Investing with Style in Corporate Bonds

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Abstract

We identify four key style measures (carry, defensive, momentum, and value) that together explain nearly 20% of the cross-sectional variation in corporate bond excess returns. The positive risk-adjusted returns to these styles are diversifying with respect to both market risk premia and equity style returns. We show that our long-short styles can be combined and implemented within a long-only portfolio that outperforms the value-weighted corporate bond market with an Information Ratio of 0.60. Using our style measures to explain the returns of actively managed credit hedge funds and mutual funds, we document a pervasive "reaching for yield" behaviour as demonstrated by significant loadings on carry but limited exposures to the other key style factors.

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1. Introduction

Corporate bonds are an enormous, and growing, source of financing for companies around the world. As of the second quarter of 2014, there was $7.65 trillion of U.S. corporate debt outstanding, and there has been a growing trend in corporate bond issuance from $343 billion in 1996 to $1.38 trillion in 2013 (Securities Industry and Financial Markets Association). Clearly, corporate bonds are an important asset class. There is, however, surprisingly little research on the cross-sectional determinants of corporate bond returns as well as the determinants of returns for actively managed credit hedge funds and mutual funds.

Prices of corporate bonds are not independent from equity prices, but nor are they simply a mirror image. Thus, an analysis of corporate bond returns requires more than a simple extension from equity returns. Standard option pricing theory shows that equity can be viewed as a call option on firm asset value and bonds can be viewed as a put option on firm asset value (e.g., Merton, 1984). This framework highlights the interdependence between bond and equity prices and suggests that styles known to explain equity returns should also be useful to explain corporate bond returns. The interdependence between equity and bonds is expected to be stronger (weaker) for riskier (safer) firms. As such, styles from the equity market (e.g., momentum and value) are expected to be more important for the high yield corporate bond market. Moreover, measures of styles need to be tailored to the corporate bond market. For example, while book-to-price, B/P, as a candidate measure of 'value' exhibits a well-known positive relation with future equity returns, its usefulness for corporate bond markets is not clear conceptually. The 'anchor' for fundamental value in credit markets is expectations of default and losses in the event of default, not the book value of equity. We therefore modify and extend measures of styles from the equity market for the corporate bond market.

Our focus is threefold. First, we explore the role of well-known styles to explain the cross-section of returns that are unique to credit, and as such we examine excess returns rather than total returns. Thus, while it is well known that changes in corporate bond prices have a component attributable to changes in interest rates (e.g., Gebhardt, Hvidkjaer and Swaminathan, 2005a) this is not part of our analysis. An extensive literature in financial economics has documented robust evidence of positive associations between measures of carry, defensive, momentum and value and future asset returns (see e.g., Koijen, Moskowitz, Pedersen and Vrugt, 2014 for 'carry'; Frazzini and Pedersen, 2013 for 'defensive'; Asness, Moskowitz and Pedersen, 2013 for 'momentum' and 'value'; and Asness, Ilmanen, Israel and Moskowitz, 2014 for a combination of all four styles). We construct measures of each of these styles in a manner that is appropriate for the credit risk embedded in corporate bonds. Using a large sample of corporate bonds for both North America and Europe, we are able to explain nearly 20 percent of the cross-sectional variation in corporate bond excess returns. As these are predictive return regressions, the explanatory power is strikingly large.

Second, we demonstrate that a long-only portfolio of corporate bonds with exposure to carry, defensive, momentum and value generates very attractive risk-adjusted returns. For example, a long-only portfolio of North American corporate bonds constructed with realistic position and trading cost constraints yields a net (of transaction cost) excess return of 4.7 percent annualized which translates to a Sharpe Ratio of 0.79. Relative to a value-weighted benchmark of corporate bonds, the long-only portfolio yields a net (of transaction cost) active return of 1.0 percent annualized which translates to an Information ratio of 0.60. We find similarly attractive risk-adjusted returns for a long-only portfolio of European corporate bonds.

Third, we conduct a detailed analysis of the time series and cross-sectional determinants of actively managed credit hedge fund and mutual fund returns. For indices of credit hedge funds and credit mutual funds, we find that a significant portion of the fund returns are attributable to passive exposure to duration and credit market returns. Kahn and Lemmon (2015) find a similar result for a sample of 121 fixed income investment managers. We further find a significantly positive exposure to 'carry' (but not for defensive, momentum and value) for a broad sample of 213 individual actively managed credit hedge funds and 218 individual actively managed credit mutual funds. Becker and Ivashina (2015) document pervasive evidence of reaching for yield for a large sample of insurance companies and pension funds. Our results extend this reaching for yield to a broad cross section of credit hedge funds and credit mutual funds.

There are several key implications from our empirical analyses. First, despite evidence of (i) a robust relation between well-known styles (i.e., carry, defensive, momentum and value) and corporate bond excess returns, and (ii) feasible implementation of exposure to these styles in a long-only portfolio, individual credit funds are under-exposed to styles that generate meaningfully positive risk-adjusted returns. Second, similar to the hidden beta exposure of equity hedge and mutual funds (see e.g., Asness, Krail and Liew, 2001), actively managed credit funds also contain significant exposure to interest rate and credit 'beta', and controlling for that 'beta' greatly reduces the positive excess returns for actively managed credit funds. As such, investors in actively managed credit funds should be aware of any beta they are exposed to, and should prefer an investment product designed to isolate exposure to well-compensated styles that are orthogonal to market beta.

The remainder of the paper proceeds as follows. In Section 2, we briefly discuss related papers exploring determinants of cross-sectional variation in corporate bond excess returns. In Section 3, we discuss our data sources, sample selection criteria, style measures and research design. In Section 4, we discuss our primary empirical analyses based on corporate bond excess returns and individual credit funds from North America. In Section 5, we describe similar evidence outside of North America and discuss various robustness tests, and Section 6 concludes.

2. Literature Review

Our paper relates to a growing literature on determinants of the cross-section of security returns. While the vast majority of past literature in this area has focussed on equity returns, there are a few related papers that have examined cross-sectional determinants of corporate bond excess returns. Correia, Richardson, and Tuna (2012) study value investing in corporate bond markets by comparing market spreads to model-implied spreads estimated using fundamental and market-based inputs. Gebhardt, Hvidkjaer and Swaminathan (2005b) document strong evidence for equity momentum in corporate bond markets by showing that past equity returns are a strong predictor of future corporate bond returns of the same issuer, even after controlling for corporate bond momentum. Koijen, Moskowitz, Pedersen, and Vrugt (2014) evaluate carry factors across several markets: for credit markets, they test corporate bond indices of varying durations and maturities. Carvalho, Dugnolle, Xiao, and Moulin (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 paper adds to this literature in a few respects. First, we not only study the standalone performance of style measures but also investigate their relationships and combined efficacy. Second, we consider not only simple unconstrained long-short portfolios but also more realistically investable long-only portfolios that take into account transaction costs and shorting constraints. Third, we link our styles to the returns of actively managed credit hedge funds and mutual funds, and document what exposures actively managed credit funds are actually providing to end investors.

For the first contribution listed above, a closely related paper to ours is Houweling and van Zundert (2014). These authors find that size, low-risk, value, and momentum are economically meaningful factors that generate significant abnormal returns in the corporate bond market. Similar to us, these authors consider the merits to combining factors within a multi-factor portfolio and also consider the impact of transaction costs. However, in addition to differences in the factors considered as well as their definitions, there are two key research design differences. First, our paper constructs optimized long-only portfolios that resemble investable corporate bond portfolios by focusing on active risk and expected transaction costs. Second, and most importantly, we use our style factors to study the time series and cross section of actively managed credit hedge funds and mutual funds.

Our paper adds new insights to the wide body of research on mutual fund performance and risk-taking behaviour. Most studies have focused almost exclusively on equity-oriented funds, but our research is conducted entirely on credit-oriented funds.[1] Our main finding here is that actively managed credit hedge funds and mutual funds load significantly on our credit carry factor. This is an interesting and important result as: 1) credit carry is surprisingly the least compensated factor among our four style factors (though it's probably the easiest factor to "implement", which may explain its widespread use), and 2) high exposures to credit carry may add (potentially undesirable) greater market risk to investor portfolios. This finding is consistent with recent empirical research showing that credit market participants tend to "reach for yield" (Becker and Ivashina, 2015).

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 December 2013 on a monthly frequency. This panel includes all constituents of the Bank of America Merrill Lynch ("BAML") investment grade ("US Corporate Master") and high yield ("US High Yield Master") corporate bond indices.

Following the criteria in Haesen, Houweling and VanZundert (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

[1] We are aware of only one paper exploring the exposures of actively managed credit funds. Kahn and Lemmon (2015) study a sample of 121 fixed income investment managers and find that two beta factors (i.e., duration and credit) on average explain about 67% of risk-taking. The funds included in their sample are core plus mandates which are exposed to both interest rate risk and credit risk. Our focus is primarily on the latter.

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. Because most companies issue the majority of their bonds as senior debt, we select only bonds corresponding to the largest rating of the issuer. To do this we first compute the amount of bonds outstanding for each rating category for a given issuer. We then keep only those bonds that belong to the rating category which 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 two 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. There are two deliberate consequences of our sample construction that focuses on liquid and cross-sectionally comparable corporate bonds. We are not interested in identification of either (i) a liquidity premium style exposure (such as issue size), or (ii) a short duration style exposure for our primary empirical analyses.

Our resulting sample includes 258,313 unique bond-month observations, corresponding to 10,825 bonds issued by 5,300 unique firms. Table 1 reports annual statistics describing the composition of our sample over time. The average month in the sample consists of 1,266 bonds representing $544 billion of total notional outstanding, of which 57% (43%) corresponds to investment grade (high yield) issues. To construct variables requiring financial statement information, we are able to link 52% of our universe to the Compustat database.[2]

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 matches 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. In order 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) respectively. As newly issued bonds tend to be more liquid, we define a measure of bond illiquidity dubbed "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 definitions are contained 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 467 basis points, duration of 5.0 years, $422 million of notional outstanding, 7.7 years to maturity, and age percent of 27%. The average issuer in our sample has a

[2] We linked individual bond issues to the Compustat database using CUSIP and Ticker identifiers contained in the BAML dataset.

distance-to-default of 5.6, a 6-month bond excess return momentum of 3%, and market leverage of 0.32.

For our empirical analysis of actively managed credit hedge funds, we source our data from HFRI (HFR database). For time series analysis examining the 'beta' and 'style' exposures of actively managed credit hedge funds we use the 'HFRI Fixed Income: Corporate Index'. We have monthly hedge fund index return data from January 1997 through to November 2013 inclusive. For our cross-sectional analysis of the 'beta' and 'style' exposures across actively managed credit hedge funds we use monthly return data for individual hedge funds whose return series are captured by HFR and who have at least 24 months of return data. This return data is the constituent level returns of the index level data that we examine. We have monthly return data for 213 individual credit hedge funds for the period January 1997 through to November 2013 inclusive. For an individual hedge fund to be included in this analysis we filter on the sub-strategy classification 'Fixed Income – Corporate' within the HFR database.

For our empirical analysis of actively managed credit mutual funds, we source our data from Morningstar Direct. We limit ourselves only to the 1,386 open ended mutual funds that fall within the global broad category "Fixed Income' and then within that universe we further limit our focus to mutual funds that have at least 80 percent of their exposures to the corporate sector and retain the oldest share class of each fund. We also require each mutual fund to have at least 24 monthly return observations. Our final sample of actively managed credit mutual funds is 218 unique funds. To compute an index return for actively managed credit mutual funds we compute an equal weighted average of the returns across the 218 unique funds. Our return data for the actively managed credit mutual funds spans the period January 1997 through to November 2013 inclusive.

3.2 Style Measures

In this section, we define our four key style factors. While we considered other definitions (as reported in Table A.2), our choices were ultimately based on identifying simple and intuitive measures.[3]

Koijen, Moskowitz, Pedersen, and Vrugt (2014) define an asset's carry as its "expected return assuming its price does not change". A simple and widely known measure of carry in fixed income instruments is yield-to-maturity. While we could use each bond's yield-to-maturity, we prefer to use its OAS for a couple reasons. First, OAS captures the credit spread in excess of the risk-free Treasury curve – hence it is not affected by duration exposure, as our goal within this paper is to focus on credit excess returns. Second, OAS is similar to yield but adjusts for any embedded optionality and is thereby more comparable across issues. However, our measure of carry does ignore the spread roll-down and any expected default losses.

We define defensive (or low-risk) issuers as those with low levels of market leverage. We measure market leverage as the book value of debt (i.e., sum of short-term and long-term debt) divided by the sum of the book value of debt and market value of equity. Both

[3] Relative to Houweling and van Zundert (2014) we consider carry but do not consider size. We exclude size as we are interested in factors investable within large and liquid corporate bond portfolios. Our definitions are quite different from the authors who define value, momentum, and defensive as residual from spread regressed onto rating and maturity, 6-month corporate bond return (with a 1-month implementation lag), and low-risk based on a combination of a high credit rating and low duration.

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. Past research has identified a tendency for safer, low-risk assets to deliver a higher risk-adjusted return (see e.g., Frazzini and Pedersen, 2014, and Carvalho, Dugnolle, Xiao, and Moulin, 2014).

Our momentum style factor is defined as the trailing 6-month bond excess return. As motivated earlier, we are interested in bond excess returns which isolate the credit risk component of returns and abstract from interest rate exposures. Prior studies have shown that trading corporate bonds using equity momentum outperforms trading the bonds using bond momentum.[4] We consider equity momentum in robustness tests, but prefer credit momentum as the former is only available for issuers with publicly traded equity and is arguably more of an alpha factor as opposed to a style factor.

We define value (or cheapness) as a bond with a high spread relative to its underlying issuer's fundamental distance-to-default.[5] Specifically, we compute our value measure by running a cross-sectional regression of the log of OAS onto the log of distance-to-default and betting on the residual. Table A.2 contains detail for the computation of distance to default which is based on the approach used in Correia, Richardson and Tuna (2012). A positive (negative) residual indicates that a credit is trading at a wider (tighter) spread relative to its default risk than other credits in the regression. Default risk in the distance-to-default measure is captured by two key variables: leverage and asset volatility.

[4] Gebhardt, Hvidkjaer, and Swaminathan (2005b) identify significant return spillovers at the issuer-level from equity to corporate bond markets.

[5] Distance-to-default is a widely accepted market-based measure of corporate default risk (Merton, 1974).

Since our universe consists of corporate bond issues (not issuers), it is important to discuss how this distinction affects our factor definitions. Note that our primary measures of carry, momentum and value are issue-specific measures, whereas defensive is an issuer-specific measure. This does not create any issue for dependence in our empirical analysis because we only include one bond for a given issuer in a given month. However, more generally for style investing in corporate bonds, this creates an opportunity that is not evident in equity markets. For a given issuer it is possible to invest in different types of issues that differ in either seniority or maturity. In the context of the 'defensive' style where the intent is to invest in safer, higher-quality assets this could be captured by more senior instruments and more short date instruments. Our primary empirical analysis does not consider these possibilities as our sample selection criteria outlined in section 3.1 attempts to ensure cross-sectional comparability in both seniority and maturity.

3.3 Portfolio Construction

We construct two types of style portfolios: long-short quintile and long-only optimized. The former corresponds to an unconstrained portfolio commonly utilized in academic anomaly studies, and the latter corresponds to a more realistic investable portfolio.

To construct long-short quintile portfolios, we first rank the universe of bonds by the raw measure of a given style and then assign each bond into one of five quintiles. We then weight each bond within each quintile according to its outstanding market value.[6] Given we have formed five long-only value-weighted portfolios (i.e., Q1 to Q5), we construct a simple

[6] While our analysis focuses on value-weighted portfolios, we also formed equal-weighted portfolios, which yielded similar (if not stronger) empirical results.

long-short portfolio by subtracting the bottom from the top quintile portfolio (i.e., "Q5 – Q1"). A potentially undesirable feature of this quintile differenced portfolio is that the risk of a given style portfolio will vary both through time and across different styles. To help ensure comparability of our results we also re-scale the returns to each quintile portfolio such that each quintile portfolio targets a constant ex-ante annualized volatility of 5%. We do this by multiplying the "Q5 – Q1" portfolio weights by a scalar equal to 5% divided by the trailing 24-month realized volatility of the "Q5 – Q1" portfolio.[7] We refer to this resulting portfolio as a constant-volatility single-style portfolio.

Given each of our single-style portfolios, we then combine them to form a composite multi-style portfolio as follows. We first linearly combine weights across each of the single-style portfolios, weighting each of the factors equally. We then follow the same steps as above (beginning with ranking and then forming quintiles) to construct a constant-volatility multi-style portfolio. As will be described later, we utilize this multi-style portfolio to construct a long-only portfolio that takes into consideration realistic implementation considerations by solving a linear optimization problem.

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 style factors

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

along with multiple control variables. Each month we run cross-sectional regressions of the form:

$$R_{i,t+1} = \alpha + \beta_1 CARRY_{i,t} + \beta_2 DEF_{i,t} + \beta_3 MOM_{i,t} + \beta_4 VALUE_{i,t} + \gamma Z + \varepsilon_{i,t+1} \qquad (1)$$

where $R_{i,t+1}$ denotes the duration-hedged excess return of issue i over month t+1. Each of the four style factors is constructed to be a normalized variable. Specifically, for each style factor on every month-end, we rank issues by their factor values (with higher factor values receiving higher ranks), subtract the mean rank, and then divide by the standard deviation of the ranks. As a result, estimated coefficients may be interpreted as the future one-month excess return difference for a one standard deviation difference in factor ranking. Control variables, as indicated by **Z**, include rating, duration, and age percent (a proxy for illiquidity).

Table 3 reports our Fama-Macbeth regression estimates for the monthly sample period from January 1997 to December 2013. Regression (1) includes just an intercept and our control variables. Regressions (2) through (5) evaluate the predictive ability of each of our style factors on a standalone basis. The average sample size varies across columns due to the availability of style measures. For our measure of 'carry' (OAS) we have this for all bond-month observations. For our measure of 'momentum' we lose a small number of observations due to the requirement of excess returns for the past 6 months. For our 'defensive' and 'value' measures which require the use of equity market and financial statement data we are restricted to about half of the full sample (see also Table 1). To allow for ease of interpretation of regression coefficients we standardize each of our style measures to have zero mean and unit standard deviation each month. All of our style factors have significant return predictability with the exception of momentum, which exhibits a positive but insignificant t-statistic of 1.7. Regression (6) includes all style factors simultaneously.

We can see that each factor is positively associated with future corporate bond excess returns, and all but momentum are statistically significant. The average R-squared of the Fama-Macbeth cross sectional regressions is 17 percent, suggesting that our styles explain a non-trivial portion of the cross sectional variation in bond excess returns. Based on these point estimates, a bond with a one standard deviation higher rank in carry, defensive, momentum, or value corresponds to earning a higher future one-month excess return of 30, 13, 10, or 22 basis points. The value style has the strongest statistical relation with future excess returns as indicated by the large Fama-Macbeth test statistic of 6.4 in the final column. The analysis reported in table 3 is based on the maximal sample size for each measure. In unreported tests, we find similar results restricting our analysis to a common sample where all measures are available.

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 very strong results. Each of the simple and constant-volatility long-short portfolios has a positive Sharpe Ratio over our sample period – with value and defensive performing the best, and carry and momentum performing well but less positively. Upon forming a portfolio that combines all of the factors at an equal weight (i.e., "Combined"), we see that the diversified portfolio performs even better with an annualized Sharpe Ratio of 1.04. Note that the realized volatilities of the constant-volatility portfolios get closer to the targeted value of 5%, confirming that our simple scalar methodology is reasonably successful in estimating the volatility of the combined portfolio.

It is worth emphasizing several patterns observed in Table 4. Across all factors, we can see that the long-short returns are driven by positive performance on the long-side and negative (or weak) performance on the short-side. In fact, reading Sharpe Ratios across each of the rows clearly illustrates that performance is generally monotonically increasing across quintiles for each of the factors (momentum as the notable exception).

Figure 1 plots cumulative excess style factor returns over time. We can see that performance is not driven by any particular sub-period and has not changed substantially over time. While different factors 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.

To better understand the potential diversifying properties of the four style factors we report return correlations for the various style factors with well-known 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 November 2013 inclusive. We consider the following estimated risk premia: (i) credit risk premium ('CREDIT') measured as the difference between our value-weighted corporate bond total return and 1-month U.S. Treasury Bills, (ii) equity risk premium measured as the difference between the total returns on the S&P500 index and 1-month U.S. Treasury Bills ('EQUITY'), (iii) treasury term premium ('TSY') measured as the difference between total returns on 10-year U.S. Treasury bonds and 1-month U.S. Treasury Bills, and (iv) excess returns for actively managed credit hedge funds (Hedge Funds).

Several of the correlations in Table 5 are worth discussing. First, the correlations within style returns are largely as expected. Our measure of carry is positively associated with value (0.65), which is to be expected as value is the residual from a regression of OAS onto distance to default. Defensive and carry measures are negatively correlated (-0.31), which is also to be expected as our primary measure of defensive is targeting issuers with lower leverage who typically trade at lower spreads. Similar to other asset classes we see a negative correlation between value and momentum (-0.36). Conditional on each style 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 styles is direct evidence of the benefit of diversifying across styles. Second, the correlations between the various style measures and well-known sources of risk premia further emphasize the diversifying benefits of styles within corporate bonds. With the exception of 'carry' the return correlations between the style factors and risk premia are all less than 0.20. Perhaps most interesting is the fact that actively managed credit hedge funds have very high exposure to credit risk premium (0.84 correlation) and very low exposures to defensive, momentum and value, all of which offer positive risk-adjusted returns. We return to the exposures of both actively managed credit mutual and hedge funds in Section 4.4.

To further examine the correlation structure of our corporate bond style factors we regress each long/short style return onto credit risk premium (CREDIT), Treasury term premium (TSY) and the Fama-French factor mimicking portfolio returns (SMB, HML and UMD). Specifically, using the full time series of data for the period January 1997 through to November 2013 inclusive we run the following regression:

$$STYLE_t = \alpha + \beta_1 TSY_t + \beta_2 CREDIT_t + \beta_3 SMB_t + \beta_4 HML_t + \beta_5 UMD_t + \varepsilon_{i,t+1} \quad (2)$$

Consistent with the simple correlations reported in Table 5, we see that the 'carry' style has a significant positive exposure to credit risk premium and a negative correlation to momentum. After controlling for other well-known sources of return the intercept is not significant for ‘carry’. The ‘defensive’ and ‘momentum’ style returns are not correlated with market risk premia or equity style risk premia. Interestingly, the ‘value’ style in credit markets is negatively associated with the HML factor, suggesting another potential diversification benefit for the credit ‘value’ style. Across all of the style measures there is no positive exposure to SMB or HML. This is important as Schafer and Strebluaev (2008) note that corporate bond excess returns have a significant positive exposure to SMB and HML, especially for SMB. Our long/short style portfolio construction removes this directional bias, suggesting that the style returns we document are quite different from those identified in the equity markets. In the final column of Table 6 we regress the combined style long-short portfolio return onto the various market risk premia and equity style risk premia. The intercept is a significant 47 basis points per month (test statistic of 3.7). While the combined style portfolio is positively correlated with credit risk premium and term premium and moderately negatively exposed to HML, the combination is a well-compensated and diversifying source of returns.

To illustrate any time varying performance across the various styles (in Figure 2), we use the full-sample regression coefficients from Table 6 to compute 36-month rolling average alphas for each respective long/short style portfolio. While outperformance has been somewhat attenuated in the recent few years, it is clear that the abnormal returns have been relatively stable and positive over time.

4.3 Long-Only Optimized Portfolio

While our long-short style portfolios are certainly useful for evaluating naïve factor performance, they do not take into account actual portfolio implementation considerations. To more realistically address the hypothetical performance of our style factors, we build and test optimized long-only portfolios with realistic portfolio implementation constraints. Hence, our optimized portfolios are designed to be comparable to 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 simple linear optimization problem.[8] Our optimization problem is specified as follows:

$$Maximize: \sum_{i=1}^{I} w_i.COMBO_i - \tau \sum_{i=1}^{I} w_i.TCOST_i$$

$subject\ to$:

$$w_i \geq 0, \forall i\ (no\ shorting\ constraint)$$

$$|w_i - b_i| \leq 0.50\%, \forall i\ (deviation\ from\ benchmark\ constraint)$$

$$\sum_{i=1}^{I} w_i = 1\ (fully\ invested\ constraint)$$

$$\sum_{i=1}^{I} \left|w_{i,t} - w_{i,t-1}\right| \leq 10\%\ (turnover\ constraint)$$

$$\sum_{i=1}^{I} \left|\left(w_{i,t} - w_{i,t-1}\right).PRICE_{i,t}\right| \geq \$100{,}000, \forall i\ \ (minimum\ trade\ size\ constraint)$$

[8] 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 require estimation of an asset-by-asset covariance matrix (i.e., an asset-level risk model).

$$\sum_{i=1}^{I} |(w_i - b_i). OAS_i| \leq 0.50\% \ (deviation\ from\ benchmark\ spread\ constraint)$$

$$\sum_{i=1}^{I} |(w_i - b_i). Duration_i| \leq 0.50 \ (deviation\ from\ benchmark\ duration\ constraint)$$

where w_i is the portfolio weight for a given bond, $COMBO_i$is an equal-weighted combination of the carry, defensive, momentum, and value long-short style factor exposures for a given bond, $TCOST_i$is the expected transaction cost for a given bond which is used both in the ex-ante portfolio optimization problem as well as ex-post in estimating our realized transaction costs,[9] τ is a transaction-cost-aversion parameter,[10] $PRICE_i$ 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 the BAML dataset.

The solution to this optimization problem is a long-only corporate bond portfolio that has maximal exposure to the combined style factors while taking into consideration transaction costs. 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 50 bps), limit the portfolio's OAS exposure to be within 50 bps of the benchmark, and limit the portfolio's duration exposure to be within 0.50 years of the benchmark. We also constrain turnover to at most 10% per month and force trades to be at least as large as \$100,000. Despite our best efforts to incorporate constraints and transaction costs, the

[9] We estimate bond-level transaction costs according to each bond's rating and maturity in line with Table 1 of Chen, Lesmond, and Wei (2007).

[10] We choose to use a value for τ equal to 1.0, but results are not sensitive to a range of parameters between 0.5 and 2.0.

trading of corporate bonds is challenging. Thus, we caveat our empirical results by noting that dynamic trading strategies in corporate bonds are not as investable 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 5.3% per year (and 4.7% after taking into account realized transaction costs based on our estimates). Given its realized annualized volatility of 6.0%, the net Sharpe Ratio over this period was 0.79. By comparison, the gross (net) benchmark earned a 3.9% (3.7%) annualized excess return with a Sharpe Ratio of 0.67 (0.64). The active portfolio (i.e., portfolio minus benchmark) realized an annualized net Information Ratio of 0.60 with a tracking error of 1.7%. While not shown, regressing net portfolio excess returns onto benchmark net excess returns yields an annualized alpha of 1.1% (t-stat of 2.5) and a beta of 0.99 (t-stat of 45.3). Figure 3 shows the cumulative performance of the portfolio and the benchmark.

4.4 Credit Fund Style Exposures

Next we investigate how actively managed credit hedge funds and mutual funds load on each of our style factors. We estimate time-series regressions at the aggregated fund-level as well as at the individual fund-level.

Table 8 reports time-series regressions of credit hedge fund and mutual fund return indices onto our style factors. The dependent variable in Panel A is the monthly excess return on the HFRI Fixed Income: Corporate Index. The dependent variable in Panel B is the monthly excess return on an equal-weighted average of all corporate bond mutual funds in our sample. Across the regression specifications, we control for monthly excess returns on

Treasury, Credit, and Equity asset classes using excess returns on 10-year Treasuries, our value-weighted corporate bond index, and the S&P 500 index. Given the high degree of collinearity between Treasuries, Credit, and Equity, we are careful to consider market controls individually (as in regressions (1) through (3)) as well as jointly in regressions (4) through (6).

Across the different regression specifications in Panel A, it is clear that the hedge fund index is significantly exposed to Carry, neutral to Defensive, slightly positive to Momentum, and slightly negative to Value. For the credit mutual fund index in Panel B, we similarly find that Carry is a very significant exposure – while the other styles are generally more neutral. Given the positive correlation between our measure of Carry and Value (0.65 from Table 5) the positive loading of actively managed credit funds on Carry and the negative loading of actively managed credit funds on Value is most likely attributable to the fact that Carry is an easy exposure to implement. Perhaps more interesting is the strong 'beta' to aggregate credit markets for both actively managed hedge funds and mutual funds. For example, the increase in R^2 from column (1) to column (2) is from 19% to 71% in panel A and from 14% to 81% in panel B. While mutual fund managers may be managing with respect to a benchmark, the strong positive exposure to actively managed credit hedge funds suggests a hidden beta exposure of hedge funds, and after controlling for that 'beta', the average positive return is almost halved (intercept decreases from 35 basis points per month in panel A of table 8 to 19 basis points as you move from the first to the second column).

As the results above are based only on aggregate indices, we next consider the cross-sectional distribution of style exposures at the individual fund-level. For each credit hedge fund and mutual fund in our sample, we run four time-series regressions that include each of the four style exposures along with controls for Treasuries and Credit.[11] Figure 4 shows the cross-sectional distribution of t-statistics on each of our style factors through density plots. At the 95th percentile, the t-statistic on Carry is 2.55 for hedge funds and 3.04 for mutual funds. Note that by chance alone we should expect these t-statistics to be around 2.0. While not reported, we find that these empirical estimates are too significant to be explained by random chance (based on bootstrapped p-values).

5. Robustness

5.1 Alternative Style Factor Definitions

Table A.2 lists various alternative measures of our four primary styles. We have examined each variant in the context of our long/short and long-only portfolios. Our main inference that the four styles generate positive risk-adjusted returns, especially when viewed in combination, is unaffected by the choice of a given style measure. Indeed, we find stronger results for some of our style measures. However, rather than report the 'best' in-sample combination of the respective style measures, we simply note the robustness of our results to alternative style definitions.

5.2 Investment Grade vs. High Yield corporate bonds

All of our empirical analysis has grouped investment grade and high yield bonds together. In unreported analyses we have separately examined our four styles across investment grade and high yield corporate bonds separately. We find that the combination

[11] Given short sample periods for some funds and concerns regarding factor and market collinearity, we utilize this simpler regression specification for all funds.

across the four styles has a very similar Sharpe ratio for both groups: 1.16 for Investment Grade and 1.12 for High Yield. In terms of the contribution of each style, we find that (i) 'carry' is much stronger for investment grade (1.15 Sharpe ratio for IG and 0.6 for HY), (ii) there is no evidence of a positive risk-adjusted return for 'defensive' within investment grade (Sharpe ratio of -0.27), and (iii) 'momentum' is strongest for investment grade (0.35 Sharpe ratio for IG and -0.02 for HY). This last result is in contrast to past research that has documented a positive relation between past equity returns for corporate bond excess returns (e.g., Gebhardt, Hvidkjaer and Swaminathan (2005b). However, our primary momentum measure is corporate bond excess returns and not equity returns. As noted above in section 5.1, in unreported tests we confirm strong evidence of equity momentum for corporate bond returns and also find that return pattern to be strongest for high yield bonds.

5.3 European Corporate Bond Returns

We have replicated our empirical analysis in Tables 1-7 using European corporate bond data and find similar results. We find positive risk-adjusted returns to carry, defensive, momentum and value for the universe of European corporate bonds. For the sake of brevity we have not included this analysis in the paper.

6. 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 style returns that have been documented in equity markets (e.g., size, value and momentum).

Realistic long-only portfolios can be constructed to achieve maximal exposure to the four styles we investigate (carry, defensive, momentum and value). For a broad sample of corporate bonds in the U.S. for the period January 1997 through to November 2013 inclusive, we find that an active long-only portfolio earns 1% in excess of the benchmark annually with an Information Ratio of 0.60. This long-only portfolio is aware of transaction costs, trading limits and position constraints, suggesting that it is possible to build meaningful portfolios with exposures to styles within the corporate bond universe.

Our final analysis examines the exposures of actively managed credit hedge funds and actively managed credit mutual funds. We find that both sets of actively managed credit funds have significant exposure to 'beta', primarily through exposure to credit risk premium, as well as minimal exposure to our documented styles with the exception of 'carry'. Thus, despite evidence of (i) a robust relation between well-known styles (i.e., carry, defensive, momentum and value) and corporate bond excess returns, and (ii) feasible implementation of exposure to these styles in a long-only portfolio, individual credit funds are under-exposed to styles that generate meaningfully positive risk-adjusted returns. Investors in actively managed credit funds should be aware of the hidden beta they are exposed to, and should prefer an investment product designed to isolate exposure to well-compensated styles that are orthogonal to market beta.

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Table 1: Universe Statistics (1997-2013)

The table below 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.

Year	Count	Total Notional	%IG	%HY	% Linked to Compustat
1997	1,096	243	59%	41%	55%
1998	1,198	280	59%	41%	55%
1999	1,132	308	60%	40%	52%
2000	1,112	352	60%	40%	50%
2001	1,146	395	62%	38%	49%
2002	1,173	451	64%	36%	51%
2003	1,298	508	60%	40%	53%
2004	1,372	543	57%	43%	54%
2005	1,309	570	59%	41%	53%
2006	1,276	560	58%	42%	52%
2007	1,265	582	56%	44%	51%
2008	1,230	623	57%	43%	51%
2009	1,180	613	59%	41%	54%
2010	1,305	703	55%	45%	55%
2011	1,426	786	52%	48%	55%
2012	1,466	833	51%	49%	54%
2013	1,544	905	50%	50%	50%
Average	1,266	544	57%	43%	52%

Table 2: Issue and Issuer Characteristics (1997-2013)

The table below reports summary statistics of bond issue and issuer characteristics (as defined in Table A.1). For each characteristic, the column statistic is computed on a monthly basis and then averaged over the full sample period.

	Mean	Std	5%	10%	25%	50%	75%	90%	95%
OAS	467	545	89	112	169	321	562	931	1,316
Duration	5.0	2.1	1.7	2.4	3.7	4.9	6.2	7.2	8.1
Total Ret.	0.7%	4.2%	-3.5%	-1.9%	-0.4%	0.7%	1.8%	3.4%	4.9%
Excess Ret.	0.2%	4.1%	-3.8%	-2.2%	-0.8%	0.2%	1.3%	2.8%	4.4%
Amt. Out.	422	435	128	150	200	293	470	785	1,086
Time to Mat.	7.7	4.9	2.9	4.0	5.5	7.0	8.7	10.4	15.5
Age Percent	27%	19%	3%	5%	11%	24%	39%	53%	64%
Rating	4.8	1.4	2.6	3.0	3.8	4.8	6.0	6.8	6.9
Dist. to Def.	5.6	3.4	1.2	1.8	3.1	5.1	7.5	10.1	11.8
Momentum	3%	9%	-12%	-6%	-1%	2%	7%	13%	19%
Leverage	0.32	0.50	-0.02	0.03	0.14	0.30	0.50	0.70	0.81

Table 3: Fama-Macbeth Regressions (1997-2013)

The table below reports Fama-Macbeth regressions of monthly bond excess returns regressed onto normalized Carry, Defensive, Momentum, and Value style measures along with controls for Rating, Duration, and Age Percent variables (as defined in Table A.1).

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.20	0.60	0.04	0.33	0.59	1.05
	[1.0]	[3.2]	[0.2]	[1.7]	[2.8]	[5.6]
Carry		0.27				0.30
		[2.3]				[2.0]
Defensive			0.13			0.13
			[2.2]			[2.0]
Momentum				0.13		0.10
				[1.7]		[1.5]
Value					0.28	0.22
					[8.4]	[6.4]
Rating	0.05	-0.06	0.08	0.02	-0.06	-0.14
	[0.8]	-[1.5]	[1.4]	[0.3]	-[1.0]	-[3.5]
Duration	-0.05	-0.02	-0.04	-0.04	-0.03	-0.02
	-[2.6]	-[0.9]	-[2.7]	-[2.4]	-[1.6]	-[1.4]
Age Percent	0.00	-0.03	0.01	-0.01	0.00	-0.01
	[0.0]	-[0.2]	[0.9]	-[0.1]	[0.1]	-[0.5]
Avg. R-squared	0.06	0.10	0.10	0.08	0.08	0.17
Avg. Num. Obs.	1,182	1,182	552	997	536	464

Table 4: Quintile Portfolio Tests (1997-2013)

The table below reports 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).

		Q1	Q2	Q3	Q4	Q5	Q5 - Q1	ConstVol
Carry	Ret.	-0.3%	1.1%	1.9%	4.0%	5.8%	6.1%	0.9%
	Vol.	3.1%	4.7%	7.3%	10.1%	18.7%	16.5%	6.0%
	S.R.	-0.10	0.23	0.27	0.39	0.31	0.37	0.15
Defensive	Ret.	0.0%	1.4%	0.9%	1.8%	2.8%	2.7%	4.5%
	Vol.	9.9%	5.9%	5.0%	4.8%	9.8%	5.6%	6.5%
	S.R.	0.00	0.24	0.19	0.38	0.28	0.49	0.70
Momentum	Ret.	2.2%	2.3%	1.1%	1.2%	3.6%	1.4%	2.1%
	Vol.	15.3%	6.3%	5.4%	5.5%	8.6%	10.3%	7.0%
	S.R.	0.14	0.37	0.20	0.21	0.42	0.13	0.29
Value	Ret.	-0.8%	-0.1%	1.6%	2.9%	4.9%	5.7%	5.6%
	Vol.	5.8%	6.0%	6.8%	8.1%	9.9%	6.3%	6.2%
	S.R.	-0.14	-0.02	0.24	0.36	0.49	0.90	0.91
Combined	Ret.	-2.0%	0.1%	2.1%	3.3%	5.8%	7.8%	6.3%
	Vol.	7.4%	6.0%	6.2%	7.1%	12.4%	7.7%	6.1%
	S.R.	-0.27	0.02	0.33	0.46	0.46	1.01	1.04

Table 5: Return Correlation Matrix (1997-2013)

The table below reports monthly excess return correlations for each of the Carry, Defensive, Momentum, Value, and Combined style factors along with market indices corresponding to Credit, Equity, Treasury, and actively managed credit Hedge Fund excess returns.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Carry	1.00								
Defensive	-0.31	1.00							
Momentum	-0.65	0.25	1.00						
Value	0.65	0.21	-0.36	1.00					
Combined	0.54	0.34	-0.08	0.73	1.00				
CREDIT	0.29	-0.03	-0.07	0.14	0.17	1.00			
EQUITY	0.38	-0.09	-0.20	0.18	0.13	0.59	1.00		
TSY	-0.04	0.04	-0.02	0.01	0.07	-0.48	-0.25	1.00	
Hedge Funds	0.29	-0.09	-0.06	0.08	0.09	0.84	0.58	-0.28	1.00

Table 6: Style Factor Return Regressions (1997-2013)

The table below reports monthly excess return regressions of the Carry, Defensive, Momentum, Value, and Combined style factors (as defined in the text) onto Treasury and Credit excess returns as well as the Fama-French equity style factors.

	Carry	Defensive	Momentum	Value	Combined
Intercept	0.04%	0.39%	0.14%	0.47%	0.47%
	[0.3]	[2.8]	[1.0]	[3.6]	[3.7]
TSY	0.23	0.06	-0.14	0.18	0.34
	[1.7]	[0.4]	-[0.8]	[1.3]	[2.4]
CREDIT	0.26	0.01	-0.02	0.16	0.21
	[3.6]	[0.2]	-[0.3]	[2.1]	[2.8]
SMB	-0.03	-0.04	0.03	-0.06	-0.03
	-[0.7]	-[1.0]	[0.7]	-[1.7]	-[0.9]
HML	-0.07	-0.05	0.05	-0.12	-0.07
	-[1.9]	-[1.3]	[1.2]	-[3.1]	-[2.0]
UMD	-0.04	0.01	0.08	-0.02	-0.03
	-[2.0]	[0.2]	[3.1]	-[1.0]	-[1.3]
R-squared	0.13	0.01	0.06	0.08	0.08

Table 7: Long-Only Backtest Portfolio Performance (1997-2013)

The table below reports performance statistics for the long-only optimized back-test portfolio based on the following optimization problem:

$$Maximize: \sum_{i=1}^{I} w_i.COMBO_i - \tau \sum_{i=1}^{I} w_i.TCOST_i$$

$subject\ to$:

$$w_i \geq 0, \forall i\ (no\ shorting\ constraint)$$

$$|w_i - b_i| \leq 0.50\%, \forall i\ (deviation\ from\ benchmark\ constraint)$$

$$\sum_{i=1}^{I} w_i = 1\ (fully\ invested\ constraint)$$

$$\sum_{i=1}^{I} \left|w_{i,t} - w_{i,t-1}\right| \leq 10\%\ (turnover\ constraint)$$

$$\sum_{i=1}^{I} \left|\left(w_{i,t} - w_{i,t-1}\right).PRICE_{i,t}\right| \geq \$100{,}000, \forall i\ \ (minimum\ trade\ size\ constraint)$$

$$\sum_{i=1}^{I} |(w_i - b_i).OAS_i| \leq 0.50\%\ (deviation\ from\ benchmark\ spread\ constraint)$$

$$\sum_{i=1}^{I} |(w_i - b_i).Duration_i| \leq 0.50\ (deviation\ from\ benchmark\ duration\ constraint)$$

	Portfolio	Benchmark	Active
Excess Return (gross)	5.33%	3.88%	1.45%
Excess Return (net)	4.73%	3.69%	1.04%
Volatility	5.96%	5.78%	1.74%
Sharpe Ratio	0.79	0.64	0.60

Table 8: Credit Fund Indices Style Exposures (1997-2013)

The table below reports regressions of monthly excess returns on indices (proxying actively managed credit hedge funds and mutual funds) onto the style factors in addition to market controls. The index used in Panel A is the "HFRI Fixed Income: Corporate Index". The index used in Panel B is an equal-weighted average of all 218 corporate bond mutual funds in our Morningstar sample. TSY, CREDIT, and EQUITY correspond to excess returns on 10-year U.S. Treasuries, the value-weighted average of all corporate bonds in our sample, and the S&P 500 index.

Panel A. Credit Hedge Fund Index

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.35%	0.19%	0.17%	0.13%	0.23%	0.12%
	[3.0]	[2.8]	[1.6]	[1.9]	[2.2]	[1.7]
Carry	0.65	0.18	0.35	0.15	0.36	0.12
	[5.4]	[2.4]	[3.1]	[2.0]	[3.2]	[1.5]
Defensive	0.10	-0.01	0.04	-0.03	0.05	-0.03
	[1.4]	-[0.3]	[0.6]	-[0.6]	[0.7]	-[0.7]
Momentum	0.20	0.07	0.17	0.07	0.16	0.07
	[2.7]	[1.6]	[2.7]	[1.5]	[2.6]	[1.6]
Value	-0.27	-0.11	-0.17	-0.10	-0.17	-0.09
	-[2.7]	-[1.9]	-[1.9]	-[1.8]	-[1.9]	-[1.6]
TSY	-0.45			0.28	-0.26	0.28
	-[4.0]			[3.7]	-[2.5]	[3.8]
CREDIT		0.68		0.75		0.70
		[20.0]		[19.9]		[16.5]
EQUITY			0.20		0.18	0.04
			[8.4]		[7.6]	[2.4]
R-squared	0.19	0.71	0.36	0.73	0.37	0.74
Num. Obs.	203	203	203	203	203	203

Panel B. Credit Mutual Fund Index

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.31%	0.19%	0.15%	0.00%	0.13%	-0.02%
	[2.2]	[2.8]	[1.3]	-[0.1]	[1.1]	-[0.7]
Carry	0.76	0.14	0.35	0.05	0.35	0.00
	[5.2]	[1.9]	[2.7]	[1.1]	[2.7]	[0.0]
Defensive	0.19	0.04	0.10	0.00	0.10	-0.01
	[2.0]	[0.9]	[1.4]	[0.0]	[1.4]	-[0.3]
Momentum	0.17	-0.01	0.12	-0.02	0.12	-0.02
	[1.9]	-[0.3]	[1.6]	-[0.9]	[1.6]	-[0.9]
Value	-0.25	-0.04	-0.12	-0.02	-0.12	0.00
	-[2.1]	-[0.7]	-[1.2]	-[0.6]	-[1.2]	-[0.1]
TSY	-0.19			0.86	0.09	0.86
	-[1.4]			[19.3]	[0.7]	[21.0]
CREDIT		0.86		1.07		1.00
		[26.3]		[48.4]		[43.3]
EQUITY			0.25		0.26	0.06
			[9.6]		[9.5]	[6.1]
R-squared	0.14	0.81	0.41	0.93	0.41	0.94
Num. Obs.	203	203	203	203	203	203

Figure 1: Cumulative Style Factor Returns (1997-2013)

The figure below shows cumulative returns for each of the Carry, Defensive, Momentum, Value, and Combined style factors (as defined in the text).

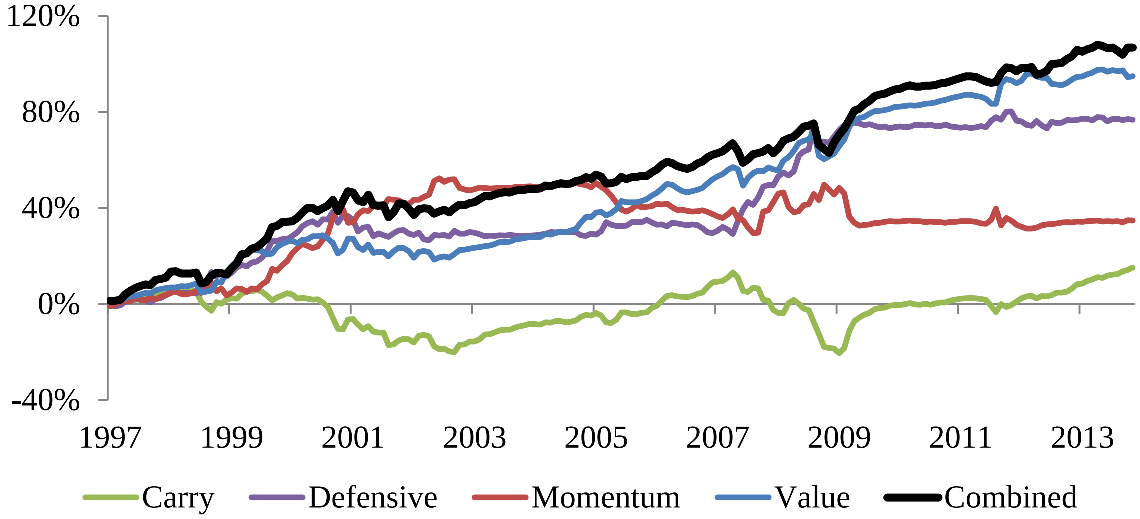

Figure 2: Rolling Regression Alphas

The figure below shows 3-year rolling average regression alphas for each of the Carry, Defensive, Momentum, Value, 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.

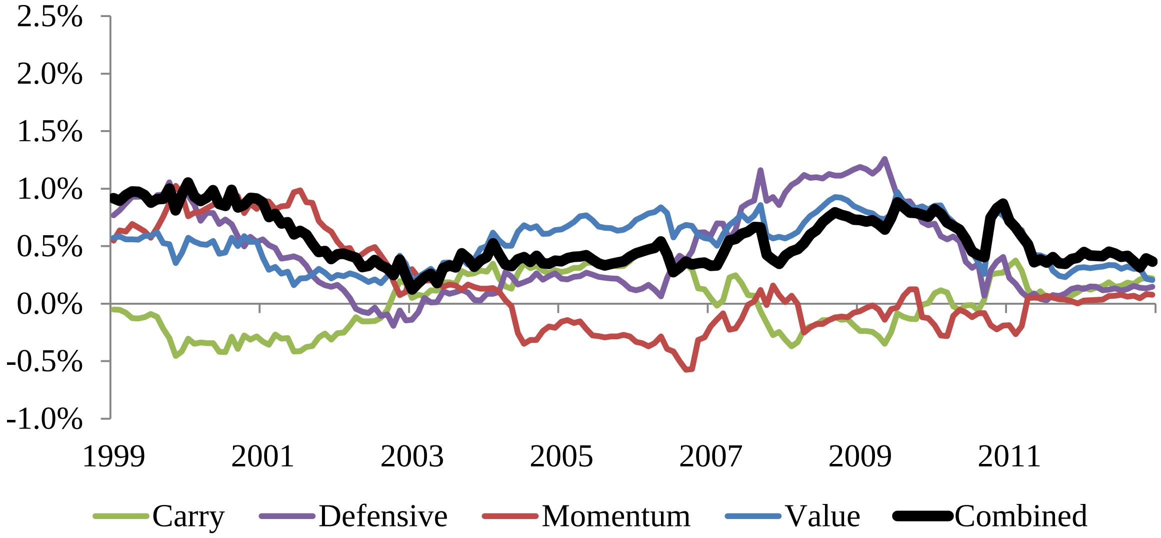

Figure 3: Cumulative Long-Only Portfolio Returns (1997-2013)

The figure below 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.

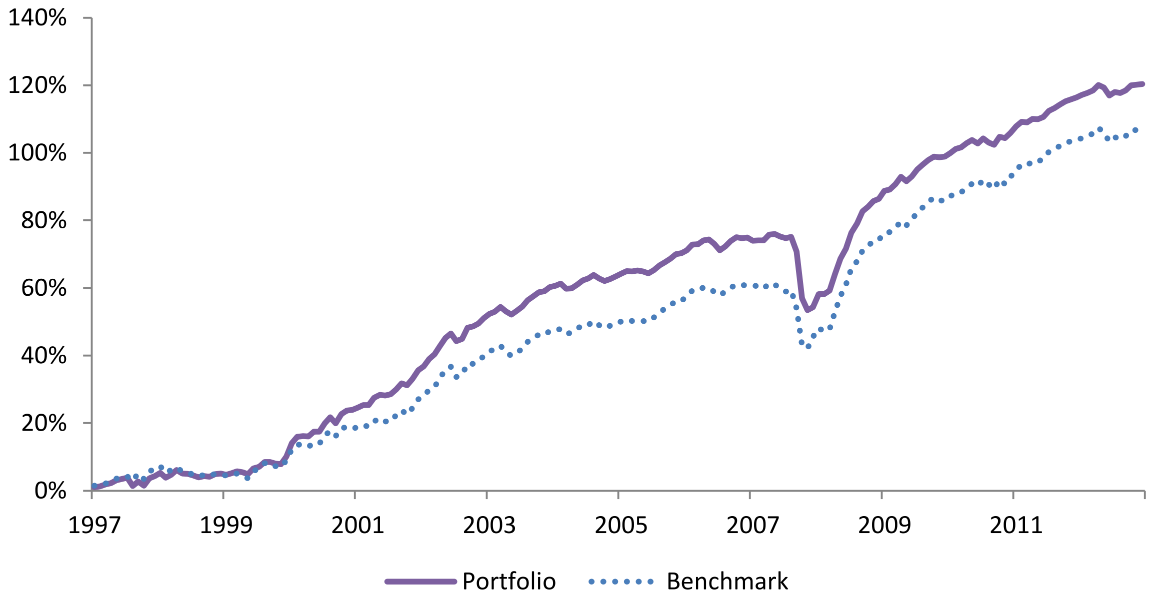

Figure 4: Distribution of Credit Hedge Fund and Mutual Fund Style Exposures

The figures below plot empirical densities of the cross-sectional distribution of t-statistics on style exposures for our sample of 213 credit-oriented hedge funds and 218 mutual funds between 1997 and 2013. The fund-level time-series regression is described in the text.

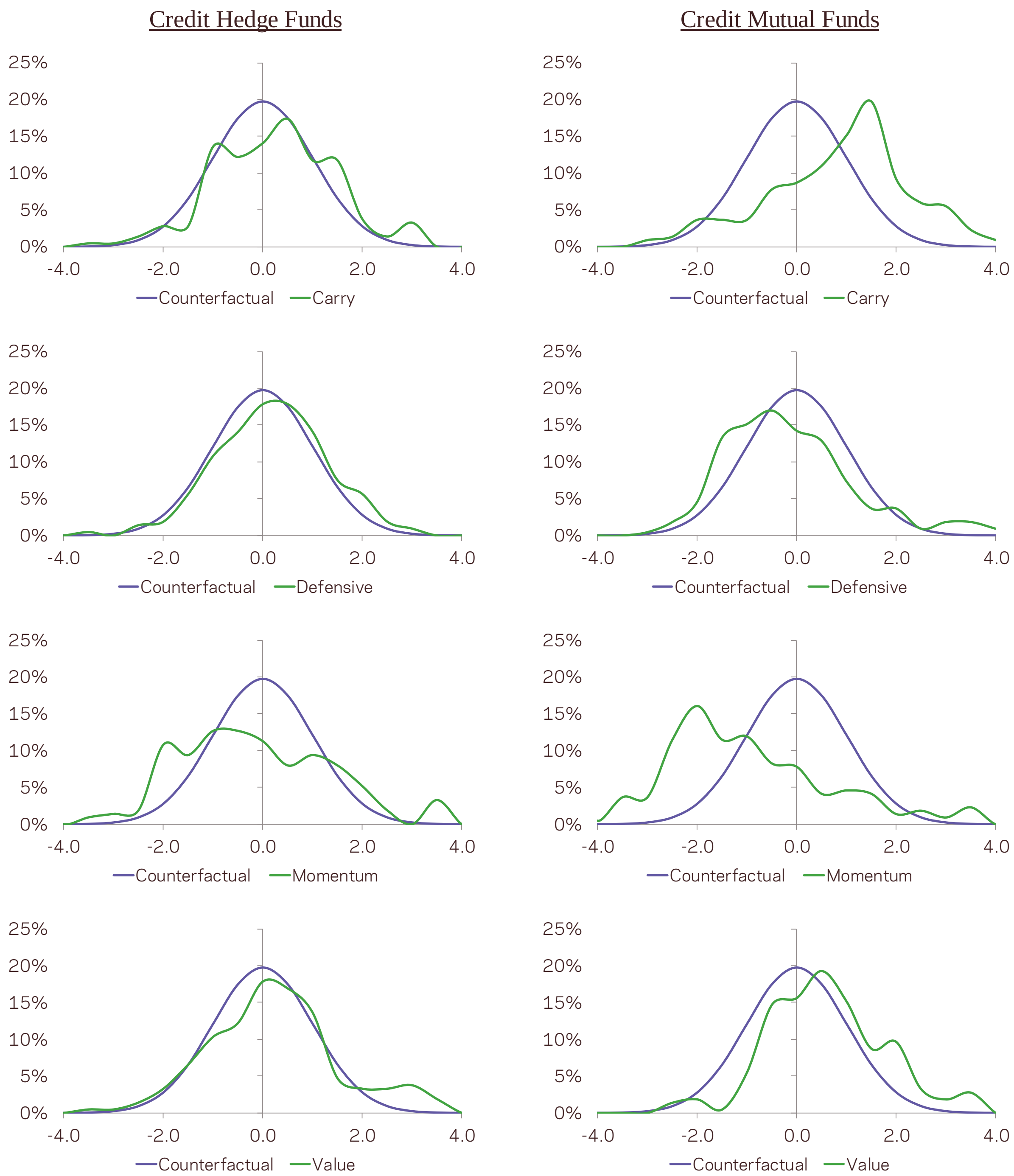

Table A.1: Variable Definitions

Variable	Definition
OAS (Carry)	Option Adjusted Spread as reported in the Bank of America Merrill Lynch (BAML) bond database.
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 US 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 and Poor's issuer level rating coded from 1 (AAA) to 10 (D).
Distance to Default (D2D)	Distance to default is measured each month as $\frac{\ln\frac{V_0}{X}+\left(\mu-\delta-\frac{\sigma_E^2}{2}\right)t}{\sigma_E\sqrt{t}}$, where V_0 is the market value of assets at the start of the month, X is the book value of debt at the start of the month, σ_E is historical equity volatility over the past year, μ is the drift in asset value, and δ is the firm's net payout ratio. Full details can be found in Correia, Kang and Richardson (2015).
Value	The residual from a cross-sectional regression of the log of OAS onto the log of D2D.
Momentum	The most recent six month cumulative corporate bond excess return.
Leverage (Defensive)	Market leverage measured as the ratio of book debt to the sum of book 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).

Variable	Definition
TSY	Excess returns to long term government bonds measured as the difference between monthly total returns on 10 year U.S. Treasury bonds and 1-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 1-month U.S. Treasury Bills.
EQUITY	Excess returns to the S&P500 Index, measured as the difference between monthly total returns to the S&P500 and 1-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

Table A.2: Alternative Style Measures

Style	Intuition	Primary Measure	Alternative Measures
Carry	The expected return assuming prices do not change (i.e., buying high-yielding assets and selling low-yielding assets)	OAS	Roll
Defensive	Buying low-risk, high-quality assets and selling high-risk, low-quality assets	Leverage	Distance to default, rating, historical volatility, DTS (duration times spread), short maturity
Momentum	Buying assets that have recently outperformed their peers and selling those that have recently underperformed	Past 6 months credit excess return	Equity momentum, fundamental momentum, risk-adjusted returns
Value	Buying assets that are 'cheap' relative to their fundamental value and selling 'expensive' assets	Credit Spread relative to Distance to Default	Reduced form default models