is priced by corporate bond investors. While there is little evidence to what extent profitability and investment effects translate to the corporate bond sector, our analysis is important for several reasons: First, the cor-

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[1] A non-exhaustive list of studies focusing on the profitability effect includes Haugen and Baker (1996), Abarbanell and Bushee (1998), Piotroski (2000), Griffin and Lemmon (2002), Mohanram (2005), Piotroski and So (2012), Frazzini et al. (2013), Novy-Marx (2013), Asness et al. (2014), and Ball et al. (2015). Empirical work on the investment effect includes Titman et al. (2004), Bradshaw et al. (2006), Cooper et al. (2008), Xing (2008), and Watanabe et al. (2013), among others. See Hou et al. (2016) for recent evidence on the pricing of the q-factors in the cross-section of U.S. stock returns.

[2] See Maio and Santa-Clara (2012), Stambaugh et al. (2012), Watanabe et al. (2013), and Penman and Zhang (2016) for existing mixed evidence.

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porate bond market constitutes an important segment of financial markets with outstanding assets of more than US$ 8.1 trillion by the end of June 2015.[3] Second, the market is characterized by a dominance of institutional investors which are likely to be more sophisticated than individuals (e.g., Bessembinder et al., 2005; Edwards et al., 2007). Third, and most importantly, the bond market allows us to provide new insight into the risk versus mispricing debate by relying on a simple argument: The market portfolio consists of all risky assets and therefore includes corporate bonds (see Roll, 1977). Rational asset pricing predicts that any security with positive exposure to a risk factor should have, all else equal, higher expected returns to compensate for this risk exposure. Hence, our main testable hypothesis is that, according to the risk-based explanation, there is a positive relation between expected bond returns and exposure to the q-factors.

Unlike most existing empirical studies, which rely on ex-post realized returns, we use an ex-ante proxy for expected bond returns in our asset pricing tests. Fama and French (2006) argue that tests based on realized returns are insufficient for a conclusive contest between the risk-based explanation and mispricing. Furthermore, realized returns can deviate from expected returns even for reasonably long sample periods (see e.g., Merton, 1980; Elton, 1999; Pastor et al., 2008). In contrast, the general relation between a forward-looking return measure and systematic risk factors should hold in every period, even though its strength may vary due to fluctuations in investors' risk tolerance. We extract this ex-ante measure, which we denote as implied risk premium or *IRP*, from corporate bond credit spreads. We thereby follow prior literature and remove components such as the compensation for expected losses to derive a measure related to a firm's systematic risk exposure (see e.g., Elton et al., 2001; Longstaff et al., 2005; Campello et al., 2008; Huang and Huang, 2012; Bongaerts et al., 2017).

In the empirical analysis, we run regression models including firm characteristics and factor loadings simultaneously to explain expected bond returns. Such characteristics versus covariances tests have been used in prior work related to *realized* returns in order to distinguish between the systematic component of a firm characteristic (i.e., its factor loading) and its idiosyncratic (firm-specific) component (see e.g., Daniel and Titman, 1997; Davis et al., 2000; Gebhardt et al., 2005a; Hirshleifer et al., 2012). Because it is the comovement with the risk factor and not the firm characteristic per se which should determine the risk premium according to rational asset pricing, characteristics versus covariances tests can help to investigate whether risk or mispricing provides a better explanation for return patterns.[4] In our context, according to the risk-based explanation, we expect loadings on the profitability and investment factor to be significantly related to the *IRP* even after controlling for corresponding firm characteristics.

Our major findings for the new asset pricing factors are as follows. With regard to profitability, we document a statistically and economically significant negative relation between the *IRP* and both the firm characteristic and the factor exposure. While the negative relation between the *IRP* and the factor exposure holds for the Hou et al. (2015b) profitability factor (denoted *ROE*) as well as for the Fama and French (2015) profitability factor (denoted *RMW*), the influence of *ROE* is almost twice as large in economic terms. This suggests that *RMW* is a noisy version of *ROE* as argued by Hou et al. (2015a). In fact, we find that exposure to the *ROE* factor is one of the strongest determinants of implied bond risk premia.

We also find that the negative relation between profitability factor exposure and expected returns is substantially more pronounced in economic downturns in which investors should require a higher compensation for holding risky assets (see e.g., Cochrane, 2008). We find similar results in periods of low-investor sentiment and high issuer quality for which recent findings suggest that rational risk-return considerations are more likely to prevail (see e.g., Stambaugh et al., 2012; Antoniou et al., 2016; Greenwood and Hanson, 2013). For bonds with shorter remaining maturities, i.e., when the implied risk premia are closer to the definition of next-period ahead returns, we observe a more pronounced negative influence of the profitability factor exposure as well.

For investment, the influence of the firm characteristic and the factor exposure on bond risk premia is economically weak and often statistically insignificant. This finding holds for both the Hou et al. (2015b) investment factor (denoted *IA*) as well as for the Fama and French (2015) investment factor (denoted *CMA*). In addition, we do not find significant differences between good and bad states of the economy, between high-sentiment and low-sentiment periods, or between high-issuer quality and low-issuer quality periods. There is no evidence that investment factor exposure is priced differently for bonds with shorter remaining maturities. In contrast to realized stock returns, we also do not find that the traditional value factor (denoted *HML*) from the Fama and French (1993) three-factor model is subsumed by any of the new investment factors. Instead, our results suggest that for corporate bonds the new investment factors are noisy versions of the value factor.

We further consider and report several additional tests confirming that the profitability factor is inversely priced among corporate bonds, whereas the investment factor does not appear to be priced. Our evidence is consistent with two potential interpretations. First, one may argue that bond investors are correct about the relation between factor exposures and expected returns, i.e., higher profitability implies lower (and not higher) systematic risk, while investment is not associated with systematic risk. This would suggest that the high stock returns of high profit firms and low investment firms cannot be explained by an increased exposure to systematic risk, but may instead indicate mispricing in the equity domain.

A related view is that the results in the equity domain are sample period specific and due to the use of noisy ex post realized returns as a proxy for expected returns. Indeed, in an additional test, we find that the relations between returns and factor exposures vanish if we use ex post realized bond returns as opposed to the forward-looking implied risk premium as dependent variable. The results of Linnainmaa and Roberts (2016), who study the profitability and investment factors in the pre-1963 sample period and find no statistically reliable premia for the factors, are also consistent with this notion.

A second possibility is that bond investors do not correctly price the factor exposures. This interpretation would suggest mispricing in the bond market that is – for some reason – not corrected. For instance, based on our findings equity investors could buy insurance against the risk(s) underlying the profitability factor by investing in the corporate bond market. However, instead of paying an insurance premium they are rewarded with receiving a premium.

Our study contributes to the literature analyzing the predictability of realized returns in the corporate bond market (e.g.,

[3] Data source is US Bond Market Issuance & Outstanding data from the Securities Industry and Financial Markets Association (SIFMA).

[4] In recent work Kozak et al. (2017) criticize this general assessment of characteristics vs. covariances tests. Relying on no-arbitrage considerations, they argue that expected returns should always be determined by a relatively small set of common factor exposures, irrespective of whether these factors exist due to rational (e.g., consumption-based) considerations or due to irrational investor sentiment. On the basis of this interpretation, one can argue that characteristics vs. covariances tests can still help to examine whether it is indeed the factor exposure (and not the underlying characteristic), which is associated with expected returns. Moreover, the tests in our study help to understand whether the factor exposures are priced similarly for bonds and stocks, which they should be based on such no-arbitrage considerations.

Kwan, 1996; Gebhardt et al., 2005b; Bhojraj and Swaminathan, 2009; Correia et al., 2012; Jostova et al., 2013; Chordia et al., 2015; Crawford et al., 2015; Bai et al., 2016; Campbell et al., 2016; Choi and Kim, 2016).[5]

Recent evidence on the relation between *realized* bond returns and profitability and investment is mixed. For instance, Campbell et al. (2016) and Chordia et al. (2016) document a negative relation between profitability and realized bond returns. In contrast, Choi and Kim (2016) do not find consistent results with respect to the influence of profitability. Campbell et al. (2016) argue that the negative relation among corporate bonds can be explained by systematic extended default risk factors that do not have the same importance for equities. Chordia et al. (2016) attribute the mixed findings in comparison to Choi and Kim (2016) to differences in the sample period. However, sample period specificity is a common problem for studies using realized returns as a proxy for expected returns. Our tests differ from these studies as we use an ex-ante expected return measure. We are therefore able to provide direct evidence on the relation between expected bond returns and profitability. Furthermore, unlike the above cited studies, we separate the characteristic from the factor loading in our tests to distinguish between risk and mispricing. In doing so, we are able to uncover a strong negative relation between exposure to the *ROE* factor from Hou et al. (2015a) and expected bond returns. This finding suggests that *ROE* is a systematic but reverse risk factor. In robustness tests, we show that this conclusion holds after controlling for the extended default risk factors proposed by Campbell et al. (2016).

We also contribute to the rather limited literature examining expected returns such as Campello et al. (2008). They study how estimates of expected returns derived from corporate bond spreads vary with firm characteristics or exposures to the factors of the Carhart (1997) model. In line with our results, Campello et al. (2008) find evidence of significantly positive market, size, and value premia in their sample. Our study complements their work in several aspects. First, we extend their focus by introducing the new asset pricing factors of Fama and French (2015) and Hou et al. (2015b). Given the prominence of the new factors in empirical asset pricing such an analysis appears warranted. Second, we provide a number of additional tests strengthening our conclusions on the documented risk-return relations. For instance, we study the influence of investor sentiment on corporate bond prices. Third, in terms of methodology, we rely on rigorous characteristics versus covariances tests to distinguish between risk and mispricing whereas Campello et al. (2008) predict risk premia either only with characteristics or only with factor exposures.[6]

Our paper is also related to Elton et al. (2001), Schaefer and Strebulaev (2008), Arnold et al. (2013), Anginer and Yildizhan (2017), Friewald et al. (2014), and Kuehn and Schmid (2014). Elton et al. (2001) show that expected default compensation reflects only a small portion of corporate bond credit spreads and that changes in the unexplained part are related to the market, size (denoted *SMB*), and value factor. Schaefer and Strebulaev (2008) analyze hedge ratios between bond and equity returns. They document a relation between excess corporate bond returns and systematic factors including *SMB* and *HML*. Anginer and Yildizhan (2017) and Friewald et al. (2014) analyze how the systematic risk component in corporate bond spreads and credit default swaps is related to equity returns, respectively. Our paper also relies on the argument that systematic risk factors should be present in both equity and debt securities but has a different research context. Finally, Kuehn and Schmid (2014) and Arnold et al. (2013) also highlight the importance of systematic (macroeconomic) risk to explain the total size of credit spreads. Both papers develop models in which a firm's asset composition, and hence its investment policy, is related to its systematic risk, and therefore determines the credit risk premium. While this investment-based view on corporate bond pricing is related to our work, neither of the two papers studies the q-factors and their influence on the credit risk premium.

The paper proceeds as follows. In Section 2, we describe our data sources. We outline the measurement of the IRP component and other important variables, and describe our empirical methodology. Section 3 contains our baseline regression results and robustness tests, while Section 4 provides additional tests. Section 5 reviews potential alternative explanations, discusses implications, and concludes.

2. Data and methodology

2.1. Data sources

We obtain corporate bond characteristics from the Mergent Fixed Income Securities Database (FISD) which contains issue details such as offer sizes, offer and maturity dates, coupon sizes, coupon payment dates, default dates, rating information etc. for a broad set of corporate, government, federal agency, and municipal debt securities. We restrict our sample to plain-vanilla corporate bonds allowing us to calculate the implied risk premium. We exclude non-corporate bonds, bonds issued by non-US corporations, bonds without fixed, semi-annual coupon payments, bonds with missing offering or maturity date, bonds with a principal amount not equal to US$ 1000, and bonds with option-like features, e.g., convertible or putable bonds. We also require bonds in our sample to be matchable to Compustat via issuer CUSIPs. In the baseline analysis, we exclude bonds issued by financial institutions (SIC codes between 6000 and 6999) due to limited comparability of financial statements with other firms.

While FISD has records of issues dating back up to the 1970s in terms of offering date, we focus on issues being offered after 1984, which applies to about 98.5\% of the original sample. However, because bond prices are, with few exceptions, not available prior to 1994 and because we need a certain upfront period to measure initial security factor exposures, 1995 and 2011 mark our sample period start and end date.

We collect bond prices from Thomson Reuters Datastream, TRACE, and FISD (in this order). Datastream provides daily quotations from a set of bond dealers that are available for approximately 70% of our bond issues. However, these quotes are largely restricted to the period after 1994. Today, TRACE reports transaction prices for basically all publicly traded securities in the US debt market. While it is arguably the most accurate data source for corporate bond prices, it only offers a limited historical coverage: TRACE started with a limited sample in July 2002 and has been fully implemented only since February 2005 (see Bessembinder et al., 2009). We therefore prefer Datastream over TRACE as primary data source particularly due to its extended sample period availability. Moreover, when regressing Datastream quotes on TRACE prices, we obtain an R^2 of 97.38% and a regression coefficient of 0.9975 indicating that the information in both data sets is comparable and not systematically biased in one way or the other.

[5] Several of these papers such as Jostova et al. (2013), who examine momentum in corporate bond returns, or Bai et al. (2016), who investigate how volatility, skewness, and kurtosis are related to future bond returns, study a longer sample period of corporate bond prices. The main difference is that these studies were able to obtain bond prices from the Lehman Brothers Fixed Income Database (1973–1998), which was not available for us.

[6] The exception is the estimated market beta which is incorporated in all regressions in Campello et al. (2008), arguably because there is no characteristic-based counterpart.

Finally, FISD reports transaction prices of trades by insurance companies since January 1994.[7]

To ensure the quality of the pricing data, we apply several filters when constructing the bond price data set. We follow the procedure proposed by Bessembinder et al. (2009) to clean the TRACE data by filtering duplicates, reversals, and same-day corrections.[8] We further eliminate commission trades from the data set. We then calculate a daily price for each issue by weighting all observed prices by transaction size. We flag suspicious large price jumps in all three data sources and correct them.[9] Moreover, corporate bonds are generally traded less frequently than stocks. To address the problem of potentially stale prices, we consider only bond-months that either have a valid Datastream quote at the end of the month or are traded according to TRACE or FISD at least once within the last ten days of a specific month. We finally exclude bonds from our tests that have a clean price below 20%, a remaining maturity of less than one year, and bonds rated as (selective) default by S&P, Moody's, or Fitch.[10]

Since all databases report clean prices, we add accrued interests in order to obtain dirty bond prices which are the prices actually experienced by investors. Based on the daily data set, we calculate monthly bond returns based on the last available price of each month to be used in the factor regressions illustrated later in the section.

We further obtain financial statement information from Compustat. We assume that financial statement data is available four months after the fiscal-year end for annual data. We also require firms to be covered by CRSP as we match the issuer sample with CRSP to obtain stock market data.

Finally, we obtain factor returns for the five-factor model and the momentum factor from Kenneth French's website.[11] Factor returns for the Hou et al. (2015b) q-factor model are provided from the original authors. In line with the results presented in Hou et al. (2015b), the two profit factor versions and the two investment factor versions are highly correlated for our sample period. Moreover, the value factor is substantially positively correlated with both investment factors. To determine whether the profitability and investment factors generate abnormal returns also in our more recent sample period, we estimate the one-factor and four-factor alphas associated with *ROE, IA, RMW*, and *CMA*. We find that the monthly long–short portfolios continue to produce statistically and economically significant alphas so that the underlying rational for these factors seems applicable to our sample period.[12]

2.2. Measurement of implied risk premia

We compute the implied risk premium (*IRP*) following a procedure similar to Elton et al. (2001) and Campello et al. (2008). In general, a bond's credit spread can be split into three major components: (i) a compensation for expected losses, (ii) a compensation for differences in the tax treatment of corporate and government bonds, and (iii) a residual arguably reflecting a compensation for systematic risk, i.e., the implied risk premium. We therefore adjust a bond's yield to maturity for expected losses and tax differences before we subtract the equivalent-maturity treasury yield to derive the implied risk premium. In the following, we provide a brief overview of the calculation. A detailed description of the methodology is provided in the Appendix.

First, we adjust the yield to maturity for expected losses. We take a bond's contractually stated cash flows (coupons and face value payment at maturity) and use information about a bond's current rating to calculate expected default probabilities and recovery rates. We take current ratings and use the one-year rating transition matrix provided by S&P to estimate default probabilities over the course of the remaining maturity assuming the transition process to be stationary and Markovian.[13] Recovery rates are from Altman et al. (2000) assuming equivalence between ratings by Moody's and S&P when matching recovery rates to the average rating class of both rating agencies.[14] Based on this information, we determine a bond's expected cash flows conditional on its expected default probabilities.

Second, we adjust a bond's expected cash flows for differences in the tax treatment of corporate and government bonds. While interest payments on corporate bonds are subject to state taxes, government bonds are not. As state taxes are deductible from income for the purpose of federal tax, the burden of state taxes is reduced by the federal tax rate. Following Elton et al. (2001), we set the applicable marginal tax rate equal to 4.875% and subtract the individual tax burden from the expected cash flow component.

Finally, we determine the adjusted yield to maturity of a bond based on the derived expected cash flows and subtract the equivalent-maturity treasury yield to arrive at the implied risk premium. We linearly interpolate treasury yields if they are not available for a specific maturity.[15]

2.3. Measurement of factor exposures

We further extract bond specific factor exposures using prior 60-month rolling-window regressions (with a minimum of at least 12 observations for each regression):

$$r_{t,i} - r_{t,f} = \alpha_i + \beta_{MKT,i} \cdot (r_{MKT,t} - r_{f,t}) + \beta_{ME,i} \cdot ME_t + \beta_{ROE,i} \cdot ROE_t + \beta_{IA,i} \cdot IA_t [+ \beta_{HML,i} \cdot HML_t + \beta_{MOM,i} \cdot MOM_t] + \varepsilon_{t,i}. \quad (1)$$

The excess return for bond i in month t is denoted as $r_{t,i} - r_{t,f}$. $r_{MKT,t} - r_{f,t}$ is the excess market return, *ME* is the size factor from Hou et al. (2015b), *ROE* denotes their profitability factor, and *IA* denotes their investment factor. While the first line in Eq. (1) captures exposure to the factors of the q-factor model, we also run regressions which additionally include the value factor (*HML*) and the momentum factor (*MOM*). Hou et al. (2015b) argue that the value factor is a noisy version of their investment factor, and that

[7] However, regressing FISD prices on TRACE prices yields an R^2 of 94.51% and a coefficient of 0.9592, raising more concerns about the accuracy of FISD prices. An additional limitation of FISD is that it misses a lot of trading information due to its concentration on insurance company related transactions (see Easton et al., 2009).

[8] We verify our cleaning approach by constructing an alternative sample following the procedure outlined by Dick-Nielsen (2009). Resulting samples are almost identical.

[9] Specifically, we assume that an observation is erroneous if a bond has an absolute return of more than 20% at day t and if that return is reversed over the next trading day. In these instances, we replace the bond's clean price at day t with the clean price from day $t-1$. Fortunately, there are only very few such error-like observations in the data. In the Datastream data set, only 0.0008% of all prices need to be corrected due to this filter. Corresponding numbers are 0.081% for TRACE, and 0.397% for FISD, respectively. We have also examined a 10% threshold as a more conservative filter, but still observe only very few necessary corrections.

[10] Low prices such as 20 suggest that the market views these issues effectively as defaulted even though rating agencies might not have updated their ratings yet or no formal bankruptcy proceedings might have started. Consequently, we view any issue that is priced below 20 on three consecutive dates or rated as (selective) default by S&P, Moody's, or Fitch as defaulted and discard all further price information. However, this step affects only a small number of observations (less than 0.1%). It is not material for our findings.

[11] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[12] Correlations as well as the results for the factor models are provided in Table A.5 in the Appendix.

[13] Specifically, we use the average one-year transition rates for the U.S. provided in Table 22 by Standard & Poor's Rating Services (2012) to calculate cumulative and conditional default probabilities, respectively.

[14] The recovery rates for bonds rated by S&P are: 68.34% (for AAA bonds), 59.59% (AA), 62.07% (A), 45.59% (BBB), 40.11% (BB), 36.82% (B), and 38.19% (CCC).

[15] For instance, for a bond with a remaining maturity of 8.5 years, the assigned treasury yield for the computation of the credit spread is the average of the 7-year and 10-year treasury yield.

the momentum factor is a noisy version of their profitability factor. The enlarged regression model enables us to see whether similar results can be observed for corporate bonds. For tests involving the five-factor model, we replace *ROE* and *IA* with the baseline profitability and investment factor versions of Fama and French (2015), denoted as *RMW* and *CMA*, respectively, in Eq. (1).

In a robustness test, we augment Eq. (1) with realized bond factors, i.e., the term structure factor and default factors (*TERM, DEF*, and *DEFPD*). In a further robustness test, we follow Lin et al. (2011) and also estimate exposure to the Pastor and Stambaugh (2003) liquidity factor. These robustness tests do not change our conclusions for the remaining factor sensitivities. The robustness tests are provided in Section 3.4. For most parts of the analysis, we therefore focus on more parsimonious models with fewer factors.

2.4. Descriptive statistics

Descriptive statistics for our final bond sample are presented in Table 1. To minimize the influence of outliers, characteristics from CRSP, Compustat, and FISD as well as IRPs, credit spreads, and yields are winsorized at the top and bottom 1%-level. We verify that our main results are not sensitive to other possible threshold levels, e.g., 0.5% or 0.1%.

The sample consists of 5232 different bonds issued by a total of 1089 non-financial firms which leads to 22,543 bond-years or 7329 firm-years, respectively. On average, these firms constitute roughly 40% of the total monthly non-financial U.S. stock market capitalization according to CRSP, which suggests that our data set is populated with economically important firms and is sufficiently large for our analysis.

Panel B of Table 1 shows summary statistics of selected characteristics from Compustat and CRSP. The average market capitalization (book-to-market ratio) is US$ 10.67 billion (0.65). In contrast, for the complete CRSP/Compustat universe the corresponding numbers amount to US$ 2.33 billion (0.64), which suggests that issuers of corporate bonds are typically larger and have about the same valuation ratio. The comparison demonstrates that asset pricing tests related to corporate bonds typically involve larger firms (see also e.g., Campello et al., 2008).[16]

Panel B also shows summary statistics for the firm characteristics used by Fama and French (2015) or Hou et al. (2015b) to construct their factor-mimicking portfolio returns. Quarterly return on equity (*ROEQ*), which is used by Hou et al. (2015b) to construct their profitability factor, is 2.5% on average. Annual operating profitability (*OP*), which is used by Fama and French (2015) to construct their profitability factor, is 33% on average. Average annual asset growth (*AG*), which is used in both studies to measure firm investment, equals 12.7%. Default risk, as evidenced by the failure predictor *PD* from Campbell et al. (2008), is on average 6.8%, and financial leverage, denoted as *LEV* and defined as total assets divided by book value of equity, is on average 3.5. Panel B indicates substantial variation for all variables in the bond sample.

Panel C reports summary statistics for the bond characteristics. The average offer size is US$ 392.52 million and the average remaining time to maturity is approximately ten years. Roughly 70% of the sample have an investment grade rating. To make use of ratings in our analysis we follow the literature standard and transform the ratings of S&P, Moody's, and Fitch into an average integer ranking (*Rating*). The average rating amounts to 9.42, which corresponds to a BBB (Baa2) rating based on S&P's (Moody's) classification. The average clean price is close to par value (101.78). Moreover, there is a large variation in credit spreads and implied risk premia for our sample firms. While the mean credit spread is 2.81%, the 25th (75th) percentile is 1.08% (3.56%). Similarly, the mean implied risk premium is 2.03% and the 25th and 75th percentiles are 0.67% and 2.52%. Hence, roughly one third of the credit spread is compensation for expected losses and tax effects, a percentage that is comparable to prior literature (e.g., Elton et al., 2001; Huang and Huang, 2012).

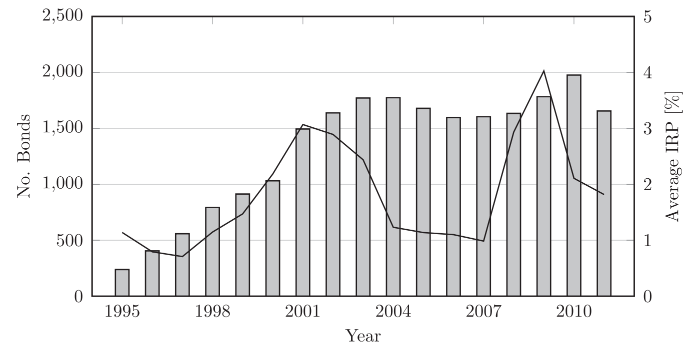

Fig. 1. Sample development.

Panel D further documents a substantial variation of estimated factor exposures in our sample. For instance, the standard deviation of the market factor loading is 0.219. The standard deviation of the *ROE* (*IA*) factor loading is 0.407 (0.363). Thus, there appear to be large cross-sectional differences in corporate bonds' factor sensitivities.

Finally, Panels E and F show averages of firm and bond characteristics when we sort observations into groups according to their profitability and investment factor sensitivities, respectively. As expected, factor loadings are correlated with their underlying characteristics. Firm profitability increases in the *ROE* factor loading, whereas asset growth decreases in the *IA* factor sensitivity. The association of the factor betas and their underlying characteristics provides a first indication that multivariate tests should control for the characteristics alongside the factor exposures. Furthermore, credit spreads as well as the IRP are decreasing in the profitability factor sensitivity while both measures show a u-shaped pattern with regard to the investment factor sensitivity. Given the various potential interdependencies between the factor loadings and other determinants of credit spreads and IRPs, it seems sensible to postpone any interpretation to the multivariate analyses.

Fig. 1 depicts the sample development over time. The sample increases substantially in the 1990s and early 2000s. Since 2001 the number of bonds included in the sample has been quite stable at around 1600 bonds each year. Fig. 1 also shows that the average implied risk premium varies substantially over time. Highest values are observed for the years 2001–2002 and 2008–2009, whereas the lowest values are in the mid-90's.

3. Main analysis

3.1. The importance of characteristics versus covariances tests

Our empirical strategy is to explain a bond's implied risk premium with variables that proxy for risk exposure. To do so, we run characteristics versus covariances tests. In these tests, we include the firm characteristics used by Fama and French (2015) or Hou et al. (2015b) to construct their factor-mimicking portfolio returns as well as bond-specific factor sensitivities as explanatory variables.

[16] We note that the validity of our tests does not depend on whether the firm sample is representative for the entire CRSP/Compustat universe. Asset pricing theory suggests that relations between systematic risk and expected return hold for the entire market portfolio, and hence also for subsets of securities. All that we need to infer these relations is sufficient cross-sectional variation in factor exposures.

Table 1
Sample description and bond characteristics. This table provides a description of the final sample. Panel A shows the number of bonds (firms) that are included in the analysis, i.e., issuing firms that are covered by CRSP/Compustat with non-missing observations for market value of equity, profitability, and investment measures. Panels B–D are based on observations as of June each year, or, if not available, the date closest to June. Panel B shows summary statistics for selected firm characteristics from CRSP/Compustat. Abbreviations are as follows: Equity market value (*MV*), book-to-market ratio (*BM*), prior 6-month stock return (*EQ MOM*), return on equity (*ROEQ*), operating profitability (*OP*), asset growth (*AG*), leverage (*LEV*), and default probability (*PD*). Panel C provides summary statistics for selected bond variables. Abbreviations are as follows: time-to-maturity (*TM*), average integer ranking of ratings provided by S&P, Moody's, and Fitch (*Rating*), indicator variable that is 0 for bonds that are rated non-investment grade, and 1 otherwise ($Non-Inv.\ Grade$), clean price (*CP*), prior 6-month bond return (*BOND MOM*), yield-to-maturity (*YTM*), credit spread (*CS*), and implied risk premium (*IRP*). Panel D gives summary statistics for the risk factor exposures. β_{MKT}, β_{ME}, β_{ROE}, and β_{IA} are the factor loadings on the respective Hou et al. (2015b) q-factors. *MKT* is the market factor, *ME* the size factor, *ROE* is the profitability factor, and *IA* is the investment factor. β_{HML} is the Fama–French value factor loading and β_{MOM} is the momentum factor loading. β_{RMW} and β_{CMA} are loadings on the Fama–French profitability and investment factor, respectively. Panels E and F provide summary statistics for selected firm and bond characteristics according to the *ROE* and *IA* factor sensitivities, respectively. High (low) refers to the highest (lowest) quintile. Construction details are in the Appendix. The sample period is M1:1995–M12:2011.

Panel A: Data coverage

	No. bonds	No. firms	No. bond-years	No. firm-years
	5232	1089	22,543	7329

Panel B: Firm characteristics

Variables	*N*	Mean	SD	P25	P50	P75
MV [Mio. US$]	7329	10,667	24,183	942	2946	9186
BM	7329	0.653	0.581	0.29	0.487	0.809
EQ MOM [%]	7325	11.034	27.816	−4.806	9.131	23.923
ROEQ	7329	0.025	0.068	0.008	0.027	0.047
OP	7329	0.330	0.327	0.177	0.276	0.396
AG	7329	0.127	0.296	−0.012	0.055	0.158
LEV	7329	3.508	3.398	2.017	2.536	3.505
PD [%]	7329	0.068	0.149	0.025	0.034	0.054

Panel C: Bond characteristics

Variables	*N*	Mean	SD	P25	P50	P75
Offer size [Mio. US$]	22,543	392.520	369.123	200.000	300.000	500.000
TM [yrs]	22,543	10.038	10.301	4.333	7.083	10.000
Age [yrs]	22,543	3.741	3.642	1.000	2.750	5.417
Rating	22,514	9.416	3.505	6.667	9.000	12.000
Non-Inv. Grade	22,514	0.300	0.458	0.000	0.000	1.000
CP [%]	22,543	101.778	10.952	98.000	101.552	106.725
BOND MOM [%]	18,566	4.047	5.690	0.907	3.116	6.307
YTM [%]	22,543	6.918	3.216	5.360	6.620	7.930
CS [%]	22,543	2.814	3.139	1.084	1.837	3.561
IRP [%]	22,543	2.027	2.654	0.670	1.300	2.523

Panel D: Factor Exposures

Variables	N	Mean	SD	P25	P50	P75
β_{MKT}	16,957	0.035	0.219	−0.086	0.021	0.136
β_{ME}	16,957	0.001	0.210	−0.087	0.004	0.089
β_{ROE}	16,957	−0.078	0.407	−0.210	−0.039	0.088
β_{IA}	16,957	−0.022	0.363	−0.178	−0.025	0.120
β_{HML}	16,957	0.052	0.354	−0.107	0.052	0.205
β_{MOM}	16,957	−0.040	0.205	−0.108	−0.029	0.041
β_{RMW}	16,957	−0.017	0.401	−0.180	−0.017	0.128
β_{CMA}	16,957	0.024	0.423	−0.158	0.002	0.172

Panel E: Profitability Exposure Sorting

	MV	BM	ROEQ	AG	CS [%]	IRP [%]
High	19,667	0.599	0.036	0.090	2.646	1.948
Medium	21,105	0.626	0.034	0.085	2.621	1.928
Low	16,825	0.725	0.022	0.090	3.600	2.705
Difference	2842	−0.126	0.014	0.000	−0.954	−0.757

Panel F: Investment Exposure Sorting

	MV	BM	ROEQ	AG	CS [%]	IRP [%]
High	18,123	0.702	0.027	0.081	3.342	2.525
Medium	20,849	0.606	0.035	0.084	2.506	1.839
Low	18,666	0.639	0.030	0.102	3.001	2.202
Difference	−542	0.063	−0.003	−0.021	0.341	0.323

We favor characteristics versus covariances tests because firm characteristics, despite their intuitive risk-based interpretation, could be related to IRPs for other reasons as well. Most importantly, firm characteristics may predict idiosyncratic default, and hence may be related to investors' required compensation for expected losses. This compensation part should be removed from IRPs if ratings accurately and completely reflect a bond's default probability and expected recovery rates. However, ratings may not fully capture the informational content of firm characteristics, for instance because they are only infrequently updated. Therefore, there is a danger of misinterpreting a potential positive relation between IRPs and a certain firm characteristic as indication of higher systematic risk whereas it actually only reflects compensation for higher idiosyncratic expected losses.

Table 2
Predicting corporate default within next 12 months. This table reports results from probit regressions of a default indicator on firm characteristics, credit rating information, and the Campbell et al. (2008) failure predictor *PD* as predictor variables. The default indicator is 1 for firms defaulting over the next 12 months, 0 otherwise. The first three columns depict results for firms included in our bond sample from 1995 to 2011. The remaining three columns show results for an enlarged sample of CRSP/Compustat firms from 1985 to 2012 for which long-term credit ratings from S&P are available in Compustat. Abbreviations are as follows: Equity market value (*MV*), book-to-market ratio (*BM*), prior 6-month stock return (*EQ MOM*), return on equity (*ROEQ*), asset growth (*AG*), and default probability (*PD*), where *PD* is measured in percentiles. To use rating information in our analysis, we follow the literature standard and transform the ratings of S&P, Moody's, and Fitch into an integer ranking. The variable is denoted as *Rating* in the table. For the bond sample, we take the average integer value of S&P, Moody's, and Fitch. For the enlarged CRSP/Compustat firm sample, we use S&P ratings only. Construction details are in the Appendix. *z*-statistics reported in parentheses are based on standard errors clustered by issue and month identifier. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Bond sample 1995–2011			CRSP/Compustat sample 1985–2012		
	(1)	(2)	(3)	(4)	(5)	(6)
MV (log)	−0.250***	−0.072	−0.059	−0.172***	−0.018	0.019
	(−5.274)	(−1.222)	(−1.026)	(−6.597)	(−0.574)	(0.610)
BM (log)	0.308***	0.333***	0.219***	0.282***	0.306***	0.223***
	(3.115)	(3.851)	(2.662)	(5.204)	(6.297)	(4.953)
EQ MOM	−0.009***	−0.008***	−0.005***	−0.007***	−0.006***	−0.003***
	(−4.511)	(−4.957)	(−3.387)	(−6.141)	(−6.669)	(−4.051)
ROEQ	−1.727***	−1.230***	−0.564*	−1.404***	−0.931***	−0.339**
	(−5.049)	(−3.669)	(−1.724)	(−8.228)	(−5.870)	(−2.218)
AG	0.233***	0.162*	0.169**	0.088***	0.040	0.041
	(2.735)	(1.954)	(2.011)	(2.675)	(1.218)	(1.256)
Rating		0.171***	0.131***		0.131***	0.108***
		(5.013)	(3.810)		(9.421)	(6.938)
PD			0.020***			0.019***
			(4.674)			(8.150)
Constant	−4.852***	−7.974***	−9.100***	−1.872***	−4.228***	−5.430***
	(−15.451)	(−11.684)	(−11.538)	(−15.345)	(−15.970)	(−19.674)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,873	65,873	65,873	306,474	306,474	306,474
Pseudo R^2	0.405	0.440	0.459	0.365	0.392	0.421

Indeed, Hilscher and Wilson (2017) show that ratings are an inferior predictor of future default compared to the state-of-the-art failure predictor of Campbell et al. (2008). As a consequence, we include this predictor as additional default control variable in our tests.[17] However, even the inclusion of additional default controls might not perfectly remove any remaining expected loss compensation from IRPs.

In this context, a characteristics versus covariances design helps to isolate the influence of factor exposures on expected returns after controlling for underlying firm characteristics. Thus, they provide an elegant way to account for the fact that characteristics may be related to both, systematic risk and expected losses, and that the IRP component may still contain some compensation for expected losses. Specifically, while the factor sensitivity should pick up the relation to systematic risk, the characteristic simultaneously controls for a potential relation to (idiosyncratic) default risk and expected loss compensation.

To investigate how severe this problem is, i.e., to what extent firm characteristics continue to explain firm default after controlling for ratings, we collect information on historical firm failures to create a default indicator.[18] We then run probit models with an indicator variable for default over the course of the next 12 months as dependent variable. The analysis is carried out separately for two samples: Our bond sample which runs from 1995 to 2011, and – because we do not need data on bond prices for this analysis – a broader CRSP/Compustat sample of firms from 1985 onwards for which we are able to collect S&P rating information from Compustat. Table 2 depicts our results. Following the suggestions of Petersen (2009), standard errors are double-clustered by firm and month and regressions include time fixed-effect dummies.

Column (1) of Table 2 shows that firm size, book-to-market, quarterly return on equity, and asset growth are all statistically significant predictors of 12-months ahead default in our bond sample if we do *not* control for ratings. In particular, large firms and high profit firms have lower default risk, whereas high book-to-market firms and high asset growth firms are more likely to default. Once we add the average rating information (*Rating*) in column (2), only the coefficient for firm size becomes statistically insignificant. In column (3), we additionally add Campbell et al. (2008) failure predictor (*PD*) as explanatory variable. However, book-to-market, quarterly return on equity, and asset growth still continue to predict future default.

Columns (4)–(6) repeat the analysis for the enlarged CRSP/Compustat sample. Results verify that findings are not specific to our firm sample. In general, firm characteristics predict default even after controlling for credit ratings. In the Appendix, we document similar results for 24-month ahead default as dependent variable. In unreported tests, we have also verified that adding squared *Rating* or rating dummies in the regression does not materially affect the predictive abilities of firm characteristics.

The default prediction analysis reinforces initial concerns that relations between IRPs and firm characteristics might be driven by investors' required compensation for idiosyncratic default and not for systematic risk. The results, which could be similar for recovery rates (we do not have testable information in this regard), suggest that the use of rigorous characteristics versus covariances tests is indeed necessary to examine the pricing of systematic risk factors among corporate bonds.

One additional concern is that the *IRP* arguably also contains a premium for illiquidity. We address this concern in Section 3.3, in

[17] The failure probability measure of Campbell et al. (2008) is derived from the 12-month-ahead logit model of Table 4 in their paper. We use the annually updated regression coefficients, provided to us by Jens Hilscher, to calculate the dynamic version of the measure which avoids look-ahead bias. In an unreported test, we also use the distance-to-default (*DD*) from Merton (1974) which forms the basics of the commercial KMV rating model as physical default probability measure and obtain similar conclusions. We also include financial leverage as control variable in our main tests reported in Section 3.2 because it likely influences recovery rates.

[18] Default is broadly defined as in Campbell et al. (2008), i.e., we use bankruptcies, financially driven delistings, or D ratings issued by S&P. Data source for bankruptcies is the LoPucki Bankruptcy Research Database which we augment by hand-collected data from bankruptcydata.com. Financially driven delistings are defined by CRSP delisting codes indicating financial difficulties, i.e., 552, 560, 574, and 580. A robustness test that uses only bankruptcy data to define defaults yields similar results.

Table 3
Determinants of the implied risk premium: Baseline tests. This table reports results from pooled panel regressions of the implied risk premium (*IRP*) on factor loadings and several firm and bond characteristics. Abbreviations are as follows: Return on equity (*ROEQ*), asset growth (*AG*), and operating profitability (*OP*), time-to-maturity (*TM*), equity market value (*MV*), book-to-market (*BM*), prior 6-month bond return (*BOND MOM*), prior 6-month stock return (*EQ MOM*), leverage (*LEV*), and default probability (*PD*). β_{MKT}, β_{ME}, β_{ROE}, and β_{IA} are the factor loadings on the respective Hou et al. (2015b) q-factors. *MKT* is the market factor, *ME* the size factor, *ROE* is the profitability factor, and *IA* is the investment factor. β_{HML} is the Fama–French value factor loading and β_{MOM} is the momentum factor loading. β_{RMW} and β_{CMA} are loadings on the Fama–French profitability and investment factor, respectively. Construction details are in the Appendix. Coefficients are based on standardized variables. *t*-statistics reported in parentheses are based on standard errors clustered by issue and month identifier. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. The sample period is from M1:1995–M12:2011.

Variables	(1) IRP	(2) IRP	(3) IRP	(4) IRP	(5) IRP	(6) IRP	(7) IRP
β_{MKT}	0.261***	0.253***	0.251***	0.242***		0.123***	0.139***
	(11.028)	(10.681)	(10.786)	(9.661)		(7.901)	(8.980)
β_{ME}	0.192***	0.156***	0.197***	0.151***		0.062***	0.057***
	(10.540)	(9.747)	(10.042)	(8.438)		(5.422)	(5.102)
β_{ROE}	−0.195***	−0.188***	−0.236***	−0.244***		−0.135***	
	(−8.012)	(−8.465)	(−9.344)	(−9.219)		(−9.022)	
β_{IA}	0.070***	0.045***	0.071***	0.052***		0.021*	
	(3.966)	(2.702)	(4.136)	(3.211)		(1.906)	
β_{HML}		0.121***		0.130***		0.071***	0.063***
		(5.242)		(5.149)		(4.495)	(4.519)
β_{MOM}			−0.019	−0.031*		−0.010	−0.022*
			(−0.986)	(−1.738)		(−0.757)	(−1.800)
β_{RMW}							−0.085***
							(−6.358)
β_{CMA}							−0.005
							(−0.344)
ROEQ					−0.117***	−0.103***	
					(−8.609)	(−8.150)	
AG					0.021***	0.020**	0.014*
					(2.678)	(2.393)	(1.653)
OP							−0.040***
							(−3.633)
Offer size (log)					0.049***	0.033***	0.036***
					(5.321)	(3.612)	(3.831)
TM (log)					0.083***	0.070***	0.071***
					(8.663)	(6.805)	(6.857)
Age (log)					0.029***	0.029***	0.030***
					(4.350)	(3.560)	(3.917)
MV (log)					−0.340***	−0.303***	−0.311***
					(−17.854)	(−17.592)	(−16.765)
BM (log)					0.147***	0.137***	0.157***
					(8.695)	(8.504)	(9.401)
BOND MOM					−0.236***	−0.235***	−0.234***
					(−8.050)	(−8.885)	(−8.328)
EQ MOM					−0.040***	−0.045***	−0.046***
					(−3.082)	(−3.571)	(−3.402)
LEV					0.144***	0.125***	0.110***
					(8.499)	(8.254)	(7.210)
PD					0.031***	0.012	0.032***
					(2.843)	(1.170)	(2.803)
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162,025	162,025	162,025	162,025	176,521	162,009	162,009
R^2	0.355	0.346	0.357	0.351	0.544	0.561	0.549

which we show that several state-of-the-art bond illiquidity measures are not systematically related to our main variables of interest.[19]

3.2. Baseline tests for the profitability and investment factors

Baseline evidence on the influence of the profitability and investment factors on expected bond risk premia is shown in Table 3. Regressions are based on monthly observations and include month fixed-effect dummies. We report *t*-values based on double-clustered standard errors (by issue identifier and month identifier). The IRP and explanatory variables are standardized to have a mean value of 0 and a standard deviation of 1 to simplify economic comparisons. Bond characteristic controls are issue offer size, issue age, remaining time to maturity, and prior 6-months bond return.

Columns (1)–(4) provide regression results using only factor exposures as explanatory variables. Column (5) displays the results if only characteristics are used as explanatory variables. Column (6) shows the results of the full baseline specification including characteristics and covariance estimates as explanatory variables. This sequential procedure allows us to discuss potentially changing inferences once we move from covariances-only or characteristics-only tests to the full model. While specifications (1)–(6) focus primarily on the factors from Hou et al. (2015b), we also repeat the full model from column (6) using the factors and characteristics from Fama and French (2015). Results for this model are shown in column (7).

Column (1) of Table 3 shows results for the q-factor model without any further controls. There is a significant positive relation between a bond's implied risk premium and its sensitivity to the market factor (β_{MKT}). The estimated slope coefficient is 0.261 stan-

[19] We report results of the tests in Table 4. We do not consider the illiquidity control variables in our main specifications because they require TRACE transaction data to be available.

dard deviations and has a t-value above 11. Given a standard deviation of 2.654% for the IRP and a standard deviation of 0.219 for the market factor exposure (see Table 1), this result indicates a market risk premium of roughly 3.2%. Hence, exposure to general market movements appears to be priced ex-ante for corporate bonds, despite rather mixed evidence from realized returns (see Fama and French, 1993; Frazzini and Pedersen, 2014). This finding is consistent with prior evidence based on expected return measures (see Elton et al., 2001; Campello et al., 2008).

Column (1) also shows a strong positive coefficient of 0.192 for the *ME* factor loading (β_{ME}) and a strong negative coefficient of −0.195 for the *ROE* factor loading (β_{ROE}). The influence of the *IA* factor loading (β_{IA}) is economically smaller in magnitude with an estimated coefficient of 0.070, but also statistically significant at the 1%-level. These findings suggest that firms with higher exposure to the size factor and higher exposure to the investment factor have higher cost of debt, which is consistent with a risk-based explanation. However, firms with higher exposure to the profitability factor appear to have lower (and not higher) cost of debt suggesting *ROE* to be a reverse risk factor.

Columns (2) and (3) provide results for specifications including the exposure to the value factor *HML* and the momentum factor *MOM*, respectively. In column (4), we add both factor exposures to the model. While Hou et al. (2015b) argue that the value factor is a noisy version of their investment factor, our results do not yield the same conclusion. In column (2), the estimated coefficient for β_{HML} is 0.121 with a t-value above 5. Hence, exposure to the value factor appears to be positively priced among corporate bonds, even after controlling for investment factor exposure. Instead, the regression coefficient for β_{IA} shrinks by about 40% to 0.045 standard deviations in column (2). In column (3), the *ROE* factor largely subsumes the *MOM* factor exposure, which is consistent with the argument in Hou et al. (2015b). Specifically, the estimated coefficient for β_{ROE} is −0.236 with a t-value of −9.34, whereas the estimated coefficient for β_{MOM} is −0.019 with a t-value of −0.95. Results in column (4), which include the value factor, are similar.

We next discuss results of our characteristics-only tests shown in column (5). Consistent with Campello et al. (2008), there is a significant positive relation between the IRP and a firm's book-to-market ratio (*BM*), and a significant negative influence of equity firm size (*MV*). Quarterly return on equity (*ROEQ*) is strongly negatively related to the IRP (coefficient: −0.117; t-value: −8.61), whereas asset growth (*AG*) has a small positive influence on the IRP (coefficient: 0.021 ; t-value: 2.68). If one interprets firm characteristics as proxies for systematic risk exposure, the result for *ROEQ* is in line with the results for the covariances-only regressions because it suggests that more profitable firms are ceteris paribus less risky. On the other hand, the result for *AG* is not consistent with the results for the covariances-only regressions because it suggests that high investment firms are ceteris paribus more risky. Both interpretations are also inconsistent with a risk-based explanation for the profitability and investment effect in stock returns.

We now turn to the characteristics versus covariance test results for the q-factor model provided in column (6) of Table 3. Several findings are noteworthy. First, the market beta coefficient is 0.123 with a t-value of 7.90, which further assures that the market factor loading is indeed priced. The test also provides novel evidence regarding the size and value factor. Specifically, both, the characteristics and factor loading estimates, retain their sign and statistical significance. The comovement with *ME* and *HML* is positively priced among corporate bonds independent of the underlying firm characteristics, which strengthens the risk-based explanation for the size and value effect. Nonetheless, the estimated regression coefficients are lower: According to column (6), a one standard deviation increase in the *ME* (*HML*) factor loading estimate increases the IRP by 0.062 (0.071) standard deviations, which is substantially lower in comparison to column (4). Thus, characteristics subsume a substantial amount of the factor loadings' influence.

Concerning the q-factors, we find a negative coefficient for both the *ROEQ* characteristic and the *ROE* loading in column (6). t-values indicate statistical significance above the 1% threshold. This finding confirms that bonds with high sensitivity to the *ROE* factor carry a lower risk premium. In fact, we find that across all factor exposures, β_{ROE} exerts the strongest economic influence on the IRP. In absolute terms, the estimated coefficient of −0.135 standard deviations exceeds even the estimated coefficient for the market factor loading. The coefficient for β_{IA} remains significantly positive at the 10%-level in column (6) with a small estimated regression coefficient of 0.021. While the positive coefficient is consistent with a risk-based explanation, the economic influence of the investment factor loading on the required return is small in comparison to the other factor exposures.

As shown in column (7) of Table 3, the results for the profitability factor *RMW* and the investment factor *CMA* from Fama and French (2015) are qualitatively similar. The economic influence of β_{CMA} on the IRP is small and the estimated coefficient of −0.005 is also statistically insignificant. β_{RMW} has a negative influence on the IRP with a coefficient estimate of −0.085 and a t-value of −6.36. The coefficient estimate is substantially smaller in magnitude than the estimate for β_{ROE} in column (6). This suggests that the Hou et al. (2015b) profitability factor is better able to explain cross-sectional differences in expected bond returns than the Fama and French (2015) profitability factor. Exposures to the traditional factors *MKT, ME*, and *HML* are priced similarly in column (7).

Overall, results with regard to the new risk factors indicate that bond investors perceive positive profitability factor exposure as less risky. Since results for the investment factor are economically small and dependent on whether one relies on *IA* or *CMA*, we postpone further conclusions for the investment factor to the following sections. These sections contain additional tests of whether bond investors perceive positive *IA* or *CMA* factor exposure as risky.

Moreover, many characteristics such as *MV, BM*, and *ROEQ* continue to be quite successful in explaining the cross-section of bond risk premia as shown in columns (6) and (7). Conclusions for this finding are not unambiguous. First, characteristics might capture compensation for expected losses not being entirely removed from the IRPs. Second, investors might like firms with certain characteristics, e.g., growth firms, high profit firms, etc. and are therefore willing to demand a lower return for these firms. However, the "like" does not arise from a desire to avoid systematic risk which is embedded in factor loadings. Third, characteristics might contain incremental information about the true ex-ante risk exposure that is not reflected in factor loadings because they have to be estimated on the basis of historical data.

The existence of these conflicting but not mutually exclusive explanations further demonstrates that interpretations for or against a risk-based explanation should be based on the coefficients for the factor loading estimates. One limitation of this approach is a potential measurement error in estimated betas potentially biasing coefficient estimates on those factor sensitivities towards zero (see e.g., Hirshleifer et al., 2012). However, in the context of Table 3, the errors-in-variables problem rather strengthens our conclusions that the market factor, size factor, and value factor are positively priced risk factors, while the profitability factor is a negatively priced risk factor.[20]

[20] To test how severe measurement errors in factor exposure estimates are, particularly for the new asset pricing factors, we follow prior literature and examine to what extent pre-formation factor loadings can produce a meaningful spread in post-formation factor loadings even after controlling for concurrent characteristics (see e.g., Daniel and Titman, 1997; Hirshleifer et al., 2012). The Appendix shows that the

3.3. Bond market illiquidity

A common concern with respect to using bond market data is that bonds are usually less liquid than stocks which potentially affects the pricing and thus, expected returns of corporate bonds. For instance, several papers investigate the possibility that the illiquidity of corporate bonds may explain why credit spreads are too large to reflect solely a compensation for default risk (the 'credit spread puzzle' documented by e.g., Elton et al., 2001). Consistent with this idea, Bao et al. (2011), Dick-Nielsen et al. (2012), and Friewald et al. (2012), among others, document that illiquidity explains bond yields in the cross-section with large economic significance.

We examine the credit spread puzzle as well, but focus on exposures to systematic risk factors as potential drivers. In this section, we therefore aim to address in detail to what extent liquidity issues among corporate bonds may influence our inferences. To account for potential illiquidity, we control for various bond market related illiquidity measures discussed in Dick-Nielsen et al. (2012) and Friewald et al. (2012). Specifically, we adapt the approach by Dick-Nielsen et al. (2012) and calculate five monthly measures for the TRACE dataset. These measures include: Amihud's measure of price impact and a measure of roundtrip cost of trading (*IRC*) as well as the variability of these two measures representing liquidity risk. We also add a summary illiquidity measure (λ) which is the equally weighted sum of these four variables all normalized to a common scale. All measures are supposed to be positively correlated with an issue's illiquidity. We report the results of regressions which control for these illiquidity measures in Table 4.

Column (1) of Table 4 first provides results for the baseline characteristics versus covariance regression reported in column (6) of Table 3 for IRPs that are solely determined on the basis of TRACE prices. Thus, column (1) fulfills two purposes: First, because the illiquidity measures are calculated for TRACE data only, it serves as a benchmark to compare the remaining regression results reported in Table 4. Second, the regression shown in column (1) addresses potential concerns about the pricing data from Datastream, which relies on dealer quotations and not market prices, or from FISD, which uses only transactions from insurance companies. An inspection of column (1) does not show marked differences in comparison to our baseline tests. The coefficient for *IA* exposure is again statistically insignificant. For the remaining factor exposures, the association with the embedded risk premium is similar if we use arguably more accurate TRACE data.

Results including the illiquidity measures are displayed in columns (2)–(6) of Table 4. In line with prior work, the illiquidity measures all load significantly positively in our specifications indicating that the IRP contains a compensation for illiquidity. For instance, the summary illiquidity measure λ of Dick-Nielsen et al. (2012) has an estimated regression coefficient of 0.088 standard deviations with a t-statistic of 7.59. However, the comparison to column (1) also shows that the inclusion of the various illiquidity measures has no material impact on the estimated regression coefficients for the other variables of interest. Hence, illiquidity does not seem to explain the influence of the factor sensitivities.[21]

3.4. Robustness tests

We next run several further refinements of our characteristics versus covariances tests to ensure the robustness of our analysis. Results of these additional tests are presented in Table 5. For the sake of brevity we restrict ourselves to the q-factor model. The same tests for the five-factor model are reported in the Appendix. Results are similar.

Column (1) of Table 5 shows results using IRPs, bond characteristics, and factor loadings value-weighted at the issuer level, i.e., we only keep one observation per issuer each month. We do not observe major changes. Most importantly, exposures to the market factor, *ME*, and *HML* continue to be significantly positively priced, while exposure to *ROE* is significantly negatively priced. *IA* exposure is not significant in column (1).

Next, we additionally control for issuer fixed-effects in column (2). Issuer fixed effects capture all issuer-specific components, including the portion of the risk exposure that does not vary for the issuer. However, asset pricing theory does not differentiate between the issuer-fixed part and the variable part of systematic risk: Both should be priced the same way. Nevertheless, we are interested to what extent our findings hold also in the presence issuer fixed-effects. Column (2) shows that the profitability beta remains negative and statistically significant at the 1% level, whereas the investment beta is statistically insignificant in Table 5, column (2). However, the magnitude of the coefficients generally declines when controlling for issuer fixed-effects, and in particular so for the exposures to the market factor and the size factor.

In column (3), we exclude small bonds which are likely to be traded less frequently. Specifically, we drop observations of bonds with an offering amount below the 5th percentile. Results are not affected by dropping these observations. We also use alternative thresholds based on the 1st, 10th, 25th, and 50th percentile, and find that the results are similar.

As a further control for illiquidity risk, we next test a regression which adds a bond's exposure to the Pastor and Stambaugh (2003) liquidity factor as independent variable. Results are shown in column (4) of Table 5. Consistent with the evidence reported by Lin et al. (2011), bonds with higher systematic liquidity risk have higher expected returns. Nevertheless, coefficient estimates for the other factor exposures are again very similar in column (4).

Column (5) provides results if a seven-factor model also containing the term and default factors is used to estimate factor exposures. While the *TERM* and *DEF* beta estimates are both statistically significant at the 1%-level, coefficients for the other factor estimates retain their sign and level of statistical significance. For instance, while the predictive power of the *ROE* factor exposure coefficient is somewhat weakend by including the default factor sensitivity, the *ROE* factor exposure remains significantly negative at the 1%-level. Including *TERM* and *DEF* beta estimates increases the overall explanatory power of the model only slightly from 56.1% to 56.5%.

In a further robustness test, we investigate regression results for factor exposures that are derived from an alternative seven-factor model which exchanges the classical default factor with the extended default factors proposed by Campbell et al. (2016). Unlike the classical default factor, the extended default factors do not only take investment grade bonds into account, but the entire cross-section of bonds. In column (6), we show results when using the default factor from Campbell et al. (2016) that is constructed on the basis of the physical default probability (denoted *DEFPD*). In line with the argument of Campbell et al. (2016) that the classical default factor does a poor job in capturing systematic default risk, column (6) shows that the significance and the magnitude of the coefficient on the alternative default beta increases substantially. Yet, the exchange has no material influence on the coefficient

predictive power of pre-formation factor loadings for the post-formation period is statistically and economically strong for all relevant factors of the Hou et al. (2015b) model (*ME, ROE, IA*) and *HML*. This suggests that the estimates are not too noisy to be ignored by investors.

[21] In regressions reported in the Appendix, we use further illiquidity measures as control variables, such as the Bao et al. (2011) measure and the related Roll (1984) measure. Our inferences are not affected.

Table 4

Determinants of the implied risk premium: Illiquidity controls. This table reports results from pooled panel regressions of the implied risk premium (*IRP*) on factor loadings and several firm and bond characteristics. Column (1) repeats the baseline characteristics versus covariance regression reported in column (6) of Table 3 with TRACE price data only. For the same set of observations, Columns (2)–(5) show the results of including the following controls for bond (il-)liquidity: the Amihud price impact measure, a measure of roundtrip cost of trading (*IRC*), as well as the variability of these two measures representing liquidity risk. In Column (6) we include a summary illiquidity measure (λ) following Dick-Nielsen et al. (2012) which is an equally weighted sum of these four variables all normalized to a common scale. Abbreviations are as follows: return on equity (*ROEQ*), asset growth (*AG*), Amihud's illiquidity measure (*Amihud*), standard deviation of Amihud's illiquidity measure (*Amihud* Risk), imputed roundtrip costs (*IRC*), standard deviation of imputed roundtrip costs (*IRC* Risk), and the summary illiquidity measure (λ). β_{MKT}, β_{ME}, β_{ROE}, and β_{IA} are the factor loadings on the respective Hou et al. (2015b) q-factors. *MKT* is the market factor, *ME* the size factor, *ROE* is the profitability factor, and *IA* is the investment factor. β_{HML} is the Fama–French value factor loading. Firm controls include: Equity market value (*MV*), book-to-market (*BM*), prior 6-month stock return (*EQ MOM*), leverage (*LEV*), and default probability (*PD*). Bond controls include: Offering size, Time-to-maturity (*TM*), prior 6-month bond return (*BOND MOM*), and bond age (*Age*). Construction details are in the Appendix. Coefficients are based on standardized variables. *t*-statistics reported in parentheses are based on standard errors clustered by issue and month identifier. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. The sample period is from M1:1995–M12:2011.

Variables	(1) IRP	(2) IRP	(3) IRP	(4) IRP	(5) IRP	(6) IRP
β_{MKT}	0.121***	0.120***	0.120***	0.114***	0.116***	0.116***
	(7.400)	(7.393)	(7.380)	(7.167)	(7.222)	(7.244)
β_{ME}	0.044***	0.044***	0.044***	0.041***	0.042***	0.042***
	(3.232)	(3.248)	(3.216)	(3.067)	(3.127)	(3.138)
β_{ROE}	−0.087***	−0.087***	−0.086***	−0.084***	−0.084***	−0.084***
	(−6.147)	(−6.137)	(−6.090)	(−5.990)	(−6.012)	(−5.996)
β_{IA}	−0.002	−0.003	−0.002	−0.006	−0.003	−0.004
	(−0.179)	(−0.203)	(−0.183)	(−0.444)	(−0.235)	(−0.288)
β_{HML}	0.068***	0.068***	0.068***	0.064***	0.066***	0.066***
	(4.037)	(4.015)	(4.038)	(3.821)	(3.941)	(3.931)
ROEQ	−0.088***	−0.088***	−0.088***	−0.086***	−0.087***	−0.087***
	(−4.945)	(−4.959)	(−4.962)	(−4.872)	(−4.935)	(−4.941)
AG	−0.000	−0.000	−0.000	0.002	0.001	0.001
	(−0.042)	(−0.009)	(−0.014)	(0.246)	(0.130)	(0.135)
Amihud		0.029***				
		(3.451)				
Amihud risk			0.049***			
			(5.347)			
IRC				0.096***		
				(7.179)		
IRC risk					0.081***	
					(8.507)	
λ						0.088***
						(7.589)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Bond controls	Yes	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59,147	59,147	59,147	59,147	59,147	59,147
R^2	0.627	0.628	0.630	0.634	0.633	0.634

for the *ROE* factor loading, which remains negative and statistically significant at the 1% level in column (6).

The specification shown in column (7) includes bond issues of financial firms. Coefficients for the firm characteristics should be interpreted with caution in this model due to the limited comparability of financial statements between financial and non-financial firms. However, factor exposure implications should be the same according to rational asset pricing. Indeed, our conclusions are not affected by including financial firms.

The regression model shown in column (8) uses the credit spread instead of the IRP as dependent variable. While the IRP computation removes (rating-)average expected losses and tax compensation from the credit spread, results in column (8) show the same basic properties for factor exposures as our baseline model.

Next, we replace the implied bond risk premium with the implied equity risk premium as measured by Campello et al. (2008). According to the Merton (1974) model, risk premia in equity and credit markets are connected according to the following relation:

$$E[r_S - r_f] = \left[\frac{\partial V_S}{\partial V_B} \cdot \frac{V_B}{V_S}\right] \cdot E[r_B - r_f]. \tag{2}$$

In Eq. (2), a firm's equity risk premium ($E[r_S - r_f]$) equals its bond risk premium ($E[r_B - r_f]$) multiplied by the elasticity of the market value of equity (V_S) to the market value of debt (V_B). Campello et al. (2008) use this insight and estimate the firm-specific equity-bond-elasticity using the fitted component from pooled panel regressions with leverage, stock volatility, and the risk-free rate as determinants.[22] Afterwards, they calculate expected excess stock returns on the basis of Eq. (2). We follow this approach and use the obtained equity risk premium in column (9) as dependent variable. For consistency, we also estimate factor exposures on the basis of equity returns as opposed to bond returns. For firms with multiple bond issues, implied equity risk premia are value-weighted.

In line with Campello et al. (2008), we observe a low power of the pooled panel regression to calculate the fitted component of the equity-bond-elasticity in the first place (R^2 of 1.5%) which suggests that the equity risk premia are subject to measurement error. Nonetheless, our main conclusions regarding the influence of the excess market return, *ME*, and *ROE* remain unchanged. However, for *HML* the coefficient turns insignificant and *IA* is now significantly negative.

Finally, we test whether our findings are also observable if we try to explain realized one-month ahead bond returns as a proxy for expected returns, instead of the forward-looking IRP. The answer is no, as an inspection of column (10) demonstrates. In this

[22] The dependent variable in the regression is the realized change in the market value of equity (i.e., stock return) divided by the realized change in the market value of debt (i.e., bond return). For further computational details we refer to pages 1313–1314 of their paper.

Table 5
Determinants of the implied risk premium and other expected return proxies: additional tests. This table reports results from pooled panel regressions of the implied risk premium (*IRP*) on factor loadings and several firm and bond characteristics. Column (1) shows results if factor loadings are value-weighted at the firm level. Column (2) repeats the analysis including issuer fixed-effects dummies. Column (3) repeats the analysis excluding small bonds below the 5th percentile of the offering amount. Column (4) shows results for loadings from a six-factor model that includes the Pastor and Stambaugh (2003) liquidity factor. Column (5) includes loadings from a seven-factor model that includes the term and default factor. Column (6) includes loadings from a seven-factor model that includes the term and an alternative default factor based on the physical default probability according to Campbell et al. (2016). Column (7) adds financial firms to the sample. Columns (8) and (9) repeat the analysis with credit spreads and equity risk premia (*ERP*) as measured by Campello et al. (2008) instead of IRPs. For column (9), we use stock returns to measure factor sensitivities accordingly. Column (10) shows results when using one-month ahead realized bond returns (*RET*) as dependent variable. Abbreviations are as follows: Return on equity (*ROEQ*), and asset growth (*AG*). β_{MKT}, β_{ME}, β_{ROE}, and β_{IA} are the factor loadings on the respective Hou et al. (2015b) q-factors. *MKT* is the market factor, *ME* the size factor, *ROE* is the profitability factor, and *IA* is the investment factor. β_{HML} is the Fama–French value factor loading. β_{PS} is the loading to the Pastor and Stambaugh (2003) liquidity factor, β_{TERM} is the loading to the return of a long-term government bond index minus the risk-free rate, and beta β_{DEF} is the loading to the return of a BBB-rated portfolio minus the return of an AAA-rated portfolio. Term and default factor information is from Datastream. Firm controls include: Equity market value (*MV*), book-to-market (*BM*), prior 6-month stock return (*EQ MOM*), leverage (*LEV*), and default probability (*PD*). Bond controls include: Offering size, Time-to-maturity (*TM*), prior 6-month bond return (*BOND MOM*), and bond age (*Age*). Construction details are in the Appendix. Coefficients are based on standardized variables. *t*-statistics reported in parentheses are based on standard errors clustered by issue and month identifier. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. The sample period is from M1:1995–M12:2011.

Variables	(1) IRP	(2) IRP	(3) IRP	(4) IRP	(5) IRP	(6) IRP	(7) IRP	(8) CS	(9) ERP	(10) RET
β_{MKT}	0.138***	0.016	0.131***	0.126***	0.107***	0.097***	0.120***	0.170***	0.131***	0.015
	(7.906)	(1.541)	(8.370)	(8.547)	(7.981)	(7.186)	(7.592)	(11.039)	(8.857)	(0.756)
β_{ME}	0.054***	0.006	0.063***	0.058***	0.048***	0.033***	0.050***	0.085***	0.058***	0.017
	(4.027)	(0.653)	(5.442)	(5.167)	(4.870)	(3.468)	(4.529)	(7.665)	(4.424)	(1.528)
β_{ROE}	−0.075***	−0.033***	−0.100***	−0.092***	−0.061***	−0.050***	−0.094***	−0.110***	−0.088***	−0.010
	(−4.713)	(−3.499)	(−7.209)	(−6.944)	(−4.931)	(−4.421)	(−7.162)	(−7.959)	(−5.790)	(−0.762)
β_{IA}	0.006	0.009	0.012	0.014	0.028***	0.000	0.010	0.008	−0.068***	−0.001
	(0.426)	(0.961)	(1.017)	(1.170)	(2.738)	(0.032)	(0.866)	(0.714)	(−3.888)	(−0.069)
β_{HML}	0.040**	0.049***	0.061***	0.085***	0.043***	0.027***	0.067***	0.060***	0.005	−0.000
	(2.437)	(4.161)	(4.127)	(6.355)	(3.854)	(2.788)	(4.615)	(4.238)	(0.350)	(−0.022)
β_{PS}				0.046***						
				(3.719)						
β_{TERM}					−0.155***	−0.148***				
					(−10.438)	(−8.915)				
β_{DEF}					0.045***					
					(3.669)					
β_{DEFPD}						0.244***				
						(11.493)				
ROEQ	−0.100***	−0.079***	−0.105***	−0.104***	−0.103***	−0.102***	−0.089***	−0.119***	−0.077***	−0.019**
	(−7.222)	(−7.506)	(−7.938)	(−8.014)	(−7.855)	(−7.779)	(−7.213)	(−9.771)	(−6.307)	(−2.324)
AG	0.010	−0.019***	0.018**	0.019**	0.015*	0.015*	0.015*	0.027***	0.014*	−0.016***
	(1.200)	(−3.046)	(2.172)	(2.290)	(1.733)	(1.820)	(1.928)	(2.976)	(1.831)	(−2.793)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58,891	162,009	160,331	162,009	162,009	162,009	200,929	162,009	55,078	162,009
R^2	0.580	0.706	0.560	0.559	0.565	0.568	0.551	0.596	0.620	0.261

regression, there is in fact no statistically significant relation between realized bond returns and any factor exposure. Hence, based on realized returns one may conclude that exposure to systematic risk does not matter at all for corporate bonds. Compared to regressions with the forward-looking IRP as dependent variable, we also observe a substantial drop in the R^2.

We find that the correlation between the IRP and realized bond returns is low at only 0.08. It is therefore not surprising to find that the results which we obtain for the IRP as dependent variable do not necessarily emerge for realized returns. Our evidence is consistent with several papers highlighting the problems of using ex-post realized returns as a proxy for expected returns (see e.g., Merton, 1980; Elton, 1999; Fama and French, 2006; Campello et al., 2008; Pastor et al., 2008; Chava and Purnanandam, 2010). Given our rather short sample period of 17 years, we would be particularly cautious to assume that average realized returns converge to ex-ante expected returns. Overall, it clearly matters which proxy for expected returns (forward-looking vs. realized) is used for asset pricing tests involving corporate bonds.

To sum up, Table 5 provides evidence that our baseline results are largely robust with respect to several plausible changes in our methodology and sample selection, as long as we use a forward-looking expected return measure. One additional impression from these tests is that the relation between embedded risk premia and the *IA* exposure is mostly insignificant. In the Appendix, we report results of various additional tests examining, among other things, the role of alternative measures of profitability, implementing further changes in the regression design and beta estimation methodology (e.g., from pooled-panel to Fama–MacBeth regressions, inclusion of industry-fixed effects and using equity-based factor loading estimates), or including additional control variables.

4. Additional analysis

4.1. Differences along the business cycle and investor sentiment

A paradigm of rational asset pricing is that the discount rate varies along the business cycle: An economic downturn in which the marginal value of wealth is high implies low current prices and high expected returns, particularly for risky assets that pay off poorly during such “bad times” (see Cochrane, 2008; 2011). It follows that a more pronounced positive relation between expected returns and the risk factor exposures is to be expected in distress periods. For instance, bonds that vary more with the market factor should have higher IRPs in bad states of the economy than in good states. The same line of reasoning may apply to the other asset pricing factors if they represent unknown sources of systematic risk. We test this prediction by using the recent growth in *GDP* and the consumption-to-wealth ratio denoted as *cay* from Lettau and Ludvigson (2001)) to differentiate between good and bad economic times.

To examine potential time-series variation in the risk-return relation we divide our sample based on the median of each of the conditioning variables. Then, we estimate the following model:

$$IRP_{i,t} = D_t \times (\boldsymbol{\beta_1} B_{i,t} + \boldsymbol{\gamma_1} X_{i,t} + \boldsymbol{\psi_1} Y_{i,t}) + (1 - D_t) \times (\boldsymbol{\beta_2} B_{i,t} + \boldsymbol{\gamma_2} X_{i,t} + \boldsymbol{\psi_2} Y_{i,t}) + \boldsymbol{\eta} Z_t + \varepsilon_{i,t}. \quad (3)$$

In the model, D_t is a dummy variable that takes the value of one if a month represents a period in which we expect a stronger influence of risk factor exposure on required returns, and zero otherwise. $B_{i,\,t}$ denotes the set of factor exposures. $X_{i,\,t}$ and $Y_{i,\,t}$ denote the set of firm as well as bond controls. The vector Z_t represents month dummies. We compare the coefficients contained in $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$.

Results for the analysis are displayed in Table 6. For the sake of brevity, we report only coefficients for the factor exposures of the q-factor model and the traditional value factor. Nevertheless, all regressions include the same list of additional bond and firm characteristics as in column (6) of Table 3. The table also shows *p*-values of one-sided Wald tests on the statistical significance of differences between the coefficients.

Columns (1)–(3) show sample split results for GDP growth, and columns (4)–(6) show sample split results for *cay*. In general, we find evidence which is consistent with the idea that the price of risk varies over time. For instance, we find that the coefficient for the value factor exposure is significantly larger in low-GDP periods (0.088) than in high-GDP periods (0.019). The coefficient for the market factor loading is about twice as large in high *cay* periods (0.202 vs. 0.107). Regarding the *ROE* factor exposure, there is also a statistically significant difference between high and low GDP-growth periods, and between high and low *cay* periods. The results provide further evidence that bond investors view firms with a positive dependence on *ROE* as less risky. In contrast, differences in the regression coefficients for *IA* between the sub-samples are small and not statistically significant. This finding is consistent with the argument that bond investors do not perceive the investment factor as a risk factor.

Besides separating between good and bad states of the economy, we additionally use the orthogonalized version of the Baker and Wurgler (2006) sentiment index to distinguish between low-sentiment and high-sentiment periods. Consistent with the idea of more mispricing in high-sentiment periods, Stambaugh et al. (2012) argue that profits for a broad set of stock market anomalies are larger in the presence of pronounced market-wide sentiment. Further, consistent with the idea of more rational pricing in low-sentiment periods, Antoniou et al. (2016) show that the security market line is upward-sloped as predicted by the CAPM in pessimistic sentiment periods, but negative otherwise. Transferring this approach to our setting, we expect a stronger association between required returns and risk factor exposures in periods of low sentiment when rational pricing is more likely to prevail.

Results are displayed in columns (7)–(9) of Table 6. We document a stronger positive relation between IRPs and the market, *ME*, and *HML* factor beta in low-sentiment periods. For the *ROE* beta, the relation moves in the other direction. The coefficient estimate amounts to −0.173 in pessimistic times, but only to −0.038 in optimistic periods (p-value$<$ 0.001). To the extent that deviations from rational pricing are more likely in periods of high investor sentiment, this finding provides further evidence that *ROE* is a reverse risk factor. There is no meaningful difference for *IA* along investor sentiment.

One concern with regard to the use of the Baker and Wurgler (2006) sentiment index is that it has been primarily created to identify sentiment in the stock market, and hence may not be an appropriate proxy for bond market sentiment. In an alternative test, we therefore consider the issuer quality measure of Greenwood and Hanson (2013) to identify periods of credit market overheating.[23] Specifically, Greenwood and Hanson (2013) argue that investors are more likely to be overoptimistic during credit booms to which low-quality firms are likely to respond by issuing overpriced debt. Following this argumentation, we expect a stronger association between the implied risk premium and risk factor exposures in periods of high issuer quality when rational pricing arguably predominates.

Results are shown in columns (10)–(12). We find a stronger positive relation between IRPs and the market and *HML* factor beta in high issuer quality periods. For the *ROE* beta, the relation is again negative. The coefficient estimate amounts to −0.158 in times of high issuer quality, but only to −0.030 in periods of low issuer quality (p-value$<$ 0.001). Arguing that deviations from rational pricing are more likely in times of low issuer quality, this finding provides further evidence that *ROE* is a reverse risk factor. We do not find a statistically significant difference for *IA*.

Overall, our findings are consistent with the idea that sentiment affects corporate bond prices. In additional tests reported in the Appendix, we also examine splits of the sample period based on market-wide measures of market and funding illiquidity (Dick-Nielsen et al., 2012; Franzoni et al., 2012; Axelson et al., 2013). These tests provide further evidence that the price of risk varies over time. Consistent with our other findings, in times of high market and funding illiquidity we observe higher expected returns for bonds that are positively exposed to the market factor and the value factor, but negatively exposed to the profitability factor. In contrast, we do not find that bonds with higher exposure to the investment factor have statistically significantly higher expected returns when illiquidity is more pronounced.

4.2. Results for bonds with short and long remaining maturity

Our expected return measure is a bond's embedded risk premium, which is an internal rate of return and therefore a long-term average. Internal rate of return estimates may differ from next-period expected returns (see e.g., Hughes et al., 2009). One critique raised by Hou et al. (2015a) with regard to the five-factor model is that Fama and French (2015) focus on an internal rate of return when they derive theoretical relations between their factors and expected returns. Specifically, Hou et al. (2015a) argue that the profitability is a short-lived phenomenon for which returns are positive only in the short-term but not in the long run.

Corporate bonds offer an interesting opportunity to test the validity of their argument without giving up the benefits of using a forward looking measure of expected returns instead of realized returns. The reason is that bonds, unlike stocks, have different maturities. For bonds with shorter remaining maturities the implied risk premia are closer to the definition of one-period ahead returns. Hence, if the profitability factor is indeed a short-lived positive risk factor, we should observe a higher relation between factor exposure and implied risk premia for bonds with short remaining maturity compared to our baseline results with the complete bond sample.

To test this conjecture, we divide our sample into two remaining maturity groups and estimate the coefficients of our baseline model for each group. The regression methodology is the same as in the previous section. Results are shown in the right-most columns of Table 6.

We find an increase in the relation between *ROE* factor exposure and bond IRPs once we move from the short remaining maturity bucket to the long bucket. The estimated coefficient is −0.113 for short remaining maturity bonds and −0.087 for long remaining maturity bonds. The *p*-value for the difference between both

[23] We thank an anonymous referee for making this suggestion.

Table 6

Determinants of the implied risk premium: sub-sample tests. This table reports results from pooled panel regressions of the implied risk premium (*IRP*) on factor loadings and several firm and bond characteristics. Columns (1) and (2) show results when separating periods along recent GDP growth. Columns (4) and (5) when separating periods along the consumption-to-wealth ratio *cay* from Lettau and Ludvigson (2001)). Columns (7) and (8) when separating periods along investor sentiment. We use the orthogonalized version of the Baker and Wurgler (2006) sentiment index to distinguish between low-sentiment and high-sentiment periods. Columns (10) and (11) when separating the sample along the expected-default-frequency version of the Greenwood and Hanson (2013) bond issuer quality measure. Columns (13) and (14) when separating the sample along the remaining time-to-maturity. For the first four conditioning variables, we use the median value to split the sample. The split on maturity is based on the monthly median time-to-maturity. We show *p*-values of one-sided Wald tests on the statistical significance of differences between the coefficients based on the theoretical considerations outlined in Section 4.2. Specifically, the alternative is a larger influence of factor exposures in periods of high distress, low sentiment and high issuer quality, respectively. Further, the alternative is a larger influence of factor exposures for issues with a lower time to maturity. For the sake of brevity, we report coefficients solely for the factor exposures. β_{MKT}, β_{ME}, β_{ROE}, and β_{IA} are the factor loadings on the respective Hou et al. (2015b) q-factors. *MKT* is the market factor, *ME* the size factor, *ROE* is the profitability factor, and *IA* is the investment factor. β_{HML} is the Fama–French value factor sensitivity. Firm controls include: equity market value (*MV*), book-to-market (*BM*), prior 6-month stock return (*EQ MOM*), leverage (*LEV*), and default probability (*PD*). Bond controls include: Offering size, time-to-maturity (*TM*), prior 6-month bond return (*BOND MOM*), and bond age (*Age*). We also include but do not table return on equity (*ROEQ*) and asset growth (*AG*). Construction details are in the Appendix. Coefficients are based on standardized variables. *t*-statistics reported in parentheses are based on standard errors clustered by issue and month identifier. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. The sample period is from M1:1995–M12:2011.

Variables	GDP growth			Consumption to wealth			Investor sentiment			Issuer quality			Maturity		
	Low	High		High	Low		Low	High		High	Low		Short	Long	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	IRP	IRP	*p*-value	IRP	IRP	*p*-value	IRP	IRP	*p*-value	IRP	IRP	*p*-value	IRP	IRP	*p*-value
β_{MKT}	0.130***	0.112***	0.221	0.202***	0.107***	0.000	0.217***	0.062***	0.000	0.198***	0.108***	0.000	0.199***	0.082***	0.000
	(6.350)	(7.075)		(7.494)	(7.710)		(10.438)	(3.674)		(8.047)	(7.017)		(7.725)	(6.276)	
β_{ME}	0.062***	0.054***	0.309	0.042**	0.074***	0.935	0.079***	0.023	0.000	0.052***	0.067***	0.764	0.110***	0.025**	0.000
	(4.542)	(4.405)		(2.009)	(7.225)		(5.873)	(1.513)		(3.415)	(3.986)		(6.141)	(2.502)	
β_{ROE}	−0.114***	−0.070***	0.019	−0.133***	−0.086***	0.044	−0.173***	−0.038***	0.000	−0.158***	−0.030***	0.000	−0.113***	−0.087***	0.062
	(−6.046)	(−5.677)		(−5.260)	(−7.056)		(−9.057)	(−2.849)		(−7.335)	(−2.841)		(−5.764)	(−7.066)	
β_{IA}	0.012	0.020**	0.690	−0.009	0.007	0.759	0.009	0.028*	0.834	0.004	0.008	0.580	0.024	0.007	0.190
	(0.818)	(1.981)		(−0.412)	(0.716)		(0.649)	(1.825)		(0.258)	(0.590)		(1.207)	(0.668)	
β_{HML}	0.088***	0.019**	0.001	0.074**	0.043***	0.147	0.106***	0.009	0.000	0.102***	0.014	0.000	0.055**	0.050***	0.398
	(3.929)	(2.037)		(2.565)	(4.079)		(5.781)	(0.581)		(4.245)	(1.346)		(2.516)	(4.113)	
Firm controls	Yes			Yes			Yes			Yes			Yes		
Bond controls	Yes			Yes			Yes			Yes			Yes		
Month dummies	Yes			Yes			Yes			Yes			Yes		
Observations	162,009			162,009			162,009			162,009			162,009		
R^2	0.577			0.590			0.571			0.593			0.575		

coefficients is 0.062. We also document significantly stronger relations for the market factor and *ME* for bonds in the short maturity bucket. Instead, for *HML* and *IA*, the difference of the factor exposure coefficients between the two maturity groups is not statistically significant.

Findings for the remaining maturity sample split might be explained by the fact that firms' risk profiles change over time. This implies that actual factor sensitivities (and also firm characteristics) become a less reliable proxy for a firms' future conditions the further away future is. Hence, one would probably expect that their influence on long-term expected returns should diminish. Most importantly, our conclusion regarding the influence of the factor exposures on the IRP are the same if we focus on bonds with shorter remaining maturities, for which the IRP is closer to the definition of the next-period expected return.

4.3. The relation between IRPs and realized equity returns

This section bridges the gap back to the stock market by examining the relation between equity returns and implied risk premia of corporate bonds. A central prediction of structural models following Merton (1974) is that equity and debt risk premia are positively related because equity and debt represent claims towards the same underlying risky firm asset. Thus, realized stock returns of firms facing high implied risk premia on their outstanding bonds should vary more with equity risk factors (e.g., the q-factors of Hou et al., 2015b) than stock returns of low-IRP firms.

To test this conjecture, we sort firms into tertiles based on their outstanding bond IRP at the end of each month. For firms with multiple debt issues, we use the average IRP. We then calculate the value-weighted next month return of the highest and the lowest IRP-tertile stock portfolio and regress the long–short difference on various risk factors. This forward-looking portfolio approach also addresses concerns about measurement errors in historically estimated firm-specific betas. It is similar to the analysis in e.g., Friewald et al. (2014).

Panel A of Table 7 shows our first set of regression results. The first row displays the regression coefficient for the excess market return in a one-factor model. The coefficient is 0.685 and highly statistically significant. Hence, in line with our previous findings based on historically estimated betas, high IRP firms have a high sensitivity to the market factor going forward. Results for the q-factor model in the next row indicate a positive influence of *IA* on long–short portfolio returns. Contrary to a risk-based explanation, the regression coefficient for *ROE* is negative (−0.970) and highly statistically significant (*t*-value: −8.476).

The explanation for the positive influence of *IA* in the second row is interesting. The next row in Panel A shows the results of a regression which adds *HML* as further explanatory variable. This time the *IA* coefficient is negative and statistically insignificant. In contrast, the *HML* coefficient is positive and statistically significant at the 1%-level. The results indicate that bond investors appear to perceive *HML* as risk factor, and that the influence of *IA* is further subsumed by *HML*.[24]

Analogous regression results for the Fama and French (2015) five-factor model, which lead to the same conclusions, are tabulated in the Appendix. The negative influence of the Fama and French (2015) profitability factor *RMW* is substantially weaker in comparison to the influence of *ROE*. This finding provides further evidence that *RMW* is a noisy factor version of *ROE*.

A potential concern is that the results are due to an implicit characteristic sorting when we form the high-minus-low IRP portfolio. Panel B of Table 7 reveals that there are indeed substantial characteristic imbalances for the long–short IRP portfolio with regard to *MV, BM*, and *ROEQ*. Because the risk-based explanation would predict comovement between the portfolio returns and the factors even independent of firm characteristics, we additionally create characteristic-neutral long–short IRP portfolios for a second set of regressions. Specifically, we employ an independent 5x3 sorting in which firms are partitioned into five bins according to their characteristic value and into 3 bins according to their IRP. We then calculate the stock return of the long–short IRP portfolio for each characteristic bin. The overall high-minus-low IRP portfolio return is the average of the five long–short returns. The procedure is conducted separately for the four characteristics used for the Hou et al. (2015b) factors and *HML* (*MV, BM, AG, ROEQ*), i.e., there are four different long–short portfolio versions.[25]

The results of this second set of regressions are reported in Panel C in Table 7. The first row in Panel C displays regression results for the size-neutralized high-minus-low IRP portfolio. The second row shows the results for a portfolio that is characteristic-neutralized with regard to *ROEQ*. Rows 3 and 4 show the results of a portfolio that is characteristic-neutralized with regard to *AG* and *BM*, respectively. The last two columns in Panel C also show how good the characteristic-neutralization works by presenting the average characteristic percentile in the long and short side of the portfolio. As intended, after neutralization no significant differences between these portfolios are observable. We find that *ROE* continues to be significantly negatively correlated with the long–short portfolio return in row 2, and that the relation between *IA* and the portfolio return remains insignificant in row 3. Overall, the section confirms our previous conclusions that *ROE* exposure is negatively related to a firm's cost of debt, and that the influence of *IA* is small when compared to *HML*.

5. Conclusion

This paper investigates to what extent implied risk premia embedded in credit spreads are related to profitability, investment, and their corresponding factor-mimicking returns as defined by Fama and French (2015) and Hou et al. (2015b). Unlike most existing studies examining realized returns, we consider a forward-looking measure of returns required by investors.

We provide new evidence on profitability and investment patterns in the cross-section of expected returns. We document lower debt financing costs for firms with high profitability factor sensitivity, while there is no reliable evidence that exposure to the investment factor matters for a firm's cost of debt. These findings cast doubt on a risk-based explanation for the abnormal stock returns of profitability-based and investment-based strategies. Our results particularly challenge arguments proposing that high profitability firms have higher stock returns because of a higher systematic risk exposure. While bond investors might indeed fail to price the risk of high profitability firms correctly, this line of reasoning in turn raises the question why other rational investors would be unwilling to exploit and correct such an apparent mispricing.

With regard to the traditional risk factors, our study further complements earlier work by Campello et al. (2008). Our evidence suggests that all three traditional factors, i.e, the market factor, size factor, and value factor, represent at least to some extent systematic risk and are priced ex-ante. In particular, our results highlight the continuing importance of the traditional value factor even considering the new extended asset pricing models.

[24] In an unreported robustness test, we also add the momentum factor as further explanatory variable. We find that the coefficient for the momentum factor is significantly negative. It does not materially affect the results for the other factors.

[25] We cannot use an independent sorting for all four characteristics at once because this would lead to 1875 portfolios ($5\times 5\times 5\times 5\times 3$) which is more than the average number of firms in our sample in a given month.

Table 7
Explaining realized stock returns of high-minus-low IRP portfolios. This table reports results from various asset pricing models explaining the realized difference in equity returns between firms with high and low implied risk premia on outstanding corporate debt. In Panel A, firms are sorted into tertiles based on their outstanding bond *IRP* at the end of each month. We calculate the difference between the value-weighted next month return of the highest and the lowest IRP-tertile stock portfolio and regress it on various factors. Panel B shows the characteristic percentile averages for the long and short side of this portfolio, and the resulting long–short difference. In Panel C, characteristic-neutral long–short *IRP* portfolio returns are examined. The portfolios result from an independent 5× 3 sorting in which firms are partitioned into five bins according to their characteristic value (*MV, ROEQ, AG, BM*) and into three bins according to their IRP. Within each characteristic bin we calculate the stock return of the long–short IRP portfolio separately. The overall high minus low IRP portfolio return is the average of the five long–short returns. The last two columns in Panel C show how good the characteristic-neutralization works. Abbreviations are as follows: Equity market value (*MV*), return on equity (*ROEQ*), asset growth (*AG*), and book-to-market (*BM*). Tested asset pricing models are the *CAPM*, the Hou et al. (2015b) q-factor model, and the Hou et al. (2015b) q-factor model augmented with the Fama–French value factor. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. *t*-statistics are in parentheses. The sample period is from M1:1995–M12:2011.

Panel A: Explaining equity returns of the single-sorted long–short high IRP minus low IRP portfolio

Model	MKT	ME	ROE	IA	HML	Constant	R^2
CAPM	0.685***					−0.003	0.296
	(9.198)					(−0.900)	
Q-factors	0.378***	0.139	−0.970***	0.344**		0.001	0.524
	(5.051)	(1.593)	(−8.476)	(2.508)		(0.312)	
Q-factors +HML	0.350***	0.152*	−1.061***	−0.289	0.592***	0.002	0.580
	(4.964)	(1.843)	(−9.723)	(−1.623)	(5.163)	(0.712)	

Panel B: Characteristic percentile averages of the single-sorted long–short high IRP minus low IRP portfolio

	MV	ROEQ	AG	BM
Long portfolio	28.64	39.83	48.62	63.17
Short portfolio	69.94	59.52	51.36	37.89
Dif. long–short	−41.31	−19.69	−2.75	25.29

Panel C: Explaining equity returns of characteristic-neutralized long–short high IRP minus low IRP portfolios

Characteristic-neutral with respect to:	MKT	ME	ROE	IA	HML	Constant	R^2	Mean characteristic percentiles	
								Long	Short
MV	0.260***	0.097	−0.918***	−0.118	0.341***	−0.002	0.535	47.76	51.95
	(4.140)	(1.316)	(−9.448)	(−0.746)	(3.341)	(−0.698)			
ROEQ	0.327***	0.373***	−0.582***	−0.248	0.625***	0.000	0.538	50.16	50.79
	(5.318)	(5.200)	(−6.126)	(−1.597)	(6.267)	(0.068)			
AG	0.405***	0.197***	−0.850***	−0.213	0.689***	0.001	0.600	50.39	50.35
	(6.376)	(2.650)	(−8.650)	(−1.328)	(6.676)	(0.329)			
BM	0.318***	0.158**	−0.846***	−0.439**	0.432***	0.001	0.531	50.89	49.33
	(4.724)	(2.012)	(−8.136)	(−2.585)	(3.956)	(0.290)			

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2017.06.005.

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