Journal Of Investment Management, Vol. 16, No. 2, (2018), pp. 17–46

JOIM
www.joim.com

COMMON FACTORS IN CORPORATE BOND RETURNS

Ronen Israel[a,c], *Diogo Palhares*[a,d] *and Scott Richardson*[b,e]

We find that four well-known characteristics (carry, defensive, momentum, and value) explain a significant portion of the cross-sectional variation in corporate bond excess returns. These characteristics have positive risk-adjusted expected returns and are not subsumed by traditional market premia or respective equity anomalies. The returns are economically significant, not explained by macroeconomic exposures, and there is some evidence that mispricing plays a role, especially for momentum.

1 Introduction

Corporate bonds are an enormous—and growing—source of financing for companies around the world. As of the first quarter of 2016, there was \$8.36 trillion of U.S. corporate debt outstanding, and from 1996 to 2015 corporate bond issuance grew from \$343 billion to \$1.49 trillion (Securities Industry and Financial Markets Association). Surprisingly little research, however, has investigated the cross-sectional determinants of corporate bond returns.

We study the drivers of the cross-section of corporate bond expected returns. To do so, we focus on a set of characteristics that has been shown to predict returns in other markets, yet researchers have not studied the viability of all these characteristics to predict returns in credit markets. The characteristics are carry, quality, momentum, and value (Koijen *et al.*, 2014 for carry; Frazzini and Pedersen, 2014 for quality; Asness *et al.*, 2013 for momentum and value). Our contribution includes (i) applying these concepts to credit markets; (ii) studying them together in a way that shines light on their joint relevance or lack thereof; (iii) evaluating their economic significance by examining both long-and-short, transaction-costs-oblivious portfolios, and also long-only, transaction-costs aware portfolios; and (iv) exploring the source of the return premia by testing both risk- and mispricing explanations.

Using traditional long-and-short portfolio analysis and cross-sectional regressions we find positive risk premiums that are highly significant (t-statistics of 3 or more) for all characteristics

[a]AQR Capital Management, Greenwich, CT.
[b]AQR Capital Management, London Business School, London, United Kingdom.
[c]E-mail: ronen.israel@aqr.com
[d]E-mail: diogo.palhares@aqr.com
[e]E-mail: scott.richardson@aqr.com

but carry. These premia are distinct from traditional long-only bond and equity market risk premia, as well as from the premium earned by long-and-short equity anomalies based on value, momentum and defensive. The strong relation among carry, defensive, value and momentum and future credit excess returns can be interpreted as out-of-sample evidence for the broader efficacy of these characteristics.

We also make a methodological contribution to long-and-short portfolio analysis for credit markets. The volatility and market beta of corporate bonds is tightly related to credit spreads and durations. Many return predictors are also correlated with credit spreads. As a consequence, if one just creates portfolios by sorting on these measures, the long-and-short portfolios will have very different risk profiles, making their expected returns hard to compare and the long-high-short-low portfolio far from market neutral. In the end, contrary to what happens in equity long-and-short portfolios that end up with small market exposures, simple long-and-short credit portfolios do not. Furthermore, credit spread itself is a return predictor so it is important to understand whether a candidate variable simply predicts returns because of its correlation with spreads or whether it has any extra forecasting power. To solve these general issues, we use a double sort on an ex-ante measure of beta (duration times spread) and the candidate characteristic.

Trading costs and liquidity are also very different in credit markets relative to equity markets. Corporate bonds are difficult to trade and the expected trading cost is high relative to the underlying volatility of the asset class (see, e.g., Harris, 2015). Thus, simple analyses of Sharpe ratios based on "academic" quintile long/short portfolios may substantially overstate the economic significance of any characteristic. Thus, when studying credit portfolios, we explicitly account for transaction costs and other potential trading restrictions.

To establish more realistic returns we also study long-only portfolios of relatively liquid corporate bonds with exposure to carry, defensive, momentum and value themes. We show that these portfolios generate high risk-adjusted returns, net of trading costs. Relative to a value-weighted benchmark of corporate bonds, the long-only portfolio yields a net (of transaction cost) active return of 2.20% annualized, which translates to an information ratio of 0.86. While the number is a point estimate out of a roughly 20-year sample, its exact magnitude is less important than the fact that it is well above zero.

We explore possible explanations for the observed return's patterns. We examine both risk explanations–characteristic portfolios expose the aggregate investor to losses at times in which those losses are particularly tough to bear–and mispricing theories–investors deviate from rationality because of mistakes or agency problems and limits-to-arbitrage stop arbitrageurs from fully correcting these mistakes and their impact on asset prices.

We examine the risk hypothesis with two tests. First we measure the exposure of each individual characteristic and a combination of all of them to traditional macroeconomic factors (e.g., Chen *et al.*, 1986). While the coefficients are statistically significant, they suggest that the characteristics have a hedging profile. That is, the returns of the combined portfolio are higher when growth expectations are lower, volatility increases and inflation expectations increase. In the second test, we replace the traditional macroeconomic factors with changes in broker–dealer leverage. Adrian *et al.* (2014) found that exposures to broker–dealer balance sheets can explain equity anomalies as well as government bond returns. We do not find evidence that broker–dealer leverage can explain credit characteristic returns. In particular, the combined portfolio, exposed to all individual characteristics, has a positive (hedging), but indistinguishable from zero, loading on leverage shocks.

We break down the drivers of mispricing into (i) factors that influence the likelihood that noise traders (Grossman and Stiglitz, 1980) are important for a given security; and (ii) factors that limit the activity of arbitrageurs (Shleifer and Vishny, 1997). We proxy for the likelihood of noise traders with (i) a measure of the investor base sophistication (institutional ownership of the bond); and (ii) a measure of firm transparency (analyst coverage of the issuing firm equity). For limits to arbitrage we measure liquidity (bond amount outstanding) and ease of shorting (as reflected by the shorting fee).

We run two tests using with those proxies. In the first test we examine whether the bonds most attractive to an arbitrageur–those with extreme values for the anomalies–are particularly hard to arbitrage or are more vulnerable to investor's errors. For the shorting fee the test is one sided: are bonds that represent the most attractive short from the point of view of arbitrageurs–those with unusually low anomaly scores–unusually hard to short? We do not find evidence of this pattern for any of the characteristics.

In the second test we look at long-and-short portfolios built on security universes which differ in expected mispricing and limits to arbitrage. The hypothesis here is that anomaly returns should be stronger among the hard-to-arbitrage-or-high-error bonds. Momentum returns are indeed larger among harder-to-arbitrage-or-high-error bonds and the result is statistically significant. The other anomalies perform similarly across the different universes.

Finally, the last test focuses on the investor mistake hypothesis. We test whether the returns can be explained by investors' errors in forecasting sales (e.g., Bradshaw *et al.*, 2001). To proxy for investors' expectations, which are unobservable, we use equity analyst forecasts. If these forecasts were rational and unfettered by agency conflicts, analyst revisions should not be predictable by public information. On the other hand, if they underestimate the sales of firms with high scores and overestimate the sales of those with low scores, the correction of those expectations may explain the anomaly premium. The evidence is in the right direction, statistically significant and quantitatively important for momentum, but not for the remaining characteristics. Overall, returns to the momentum characteristic seem to be the most tightly linked to mispricing, with the evidence being less clear about the source of the returns of other characteristics.

The remainder of this paper proceeds as follows. Section 2 discusses a simple framework for corporate bond excess returns and links our analysis to earlier papers exploring determinants of cross-sectional variation in corporate bond expected excess returns. Section 3 explains our data sources, sample-selection criteria, characteristic measures and research design. Section 4 describes our empirical analyses and Section 5 concludes.

2 A framework for expected corporate bond excess returns

Unlike equity markets with variants of the dividend discount model to guide empiricists in their measurement of expected returns, there is not an agreed upon framework for estimating excess credit returns. Ex post, researchers agree that credit excess returns can, and should, be measured as the difference between the returns to a corporate bond and an appropriately cash flow-matched treasury bond (see, e.g., Hallerbach and Houweling, 2013; Asvanunt and Richardson, 2017). Ex ante, as credit and equity are related securities, one approach would be to simply explore whether characteristics known to explain cross-sectional variation in equity excess returns also explain credit excess returns. Indeed, some recent research has followed this approach (e.g., Chordia *et al.*, 2016). This approach amounts to testing whether priced sources of risk span across markets (e.g., Fama and French, 1993). Whilst this approach is useful in commenting on whether characteristics share similar returns across equity and credit markets, this approach misses an important point that the relevant risk across credit and equity markets are not identical. After all, simply documenting that: (i) X is correlated with equity excess returns, (ii) equity excess returns and credit excess returns are correlated, and hence (iii) X is therefore correlated with credit excess returns is not that exciting (see e.g., Lok and Richardson, 2011).

Prices of corporate bonds are not independent from equity prices, but nor are they simply a mirror image. First, while the fundamental value of bonds and equities both depend on the underlying value of the assets of the firm (e.g., Merton, 1974), the way these two assets respond to changes in properties of asset values is not identical. Second, equity and bond values can change even when the underlying value of the firm business does not. Corporate events such as leveraged buyouts, for example, tend to benefit shareholders at the expense of debtholders. Third, bonds and equities are traded in two different markets and typically held by different investors. This can make stock and bond valuations diverge, as they are anchored to the risk aversion, liquidity demands and sentiment of different investor clienteles. As a consequence, knowledge about the cross-section of expected stock returns does not translate one-to-one to bond returns (see, e.g., Chordia *et al.*, 2016; Choi and Kim, 2015).

Our approach is to directly measure characteristics that could inform about expected credit excess returns. A natural candidate is the spread of the corporate bond, which we call 'carry'. This is a suitable measure of expected returns if, and only if, there is no change in either default expectations or aggregate risk premium. To complement a measure of spread, we also look to multiple characteristics that could potentially inform about future changes in spreads. Such measures include dimensions of value, momentum and quality that have been examined in equity markets. But we need to tailor these measures to reflect the type of risk priced in the credit market (notably the risk of default). As such, our paper is related to prior research exploring cross-sectional determinants of corporate bond excess returns.

Correia *et al.* (2012) study value investing in corporate bond markets by comparing market spreads with model-implied spreads estimated using fundamental and market-based inputs. Kwan (1996) and Gebhardt *et al.* (2005b) document strong evidence for equity momentum in corporate bond markets by showing that past equity returns strongly predict future corporate bond returns of the same issuer, even after controlling for corporate bond momentum. Jostova *et al.* (2013) examine credit momentum and show that it is profitable when used to trade high-yield U.S. corporate bonds—even when controlling for equity momentum.

Koijen *et al.* (2014) evaluate carry factors across several markets: for credit markets, they test corporate bond indices of varying durations, maturities and rating categories. Carvalho *et al.* (2014) identify a low-risk anomaly across a broad universe of fixed income assets for various measures of risk. Similarly, Frazzini and Pedersen (2014) document positive risk-adjusted returns for portfolios that take long positions for short duration and higher-rated corporate bonds and take short positions for long duration and lower-rated corporate bonds. In contrast, Ng and Phelps (2014) note that the low-risk anomaly in corporate bonds is sensitive to the selected measure of risk.

Our work extends this literature. First, we study the stand-alone performance of characteristics and investigate the relation between them and their combined efficacy. Second, we consider simple unconstrained long–short portfolios and also more realistically investable long-only portfolios, which account for transaction costs and shorting constraints typical for corporate bonds. The investable portfolios show that our results are economically meaningful. Third, we investigate the sources of return predictability. We explore risk-based and non-risk-based explanations and find that macroeconomic exposures are not consistent with a positive premia for the anomalies, whereas limits to arbitrage and investor errors seem to play a role in momentum strategies, though not the others.

3 Data and methodology

3.1 Corporate bond data

Our analysis is based on a comprehensive panel of U.S. corporate bonds between January 1997 and April 2015 measured at a monthly frequency. This panel includes all constituents of the Bank of America Merrill Lynch ("BAML") investment-grade ("U.S. Corporate Master") and high-yield ("U.S. High Yield Master") corporate bond indices. The BAML dataset relies on the industry standard for valuations, aggregating data from TRACE as well as other sources. For an academic use of the data see Schaefer and Strebulaev (2008).

Following the criteria of Haesen *et al.* (2013), we select a representative bond for each issuer every month. The criteria used for identifying the representative bond are selected so as to create a sample of liquid and cross-sectionally comparable bonds. Specifically, we select representative bonds on the basis of (i) seniority, (ii) maturity, (iii) age and (iv) size.

First, we filter bonds on the basis of seniority, limiting ourselves to only senior debt. We then select only the bonds corresponding to the most prevalent rating of the issuer. To do this, we first compute the amount of bonds outstanding for each rating category for a given issuer. We keep only those bonds that belong to the rating category that contains the largest fraction of debt outstanding. This category of bonds tends to have the same rating as the issuer. Second, we filter bonds on the basis of maturity. If the issuer has bonds with time to maturity between 5 and 15 years, we remove all other bonds for that issuer from the sample. If not, we keep all bonds in the sample. Third, we filter bonds on the basis of time since issuance. If the issuer has any bonds that are at most 2 years old, we remove all other bonds for that issuer. If not, we keep all bonds from that issuer in the sample. Finally, we filter on the basis of size. Of the remaining bonds, we pick the one with the largest amount outstanding. A deliberate consequence of our bond selection criteria is that we will not be exploring a liquidity premium (such as issue size) for our primary empirical analyses.

Our resulting sample includes 274,665 unique bond-month observations, corresponding to 11,804 bonds issued by 4,296 unique firms. Table 1 reports annual statistics describing the composition of our sample over time. The average month in the sample consists of 1,247 bonds representing \$573 billion of total notional outstanding, of which 59% (41%) corresponds to investment grade (high yield) issues. To construct variables requiring financial statement information, we can link 48% of our universe to the Compustat database (using CUSIP and Ticker identifiers contained in the BAML dataset).

Table 1 Universe statistics (January 1997–April 2015).

Year	Count	Total notional	%IG	%HY	% Linked to Compustat
1997	1,096	239	60%	40%	54%
1998	1,188	278	61%	39%	53%
1999	1,104	306	63%	37%	52%
2000	1,026	335	65%	35%	50%
2001	1,026	375	70%	30%	49%
2002	1,099	443	70%	30%	49%
2003	1,263	511	63%	37%	49%
2004	1,398	562	60%	40%	47%
2005	1,291	569	59%	41%	45%
2006	1,268	560	58%	42%	43%
2007	1,256	578	56%	44%	43%
2008	1,046	553	64%	36%	47%
2009	967	540	66%	34%	49%
2010	1,269	689	56%	44%	46%
2011	1,380	768	53%	47%	46%
2012	1,406	812	53%	47%	46%
2013	1,521	893	51%	49%	45%
2014	1,564	936	50%	50%	45%
2015	1,533	948	51%	49%	46%
Average	1,247	573	59%	41%	48%

The table reports annual summary statistics of the Bank of America Merrill Lynch (BAML) bond sample. Each column statistic is computed monthly and averaged within the specified year. Investment grade (IG) and high yield (HY) classifications are based on S&P ratings. Bond issues are linked to Compustat based on CUSIPs and Tickers as described in the text. Total notional is reported in billions of dollars.

Next, we describe a few key variables contained in the BAML dataset. Option-adjusted spread (OAS) is the fixed spread that needs to be added to the Treasury curve such that the corporate bond's discounted payments match to its traded market price (accounting for embedded options). Duration, which measures a bond's sensitivity to interest rates, is also adjusted for embedded optionality. BAML provides total returns as well as excess returns, which are equal to total returns minus the return of a duration-matched Treasury. Credit ratings are based on Standard & Poor's ratings classification system. To construct numerical ratings that can be used in our regressions, we map ratings of AAA, AA, A, BBB, BB, B, CCC, CC, C and D to scores of 1, 2, 3, 4, 5, 6, 7, 8, 9 and 10, respectively. A rating less (greater) than or equal to 4 (5) therefore corresponds to investment grade (high yield). As newly issued bonds tend to be more liquid, we define a measure of bond illiquidity labelled "age percent," which is computed as time-since-issuance (in days) divided by original maturity (in days).

Table 2 provides a description of several issue and issuer characteristics. All of our variable

Table 2 Issue and issuer characteristics (January 1997–April 2015).

	Mean	Std.	5%	10%	25%	50%	75%	90%	95%
OAS	386	308	85	107	161	302	512	783	1,002
Duration	5.1	2.2	1.6	2.4	3.8	5.0	6.3	7.3	8.2
Total Ret.	0.6%	3.1%	−2.9%	−1.6%	−0.4%	0.6%	1.7%	3.0%	4.2%
Excess Ret.	0.2%	3.0%	−3.2%	−1.9%	−0.7%	0.2%	1.2%	2.4%	3.6%
Amt. Out.	437	442	134	159	208	309	495	811	1,123
Time to Mat.	7.8	5.1	2.7	3.9	5.5	7.1	8.7	10.4	15.5
Age Percent	28%	19%	5%	7%	12%	24%	39%	54%	67%
Rating	4.7	1.4	2.5	3.0	3.8	4.7	6.0	6.6	6.9
Dist. to Def	6.0	3.5	1.4	2.0	3.4	5.5	8.0	10.6	12.2
Momentum	5%	16%	−16%	−10%	−3%	2%	11%	24%	36%
Leverage	0.31	0.41	−0.02	0.03	0.13	0.28	0.47	0.66	0.77

The table reports summary statistics of bond issue and issuer characteristics (as defined in Table A.I). For each characteristic, the column statistic is computed on a monthly basis and then averaged over the full sample period.

definitions are presented in Table A.1. For each characteristic, we compute several statistics (e.g., mean, standard deviation and various percentiles) on a monthly basis and report the average of these monthly statistics in the table. The average issue in our sample has an OAS of 386 basis points, duration of 5.1 years, $437 million of notional outstanding, 7.8 years to maturity, and age percent of 28%. The average issuer in our sample has a six-month average credit and equity excess return of 5% and market leverage of 0.31.

3.2 *Characteristic measures*

In this section, we define the four key characteristics that we use to explain cross-sectional variation in corporate bond excess returns. Our choices are driven by the desire to have intuitive and, to the extent possible, standard measures that span both public and private issuers of corporate bonds. When multiple measures satisfy those criteria, we combine them using equal-risk weights to obtain a more robust portfolio and make the results less susceptible to a specific variable selection.[1] We deliberately do not select size as a characteristic, as the corporate bond market is notoriously expensive to trade. Our interest is in the identification of characteristics that explain excess returns of large and liquid corporate bonds.

Carry is the return of a security if time passes but market conditions do not change and we measure it using the option-adjusted spread (OAS). We use OAS rather than bond yield because we are interested in credit returns in excess of key-rate-duration-matched treasuries. Bond yield reflects both the credit component and the Treasury component.

OAS also has its problems. It is a perfect measure of carry only if the credit curve is flat. If the curve has a positive or negative slope, OAS will underestimate and overestimate carry respectively. Most issuers have upward sloping credit spread term structures, implying that the OAS will be an imperfect measure of carry. The alternative, however, is to estimate credit spread curves for each issuer. While potentially more precise, the curve interpolation exercise is model dependent and adds considerable complexity and opaqueness to the carry measure. In our view, OAS strikes a reasonable balance between precision on one hand and simplicity and transparency on the other.

Past research has identified a tendency for safer low-risk assets to deliver a higher risk-adjusted return (e.g., Frazzini and Pedersen, 2014; Carvalho *et al.*, 2014). We apply this idea to corporate bonds by building a *defensive* (or low-risk) measure using multiple variables. Our first measure is market leverage, measured as the value of net debt (book debt + minority interest + preferred stocks − cash) divided by the sum of the value of net debt and market value of equity. Both intuitively and theoretically speaking, firms with higher levels of leverage (or greater use of debt) are more likely to default and are hence fundamentally riskier (e.g., Altman, 1968; Shumway, 2001).

Our second measure of safety is gross profitability as defined in Novy–Marx (2013). Unlike other profitability measures, such as net income over equity value, gross profitability speaks to the quality of the overall assets owned by the firm. As such, it reasonably proxies for the safety of the enterprise, covering both equity and debt claims.

Our third measure of safety is simply low duration. Binsbergen and Koijen (2015) document that short maturity securities across different asset classes tend to have higher risk-adjusted returns. Palhares (2013) has shown that this also holds among single-name credit default swaps. Here we apply the same concept to corporate cash bonds.

For financial instruments that trade in cash markets (i.e., government bonds and equities), there is reliable evidence of a negative relation between beta and future excess returns (e.g., Frazzini and Pedersen, 2014). One reason for this negative relation is the prevalence of leverage-averse investors in cash markets who seek higher returns by buying higher beta assets as opposed to levering up the mean–variant efficient portfolio. Indeed, evidence from holdings of equity mutual funds shows that the average stock held has a beta of about 1.08 (see Table 11 of Frazzini and Pedersen, 2014).

For credit markets, both systematic and idiosyncratic volatility can be captured by the product of duration and spread, or DTS (e.g., Ben Dor *et al.*, 2007). The first component, duration, has been shown to be negatively associated with risk-adjusted returns in equities, bonds and several other asset classes (e.g., Palhares, 2013; Binsbergen and Koijen, 2015). The second component, credit spread, simply measures carry in credit markets. Beta and idiosyncratic volatility, therefore, implicitly combine two measures that have confounding effects on expected returns, leading to their inadequacy as suitable characteristics to explain corporate bond excess returns. As a consequence we have excluded beta and volatility as measures of the defensive theme.

For our *momentum* characteristic, we use two widely studied momentum measures. The first is credit momentum defined as the trailing six-month bond excess return. Jostova *et al.* (2013) shows that, in a broad sample of corporate bonds, including both high-yield and investment-grade securities, past winners tend to outperform past losers. The second momentum measure is the six-month equity momentum of the bond issuer. Kwan (1996) and Gebhardt *et al.* (2005b) show that stock returns tend to lead corporate bond returns.

To construct a value signal, we need a market value measure (price, yield, spread, etc.), a fundamental value measure and a way to compare the two. For example, Fama and French (2003) use the price of a stock for the market measure, the book value for the fundamental measure and the ratio to make a comparison. For credit markets we use the spread of the bond and credible measures of default risk as the fundamental anchor. A cheap bond has high spread relative to default risk.

We use two proxies for default risk. First, we follow Correia *et al.* (2012) and use the issuer default probability. We measure the default probability as in Bharath and Shumway (2008). One drawback of this approach is that it can only be computed for issuers with publicly traded equity. To increase coverage, we use a second value anchor that combines three broadly available fundamental measures: credit rating, bond duration and the volatility of bond excess return returns in the last 12 months.

3.3 Portfolio construction

The traditional way of examining the relationship between expected returns and a candidate predictor in the equity literature consists of constructing portfolios based on the cross-sectional rank of the characteristic, averaging the returns within the portfolio and then averaging those over time (e.g., Fama and French, 1993). This approach does not guarantee that the different quantile portfolios will have similar ex-ante volatilities and beta, and, as consequence, that the long-top-minus-short-bottom portfolios will be market neutral. In spite of that, in the equity literature, the different anomaly portfolios do tend to have similar risk and the long-and-short risk factors tend to have moderate betas—though not zero, for example, the SMB and HML factors are notorious for their positive and negative betas respectively (e.g., Fama and French, 1993) and the betting-against-beta factor (e.g., Frazzini and Pedersen, 2014) has negative beta.

This quirk of the traditional portfolio construction methodology is important for this paper because the cross-section of corporate bonds has a much larger dispersion in beta and risk than equity markets. Furthermore, many of the characteristic we examine correlate with beta. As a consequence, the long-and-short portfolios formed using those characteristics will not be beta neutral, complicating the interpretation of their expected returns and time-series properties as the reflection of something other than their embedded market exposure. To obtain long-and-short portfolios that are closer to market neutrality we demean characteristics within five ex-ante beta quintiles, with beta being measured as duration times spread (DTS). We exclude duration and carry from that step because, mechanically, that would induce a portfolio that mixes high carry and low duration together.

We construct two types of characteristic portfolios. First, we follow the standard convention of computing a zero-cost portfolio, that is, long corporate bonds in the highest quintile of a given characteristic and short corporate bonds in the lowest quintile of a given characteristic. Within quintiles, we report excess returns based on value-weighted returns. Our inferences are unaffected if we instead use equal weighting. We also display a constant 5% volatility version of each long-and-short portfolio (Muir and Moreira, 2016). We use the 24-month realized volatility of the unsealed portfolio as the measure of ex-ante risk.[2]

We construct the quintiles and long-and-short portfolios for each characteristic individually and for a combination of them all. The combination sorting variable is an inverse-of-risk-weighted sum of the four characteristics. More precisely, for each characteristic we form a portfolio that is linear in ranks (Asness *et al.*, 2014) and then multiply it by 5% and divide it by its 24-month realized volatility—the outcome is an alternative constant-volatility portfolio with linear weights instead of just having non-zero values for the most extreme quintiles. The combined characteristic is then just an equal-weighted average of those single-characteristic, linear-in-ranks portfolio weights.

A critical part of this paper is to examine the return-forecasting characteristics jointly. Each single characteristic informs us about properties of the stochastic discount factor that prices corporate credit securities, but the single portfolio that makes optimal use of the multiple characteristics goes beyond: it alone is sufficient to fully characterize that discount factor (e.g., Cochrane, 2009). From the point of view of an investor, that single portfolio is also interesting. For example, for a mean–variance investor allocating between these long-and-short credit strategies and cash, the allocation to that optimal portfolio would be sufficient to summarize its asset allocation policy.

The question is then how to build this optimal portfolio. Without observing expected returns and covariance matrices, one cannot observe the optimal portfolio weights. Using sample moments is problematic because of look-ahead bias and the relative shortness of a 20-year sample to estimate expected return. Our answer to the problem is an equal-weighted portfolio. It generalizes the robustness of the $1/N$ portfolio (e.g., DeMiguel *et al.*, 2009) by applying it to similarly risky characteristic portfolios rather than underlying assets.

For the combination of characteristics, we also analyze a second type of portfolio: a long-only portfolio that takes into consideration realistic implementation by solving a linear optimization problem. The analysis of a long-only portfolio is unusual when studying cross-sectional return predictability. But given the well-known challenges in shorting corporate bonds (e.g., Asquith *et al.*, 2013) and the significant costs in trading corporate bonds relative to their underlying volatility (e.g., Bessembinder *et al.*, 2006; Edwards *et al.*, 2007), it is important to test whether the characteristic's premia survives difficult but realistic real-world constraints.

4 Results

4.1 Regression analysis

Before reporting the performance of our portfolios, we first report Fama–Macbeth regressions of monthly corporate-bond excess returns regressed onto lagged characteristics along with control variables. Each month, we run cross-sectional regressions of the form:

$$\begin{aligned} R_{i,t+1} = \alpha &+ \beta_1 CARRY_{i,t} + \beta_2 DEF_{i,t} \\ &+ \beta_3 MOM_{i,t} + \beta_4 VALUE_{i,t} \\ &+ \gamma Z + \varepsilon_{i,t+1}, \end{aligned} \tag{1}$$

where $R_{i,t+1}$ denotes the duration-hedged excess return of bond i over month $t+1$. Each of the four characteristics is converted to a normalized variable. Specifically, for each characteristic, for every month, we rank issues by their characteristic values, subtract the mean rank and then divide by the standard deviation of the ranks. We also fill missing values with zero, but the results are robust if we do not. As a result, estimated coefficients may be interpreted as the future one-month excess return difference for a one standard deviation difference in characteristic ranking. To rule out the hypothesis that the characteristics predict returns because they proxy for traditional measures of risk, we include control variables in the regression. The first variable is a market beta, where the market is defined as the credit return of the cap-weighted portfolio of all bonds in our database and the beta is computed using a 12-month rolling regression. For robustness, we also include two other traditional measures of risk in credit markets—rating and duration—as well as a proxy for illiquidity, age percent (e.g. Gebhardt *et al.*, 2005a).

Table 3 reports our Fama–Macbeth regression estimates for the monthly sample period from January 1997 to April 2015. Regression (1) includes just an intercept and beta, and Regression (2)

Table 3 Fama–Macbeth regressions (January 1997–April 2015).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.10	−0.02	0.04	−0.01	0.05	−0.10	−0.02
	[1.5]	−[0.2]	[0.5]	−[0.1]	[0.5]	−[1.2]	−[0.2]
Carry			0.00				0.14
			[1.0]				[2.3]
Defensive				0.15			0.03
				[5.0]			[0.9]
Momentum					0.15		0.22
					[3.3]		[7.1]
Value						0.26	0.30
						[5.8]	[10.7]
Mkt beta	0.05	0.04	0.10	0.04	0.06	0.08	0.14
	[0.7]	[0.6]	[1.6]	[0.7]	[0.9]	[1.2]	[2.3]
Rating		0.02	−0.03	0.02	0.00	0.03	0.00
		[0.8]	−[1.0]	[0.6]	[0.1]	[1.0]	−[0.1]
Duration		−0.01	−0.01	0.01	0.00	0.01	0.01
		−[0.5]	−[0.5]	[0.8]	−[0.4]	[1.1]	[1.1]
Age percent		0.25	0.23	0.22	0.23	0.14	0.09
		[2.2]	[2.0]	[1.9]	[2.0]	[1.2]	[0.9]
Avg. R-squared	0.07	0.10	0.14	0.10	0.11	0.11	0.15
Avg. Num. Obs.	723	671	671	671	671	671	671

The table reports Fama–Macbeth regressions of monthly bond excess returns regressed onto normalized carry, defensive, momentum and value style measures along with controls for market beta, rating, duration and age percent variables (as defined in Table A.1).

adds our control variables, which reduce the average number of bonds in the cross-section from 723 to 671. Regressions (3) through (6) evaluate the predictive ability of each of our characteristics on a stand-alone basis. Both individually and combined, the value and momentum characteristics have explanatory power for corporate bond excess returns. The carry characteristic does not exhibit a reliable association with future bond excess returns as a stand-alone variable but it is marginally significant when controlling for the remaining characteristics. The opposite is true with defensive: it is highly significant as a stand-alone variable but loses significance when controlling for value and momentum. This suggests that the defensive theme in credit may be spanned by the value and momentum themes. This is not surprising as the value factors we build for credit make explicit use of fundamental information. Our value measures identify a bond as cheap when its spread is wide relative to default probabilities. Our measures of default probabilities include distance to default and rating information. These fundamental anchors incorporate measures of leverage and expected profitability. As a consequence, it is not surprising that they help explain the defensive premium.

The average R-squared of the Fama–Macbeth cross-sectional regressions is 15%, suggesting that our characteristics collectively explain a non-trivial portion of the cross-sectional variation in bond excess returns. The interpretation of the 15% average explanatory power is not that we can predict 15% of the variation in corporate bond excess returns but rather that knowledge of the four characteristics combined with (unknown ex ante) time-varying loadings to our four characteristics can explain 15% of the variation in corporate bond excess returns. To put that number in context, Lewellen (2015) finds that 15 equity characteristics explain 7.6% of the cross-sectional variation of equity returns. The value and momentum characteristics have the strongest statistical relation with future excess returns, as indicated by the large positive Fama–Macbeth test statistics in the final column.

4.2 Long–short quintile portfolios

Table 4 reports performance statistics of our long–short quintile portfolios. Consistent with the Fama–Macbeth results, we see the strongest positive association between characteristics and returns for defensive, momentum and value. A portfolio that combines all of the factors at an equal-risk weight ("combined") performs even better, with an annualized Sharpe ratio of 2.19, indicating that the different characteristics are weakly correlated amongst themselves. Note also that the realized volatilities of the constant-volatility portfolios are close to the targeted value of 5%, confirming that our simple scalar methodology succeeds reasonably in estimating the volatility of the combined portfolio.

Across all characteristics, we can see that the long–short returns are driven by positive performance on the long-side and negative (or weaker) performance on the short-side. In fact, reading Sharpe ratios across each of the rows clearly illustrates that performance is generally

Table 4 Quintile portfolio tests (January 1997–April 2015).

		Q1	Q2	Q3	Q4	Q5	Q5-Q1	ConstVol
Carry	Ret.	−0.4%	1.1%	1.5%	3.7%	3.7%	4.1%	1.1%
	Vol.	2.9%	4.4%	6.6%	8.7%	13.9%	11.7%	5.8%
	S.R.	−0.12	0.26	0.22	0.43	0.27	0.35	0.19
Defensive	Ret.	0.0%	1.4%	2.0%	1.9%	2.7%	2.7%	8.3%
	Vol.	6.0%	5.8%	6.4%	6.2%	5.6%	2.4%	6.9%
	S.R.	0.00	0.24	0.31	0.32	0.49	1.11	1.21
Momentum	Ret.	−0.2%	1.3%	1.5%	1.4%	2.7%	2.9%	7.5%
	Vol.	7.2%	6.1%	5.2%	5.3%	6.5%	3.4%	6.7%
	S.R.	−0.03	0.21	0.28	0.27	0.41	0.85	1.12
Value	Ret.	−0.4%	0.7%	1.6%	2.4%	3.5%	3.9%	10.7%
	Vol.	5.5%	5.8%	6.3%	6.8%	5.6%	2.2%	6.0%
	S.R.	−0.07	0.13	0.25	0.35	0.62	1.75	1.80
Combined	Ret.	−0.5%	1.0%	1.5%	2.3%	4.9%	5.4%	14.0%
	Vol.	5.6%	5.6%	6.3%	6.8%	6.0%	2.5%	6.0%
	S.R.	−0.09	0.18	0.24	0.34	0.81	2.19	2.32

The table reports performance annualized performance statistics for value-weighted quintile portfolios formed on carry, defensive, momentum, value and combined style factors (as described in the text). "ConstVol" corresponds to quintile long–short portfolios targeting a constant volatility of 5% per annum (as described in the text).

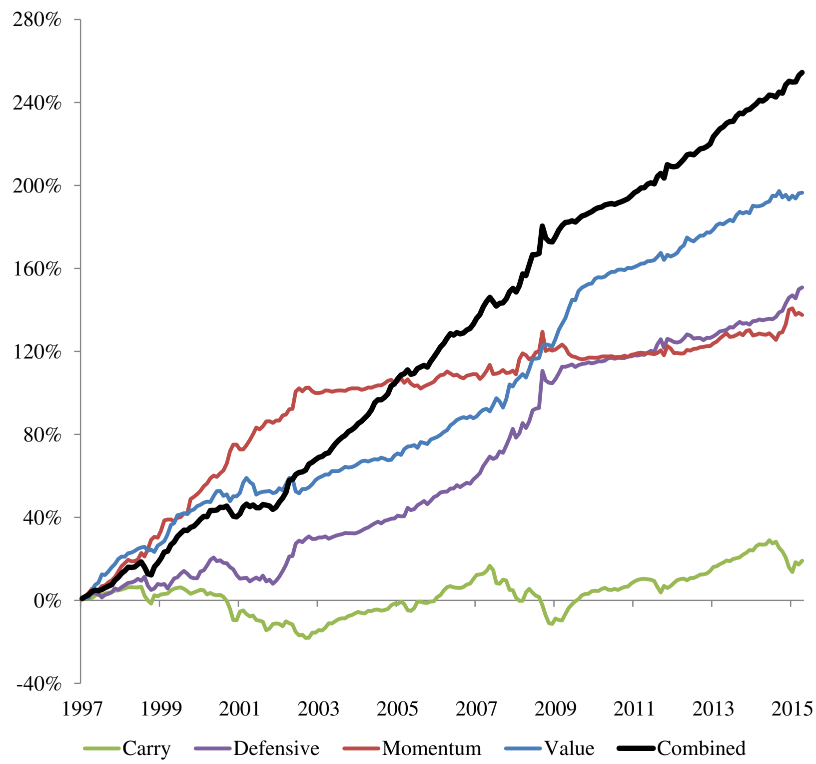

Figure 1 Cumulative style factor returns (January 1997–April 2015).

The figure shows cumulative arithmetic returns for each of the carry, defensive, momentum, value and combined style factors (as defined in the text).

monotonically increasing across quintiles for each of the characteristics.

Figure 1 plots cumulative excess characteristic returns over time. We can see that performance, especially for the combination of characteristics, is not driven by any particular sub-period and has not changed substantially over time. While different characteristics performed better and worse over different sub-periods, it is clear that the combined portfolio has been relatively stable in its outperformance. Not surprisingly the most visible drawdown is carry during the Global Financial Crisis, when investors sought safe assets and shunned riskier ones like high-yield bonds (e.g., Koijen *et al.*, 2014). Whilst we are hesitant to draw too strong inferences from a relatively short time period, the relative smoothness of the returns of the combined portfolio is initial evidence that risk-based explanations will be challenging to support.

To better understand the source of the characteristic's premia, we report return correlations for the various constant-volatility, long-and-short characteristic portfolios and well-known sources of risk premia. We report the various pairwise return correlations in Table 5 using the full time series of data for the period January 1997 through to April 2015, inclusive. We consider the following traditional risk premia: (i) credit risk premium ("CREDIT"), measured as the value-weighted corporate-bond excess returns; (ii) equity risk premium, measured as the difference between the total returns on the S&P500 index and one-month U.S. Treasury bills ("EQUITY"); and (iii) Treasury term premium ("TSY"), measured as the difference between total returns on 10-year U.S.

Table 5 Return correlation matrix (January 1997–April 2015).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Carry	1.00							
Defensive	−0.18	1.00						
Momentum	−0.30	0.40	1.00					
Value	−0.09	0.28	−0.16	1.00				
Combined	0.15	0.79	0.43	0.38	1.00			
CREDIT	0.80	−0.24	−0.17	−0.10	0.01	1.00		
EQUITY	0.55	−0.27	−0.05	−0.17	−0.05	0.59	1.00	
TSY	−0.49	0.02	0.03	0.10	−0.16	−0.50	−0.25	1.00

The table reports monthly excess return correlations for each of the constant-volatility, long-top-quintile-short-bottom-quintile portfolios for the carry, defensive, momentum, value and combined characteristic portfolios along with market indices corresponding to credit returns in excess of duration matched treasures, equity returns in excess of the risk-free rate and treasury returns in excess of the risk-free rate. All variables are defined in the Appendix.

Treasury bonds and one-month U.S. Treasury bills.

Several of the correlations in Table 5 are worth discussing. First, among the four characteristics, we see negative correlations between carry and the other three measures. This is not surprising as issuers with higher spreads will typically have considerable leverage and low profit margins (part of defensive), will have experienced poor recent performance (poor momentum) or both. The correlations reported here are still negative even after our attempt to mitigate the negative correlation with carry by first ranking bonds into duration-times spread groups and then ranking on characteristic measures within those groups. But they are considerably less negative than without this adjustment. While the carry characteristic is relatively less attractive on a stand-alone basis, it has low correlation with the other characteristics (see the correlations reported in Table 5). Conditional on each characteristic generating a positive risk-adjusted return on a stand-alone basis as was evident in Tables 3 and 4, the relatively low (and sometimes negative) correlations across characteristics suggest that characteristics do not span each other. Second, the correlations between the various characteristic measures and well-known sources of risk premia show that the characteristic premia are not simply a manifestation of these other well-known risk premia. With the exception of carry, the return correlations between the characteristic factors and risk premia are all less than 0.30 and are often *negative.*

We next test the hypothesis that the characteristic's long-and-short portfolio expected returns cannot be explained by loadings on traditional sources of market risk premia (CREDIT, EQUITY and TSY) as well as exposures to well-known equity anomalies (SMB, HML and UMD from Ken French's data library and QMJ from Asness *et al.* (2014)). The latter test examines whether stocks and bonds with a certain characteristic both earn their expected return due to a common exposure. For example, do cheap stocks (high book-to-market) and cheap bonds (high spread in relation to default risk) earn high average returns due to a common, shared exposure or are the two expected return sources distinct? To answer those questions, we run regressions of constant-volatility, long-and-short characteristic portfolio returns on market and equity anomaly returns as follows:

$$
\begin{aligned}
&CONST\_VOL\_CHAR_t \\
&\quad = \alpha + \beta_0 EQUITY_t + \beta_1 TSY_t + \beta_2 CREDIT_t \\
&\qquad + \beta_3 SMB_t + \beta_4 HML_t + \beta_5 UMD_t \\
&\qquad + \beta_6 QMJ_t + \varepsilon_{i,t}. \qquad (2)
\end{aligned}
$$

Consistent with the simple correlations reported in Table 5, we see in Table 6 that the carry characteristic has a significant positive exposure to credit risk premium. After controlling for other well-known sources of return, the intercept is not significant for carry. The defensive characteristic is negatively correlated with market risk premia (e.g. credit risk premium), consistent with it reflecting a flight to quality or a risk-on/risk-off tendency of investors.

Momentum has a positive correlation with UMD and nothing else. Credit value exhibits a negative loading on SMB and QMJ, −2.0 and −2.3 t-statistics, respectively. Interestingly, the value characteristic in credit markets is mildly negatively associated with the HML factor, a result consistent with the evidence that characteristic portfolios in one asset class have limited correlations with those in other asset classes (Asness *et al.*, 2015). In the fifth column of Table 6, we regress the combined characteristic long–short portfolio return onto the various market risk premia and equity factor returns. The combined portfolio does not have a statistically significant

Table 6 Long-and-short portfolio Alphas and Betas with Respect to Market and Equity Factors (January 1997–April 2015).

	Carry	Defensive	Momentum	Value	Combined
Intercept	0.05%	0.75%	0.55%	1.02%	1.23%
	[0.7]	[5.3]	[3.9]	[8.1]	[9.6]
CREDIT	0.58	−0.22	−0.19	−0.02	−0.07
	[10.5]	−[2.1]	−[1.8]	−[0.2]	−[0.7]
EQUITY	0.04	−0.07	0.09	−0.11	−0.02
	[0.0]	[0.0]	[0.0]	[0.0]	[0.0]
TSY	−0.12	−0.12	−0.10	0.05	−0.18
	−[2.9]	−[1.4]	−[1.2]	[0.7]	−[2.4]
SMB	0.01	0.06	0.01	−0.08	0.02
	[0.4]	[1.3]	[0.2]	−[2.0]	[0.5]
HML	−0.02	0.05	0.06	−0.02	0.06
	−[0.7]	[1.2]	[1.4]	−[0.6]	[1.4]
UMD	0.00	−0.01	0.06	−0.01	0.04
	[0.1]	−[0.2]	[2.3]	−[0.4]	[1.6]
QMJ	−0.04	0.03	0.11	−0.14	−0.06
	−[1.2]	[0.4]	[1.6]	−[2.3]	−[0.9]
R-squared	0.67	0.10	0.09	0.07	0.05

The table reports monthly excess return regressions of the carry, defensive, momentum, value and combined characteristic long-top-quintile-short-bottom-quintile, constant-volatility factors onto (i) market excess returns for treasuries, credit and equity; (ii) equity anomaly factors SMB, HML and UMD from Ken French's website and QMJ from Asness *et al.* (2014). All variables are defined in the Appendix.

loading on any of the equity factors and a mildly negative relation with term premium. As a consequence, its intercept is a significant 123 basis points per month with a t-statistic of 9.6 and an information ratio of 2.25. The combination portfolio is superior to any individual characteristic portfolio reassuring us that the equal-risk approach is a sensible way to combine the different characteristics. Furthermore, the fact that the combination portfolio does not load on traditional market risk premia and equity anomalies suggests that the source of return predictability is distinct from those.

The economic magnitude of the intercept requires further discussion. The literal interpretation would suggest that a 2.25 information ratio is available for investors. Such a statement needs to be interpreted very cautiously. Corporate bond and equity markets differ substantially in terms of their trading costs.

For example, Chen *et al.* (2007) show that the average bid-mid spread for BBB-rated and B-rated medium maturity bonds are 22 bps and 30 bps, respectively. Frazzini *et al.* (2012) report average value-weighted trading costs for global equities of 20 bps. These numbers, however, severely understate the impact of transaction costs, as stocks are much more volatile than bonds. Andersen *et al.* (2001) find that the median stock volatility is 22%, whereas the median bond in our sample has an excess return volatility close to 7%. More importantly, whereas our combined one-dollar-long-and-one-dollar-short portfolio from Table 4 has a 2.5% annualized volatility, Fama–French HML's factor—long 1 dollar of cheap stocks and short 1 dollar of expensive stocks—achieves 11.6% annual volatility over the same period.

Given the similarity in dollar transaction costs estimates across bonds and stocks, and similar turnover across bond and stock portfolios, the bond portfolio transaction cost per unit of risk is more than four times larger than that of equity. As a consequence, if a long-and-short portfolio of stocks and bonds are to have similar net-of-transaction costs Sharpe ratios, the bond portfolio must have a much larger gross-of-transaction cost Sharpe ratio.

To illustrate any time-varying performance across the various characteristics (in Figure 2), we use the full-sample regression coefficients from Table 6 to compute 36-month rolling average alphas for each respective long-and-short, constant-volatility characteristic portfolio. While outperformance has been marginally attenuated in recent years, it is clear that excess returns have been relatively stable and positive. Again the smoothness of the returns, albeit over a short time series, is difficult to reconcile with a risk-based explanation. We formally examine this issue in Section 4.4.

4.3 Long-only optimized portfolio

While our long–short characteristic portfolios suggest a robust relation between credit excess returns and each of the considered characteristics, they do not take into account actual portfolio implementation considerations. To more realistically address the hypothetical performance of our characteristic portfolios, we build and test optimized long-only portfolios with explicit portfolio implementation constraints. Hence our optimized portfolios are designed to be comparable with traditional actively managed corporate bond portfolios, which tend to be long-only (as individual bonds are difficult to short).

We build and rebalance long-only portfolios on a monthly frequency by solving a linear optimization problem. While mean–variance optimization is a commonly utilized objective function in portfolio construction, here we build our portfolios using a simpler objective function that does not

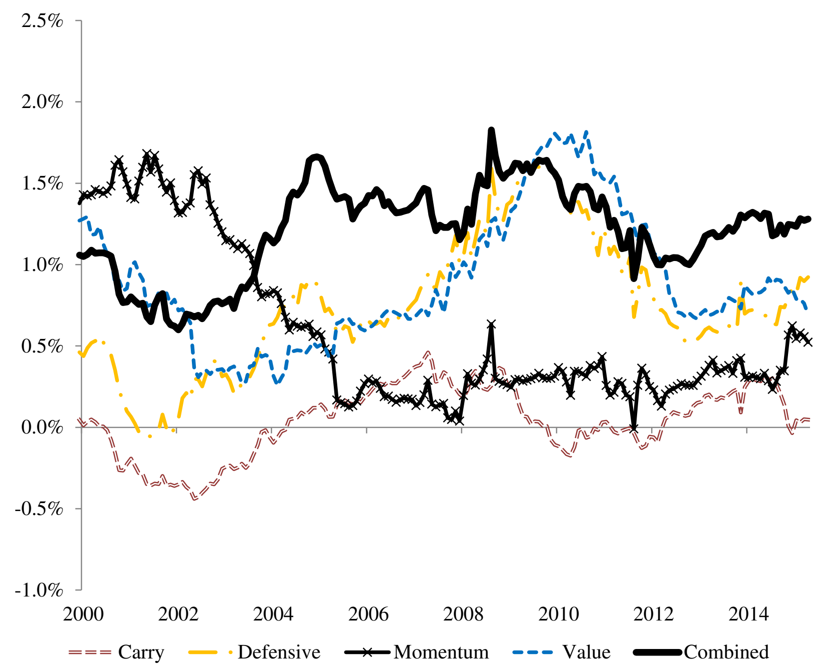

Figure 2 Rolling regression alphas.

The figure shows 3-year rolling average regression alphas for each of the value, momentum, carry, defensive and combined style factors (as defined in the text). Regression alphas are computed monthly using the full-sample beta estimates (as reported in Table 6) and averaged over a trailing 36-month period.

require estimation of an asset-by-asset covariance matrix (i.e., an asset-level risk model). Our optimization problem is specified as follows:

$$\begin{aligned}
&\textit{Maximize}:\\
&\quad \sum_{i=1}^{I} w_i \cdot COMBO_i\\
&\textit{subject to}:\\
&\quad w_i \geq 0, \quad \forall\, i(\textit{no shorting constraint})\\
&\quad |w_i - b_i| \leq 0.25\%,\\
&\qquad \forall\, i(\textit{deviation from benchmark constraint})\\
&\quad \sum_{i=1}^{I} w_i = 1\ (\textit{fully invested constraint})\\
&\quad \sum_{i=1}^{I} |w_{i,t} - w_{i,t-1}|\\
&\qquad \leq 10\%\ (\textit{turnover constraint})\\
&\quad \sum_{i=1}^{I} |(w_{i,t} - w_{i,t-1}) \cdot PRICE_{i,t}|\\
&\qquad \geq \$100,000, \quad \forall\, i(\textit{minimum trade size constraint})\\
&\quad \sum_{i=1}^{I} |(w_i - b_i) \cdot OAS_i|\\
&\qquad \leq 0.50\%\ (\textit{deviation from benchmark spread constraint})\\
&\quad \sum_{i=1}^{I} |(w_i - b_i) \cdot Duration_i|\\
&\qquad \leq 0.50\ (\textit{deviation from benchmark duration constraint}),
\end{aligned}$$

where ω_i is the portfolio weight for a given bond, and $COMBO_i$ is an equal-weighted combination of the carry, defensive, momentum and value long–short characteristic portfolios for a given bond. When computing the realized returns from our optimal portfolio holdings, we subtract an estimate of transaction costs based on each bond's rating and maturity in line with Table 1 of Chen *et al.* (2007). $PRICE_i$ is the bond price for a given bond, OAS_i is the option-adjusted spread for a given bond, $Duration_i$ is the effective duration for a given bond and b_i is the benchmark portfolio weight for a given bond based on a value-weighted benchmark of all corporate bonds in our one-bond-per-issuer dataset.

The solution to this optimization problem is a long-only corporate bond portfolio that has maximal exposure to the combined characteristic portfolio while taking into consideration the challenges of trading corporate bonds as well as the risk contribution of individual positions to the final portfolio. Importantly, we limit the portfolio's differences from (or tracking error to) the benchmark by limiting the portfolio's active weights relative to the benchmark (i.e., at most 25 bps), limit the portfolio's aggregate OAS exposure to be within 50 bps of the benchmark and limit the portfolio's aggregate duration exposure to be within 0.50 years of the benchmark. As discussed earlier, Ben Dor *et al.* (2007) document that spread and duration are the key determinants of volatility in credit markets. Hence constraining the aggregate active weights on these two dimensions is a simple and transparent way to control the active risk of the long-only portfolio. We also constrain turnover to at most 10% per month and force trades to be at least \$100,000 (small trades are much more costly, e.g., Edwards *et al.*, 2007). Despite our best efforts to incorporate constraints and transaction costs, the trading of corporate bonds is challenging. Thus we add the caveat to our empirical results that dynamic trading strategies in corporate bonds are not as implementable as those in more liquid assets.

Table 7 reports performance statistics for the optimized long-only portfolio as well as the benchmark. The portfolio earned an annual average excess return of 5.72% per year (and 5.26% after taking into account estimated transaction costs). Given its realized annualized volatility of 5.1%, the net Sharpe ratio over this period was 1.03. By comparison, the gross (net) benchmark earned a 4.14% (3.84%) annualized excess return with a Sharpe ratio of 0.69. The active portfolio (i.e., portfolio minus beta times the benchmark) realized an annualized net information ratio of 0.86 with a tracking error of 2.56%. Figure 3 shows the cumulative performance of the portfolio and the benchmark.

4.4 *Investigating risk and behavioral explanations*

So far we have documented that value, momentum, carry and defensive measures can predict corporate bond excess returns. In other markets where these anomalies have been studied, both behavioral and risk-based explanations have been suggested. We run additional tests on credit characteristic portfolios aiming to distinguish between risk and behavioral explanations for their respective premiums.

4.4.1 *Risk-based explanations*

In the first test, we ask whether exposures to traditional macroeconomic variables can explain the premiums that we uncover. We add three macroeconomic variables to the time-series regressions that we had previously run in Table 6, specifically we run:

$$\begin{aligned} &CONST\_VOL\_CHAR_t \\ &\quad = \alpha + \beta_1 X_t^{Market} + \beta_2 X_t^{Equity} \\ &\qquad + \beta_7 \Delta LOGVIX_t + \beta_8 \Delta ALOGINDPRO_t \\ &\qquad + \beta_9 \Delta LOGCPI_t + \varepsilon_{i,t}, \qquad (3) \end{aligned}$$

Table 7 Long-only backtest portfolio performance (January 1997–April 2015).

	Optimized Portfolio	Benchmark	Active: Portfolio − Beta * Benchmark
Excess return (gross)	5.72	4.14	2.45
Excess return (net)	5.26	3.84	2.20
Volatility (net)	5.10	5.59	2.56
Sharpe ratio (net)	1.03	0.69	0.86

The table reports performance statistics for the long-only optimized backtest portfolio based on the optimization problem outlined below. The optimized portfolio refers to the stream of returns generated by the optimized long-only portfolio that maximizes the score of the bonds held as explained in the text. Benchmark is a cap-weighted portfolio of all the corporate bonds in our database; i.e., it includes both investment-grade and high-yield bonds. The active returns reported below are the returns from the optimized portfolio less the benchmark using a 24-month rolling beta. Gross returns are returns in excess of the risk-free rate only. Net returns subtract estimated transaction costs from gross returns.

$$
\begin{aligned}
\textit{Maximize}: \quad & \sum_{i=1}^{I} w_i \cdot COMBO_i \\
\textit{subject to}: \quad & w_i \geq 0, \quad \forall\, i (\textit{no shorting constraint}) \\
& |w_i - b_i| \leq 0.25\%, \quad \forall\, i (\textit{deviation from benchmark constraint}) \\
& \sum_{i=1}^{I} w_i = 1\ (\textit{fully invested constraint}) \\
& \sum_{i=1}^{I} |w_{i,t} - w_{i,t-1}| \leq 10\%\ (\textit{turnover constraint}) \\
& \sum_{i=1}^{I} |(w_{i,t} - w_{i,t-1}) \cdot PRICE_{i,t}| \geq \$100,000, \quad \forall\, i (\textit{minimum trade size constraint}) \\
& \sum_{i=1}^{I} |(w_i - b_i) \cdot OAS_i| \leq 0.50\%\ (\textit{deviation from benchmark spread constraint}) \\
& \sum_{i=1}^{I} |(w_i - b_i) \cdot Duration_i| \leq 0.50\ (\textit{deviation from benchmark duration constraint}),
\end{aligned}
$$

where ΔLOGVIX, ΔLOGINDPRO and ΔLOG CPI are respectively the one-month change in the log of the VIX, seasonally-adjusted industrial production index and seasonally-adjusted consumer price index (CPI). While the intercept cannot be interpreted as a portfolio alpha because the macro variables are not tradable portfolios, we can still examine the regression slope coefficients which are what we report in Panel A of Table 8. The combination portfolio tends to have higher returns when volatility and inflation rise and when growth falls. If anything, the combo portfolio behaves as a macroeconomic hedge and should have negative expected returns if that hedge is valuable, making its high and positive expected returns even more puzzling.

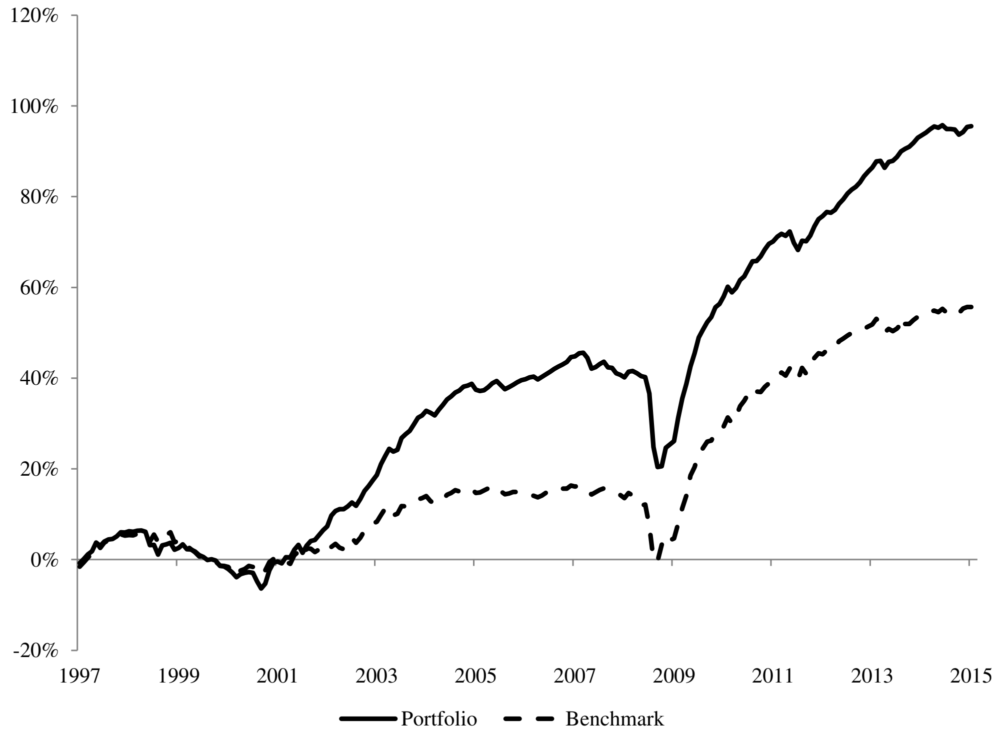

Figure 3 Cumulative long-only portfolio returns (January 1997–April 2015).

The figure shows cumulative returns for the optimized multi-style long-only portfolio (as described in the text) as well as a corporate bond market index constructed based on the value-weighted average of all corporate bonds in the BAML bond sample.

The single-characteristic portfolios behave much in the same way as the combo—coefficients suggest a macro hedge rather than macro risk profile. Carry is the exception. Its coefficient signs are consistent with the risk story, but only statistically significant for ALOGVIX. This suggests that macroeconomic risk may play a role in the carry anomaly but not for the remainder. The conclusions from the time-series regressions, however, have to be caveated by the relatively small sample (about 20 years) for this type of exercise.

In recent years, another class of rational models emerged that focus on financial intermediaries rather than on a single aggregate consumer (e.g. He and Krishnamurthy, 2013). In these models, the conditions of financial intermediaries (wealth, risk aversion, etc.) determine asset prices. Adrian *et al.* (2014) apply this idea to equity markets and find that exposures to increases in broker–dealers leverage can explain traditional stock factors: size, book-to-market and momentum. We test whether shocks to broker–dealer leverage can explain characteristic factor returns in credit by running time-series regressions of those quarterly returns on quarterly log changes in broker–dealers leverage, controlling for market and equity factor returns. Panel B of Table 8 shows that value has a statistically significant loading on broker–dealers leverage shocks of -0.18 (t-statistic of 2.2). This suggests that some of the value premium may be due to it being exposed to deterioration in dealer–brokers balance sheet. All other characteristics either have positive loadings (momentum) or loadings that are indistinguishable from zero. In particular, the combo portfolio is a hedge to broker–dealer leverage shocks, though that exposure is not statistically significant. As a

Table 8 Long-and-short portfolio betas with respect to macroeconomic variables (January 1997–April 2015).

	Carry	Defensive	Momentum	Value	Combined
Panel A: Monthly volatility, growth and inflation					
Intercept	0.00	0.01	0.01	0.01	0.01
	[1.1]	[4.4]	[3.2]	[5.6]	[7.9]
ΔLOGVIX	−0.01	0.03	0.02	0.02	0.02
	−[2.5]	[3.1]	[2.2]	[2.3]	[2.2]
ΔLOGINDPRO	0.09	−0.70	−0.41	−0.32	−0.68
	[1.0]	−[4.0]	−[2.2]	−[2.0]	−[4.2]
ΔLOGCPI	−0.02	0.91	0.23	1.08	1.12
	−[0.1]	[2.2]	[0.5]	[2.8]	[2.9]
Market controls	Yes	Yes	Yes	Yes	Yes
Equity factor controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.70	0.24	0.14	0.14	0.17
Panel B: Quarterly broker–dealer change in log leverage					
Intercept	0.00	0.03	0.02	0.03	0.04
	[1.4]	[5.0]	[4.1]	[6.0]	[8.4]
ΔLEV	−0.08	0.14	0.26	−0.18	0.07
	−[1.5]	[1.5]	[2.8]	−[2.2]	[0.8]
Market controls	Yes	Yes	Yes	Yes	Yes
Equity factor controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.77	0.17	0.33	0.26	0.20

The table reports monthly excess return regressions of the carry, defensive, momentum, value and combined characteristic long-top-quintile-short-bottom-quintile, constant-volatility factors onto (i) market excess returns for treasuries, credit and equity; (ii) equity anomaly factors SMB, HML and UMD from Ken French's website and QMJ from Asness *et al.* (2014); (iii) macroeconomic variables: one-month change in log VIX, one-month change in log industrial production and one-month change in log CPI; (iv) broker–dealer log leverage change (deseasonalized as in Adrian *et al.* 2014).

consequence, although dealer's balance sheet may play a role in explaining the value characteristic, it cannot be a unified explanation for them all.

4.4.2 *Mispricing explanations*

In the next set of empirical tests, we focus on deviations from market efficiency as explanations for the characteristic portfolios positive risk-adjusted returns. Investors deviate from rationality either because they make mistakes or because they are subject to portfolio management frictions (e.g., agency problems due to intermediation and regulations limiting their portfolio choices); and limits-to-arbitrage (Shleifer and Vishny, 1997) impede arbitrageurs from eliminating the ensuing price distortions. If these deviations from market efficiency are empirically descriptive, then we would expect to see bonds in the most extreme portfolios—those that end up in the top and bottom quintiles—to be illiquid, traded by more error-prone investors, issued by more obscure firms and on the short side would be costlier to

Table 9 Average mispricing susceptibility of quintile portfolios.

	Carry	Defensive	Momentum	Value
Equity Analyst Coverage				
Low	19.36	14.87	15.19	16.48
40	15.13	13.90	15.20	15.61
60	12.46	14.50	15.04	14.47
80	9.42	14.95	14.59	12.98
High	7.64	15.41	12.88	11.37
High–low	−11.73	0.55	−2.31	−5.11
High–low t-statistic	−18.66	2.03	−4.87	−13.38
Issue market value in billions				
Low	1.28	1.34	1.06	1.10
40	1.04	0.87	0.98	1.05
60	0.79	0.85	0.93	0.93
80	0.66	0.72	0.85	0.74
High	0.54	0.66	0.80	0.71
High–low	−0.73	−0.69	−0.25	−0.39
High–low t-statistic	−17.24	−9.93	−3.81	−5.27
Institutional ownership of bond				
Low	0.50	0.48	0.49	0.51
40	0.54	0.52	0.50	0.49
60	0.50	0.50	0.50	0.48
80	0.46	0.47	0.49	0.49
High	0.40	0.47	0.46	0.49
High–low	−0.10	−0.02	−0.03	−0.02
High–low t-statistic	−5.18	−2.20	−3.50	−2.66
Average shorting cost score of bond				
Low	0.05	0.10	0.14	0.10
40	0.05	0.09	0.10	0.10
60	0.08	0.12	0.10	0.14
80	0.17	0.20	0.12	0.19
High	0.52	0.18	0.21	0.17
High–low	0.47	0.07	0.07	0.07
High–low t-statistic	9.79	7.73	4.90	3.70

For each characteristic and mispricing susceptibility proxy, the table reports the cap-weighted average value of the proxy for each one of the quintile portfolios formed on carry, momentum, value and defensive. The proxies for susceptibility are firm transparency measured by the number of equity analysts that follows the issuing company; liquidity as measures by bond issue size; investor base sophistication as measured by institutional ownership and easiness of shorting as measured by the shorting fee score (0 is lowest fee and 5 the highest). The table also displays the difference between the top and bottom quintile portfolios as well as its t-statistic computed using Newey–West standard errors and 18 lags.

borrow (for the bottom quintile). We test these hypotheses by measuring each of these attributes for each characteristic long and short portfolios separately.

We measure liquidity using bond issue size. We use this measure as it has the broadest coverage and has a high correlation with average daily trading volume (Hotchkiss and Jostova, 2007). Volume-based measures typically require coverage in TRACE which is limited for the high-yield market because a large fraction of high-yield bonds are issued under 144A regulations and are not disseminated by TRACE before late 2014. We measure the investor population sophistication by the fraction of a bond which is owned by institutional investors, presumably better equipped than retail investors to avoid mistakes. We measure firm transparency by the number of analysts following the issuer equity (Hong *et al.*, 2000) and, lastly, the cost of shorting is measured by the shorting fee score from MarkitDataExplorers.

Table 9 reports the results. If deviations from market efficiency and/or market frictions are empirically descriptive we would expect to see (i) lower analyst coverage, (ii) lower institutional ownership and (iii) smaller bonds in the extreme portfolios for each characteristic. We would also expect to see greatest short selling costs in the lowest portfolio for each characteristic. Across all four characteristics we do not see any consistent evidence supporting these explanations. Bonds that score high in carry, momentum and value tend to be smaller, issued by more sparsely covered and owned by fewer institutions. Bonds, on the short side, however, display opposite rather than similar behavior. They are bigger, well covered and owned at a higher rate by institutional investors. Finally, the short side of each characteristic portfolio is in fact cheaper to borrow than its long side. Collectively, these patterns suggest that a simple mispricing hypothesis does not fit the data.

A separate implication of the mispricing hypothesis is that the relation between characteristics and future returns will be stronger among bonds in the segment of the corporate bond universe

Table 10 Average returns of characteristic portfolios across bonds with varying levels of mispricing susceptibility.

	Low	Medium	High	High-minus-low
Panel A: Characteristic returns across equity analyst coverage terciles				
Carry	0.35%	0.25%	0.15%	−0.20%
	[1.9]	[1.6]	[1.1]	−[1.8]
Defensive	0.14%	0.08%	0.17%	0.02%
	[2.0]	[1.2]	[2.6]	[0.4]
Momentum	0.40%	0.18%	0.16%	−0.23%
	[4.4]	[2.6]	[2.1]	−[2.8]
Value	0.42%	0.39%	0.22%	−0.20%
	[6.7]	[7.0]	[2.9]	−[2.0]

The table displays the average credit excess returns and t-statistics of long-and-short characteristic portfolios built from subsets of firms with different values for mispricing susceptibility measures. The proxies for susceptibility are firm transparency measured by the number of equity analysts that follows the issuing company; liquidity as measures by bond issue size; investor base sophistication as measured by institutional ownership and easiness of shorting as measured by the shorting fee score (0 is lowest fee and 5 the highest).

Table 10 (*Continued*)

	Low	Medium	High	High-minus-low
Panel B: Characteristic returns across institutional ownership terciles				
Carry	0.32%	0.30%	0.28%	−0.03%
	[1.6]	[1.5]	[1.8]	−[0.3]
Defensive	0.11%	0.10%	0.17%	0.05%
	[1.7]	[2.5]	[4.5]	[0.9]
Momentum	0.26%	0.15%	0.06%	−0.20%
	[3.1]	[2.1]	[1.2]	−[2.3]
Value	0.21%	0.29%	0.31%	0.10%
	[3.6]	[4.6]	[6.7]	[1.7]
Panel C: Characteristic returns across bond market value terciles				
Carry	0.28%	0.34%	0.23%	−0.06%
	[1.8]	[2.1]	[1.4]	−[0.6]
Defensive	0.14%	0.15%	0.11%	−0.02%
	[2.8]	[4.3]	[2.7]	−[0.4]
Momentum	0.37%	0.15%	0.12%	−0.25%
	[6.2]	[3.4]	[2.0]	−[3.4]
Value	0.28%	0.29%	0.19%	−0.08%
	[5.8]	[7.2]	[4.4]	−[1.4]
Panel D: Characteristic returns across of shorting costs				
	Fee = 0	Fee > 0	Fee 0 minus Fee > 0	
Carry	0.36%	0.35%	−0.01%	
	[1.3]	[1.0]	[0.0]	
Defensive	0.16%	0.52%	0.36%	
	[2.2]	[1.8]	[1.3]	
Momentum	0.06%	0.08%	0.02%	
	[0.6]	[0.2]	[0.1]	
Value	0.32%	0.53%	0.21%	
	[4.4]	[2.1]	[0.9]	

that are harder to arbitrage, less transparent or populated with a less sophisticated investor base. In Table 10, we test this hypothesis by comparing long-and-short portfolios formed on different universes of corporate bonds distinguished by the dimensions discussed above. We find that momentum long-and-short portfolios perform better in the less liquid, less transparent and less sophisticated segments of the corporate bond market. For carry, defensive and value the evidence is more mixed, sometimes performing better in the more mispricing prone arbitrage segments of the market, sometimes performing better in the less vulnerable one, but rarely statistically significant.

As a final test of behavioral explanations, we look at errors in expectations of equity analysts' sales forecasts. A systematic pattern between a characteristic and both future returns and revisions is consistent with mispricing (see, e.g., Bradshaw *et al.*, 2001). We focus on sales instead of EPS because we are assessing senior claims. Increases in EPS can be detrimental for credit if the increase came about through re-leveraging. Our hypothesis is that analysts and investors have similar beliefs and, therefore, we can learn about the (unobservable) mistakes of the latter from the (observable) mistakes of the former. In other words, do the firms in the good carry, momentum, value and defensive portfolio experience more positive revisions than those in the bottom quintile of those characteristics?

To study analyst errors we focus on their forecast revisions for the next 12 months of sales. If analysts are fully rational and free from agency concerns, their revisions should not be predictable by any model relying on public information. If, on the other hand, their revisions are found to be predictable, it means they are ignoring certain information. To the extent that investors and analysts share the same beliefs, prices would not reflect that information as well and as a consequence would be predictable.

We build next-12-month revisions by averaging revisions over the next fiscal year sales number

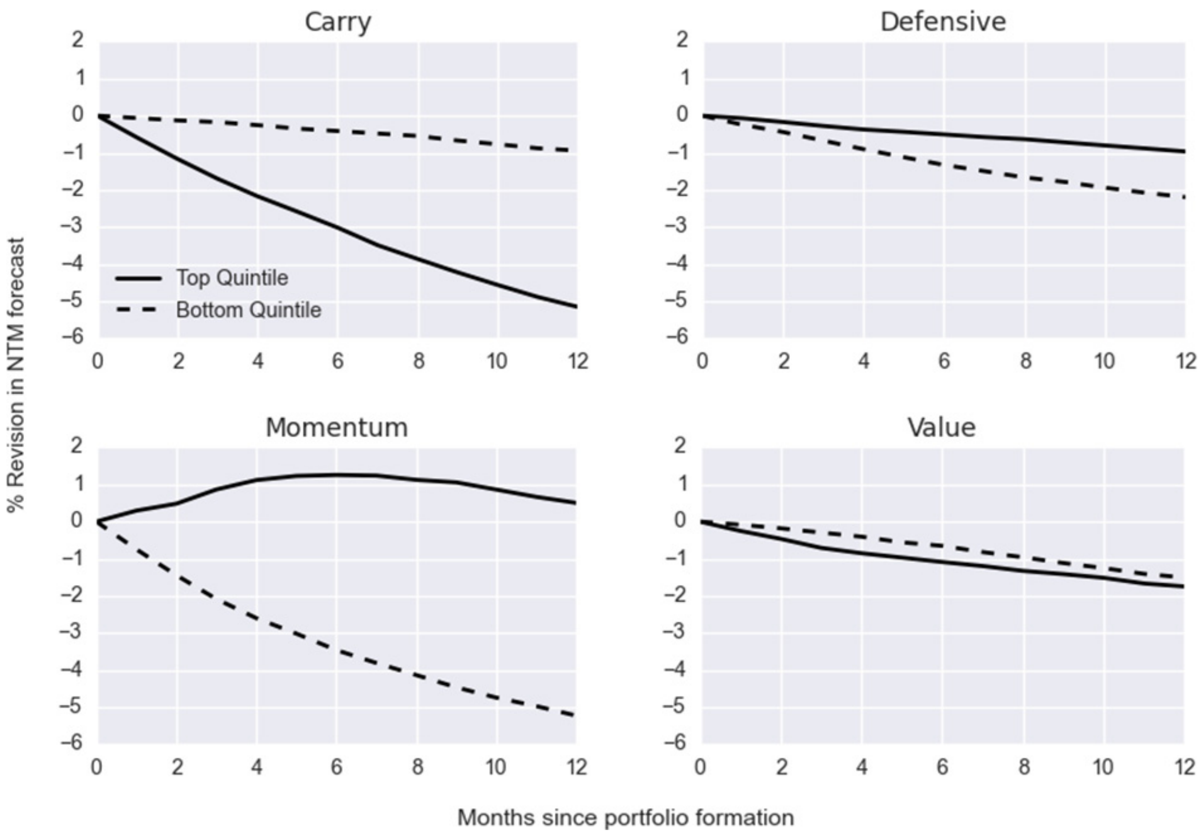

Figure 4 Analysts revisions of top and bottom quintile portfolios formed on different characteristics (January 2001–April 2015).

Average cumulative monthly revisions of analysts sales forecasts for the next 12 months since portfolio formation for issuers in the top and bottom quintiles of the four characteristics: carry, defensive, momentum and value as defined in the text. For every firm, analyst forecasts revisions for the next 12 months are built from an average of the revisions (log difference) of forecasts for the next fiscal year (FY1) and the following (FY2), with weights set to make the average horizon be 12 months. For every portfolio, the revision number is an equal weight of the revisions of all the firms that comprise that portfolio.

(FY1) and that of the subsequent fiscal year (FY2). We set the weights dynamically to assure that the weighted average horizon of the forecast is always 12 months.

The results are displayed in Figure 4. The dark lines are the cumulative revisions of the long portfolio and the dotted lines are the revisions for the short portfolio. If there are systematic predictable errors in sales forecasts, then we expect greater downward revisions for the short portfolio and greater upward revisions for the long portfolio. The mispricing hypothesis is consistent with what we see for the momentum portfolio and to a lesser extent for the defensive portfolio: after 12 months the long portfolio experiences sales revisions that are larger than short by 5.7% (t-statistic = 7.28) and 1.2% (t-statistic = 1.86) for momentum and defensive, respectively. For value and carry the result goes in the opposite direction of that predicted by the mispricing hypothesis but the difference is only statistically significant for carry (t-statistic = 6.17). As a consequence mispricing seems to play less of an obvious role for these two characteristics.

While the revision number for momentum is a sizeable 5.7% sales drop, it is hard to evaluate its impact on the long-and-short portfolio return. To facilitate interpretation we compute the impact on credit spreads of a 5.7% sales drop for the median firm using a simple structural model. The median bond in our sample has an OAS of 302 bps and duration of 5, while its issuer has a leverage of 0.28. We feed those numbers through a structural model (Merton, 1974) to invert the asset volatility that is consistent with this quantity—the credit-implied volatility (Kelly *et al.*, 2016). We then shock asset value by 5.7% assuming that it drops by the same value as sales and, keeping volatility constant, compute the new credit spread and the credit returns associated with this change. For momentum, a 5.7% sales increase translates into a roughly 112 bps return: about one-third of the 290 bps momentum premium displayed in Table 4. Errors in expectations offer a partial explanation to the momentum returns in corporate bond markets.

5 Conclusion

We undertake a comprehensive analysis of the cross-sectional determinants of corporate bond excess returns. We find strong evidence of positive risk-adjusted returns to measures of carry, defensive, momentum and value. These returns are diversifying with respect to both known sources of market risk (e.g., equity risk premium, credit risk premium and term premium) and characteristic returns that have been documented in equity markets (e.g., size, value and momentum). These conclusions hold whether one examines traditional long-and-short academic portfolios or a long-only, transactions-cost aware portfolio. The latter helps dismiss the hypothesis that the returns are not economically significant.

In our final analysis we examine the source of the value, momentum, carry and defensive premiums in credit. We investigate risk and mispricing explanations. We do not find evidence that the anomalies earn their premiums through traditional risk exposures or to shocks to financial intermediaries' balance sheets – characteristic returns tend to be a hedge to traditional macroeconomic factors and exhibit mostly insignificant loadings on shocks to broker–dealers leverage. Mispricing evidence is strongest for momentum: the momentum strategy has better performance among less liquid bonds issued by less transparent firms and owned by less sophisticated investors; it is also long (short) bonds of firms where analyst forecasts of sales are relatively too pessimistic (optimistic). The evidence for mispricing is mixed for the other characteristics.

Appendix

Table A.1 Variable definitions.

Variable		Definition
	Duration	Option-adjusted duration as reported by BAML.
	Total return	Monthly total return on the corporate bond, inclusive of coupons and accrued interest.
	Excess return	Monthly excess return on the corporate bond, computed as the difference between the monthly total return on the corporate bond and the monthly return of a duration-matched U.S. Treasury bond.
	Amt. Out.	The face value of the corporate bond measured in USD millions.
	Time to maturity	Number of years before bond matures.
	Age percent	Fraction of bond life that has expired (time since issuance divided by original maturity).
	Rating	Standard & Poor's issuer-level rating, coded from 1 (AAA) to 10 (D).
	Market beta	Slope froml2-month rolling regression of credit excess returns on the credit market excess return (see CREDIT below).
Carry	OAS	Option-adjusted spread as reported in the Bank of America Merrill Lynch (BAML) bond database.
Value	Empirical	The residual from a cross-sectional regression of the log of OAS onto the log of duration, rating and bond excess return volatility (12 month).
	Structural	The residual from a cross-sectional regression of the log of OAS onto the log of the default probability implied by a structural model (Shumway, 2001).
Momentum	Credit	The most recent six-month cumulative corporate-bond excess return.
	Equity	Equity momentum, defined as the most recent six-month cumulative issuer equity return.
Defensive	Leverage	Market leverage, measured as the ratio of net debt (book debt + minority interest + preferred stocks − cash) to the sum of net debt and market capitalization. Measured using data available at the start of each month (assuming a six-month lag for the release of financial statement information).
	Duration	Effective duration as reported in the Bank of America Merrill Lynch (BAML) bond database.
	Profitability	Gross profits over assets.
	CONST_VOL_CHAR	Credit excess returns of a characteristic portfolio that goes long bonds in the top characteristic quintile and short those in the bottom. Every month the portfolio is scaled to have an ex-ante volatility of 5%, where the ex-ante volatility is the realized volatility over the last 2 years.

(*Continued*)

Table A.1 (*Continued*)

Variable	Definition
TSY	Excess returns to long-term government bonds, measured as the difference between monthly total returns on the Bank of America Merrill Lynch U.S. Treasuries 7–10 year index and one-month U.S. Treasury bills.
CREDIT	Excess returns to corporate bonds, measured as the difference between the value-weighted monthly total returns of corporate bonds included in the BAML dataset and a portfolio of duration-matched U.S. Treasury bonds.
EQUITY	Excess returns to the S&P 500 Index, measured as the difference between monthly total returns to the S&P 500 and one-month U.S. Treasury bills.
SMB	Monthly mimicking-factor portfolio return to the size factor, obtained from Ken French's website.
HML	Monthly mimicking-factor portfolio return to the value factor, obtained from Ken French's website.
UMD	Monthly mimicking-factor portfolio return to the momentum factor, obtained from Ken French's website.
QMJ	Monthly mimicking-factor portfolio return to the quality factor, obtained from AQR's library website.
ΔLOGVIX	One-month change in log VIX (VIXCLS) from FRED website.
ΔLOGINDPRO	One-month change in log seasonally adjusted industrial production index (INDPRO) from FRED website.
ΔLOGCPI	One-month change in log seasonally adjusted CPI (CPIAUCSL) from FRED website.
ΔLEV	Change in log broker–dealers $leverage = \frac{financial\ assets}{financial\ assets - total\ liabilities}$. From FED's flow of funds data and seasonally adjusted (Adrian *et al.*, 2014)
Equity analyst coverage	The number of analysts covering the issuer equity, from I/B/E/S.
Credit institutional ownership	Fraction of bond amount outstanding owned by non-retail investors, from Lipper emaxx database.
Bond shorting score	Score between 0 and 5 from Markit: 0 represents lowest cost to borrow and 5 represents the highest.
Equity analyst revisions in sales expectations	Weighted average change in the next fiscal year (FYl) and the one after (FY2) sales forecasts. The weights are chosen such that the forecast is refers to a number that is on average 12 months into the future.

Acknowledgement

A previous version of this paper was titled "Investing with style in corporate bonds." We thank Demir Bektic, Maria Correia, Wayne E. Ferson, Patrick Houweling, Antti Ilmanen, Sarah Jiang, Toby Moskowitz, Narayan Naik, Lasse Pedersen, Kari Sigurdsson and participants at the 4th Alliance Bernstein Quant Conference, 24th European Pensions Symposium, 7th Inquire UK Business School Meeting, Norwegian Ministry of Finance and University of Cambridge, 2016 SFS Finance Cavalcade, London Quant Group, University of Notre Dame and UBS Quantitative Investment Conference 2016 for their helpful discussion and comments. We acknowledge the outstanding research assistance of Peter Diep, Johnny Kang and Mason Liang. The views and opinions expressed herein are those of the authors and do not necessarily reflect the views of AQR Capital Management LLC ("AQR"), its affiliates, or its employees. This information does not constitute an offer or solicitation of an offer, or any advice or recommendation, by AQR, to purchase any securities or other financial instruments and may not be construed as such.

Notes

[1] If one of the standardized measures is missing, we assign a zero score such that the combination will have a non-missing score for the union of names which have at least one non-missing score.

[2] Between January 1997 and December 1998, we set the scalar equal to its value as of January 1999.

References

Adrian, T., Etula, E., and Muir, T. (2014). "Financial Intermediaries and the Cross-Section of Asset Returns," *The Journal of Finance* **69**(6), 2557–2596.

Altman, E. I. (1968). "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy," *Journal of Finance* **23**(4), 189–209.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Ebens, H. (2001). "The Distribution of Realized StockReturn Volatility," *Journal of Financial Economics* **61**(1), 43–76.

Asness, C. S., Andrea, F., and Lasse, H. P. (2014). "Quality Minus Junk," Working Paper.

Asness, C., A., Ilmanen, R. I., and Moskowitz, T. (2015). "Investing with Style," *Journal of Investment Management* **13**, 27–63.

Asness, C., Moskowitz, T., and Pedersen, L. (2013). "Value and Momentum Everywhere," *Journal of Finance* **68**, 929–985.

Asquith, P., Au, A. S., Covert, T., and Pathak, P. A. (2013). "The Market for Borrowing Corporate Bonds," *Journal of Financial Economics* **107**, 155–182.

Asvanunt, A. and Richardson, S. (2017). "The Credit Risk Premium," *Journal of Fixed Income*, Winter 2017.

Ben Dor, A., Dynkin, L., Hyman, J., Houweling, P., Van Leeuwen, E., and Penniga, O. (2007). "DTS (Duration Times Spread)," *The Journal of Portfolio Management* **33**, 77–100.

Bessembinder, H., Maxwell, W., and Venkataraman, K. (2006). "Market Transparency, Liquidity Externalities, and Institutional Trading Costs in Corporate Bonds," *Journal of Financial Economics* **82**, 251–288.

Bharath, S. T. and Shumway, T. (2008). "Forecasting Default with the Merton Distance to Default Model," *Review of Financial Studies* **21**(3), 1339–1369.

Binsbergen, J. H. and Koijen, R. S. J. (2015). "The Term Structure of Returns: Facts and Theory," Working Paper.

Bradshaw, M. T., Richardson, S. A., and Sloan, R. G. (2001). "Do Analysts and Auditors Use Information in Accruals?," *Journal of Accounting Research* **39**(1), 45–74.

Carvalho, R., Dugnolle, P., Xiao, L., and Moulin, P. (2014). "Low-Risk Anomalies in Global Fixed Income: Evidence from Major Broad Markets," *The Journal of Fixed Income* **23**, 51–70.

Chen, L., Lesmond, D. A., and Wei, J. (2007). "Corporate Yield Spreads and Bond Liquidity," *Journal of Finance* **62**, 119–149.

Chen, N. F., Roll, R., and Ross, S. A. (1986). "Economic Forces and the Stock Market," *Journal of Business* 383–403.

Choi, J. and Kim, Y. (2015). "Anomalies and Market (Dis)integration," Working Paper, UIUC.

Chordia, T., Goyal, A., Nozawa, Y., Subrahmanyam, A., and Tong, Q. (2016). "Are Capital Market Anomalies Common to Equity and Corporate Bond Markets?," Working Paper, Emory University.

Cochrane, J. H. (2009). *Asset Pricing*: (Revised Edition). Princeton University Press.

Correia, M., Richardson, S., and Tuna, I. (2012). "Value Investing in Credit Markets," *Review of Accounting Studies* **17**(3), 572–609.

DeMiguel, V., Garlappi, L., and Uppal, R. (2009). "Optimal versus Naive Diversification: How Inefficient is the 1/N Portfolio Strategy?," *Review of Financial Studies* **22**(5), 1915–1953.

Edwards, A. E., Harris, L. E., and Piwowar, M. S. (2007). "Corporate Bond Market Transaction Costs and Transparency," *Journal of Finance* **62**, 1421–1451.

Fama, E. F. and Kenneth, R. F. (1993). "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics* **33**(1), 3–56.

Frazzini, A., Israel, R., and Moskowitz, T. J. (2012). "Trading Costs of Asset Pricing Anomalies," Working Paper, AQR Capital Management.

Frazzini, A. and Pedersen, L. H. (2014). "Betting Against Beta," *Journal of Financial Economics* **111**, 1–25.

Gebhardt, W. R., Hvidkjaer, S., and Swaminathan, B. (2005a). "The Cross-Section of Expected Corporate Bond Returns: Betas or Characteristics?," *Journal of Financial Economics* **75**, 85–114.

Gebhardt, W. R., Hvidkjaer, S., and Swaminathan, B. (2005b). "Stock and Bond Market Interaction: Does Momentum Spill Over?," *Journal of Financial Economics* **75**, 651–690.

Grossman, S. J. and Stiglitz, J. E. (1980). "On the Impossibility of Informationally Efficient Markets," *The American Economic Review* **70**(3), 393–408.

Haesen, D., Houweling, P., and van Zundert, J. (2013). "Residual Equity Momentum for Corporate Bonds," Working Paper, Robeco Quantitative Strategies.

Hallerbach, W. G. and Houweling, P. (2013). "Ibbotson's Default Premium: Risky Data," *The Journal of Investing* **22**, 95–105.

Harris, L. (2015). "Transaction Costs, Trade Throughs, and Riskless Principal Trading in Corporate Bond Markets," Working Paper, USC.

He, Z. and Krishnamurthy, A. (2013). "Intermediary Asset Pricing," *The American Economic Review* **103**(2), 732–770.

Hong, H., Lim, T., and Stein, J. C. (2000). "Bad News Travels Slowly: Size, Analyst Coverage and the Profitability of the Momentum Strategies," *The Journal of Finance* **55**(1), 265–295.

Hotchkiss, E. S. and Jostova, G. (July 9, 2007). "Determinants of Corporate Bond Trading: A Comprehensive Analysis," Working Paper.

Houweling, P. and van Zundert, J. (2014). Factor Investing in the Corporate Bond Market," Working Paper, Robeco Quantitative Strategies.

Jostova, G., Nikolova, S., Philipov, A., and Stahel, C. W. (2013). "Momentum in Corporate Bond Returns," *Review of Financial Studies* **26**(7), 1649–1693.

Kelly, B. T., Manzo, G., and Palhares, D. (2016). "Credit-Implied Volatility," Manuscript.

Koijen, R., Moskowitz, T., Pedersen, L., and Vrugt, E. (2014). "Carry. Working Paper, University of Chicago Booth School of Business," New York University, University of Amsterdam.

Kwan, S. H. (1996). "Firm-Specific Information and the Correlation Between Individual Stocks and Bonds," *Journal of Financial Economics* **40**, 63–80.

Lewellen, J. (2015). "The Cross-Section of Expected Stock Returns," *Critical Finance Review* **4**, 1–44.

Lok, S. and Richardson, A. (2011). "Credit Markets and Financial Information," *Review of Accounting Studies* **16**, 487–500.

Merton, R. (1974). "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance* **29**, 449–470.

Moreira, A. and Muir, T. (2016). "Volatility Managed Portfolios (No. w22208)," *National Bureau of Economic Research.*

Ng, K. Y. and Phelps, B. (2014). "Structure of U.S. Corporate Excess Returns: The Hunt for a 'Low-Risk' Anomaly," Working Paper, Barclays.

Novy-Marx, R. (2013). "The Other Side of Value: The Gross Profitability Premium," *Journal of Financial Economics* **108**(1), 1–28.

Palhares, D. (2013). "Cash-Flow Maturity and Risk Premia in CDS Markets," Working Paper, AQR Capital Management.

Schaefer, S. M. and Strebulaev, I. A. (2008). "Structural Models of Credit Risk are Useful: Evidence from Hedge Ratios on Corporate Bonds," *Journal of Financial Economics* **90**(1), 1–19.

Shleifer, A. and Vishny, R. W. (1997). "The Limits to Arbitrage," *The Journal of Finance* **52**(1), 35–55.

Shumway, T. (2001). "Forecasting Bankruptcy More Accurately: A Simple Hazard Model," *Journal of Business* **740**, 101–124.

Keywords: Corporate bonds; mispricing

JEL Classification: G12; G14; M41