Implementable Corporate Bond Portfolios *

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Abstract

We investigate the scope for active investing in corporate bonds by estimating an optimal portfolio using asset characteristics. Our portfolio weights are modeled to account for the severe trading frictions present in OTC bond markets. A portfolio based on maturity, rating, coupon, and size outperforms passive benchmarks and univariate sorts after transaction costs in and out of sample. Further, it predicts macroeconomic activity, suggesting bond characteristics provide hedging against macro-fluctuations. Active funds appear constrained by narrow investment mandates from holding the optimal portfolio. Overall, while active corporate bond portfolios are feasible, institutional constraints might limit their accessibility.

JEL-Classification: G11, G12, C13, C58
Keywords: corporate bonds; empirical portfolio choice; characteristics

*We thank Andrei Goncalves, Rainer Jankowitsch, Mark Kamstra, Hugues Langlois, Jun Liu, Michael Melvin, Stefan Pichler, Otto Randl Leopold Sögner, Allan Timmermann, Marliese Uhrig-Homburg, Pietro Veronesi, Christian Wagner, Dacheng Xiu, Josef Zechner, seminar participants at the University of Chicago Booth, UCSD Rady School of Management, Arizona State, Victoria University of Wellington, IFS-SWUFE in Chengdu, FGV Rio de Janeiro, FGV/EPGE Sao Paulo, and participants at the VGSF Conference, FMA European Conference, EFMA Conference, IAAE Conference, DGF Conference, FMA Conference, and the HEC McGill Winter Finance Workshop, Lubrafin Conference for useful comments. All remaining errors are our own.

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1 Introduction

The value of U.S. corporate debt outstanding has increased from $460 billion in 1980 to $9.57 trillion in 2019, making corporate bonds an asset class of first order relevance for investors. Bond mutual funds and ETFs have grown at a similar pace, making this OTC market more accessible. [1] Failure to properly manage corporate bond portfolios has been shown to result in sudden outflows, increasing the odds of instability in that market and the aggregate economy (Falato et al., 2021; Falato, Goldstein, and Hortacsu, 2020; Haddad, Moreira, and Muir, 2021). Despite a large number of papers investigating which characteristics best predict corporate bond returns, the question of how to actively construct a tradeable portfolio of corporate bonds by exploiting their characteristics has largely been ignored.[2] This issue is especially relevant in light of recent evidence showing that actively managed corporate bond portfolios are pervasive and less prone to fragility (Choi, Cremers, and Riley, 2021).

Our paper fills this gap by estimating an optimal corporate bond portfolio and investigating the economic drivers of its performance. The weights of the portfolio are modeled as a smooth maximum function of observable bond characteristics, while taking into account asset-specific real transaction costs. This methodology allows to internalize the illiquid nature of the OTC corporate bond market, which render traditional portfolio approaches used for stocks infeasible. We find that a portfolio conditioned on four simple bond characteristics (time to maturity, credit rating, coupon and size) significantly outperforms in and out of sample passive benchmarks and univariate portfolio sorts, while keeping low levels of turnover and short positions.

The optimal portfolio has several interesting properties. First, it predicts various measures of macroeconomic activity above and beyond the information content of yield spreads, meaning it provides a hedge against undesirable states of the economy. Second, our evidence suggests the optimal allocation cannot be reached by active fund managers in the market

[1] Investment in corporate bonds by mutual funds and ETFs grew from $0.52 trillion in 2008, to above %2.0 trillion in 2019.

[2] See for example (Kelly, Palhares, and Pruitt, 2021; Bartram, Grinblatt, and Nozawa, 2020; Elkamhi, Jo, and Nozawa, 2020; Bai, Bali, and Wen, 2019; Chordia et al., 2017; Gebhardt, Hvidkjaer, and Swaminathan, 2005) among others.

due to narrow investment mandates that are based on the same characteristics we use for the optimal allocation. While the optimal portfolio deviates from passive funds or benchmarks in a similar way those of active bond funds do, our deviations are larger. Further, larger deviations of our portfolio from active bond funds' allocation, predict a higher out-performance of the optimal portfolio over those funds. Third, adding to the baseline specification other characteristics that have been found to predict bond returns (e.g. downside risk, stock characteristics, etc) does not improve the performance of the optimal portfolio out of sample. Overall, we show that even when accounting OTC bond market frictions, it is possible to create a superior portfolio by exploiting macroeconomic information embedded in bond characteristics. However, the set of tradeable characteristics is not as large as previously thought. Further, narrow investment mandates might prevent institutional investors from holding the optimal portfolio, hence representing an important limit to arbitrage in this market.

Our starting point is an investor (say, a bond fund manager) whose objective is to choose an optimal portfolio of corporate bonds. There are several issues related to the nature of this asset class and the structure of the market that render the portfolio choice problem particularly challenging. First, the investor has to consider a large cross-section of highly heterogeneous securities. Some of that heterogeneity is captured in various bond characteristics – such as maturity, credit rating, coupon rate, issue size – which are linked to the pricing of these assets. Second, investors in that market face high trading costs, which reflect illiquidity and the complex structure of this OTC market, in which participants face search and bargaining frictions, while limited pre-trade transparency and infrequent trading slow the information flow relative to the more efficient centralized markets (Duffie, Gârleanu, and Pedersen, 2005; Bessembinder et al., 2018). Third, short-selling constraints in that market are significantly higher than for equities (Asquith et al., 2013). Finally, implementing the traditional mean-variance approach with corporate bond data is daunting, as it involves estimating expected returns, variances, and covariances with a short time series, a large cross-section, and an unbalanced data set.[3] Incorporating asset-specific conditioning information adds another layer of intractability.

We construct portfolios of corporate bonds by directly specifying their weights as a function of observable asset-specific characteristics and unknown parameters. This so-called "parametric portfolio approach", introduced by Brandt, Santa-Clara, and Valkanov (2009), has several conceptual advantages. One is to sidestep the challenge of modeling the joint distribution of bond returns and characteristics, and instead focusing directly on the object investors care most about: the portfolio weights. There are only as many parameters in this method as there are characteristics, which tremendously reduces the dimensionality of the estimation problem. The parameters capture the marginal impact of the conditioning variables on the optimal weights, relative to a benchmark allocation. As the weights are a function of a multitude of variables, this approach is, in principle, more flexible and conditions on a larger information set than long-short portfolios based on univariate sorts. The parametric weights are estimated by maximizing the average utility of an investor over the sample period and hence can be interpreted as capturing the revealed preferences of investors for certain characteristics. Another advantage of the parametric approach is that the functional form of the weights is specified depending on the asset class of interest. For corporate bonds, we introduce a novel smooth maximum specification which allows us to limit short positions and turnover, while accounting for bond-specific transaction costs.

To estimate the portfolio weights of an optimal corporate bond portfolio, we use individual bond data from January 1993 to December 2017. On average, our sample contains about 900 assets. For each bond, we start applying 4 characteristics – time to maturity (TTM), credit rating (RAT), coupon (COUP), size of the issue (SIZE) – that are easily observable and often used by fund managers to characterize their investment mandates. In a second step, we also explore variations with a larger number of bond and firm-specific variables, fol-

[3]Corporate bond maturity rarely exceeds 15 years. Moreover, the cross-section of bond returns is large, as many companies have multiple bonds outstanding at a given time. In addition, the panel data of bond returns is severely unbalanced because securities enter and exit the sample frequently as new bonds are issued or existing debt matures.

lowing recent papers in this literature. We estimate the weights for an investor with CRRA utility and risk aversion of 5.

Our findings can be summarized as follows. The optimal corporate bond portfolio weights load significantly on the asset characteristics. Compared to passive equally or value-weighted benchmarks, the optimal allocation is tilted toward bonds with higher time to maturity, credit risk, coupon and issue size. Hence, the optimal portfolio puts more weight on characteristics that the previous literature has found to proxy for various sources of risk in that market. For instance, placing more weight on high maturity bonds is a strategy that emphasizes the term premium and interest rate risk (e.g., Campbell and Shiller, 1991). The tilt toward bonds with higher credit risk is in line with Longstaff, Mithal, and Neis (2005) or Bai, Bali, and Wen (2019), who find a strong link between credit risk and corporate yield spreads. A tilt toward bonds that pay higher coupons is essentially a “reaching for yield” strategy, as described in Becker and Ivashina (2015).

To measure the economic contribution of the bond characteristics, we compare the annualized certainty equivalent return and Sharpe ratio of the optimal portfolio to that of an equally or value-weighted benchmark. In our baseline specification, our parametric portfolio yields an annualized CE return of 9.1% after transaction costs and outperforms the value weighted (equally-weighted) benchmark by 65.6% (56.9%). Thanks to the smooth maximum weight function, the optimal portfolio maintains low level of short positions (12.7%) and yearly turnover (116%), that are both in line with the levels observed in practice in fixed income funds. The superior perfromance holds within an out of sample exercise that spans a period of 15 years between January 2002 and December 2017. In this case, our parametric portfolio yields outperforms the value weighted (equally-weighted) benchmark by 62.1% (49.1%), while keeping short positions similar to those observed in-sample. In strong support of our approach, the out of sample performance (8.2% CE return) is superior to strategies based on single characteristics' portfolio sorts, both with and without transaction costs. Our results are consistent with recent findings by DeMiguel et al. (2020), who document that combining characteristics can reduce transaction costs, as trades in the underlying assets can be netted against each other. This idea is further supported by the significant cross-correlations among long-short portfolios of univariate sorts we document in our data.

In attempt to shed further light on the properties of our portfolio, and motivated by evidence that corporate bond spreads anticipate business cycles, we investigate whether the active component of the optimal portfolio returns predicts economic activity.[4] To do so, we regress three-month-ahead and twelve-month-ahead changes in GDP growth and in consumption growth (CONS) on our portfolio returns, decomposed in active and passive component. Optimal portfolios are estimated using an expanding window that ends before the period over which changes in the macroeconomic variables are calculated. We control for lagged GDP or consumption growth and the yield spread from (Gilchrist and Zakrajšek, 2012), that has been shown to be a strong predictor of macro variables. At all horizons, the active component of the portfolio return predicts future GDP and consumption growth. A one-standard-deviation increase in our active portfolio return leads to an increase of GDP (consumption) growth of 0.178 (0.16) standard deviations in the three-month-ahead regressions and of 0.489 (0.275) standard deviations at the yearly horizon. We find similar results for other macro variables such has industrial production growth and changes in unemployment rate. Our findings are consistent with the view that the bond characteristics are capturing hedging demands. To the extent that the time-varying characteristics proxy for changes in investment opportunities, Brandt and Santa-Clara (2006) argue that the optimal weights of a static portfolio choice problem are "conditional managed portfolios" and can be seen as approximating a dynamic portfolio. In other words, the optimal weights are chosen to partially hedge against undesirable innovations in economic conditions (Merton, 1969).

Our results show that, even when carefully accounting for the trading frictions present in the corporate bond market, it is possible to create active portfolios with a superior per-

[4]For evidence on the predictive power of credit spreads on the macroeconomy see (Gilchrist and Zakrajšek, 2012),(López-Salido, Stein, and Zakrajšek, 2017; Ben-Rephael, Choi, and Goldstein, 2018).

formance. A natural question that arises is whether active investors (e.g. active corporate bond funds) are taking full advantage of the information contained into bond-specific characteristics, achieving the risk-adjusted performance of our optimal portfolio. To answer this, we first compare the average characteristics in our optimal portfolio with those of active and passive corporate bond funds. Interestingly, the portfolio of passive funds is fairly close to our benchmark, while that of active funds deviates from it in the same direction of our optimal portfolio. However, the deviations are not as large as those of our optimal portfolio, indicating that they are not exploiting the full potential of our optimal strategy. OTC market frictions, captured by transaction costs which we carefully estimate in our portfolio, cannot explain such divergence. A potential explanation is the presence of narrow characteristics-based investment mandates. For example, some funds can only invest into investment grade bonds, while some others can only invest into short term assets. Such constraints might stop fund managers from trading all the way towards the optimal portfolio. In an attempt to shed light on this, we regress the one-month ahead difference in performance between our out of sample optimal portfolio and active corporate bond funds on the distance in characteristics between our portfolio and the average active bond fund. A larger deviation from active bond funds portfolios in month t predicts a larger outperformance during the following month. Our evidence points at narrow investment mandates as an important constraint for active fund managers in the corporate bond market.

In the last part of the paper, present various extensions of our methodology. First, we add to the baseline specification downside risk, which has been recently found to be a powerful predictor of bond returns (see Bai, Bali, and Wen (2019)). Second, we include several popular stock characteristics[5]. In both cases, increasing the set of characteristics does not improve the performance in-sample and out of sample. Our results indicate that not all characteristics that predict corporate bond returns are useful in an optimal portfolio allocation when properly accounting for transaction costs and limiting short positions. Third,

[5]Market capitalization (FME), book-to-market ratio (FBTM), momentum (FMOM), beta (FBETA), idiosyncratic volatility (FIVOL), and skewness (FSKEW) for a total of 11 conditioning variables

we split the sample into investment grade and high yield bonds to show that our findings are not exclusively concentrated in the speculative segment.

Our paper differs for two reasons from recent applications of the parametric portfolio method, such as Barroso and Santa-Clara (2015) (currencies), Ghysels, Plazzi, and Valkanov (2016) (international portfolios) or DeMiguel et al. (2020) (equity portfolios with a multitude of signals). First, we tackle the optimal asset allocation of corporate bonds, a problem that is hugely important and that has previously been unexplored. Second, we are the first to introduce a smooth maximum parametrization, a specification that allows to control turnover and short positions more efficiently than previous papers.[6] The latter is particularly important in the corporate bond market, whose OTC structure makes frequent trading and short-selling challenging.

A large and growing literature investigates which characteristics best predict the cross-section of corporate bond returns using traditional factor models (Bartram, Grinblatt, and Nozawa, 2020; Elkamhi, Jo, and Nozawa, 2020; Bai, Bali, and Wen, 2019; Chordia et al., 2017; Gebhardt, Hvidkjaer, and Swaminathan, 2005)) or machine learning techniques ((Kelly, Palhares, and Pruitt, 2021; Bali et al., 2020). Our paper is the first to tackle this question from the asset allocation perspective, asking how characteristics can be used to form a tradeable portfolio. Our findings that not all characteristics that predict returns can be easily incorporated in an investment strategy opens sets the stage for additional research on the persistence of risk factors/anomalies in this market.

Last but not least, our findings on optimal corporate bond investing are related to the literature that analyzes the demand of institutional corporate bond investors through their holdings ((Becker and Ivashina, 2015; Choi and Kronlund, 2018; Anand, Jotikasthira, and Venkataraman, 2020) among others). The focus of our paper is very different and complements that literature with a normative analysis of how to invest optimally, given the cross-sectional features of the data. Our evidence that active managers cannot hold an op-

[6] In a recent paper Langlois (2020) develops a dynamic mean-variance portfolio allocation that accommodates transaction costs and short-sale constraints and applies it to equity portfolios.

timal bond portfolio contributes to the recent debate on how narrow investment mandates limit corporate bond arbitrage (Nielsen and Rossi, 2020) and push institutional corporate bond demand away from representative agent models (Bretscher et al., 2020)).

The remainder of the paper proceeds as follows. We develop the smooth maximum parametric specification of the portfolio weights in Section 2. Section 3 describes the data. The main results are presented in Section 4 and several extensions are discussed in Section 5. We conclude in Section 7.

2 Methodology

In this section, we lay out the methodology of constructing corporate bond portfolios as a function of bond-specific characteristics. We introduce a novel functional form of the weights that is suitable for the corporate bond market while paying particular attention to limit short positions and transaction costs.

2.1 Parametric corporate bond portfolios

At each date t, there is a large number N_t of corporate bonds in the investable universe. Each bond i has a return $r_{i,t+1}$ from date t to $t+1$ and an associated vector of bond-specific characteristics $x_{i,t}$, observed at time t. For example, the characteristics can be the bond's maturity (or duration), credit rating, coupon rate, and issuing amount. The portfolio return of corporate bonds between t and $t+1$ is $r_{p,t+1} = \sum_{i=1}^{N_t} w_{i,t} r_{i,t+1}$, where $w_{i,t}$ are the portfolio weights. An investor chooses the weights to maximize her conditional expected utility,

$$\max_{\{w_{i,t}\}_{i=1}^{N_t}} E_t \left(u \left(r_{p,t+1} \right) \right). \tag{1}$$

The portfolio weights are parameterized to be a function of bond characteristics,

$$w_{i,t} = g(\bar{w}_{i,t}; x_{i,t}; \theta), \tag{2}$$

where $\bar{w}_{i,t}$ denotes the weight of a benchmark portfolio, such as a value-weighted weighted index of all securities available in the market. The function $g(\cdot)$ captures deviations of the portfolio weights $w_{i,t}$ from the benchmark and is parameterized by a vector θ, to be estimated. Its functional form is dictated by the application at hand.

Linear specifications of the weights have been used by Brandt, Santa-Clara, and Valkanov (2009), Barroso and Santa-Clara (2015), Ghysels, Plazzi, and Valkanov (2016), and DeMiguel et al. (2020) in the context of equity or currency portfolios.[7] The linearity of $g(\cdot)$ is appealing from a tractability standpoint and yields economically sensible weights when the characteristics do not exhibit significant variability over time (e.g., firm size). A linear specification also treats positive and negative weights symmetrically, and is suitable when portfolios with significant short positions are practically feasible.

In the context of corporate bond portfolios, the linear parametrization is not appropriate for two important reasons. First, corporate bond characteristics are prone to large changes, which translate into significant time series variation in the weights and a high turnover. Portfolios with high turnover are unimplementable in OTC markets where transaction costs are significantly higher than for equities (Bessembinder et al., 2018). Second, there is no good way to limit short positions in a linear specification. Therefore, the optimal portfolio will likely imply large (in absolute magnitude) negative positions. This would only be appropriate if there are no significant short-sale constraints in this market, which is not the case. Indeed, despite having the same amount of securities available for lending (around 20% of the market), the aggregate short positions in corporate bonds are about half of what they are in equities. According to (Hendershott, Kozhan, and Raman, 2020), just 1.8% of bonds outstanding is shorted vs. 4.4% of stocks outstanding. As a consequence, limiting short positions and turnover is crucial when forming bond portfolios. We next propose a novel specification of $g(\cdot)$ that is suitable in our context.

[7] Specifically, Brandt, Santa-Clara, and Valkanov (2009) use $g\left(x_{i,t};\theta\right) = \theta' x_{i,t}/N_t$, where $x_{i,t} = \left(\tilde{x}_{i,t} - \bar{x}_{i,t}\right)/\sigma_{x,t}$ are the raw characteristics $\tilde{x}_{i,t}$, standardized by their cross-sectional variances $\sigma_{x,t}$, and demeaned by the cross-sectional average $\bar{x}_t = \frac{1}{N_t}\Sigma_{i=1}^{N_t}\tilde{x}_{i,t}$.

2.1.1 A specification that limits short positions

We let the weights enter our portfolio through a smooth maximum function:

$$g(\bar{w}_{i,t}; x_{i,t}; \theta) = \frac{h(\bar{w}_{i,t}; x_{i,t}; \theta) \times e^{(\alpha \times h(\bar{w}_{i,t}; x_{i,t}; \theta))}}{e^{(\alpha \times h(\bar{w}_{i,t}; x_{i,t}; \theta))} + 1}, \tag{3}$$

$$h(\bar{w}_{i,t}; x_{i,t}; \theta) = \bar{w}_{i,t} + \theta' x_{i,t}/N_t. \tag{4}$$

The specification in expression (3) effectively attenuates the impact of extreme realizations of $x_{i,t}$ on the weights by reducing leverage stemming from short positions. We re-scale $g(\bar{w}_{i,t}; x_{i,t}; \theta)$ to ensure that portfolio weights sum up to one, or $\Sigma_{i=1}^{N_t} g(\bar{w}_{i,t}; x_{i,t}; \theta) = 1$. The expression in (4) follows the linear specification used in Brandt, Santa-Clara, and Valkanov (2009). The normalization $1/N_t$ allows the number of bonds in the portfolio to be time-varying. Without it, doubling the number of bonds without otherwise changing the cross-sectional distribution of the characteristics results in an allocation that is twice as aggressive, even though the investment opportunities are fundamentally unchanged.

With out choice of $g(\cdot)$, we consider the impact of shorting on the optimal allocation, as it might reduce the gains from trading on information in $x_{i,t}$. Investors with large α will effectively be facing a no-short-sale constraint. By varying the magnitude of α, we can map out the impact short-sale constraints have on the optimal portfolio.

The parametric approach effectively reduces the parameter space to a low-dimensional vector θ. The coefficients in θ do not vary across assets or through time, which implies that bonds with similar characteristics will have similar portfolio weights, even if their sample returns are different. In other words, the bond characteristics fully capture all aspects of the joint distribution of bond returns that are relevant for forming optimal portfolios. Constant coefficients through time means that the θs that maximize the investor's conditional expected utility at a given date are the same for all dates, and therefore also maximize the investor's unconditional expected utility. This setup also implies that misspecification of the variables in $x_{i,t}$ will translate into misspecification in the portfolio weights. The choice of conditioning information $x_{i,t}$ is important as it is in any estimation problem.

2.1.2 Transaction costs and turnover of corporate bond portfolios

The corporate bond market is characterized by significant transaction costs. In addition, passive and active bond funds exhibit high levels of turnover. Some of it is "mechanically" due to bonds maturing and new bonds being issued, while the rest stems from active trading decisions. In the following, we modify the parametric weights to capture these peculiarities of corporate bond trading.

The turnover in corporate bond funds is sizable, partly due to the periodic rebalancing related to the maturity of the assets. For example, the Vanguard Intermediate-Term Bond Index fund reports an average annual turnover of 100% for the 2013-2017 period, which is on the low end of the spectrum. Funds that trade actively have a much higher turnover. For instance, Pimco's Total Return fund, one of the most widely held bond funds, has an average annual turnover of approximately 748% over the 2013-2017 period.[8] Not surprisingly, reducing the turnover is an important consideration for corporate bond funds.

Significant transaction costs in the corporate bond market might render some highly volatile strategies unprofitable. A large literature studies optimal selection with trading costs proportional to the bid-ask spread.[9] The parametric nature of the portfolio policy allows us to compute turnover and to optimize the after-transaction-cost returns. To do that, we define the bond portfolio return, net of transaction costs, as

$$r_{p,t+1} = \sum_{i=1}^{N_t} w_{i,t} r_{i,t+1} - \sum_{i=1}^{N_t} c_{i,t} |w_{i,t} - w_{i,t-1}|, \tag{5}$$

where $c_{i,t}$ are the one-way trading costs of a particular bond at time t and $\sum_{i=1}^{N_t} |w_{i,t} -$

[8]The turnover data for the Vanguard Intermediate-Term Bond Index fund (VBIIX) and Pimco's Total Return Fund (PTTAX) are from Morningstar, see `http://www.morningstar.com`. Detailed turnover figures for several corporate bond funds are reported in the Internet Appendix.

[9]Important papers in that literature include Magill and Constantinides (1976), Constantinides (1986), Amihud and Mendelson (1986), Taksar, Klass, and Assaf (1988), Davis and Norman (1990), Vayanos (1998), Vayanos and Vila (1999), Leland (2013), Lo, Mamaysky, and Wang (2004), Liu (2004), Gârleanu (2009), Acharya and Pedersen (2005).

$w_{i,t-1}|$ is the overall portfolio turnover between $t-1$ and t. As transaction costs penalize proportionately large fluctuations in $w_{i,t}$, the characteristics in the policy function (3-4) will lead to improvement in portfolio performance only if they generate significant after-transaction-cost returns. There is considerable evidence that transaction costs vary across bonds and over time (Edwards, Harris, and Piwowar, 2007; Dick-Nielsen, Feldhütter, and Lando, 2012; Bessembinder et al., 2018). In our empirical application, we will make use of bond specific transaction costs that are estimated from trading data. Figure 1 presente the time series of average transaction costs in our sample, while details on their calculation can be found in Appendix A.

Under weight specification (2), we can decompose the after-transaction-cost portfolio return (5) into three parts,

$$r_{p,t+1} = r_{passive,t+1} + r_{active,t+1} - TC_t, \tag{6}$$

where $TC_t = \sum_{i=1}^{N_t} c_{i,t}|w_{i,t} - w_{i,t-1}|$ are the transaction costs, $r_{passive,t+1} = \sum_{i=1}^{N_t} \bar{w}_{i,t} r_{i,t+1}$ is the benchmark return, and $r_{active,t+1} = r_{p,t+1} - r_{passive,t+1} + TC_t$ is the active part (due to the characteristics).

2.2 Benchmark portfolios

The benchmark portfolio weights $\bar{w}_{i,t}$ should be chosen appropriately as the empirical and economic gains of the optimal allocation are expressed as deviations from it. With equities, the benchmark portfolio is often the equally or value-weighted portfolio. Both are transparent, investable (feasible), and fairly passive in the sense that they involve little turnover.

For corporate bonds, we use the following two benchmarks. The first benchmark sets the portfolio weights equal to the outstanding amount of a bond relative to the outstanding amount of all bonds in the sample at that time. This portfolio is value-weighted in the sense that the weights are proportional to the bond's outstanding amount. Its weights change when bonds exit (e.g., due to maturity or default) or new issues enter the sample and it captures the spirit of a value-weighted index while keeping turnover low.

The second benchmark is equally weighted. Similarly to the value-weighted portfolio, its turnover is low as weights change only when bonds exit or enter the sample. The equally weighted portfolio puts more weight, relative to the value-weighted one, on small issues. It is an important benchmark, because in the case of equities, it has been shown to perform particularly well not only relative the value-weighted benchmark but also to actively managed portfolios (DeMiguel, Garlappi, and Uppal, 2009). For corporate bonds, however, its relative performance is not known.

We check that the returns of our equally and value-weighted benchmarks are highly correlated (around 80%) with the returns of widely-used bond indexes, such as the Bloomberg Barclays US Corporate Investment Grade + High Yield index. Hence, we conclude that they are suitable benchmarks for our analysis.[10]

2.3 Estimation

For a given functional form of the utility (e.g., CRRA or quadratic) and the weights in (2-4), we estimate the parameters by maximizing the sample analogue of expression (1),

$$\max_{\theta} \frac{1}{T} \sum_{t=1}^{T} (u(\sum_{i=1}^{N_t} w_{i,t} r_{i,t+1})), \tag{7}$$

where the returns are after-transaction-costs, as in expression (5).

As bond returns are negatively skewed, we use a CRRA utility function in this paper. Thus, our framework captures the relation between the $x_{i,t}$'s and the first, second, and higher-order moments of returns, to the extent that the characteristics affect the distribution of the optimized portfolio's returns, and therefore the investor's expected utility.

[10] Another commonly used benchmark in dynamic asset allocation is a "hold" strategy (i.e., keep the weights unchanged from period $t-1$ to t), which involves no trading and incurs no transaction costs. With corporate bonds, implementing a true hold strategy is difficult, because on average, about 36% of bonds mature in any given year and drop out of our sample. Therefore, the portfolio has to be re-balanced periodically and new investments have to be made on a monthly basis for the funds to be fully invested in corporate bonds. The weights of the equally and value-weighted portfolios that we consider change little and are very close in spirit to a passive hold portfolio.

The estimation of θ is within the class of extremum estimators and its properties are well-known (Amemiya, 1985). This approach is also used by Brandt, Santa-Clara, and Valkanov (2009) and Ghysels, Plazzi, and Valkanov (2016). Given the presence of cross-sectional dependence in the characteristics, we bootstrap the standard errors. Details of the estimation and bootstrap procedure are spelled out in Appendix B.

3 Data

3.1 Sample construction

We employ multiple data sources in our paper. From MERGENT FISD, we obtain information on bond characteristics. Datastream is our source of monthly US corporate bond prices for the period between January 1993 and December 2004. From January 2005 until December 2017, we get corporate bond transaction prices from the TRACE database.[11] Our main sample thus covers roughly 24 years of data. For additional analyses, we also collect US corporate bond funds portfolio holdings from Morningstar for the period from January 2002 till December 2017.

In TRACE, we follow standard data cleansing and price filtering procedures described by Dick-Nielsen (2009), Edwards, Harris, and Piwowar (2007) and Friewald, Jankowitsch, and Subrahmanyam (2012). We consider only straight corporate bonds without complex optionalities.[12] We compute the return of bond i in month t as

$$r_{i,t} = \frac{(P_{i,t} + AI_{i,t} + C_{i,t}) - (P_{i,t-1} + AI_{i,t-1})}{(P_{i,t-1} + AI_{i,t-1})}, \tag{8}$$

where $P_{i,t}$ is the price of bond i at the end of month t. $AI_{i,t}$ is the accrued interest of the bond and $C_{i,t}$ is the coupon paid between month-ends $t-1$ and t. $P_{i,t-1}$ and $AI_{i,t-1}$ are the price and accrued interest in the previous month, respectively. We rebalance the

[11]TRACE collects disseminated data since September 2002, but almost full coverage of the market starts end of 2004.

[12]This is equivalent to excluding foreign government bonds, U.S. agency debentures, retail notes, corporate strips, pay-in-kind bonds, rule 144a-bonds, convertible and preferred securities.

portfolio on the last trading day of each month. To prevent stale prices from entering the return calculation, we consider only bonds that trade at least once in the last 5 working days of the month and take the last daily volume-weighted average price available when using the TRACE sample, as in Bessembinder et al. (2009). Bonds are included in the sample one month after issuance and excluded two months before maturity to guarantee tradeable prices. Further, to avoid including extremely illiquid bonds in our portfolio that might not be consistent with an active investment approach, we consider only assets that had available secondary market prices in each of the last six months.

3.2 Bond characteristics

The bond-specific characteristics that we use as conditioning variables in our portfolio optimization are time to maturity (TTM), credit rating (RAT), coupon (COUP), and the outstanding amount of the bond (SIZE). All these characteristics are directly available from MERGENT, which means they are easily observable by any investor.[13] Moreover, such characteritics are often used in corporate bond funds to define investment mandates. TTM is the difference in years between the maturity date of the bond and the day on which the monthly return is calculated.[14] RAT is the average credit rating across the major rating agencies Moody's, Standard and Poor's, and Fitch. We assign integer values to the different rating grades, with 1 being the highest and 21 the lowest credit score. Hence, bonds with high RAT have a high ex-ante probability of default. Bonds not rated by at least one of the agencies are dropped from the sample. COUP is expressed as annualized percentage of face value. SIZE is the dollar value of the outstanding amount of the respective bond issue. In the portfolio optimization, we take the logarithm of TTM and SIZE to attenuate the impact of outliers (bonds outstanding for up to 100 years and bonds with an outstanding amount

[13]Bond illiquidity has been shown to impact bond prices by Bao, Pan, and Wang (2011) and Lin, Wang, and Wu (2011), among others. We do not include illiquidity in our baseline specification for two reasons. First, we already consider real transaction costs in our portfolio optimization. Second, when including illiquidity as a characteristic, the tilt is not significant once we consider transaction costs, see Table IA4 in the Internet Appendix.

[14]We prefer TTM over duration as calculating the latter requires the bond yield, which is not available in Datastream and often not populated in TRACE. Our results hold if we use duration instead of TTM for a subset of bonds.

of up to \$15 billion).

We leave a one-month lag between the bond characteristics and the determination of portfolio weights to ensure that the information would have been available to the investor at the time of the investment decision. An observation is dropped from the sample when information about at least one characteristic is missing. Our cleaned data set contains 266,851 bond-month observations.

3.3 Summary statistics

Table 1 reports summary statistics of our bond data in Panel A and of bond-specific characteristics in Panel B. Our main sample consists of 914 bonds per month on average. In total, 6,084 bonds appear at least once in our sample, amounting to approximately \$3.3 trillion of outstanding debt. As bonds mature and new bonds are issued frequently, our sample changes monthly. On average, about 4% $((20 + 17)/914)$ of the bonds enter or exit every month, resulting in an annualized (equally weighted) turnover of 65%. This "automatic" turnover amounts to 3.9% $((11 + 7)/456)$ of the monthly debt outstanding in our data. The changing composition of the sample implies that even a passive corporate bond portfolio involves a significant amount of rebalancing.

In Panel B, we present summary statistics of bond characteristics without further transformations to preserve economic magnitudes. The median bond has a time to maturity of 9.239 years, a rating score of 6.69 (which corresponds to an A rating), a coupon of 6.064% of face value, and an outstanding amount of about \$500 million. The characteristics show generally low cross-correlations. The variable that exhibits the highest correlation with the other characteristics is COUP, but it is never above 23.9%. In our sample, bonds with high COUP tend to have a longer TTM and a higher RAT (higher ex-ante default risk). SIZE has a negative correlation with the other variables, COUP in particular.

4 Empirical Findings

We present results for several specifications of the optimal parametric portfolio weights for a CRRA investor with $\gamma = 5$. In the baseline case, the investor takes into account four bond-specific characteristics and faces bond-specific transaction costs. First, we show both the in-sample and out-of-sample performance of the baseline strategy. Second, we dig deeper and analyze the drivers of our portfolio performance and provide evidence that the active portfolio component predicts macroeconomic activity, on top of established credit-market based predictors. Third, we compare our portfolio performance to traditional investment strategies that are based on univariate sorts. Fourth, we analyze how our portfolio differs from actual holdings of fixed-income funds. The evidence suggests that the outperformance of our portfolio relative to active bond mutual funds can be explained by market segmentation, which is the result of narrow investment mandates.

4.1 Smooth maximum parametric portfolio

Table 2 contains the results of our base case in which the parametric portfolio weights in (2) are a function of the four corporate bond characteristics TTM, RAT, COUP, and SIZE. The first two columns display the value-weighted (VW) and equally weighted (EW) benchmark portfolios that take into account transaction costs.

The next four columns show optimal parametric portfolios for a grid of the smooth maximum parameter α: 0, 150, 300 and 750. The case of $\alpha = 0$ is the standard linear specification. In the first part of the table, we report the marginal impact of each bond characteristic on the portfolio weights, in percent.[15] The p-values of estimated θs, reported in parentheses, are based on bootstrapped standard errors. The optimal portfolio is generally tilted toward bonds with longer time to maturity (TTM), higher ex-ante default risk (RAT), and higher

[15]The non-linearity of $g(\cdot)$ implies that the parameters θ cannot be interpreted as the marginal impact of changes in the characteristics $x_{i,t}$ on the portfolio weights. The coefficients θ capture the marginal impact only if $g(\cdot)$ is linear in the characteristics, as in Brandt, Santa-Clara, and Valkanov (2009). Hence, we evaluate the marginal impact by computing changes in $w_{i,t}$ that result for a one-standard-deviation change in each conditioning variable in $x_{i,t}$, evaluated at the average value of the other characteristics and at the estimated θ. This is the standard approach used to measure economic impact in non-linear models. C contains the exact steps of the computation.

coupon (COUP). The tilt on SIZE is towards smaller bonds, except for relatively high levels of α. As expected, introducing the smooth maximum parameter ($\alpha > 0$) significantly reduces turnover and short positions without decreasing performance. We focus most of our discussion on the case with $\alpha = 300$, which is presenting an average level of short positions and turnover which is in line with what can be observed in practice for active bond funds.[16]

To understand the economic magnitudes of the results, we discuss the parameter estimates in more detail. The marginal impact of RAT is 1.128% (for $\alpha = 300$). The average bond in our sample has a rating of about 7 (A rating) with a standard deviation of roughly 3 (see Table 1). Take two bonds, one with RAT one standard deviation above the mean (10 or BBB-) and another with RAT one standard deviation below the mean (4 or A). Everything else equal, the weight on the first bond will be 1.128% higher than average, whereas the weight on the second bond will be lower by the same amount. Similarly, if we consider COUP and its marginal impact of 0.02%, a one-standard-deviation increase (decrease) of the coupon rate of an average bond from about 6% to 8% (4%) implies that the weight will increase (decrease) by about 0.02%. These numbers are for the optimal portfolio weights of individual bonds. If we aggregate them over the entire cross-section of about 914 bonds per month, or even a fraction thereof, we observe that the overall impact of the bond-specific characteristics on portfolio weights is economically large.

The second set of rows in Table 3 displays annualized performance measures and average weight statistics of the bond portfolios. While the value-weighted benchmark has a CE of 5.5%, the optimal portfolios deliver a CE in the range of 9.6% to 8.6%. As expected, when applying the smooth maximum ($\alpha > 0$), a higher α negatively impacts the CE. Nevertheless, we observe more than a 56% increase in CE even after accounting for the most conservative level of $\alpha = 750$, where short positions are basically 0. These numbers are statistically and economically highly significant.[17] The reference portfolio with $\alpha = 300$ exhibits a higher

[16]Using data on active corporate bond funds from Morningstar, we find that the average short positions between 2003 and 2018 are around 13% and the average annualized turnover is 157%.

[17]Note that %ΔCE in Table 3 is calculated on the basis of a benchmark that takes into account the same transaction costs as the respective optimal portfolio. See B for details on how we determine the statistical significance of gains in CE.

return than the benchmark and a slightly higher volatility, which translates into a Sharpe ratio of 0.935 compared to 0.678 for the benchmark. The last two rows summarize the distribution of the portfolio weights. The optimal portfolio has an average short position of just 11.6%. The annual turnover of 116.1% is less than twice the turnover of the benchmark portfolio. As mentioned above, short positions and turnover levels are in line with those of major active corporate bond mutual funds. Interestingly, increasing α up to 750 leads to a portfolio that has virtually no short positions (0.04%) but still keeps a significant part of the outperformance.

Comparing the portfolios that are based on a weight function that includes a smooth maximum ($\alpha > 0$) to those based on the linear specification ($\alpha = 0$) strikingly highlights the importance of this novel approach. The linear case requires an amount of short positions (148.2%) and turnover (334.7%) that are at best unrealistic when looking at actual portfolios of bond funds or other institutional investors in the market. Introducing a smooth maximum specification does not significantly hurt performance ($\alpha = 150$ performs even better), while it massively reduces short positions and portfolio turnover to levels that are in line with what can be observed in practice. The advantages of our approach become even clearer when looking at the out-of-sample performance, which is the focus of the next section.

4.2 Out-of-sample performance

In this section, we provide out-of-sample evidence for the performance of our portfolio approach. The optimal tilts are applied out-of-sample from January 2002 until December 2017, using an expanding window estimation. At the end of each month, we use the optimal tilts estimated using data up to this month to make an investment decision. We analyze the portfolio performance in the following month. The smallest estimation window (September 2003-December 2001) includes 100 months. Our out-of-sample period covers 15 years of data, which represents more than half of the overall sample period.

Table 3 shows the out-of-sample performance of the parametric portfolios for $\alpha = 0$

(linear case), $\alpha = 150$, $\alpha = 300$, and $\alpha = 750$. All specification are based on the bond characteristics TTM, RAT, COUP, and SIZE. Whenever the smooth maximum is used ($\alpha > 0$), the parametric portfolios show a significant outperformance relative to the corresponding value-weighted benchmark. The CE return ranges from 7.5% to 8.5%, which translates into an increase in CE relative to the benchmark of at least 48%. The outperformance is obtained with levels of short positions and turnover which are in line with what can be observed in corporate bond funds. Figure 2 shows the cumulative out-of-sample returns and short positions over time for selected optimal portfolios, the VW benchmark, and the Bloomberg Barclays index for the whole corporate bond market (investment grade and high yield). The graphs confirm that our out-of-sample performance is stable over time and not driven by extreme outliers. Reassuringly, the performance of our VW benchmark is extremely close to that of the Bloomberg index, confirming that our benchmark is a proper reference point when evaluating our optimal portfolios.

In strong support of our methodology, the out-of-sample test with the linear specification ($\alpha = 0$) leads to an extreme and unrealistic portfolio, which underperforms the benchmark and takes extreme short positions, coupled with high turnover. These results underline the instability of the linear specification when faced with a large cross-section of illiquid assets that mature frequently and are highly heterogeneous. Overall, the out-of-sample results confirm the stability and performance of parametric portfolios that are based on a weight function that includes a smooth maximum. In the next sections we will investigate the drivers of such performance.

4.3 Multiple characteristics vs. univariate sorts

In this section, we compare the benefits of choosing a portfolio by jointly conditioning on several characteristics relative to univariate sorts. In a first step, we present in Panel A of Table 4 the returns of long-short portfolios constructed using each of the four characteristics TTM, RAT, COUP, and SIZE. At the end of each month t, we sort bonds into value-weighted portfolios based on a given characteristic, observed at the end of month $t-1$, and compute subsequent portfolio returns over month $t+1$. Portfolio P1 contains bonds in the lowest quintile of a sorting variable and portfolio P5 contains bonds in the highest quintile. We display returns of zero-cost, long-short positions in portfolios P5 and P1 and the certainty equivalent return of such strategies both without and with transaction costs.

Bonds with a longer time to maturity, with worse credit rating, and with higher coupon earn significantly positive excess returns.[18] The signs of these results are consistent with the optimal portfolio tilts in Table 2. However, when we calculate the certainty equivalent return for those strategies, we find that none of the hedge portfolios outperforms our baseline portfolio with $\alpha = 300$, with and without transaction costs. The relevant out-of-sample CE return presented in Table 3 is 8.2%, while the hedge portfolios based on univariate sorts reach at most a CE return of 2.3%. When accounting for transaction costs, the CE return reaches at most 1.8%. This finding suggest that univariate sorts produce inferior and noisy results, which we conjecture is due to the underlying correlations with the other characteristics.

To explore this line of reasoning, we report correlations across the long-short portfolios in Panel B. The returns of these portfolios are significantly correlated, with values ranging from -0.611 to 0.767. For instance, while the hedge portfolio return for COUP is positively correlated with those for TTM and RAT, it exhibits negative correlations with that for SIZE. The high correlations present a problem for univariate sorts, which is reflected in the fact that, when taking into account characteristics jointly, the performance improves significantly. To further support this point, we estimate our optimal portfolio by taking into account only a single characteristic at time. The results are displayed in Tables IA1 and IA2 in the Internet Appendix. We find that the performance is significantly worse compared to that of a portfolio that takes into account all four characteristics jointly. Another reason for considering a joint approach is to reduce turnover. Indeed, the significant cross-correlations indicate that there might be a great potential for saving up on transaction costs when con-

[18]While hedge portfolio returns for characteristic SIZE are not significantly different from zero, the premium is consistent with a risk-based interpretation.

sidering characteristics jointly. Our results are consistent with recent findings by DeMiguel et al. (2020), who document that combining characteristics can reduce transaction costs, as trades in the underlying assets can be netted against each other. Given the dependence across characteristics, we conclude that it is essential to condition on them *jointly* when estimating optimal portfolio weights.

4.4 Stock characteristics

We extend our portfolio weights to include the following stock characteristics of the firms that issue corporate bonds: market capitalization (ME), book-to-market ratio (BTM), momentum (MOM), idiosyncratic volatility (IVOL), beta (BETA), and historical skewness (SKEW). These variables are motivated by the extensive literature on equity factors. To the extent that these characteristics are not spanned by the bond variables, they could provide valuable information when estimating optimal bond portfolio weights. We match our sample of corporate bonds to stock returns in CRSP and accounting variables in Compustat, which leaves 135,070 bond-month observations between September 1993 and December 2017.[19]

In Table 10, we report the in-sample and out-of-sample results of our optimal portfolios for $\alpha = 300$ taking into account only bond characteristics (B), only stock characteristics (S) and both (B+ S). The in-sample results for our baseline specification are comparable to the full sample, with the exception of the coefficient for COUP, which turns negative.The outperformance relative to the benchmark remains high, amounting to an increase in CE of 32.2%. When taking into account only stock-specific characteristics, we find that the marginal impact of those characteristics is consistent with a risk-taking behavior. The optimal corporate bond portfolio is tilted toward bonds of companies with a lower market capitalization, higher book-to-market ratio, and higher past returns. Furthermore, we observe a negative tilt for BETA and a negative tilt for IVOL, consistent with the findings of Frazzini and Pedersen (2014) and Ang et al. (2006) on low-risk anomalies. Among others, Boyer, Mitton, and

[19]See D for a description of how we match bonds with stocks and how the single stock characteristics are calculated.

Vorkink (2010) show that stocks with positive idiosyncratic skewness earn lower returns, as investors require a compensation for negative skewness. In line with this reasoning, we find a negative tilt for SKEW. The increases in CE relative to the benchmark is significant and amounts to 16.9%, which, however, is lower than the one obtained when only accounting for bond characteristics. Taking into account bond and stock characteristics jointly leads to a significant increase in CE by up to 32.2% with respect to the value-weighted benchmark. The gain in CE is the same an investor would have obtained by considering only bond characteristics. In all cases, short positions an turnover are kept low.

The out-of-sample results provide a similar picture. Including only bond characteristics leads to a 17.2% increase in CE relative to the benchmark, while keeping short positions and turnover relatively low at -10.7% and 223.5%, respectively. Considering only stock characteristics leads to an under-performance relative to the benchmark, with a CE return of only 4.8%, which means a decrease of 8.3% relative to the VW portfolio. When considering both stock and bond characteristics, our portfolio does better out-of-sample than the benchmark. However, the outperformance is lower than when accounting just for bond characteristics (a 13.1% increase in CE instead of 17.2%). Overall, our results show that the information included in bond characteristics that is relevant for bond returns subsumes the information provided by stock characteristics. Not only does the inclusion of stock characteristics leave the in-sample performance unaffected, but it can also hurt performance out-of-sample. Our findings are consistent with Bali et al. (2020), who use machine learning techniques to assess how well bond and stock characteristics predict the cross-section of bond returns.

4.5 Robustness and Extensions

In this section, we show that our approach is robust to adding characteristics ot the baseline specification and splitting the sample between investment grade and high yield bonds.

Downside Risk: While our baseline specification is kept simple by including four well-accepted bond characteristics (TTM RAT, COUP, and SIZE), the methodology we present allows to take into account as many characteristics as the investor wants to condition the portfolio on. In this section, we investigate the performance of our portfolio when including downside risk (DSIDE henceforth) in addition to TTM, RAT, COUP, and SIZE. DSIDE has been found to be an important bond specific factor in explaining the cross-section of corporate bond returns. We follow Bai, Bali, and Wen (2019) and define bond-specific DSIDE as the second lowest monthly return observation over the past 36 months, provided that there are at least 24 return observations available for that bond. We do not include DSIDE in our main specification because it would eliminate from the sample all bonds that are outstanding for less than 3 years. Eliminating those bonds from the sample would significantly reduce our investment universe, and would not reflect how fund managers invest, as they are holding bonds as soon as they are issued on the secondary market. Table 9 displays the in-sample and out-of-sample results of our portfolio with (CH + D) and without (CH) DSIDE. As before, we focus on a specification with $\alpha = 300$. Due to the filter applied to calculate DSIDE, our sample drops to 182,062 observations, a reduction by nearly one third. When looking at the in-sample results, three findings stand out. First, our original portfolio specification shows a similar composition and performance for the smaller sample when compared to the full sample: the tilts for TTM, RAT, COUP, and SIZE have the same sign as those in Table 2, the improvement in CE return is comparable (59.6% vs 65.5%), while the level of short positions (-6.3% vs -11.6%) and turnover (113% vs 116.1%) is even slightly lower. Second, DSIDE enters with a negative and significant tilt (meaning that our portfolio is tilted towards bonds with more negative returns, hence higher downside risk) but does not affect the magnitudes of the other characteristics. Third, the inclusion of DSIDE does not improve the in-sample performance (CE returns are the same), leaving almost unaffected the percentage of short positions and turnover. The out-of-sample results provide a similar picture. Our baseline specification outperforms the benchmark by 2.1% in CE returns, while keeping short positions and turnover low at -5.8% and 162.7%, respectively. Adding DSIDE does not improve the performance of our portfolio out-of-sample, but even slightly worsens it, with the CE return dropping from 7.6% to 7.5%. Our findings show that, when properly accounting for realized transaction costs and keeping a realistic level of short positions, adding downside risk is not beneficial for our portfolio.

Bond Momentum: Next to downside risk, we also investigate bond momentum (MOM) as another return-based characteristic (Jostova et al. (2013)). We find that the information in MOM about bond returns is spanned by the characteristics TTM, RAT, COUP, and SIZE that are included in the base specification (see Table IA5 in the Internet Appendix). The coefficient for MOM is positive but not statistically significant. Accordingly, the portfolio's CE return, is not affected when accounting for MOM. Similar to the results for DSIDE, the out-of-sample performance of the optimal portfolio drops slightly by 0.1% when accounting for MOM.

Investment Grade vs High Yield Bonds: In this section, we analyze whether our findings are robust to probably the most common segmentation in corporate debt markets: investment grade vs high yield. Many corporate bond funds hold exclusively either investment grade (IG) or high-yield (HY) bonds. This type of investment constraint is present also among other institutions such as insurance companies and pension funds. We present optimal portfolios consisting only of IG or HY bonds, respectively. The overall sample of 266,851 bond-month observations is divided into a subsample of 248,165 bond-month observations for IG and 18,686 bond-month observations for HY.

In Table 11, we report the in-sample and out-of-sample results of our optimal portfolios for $\alpha = 300$. The signs of the tilts toward the single bond-specific characteristics for portfolios based on the IG subsample is similar to those found for the full cross-section of corporate bonds, as reported in Table 2. The optimal portfolio is tilted toward bonds with larger TTM, RAT, and COUP and toward bonds with smaller SIZE. The marginal impact for the HY subsample is greater in magnitude for all characteristics, with RAT and SIZE being the largest. TTM is not significant in the HY subsample, while COUP switches the sign from positive to negative. Both IG and HY portfolios outperform the benchmark portfolio and have low short positions (-11.2% for IG and -0.02% for HY) and turnover (105.8 % for IG and 168.1% for HY).

When looking at the out-of-sample performance, the portfolio based on the IG (HY) subsample has a CE return of 4.9% (7.7%), which is 1.1 (3.2) percentage points larger than those of the corresponding benchmarks. The larger out-of-sample performance for the HY subsample is consistent with the idea that there is more room for active management in the high-yield segment of the corporate bond market. Interestingly, both out-of-sample portfolios reach a lower CE return than a similar portfolio that includes all corporate bonds (see Table 3). This is consistent with the idea that narrow investment mandates might represent and obstacle to performance. Overall, the evidence displayed in Table 11 confirms that our methodology is robust to the split of the sample between IG and HY bonds.

5 Optimal Corporate Bond Portfolios and Macroeconomic Activity

In this section, we document a significant correlation between our optimal portfolio return and future macroeconomic activity. This fact is of economic importance for two reasons. First, it is plausible that the portfolio weights capture time-variation in investment opportunities (Brandt and Santa-Clara, 2006). If the optimal weights are chosen to hedge against undesirable innovations in economic conditions, the return of the portfolio must be correlated with fluctuations in state variables (Merton, 1969). Second, as imbalances in the corporate bond market have been shown to precede downturns in the economy (Gilchrist and Zakrajšek, 2012) (GZ hereafter),(López-Salido, Stein, and Zakrajšek, 2017; Ben-Rephael, Choi, and Goldstein, 2018), it is interesting to see whether the optimal corporate bond portfolio return is also able to capture information on macroeconomic activity. To explore these points, we decompose the portfolio return into its passive and active component.[20] Exam-

[20]The active component is calculated by simply subtracting the value-weighted benchmark portfolio return (the passive component) from the overall portfolio return. The results for the equally weighted portfolio are almost identical and available

ining the passive component is essentially testing the predictability documented in GZ by using portfolio returns rather than yields. Our main goal is to analyze whether the active part plays a role in predicting various measures of economic activity, on top of the passive part.

In Table 5, we present results from regressing three-months-ahead and twelve-months-ahead changes in GDP growth and in consumption growth (CONS), which we use as a monthly proxy for macroeconomic activity, on our decomposed portfolio returns. Optimal portfolios are estimated using an expanding window that ends before the period over which changes in the macroeconomic variables are calculated. The portfolio return during the final month of each estimation period is used to forecast the macroeconomic variables. We control for the GZ yield spread and lagged GDP or consumption growth (lagged GDP and consumption growth are constructed without overlapping the observations, which insures that we do not introduce artificial serial correlation in the series (Valkanov, 2003)). At all horizons, both the passive and the active component of the portfolio return is positively and significantly correlated with future GDP and consumption growth. A one-standard-deviation increase in our active portfolio return leads to an increase of GDP (consumption) growth of 0.178 (0.160) standard deviations in the three-month-ahead regressions. At the yearly horizon the effect gets stronger: a one-standard-deviation increase in our active portfolio return leads to an increase of GDP (consumption) growth of 0.489 (0.275) standard deviations. Further, adding the parametric portfolio returns increases the R^2 of about 13% at short horizons and 35% (GDP) or 11% (CONS) at long horizons. The coefficient on the yield spread is also significant and negative, which is essentially a replication of the GZ results with our data set. We note that the positive coefficient for returns is consistent with the negative coefficient for the GZ spread: an unexpected increase in the yield spread implies an unexpected drop in bond prices, and hence a negative return of the bond portfolio. Our conclusions are not limited to GDP and consumption growth, but hold for other measures of macroeconomic

upon request.

activity as well.[21]

Our findings so far imply that the active component of our portfolio return contains information, beyond that in the GZ spread, about the future state of the economy. If this is true, the active component of our portfolio should predict the GZ spread. To explore this point further, we present in Table 6 results from regressing three-month-ahead and twelve-month-ahead GZ spread in levels and in changes on our decomposed portfolio returns. We control for the lagged dependent variable, again without overlapping the observations. Consistent with the previous findings, the active component of the portfolio return is negatively and significantly correlated with future GZ levels and changes. The relationship is stronger for changes in the GZ spread, supporting the idea that our investment strategy anticipates fluctuations in credit markets. A one-standard-deviation increase in our active portfolio return leads to a stronger decrease in GZ of 0.239 standard deviations at short horizons and 0.210 standard deviations at long horizons. Moreover, adding our portfolio returns increases the R^2 for both levels (between 5% and 6%) and changes (11% at short horizons and 3.5% at long horizons) in the GZ spread. From this evidence, we conclude that the active part of the portfolio does indeed serve to hedge against undesirable states of the economy.

6 Can active bond funds hold the optimal portfolio?

Our evidence so far has demonstrated that the performance of the optimal portfolio might stem from its ability to hedge against future states of the economy, thanks to accounting for multiple characteristics at once. However, it is unclear whether other investors are taking advantage of the information contained into bond-specific characteristics and if not, why this is the case. We will focus in this section on actively managed corporate bond mutual funds, and show in this section that the reason they are only partially holding the optimal portfolio is likely the presence of narrow investment mandates. Such narrow mandates create bond

[21] In Table IA3 in the Internet Appendix we repeat the exercise by using industrial production growth and changes in the unemployment rate as proxies for macroeconomic activity, and find similar results.

market segmentation, by forbidding active mangers to hold certain securities even when it might be profitable to do so. We focus on bond mutual funds as they represent the closest type of investors to our portfolio allocation problem.[22]

For the remainder of this section, we consider our out-of-sample optimal portfolios reported in Table 3. We start off by analyzing whether the holdings of actual corporate bond mutual funds are similar to those of our optimal parametric portfolio. In Table 7, we report the average characteristics of our equally weighted, value-weighted, and optimal parametric portfolio (CBPP), along with those of passive funds, active funds, and all funds combined. Average bond characteristics are calculated by taking the value-weighted average of all mutual fund holdings reported in the Morningstar database, following the methodology of Choi and Kronlund (2018). Consistent with Table 2, our optimal portfolio has on average a higher TTM, RAT, COUP and a lower SIZE than our EW and VW benchmarks. When looking at the average characteristics of bond funds, those of the passive funds are close to our VW benchmark, while those of the active funds tilt to our optimal portfolio, with the exception of TTM. Interestingly, our optimal portfolio has deviations from the benchmark that are larger than those observable in active funds. As shown in the last row of Table 7 those differences are statistically significant. Our optimal portfolio has on average a longer TTM (1.446 years more), a higher RAT (2.226 notches more), a higher COUP (0.415% more) and a smaller SIZE (165$ million less) than the average portfolio of active bond funds in the same time period.

The evidence in Table 7 is consistent with our interpretation that narrow mandates limit active investors from holding optimal portfolios, forcing them to have less than optimal tilts towards the bond characteristics. If this was true, whenever our portfolio deviates the most from active bond funds holdings, the out-performance relative to active funds should get larger. In other words, a greater deviation of our weights from those of active bond funds

[22]We gather data on bond funds holdings and performance from Morningstar for the period from January 2002 till December 2017. We consider funds in the following Morningstar categories: Corporate Bond, High-Yield Bond, Multisector Bond, Nontraditional Bond, Bank Loan, Preferred Stock, Short-Term Bond, Intermediate-Term Bond, and Long-Term Bond.

along the bond characteristics should predict larger out-performance. We test this conjecture by running the following regression:

$$r_{CBPP,t+1} - r_{ACT,t+1} = a + \beta_1 \Delta CHARS_t + \beta_2 (r_{CBPP,t} - r_{ACT,t}) + \epsilon_{t+1}, \tag{9}$$

where $r_{CBPP,t+1}$ is the optimal portfolio return in month $t+1$ and $r_{ACT,t+1}$ is average value-weighted active fund return in month $t+1$. $\Delta CHARS_t$ is the sum of the standardized differences in absolute value between the optimal portfolio's and the average active fund's characteristics (TTM, RAT, COUP, SIZE) in month t. We use one-month ahead return spread as dependent variable as the portfolio is rebalanced monthly, and the portfolio allocation decided in month t influences the performance in the following month $(t+1)$. Table 8 displays the results along with those of other four regressions where instead of $\Delta CHARS_t$ we use the difference relative to one single characteristic. First, our portfolio outperforms, on average, active bond funds by around 0.48% per month. Consistent with our story, a larger deviation from active bond funds portfolios in month t predicts a larger outperformance during the following month. A one standard deviation change in the distance between the optimal portfolio and the average active fund portfolio leads to an increase in outperformance of the parametric portfolio by 0.423%. Decomposing the distance across single characteristics suggests that RAT, COUP and SIZE are those characteristics that contribute to the outperformance. This is not surprising, as generally investment mandates limit fund managers along such characteristics. For example, some funds cannot hold high yield bonds, while other cannot buy bonds with a small outstanding amount because they are not included in major benchmarks.

Overall, these results suggest that narrow investment mandates potentially i) represent an important constraint for active fund managers in reaching an optimal portfolio and ii) might be a driver of the parametric portfolio's outperformance relative to active investors in bond markets.

7 Conclusion

We optimally select corporate bond portfolios based on asset-specific characteristics. Portfolio weights are modeled through the smooth maximum function, which allows for a large cross-section, asset-specific transaction costs a parsimonious use of turnover and short positions. We find that a portfolio based on four simple characteristics -time to maturity, rating, coupon, issue size- outperforms passive benchmarks after transaction costs in and out of sample, while keeping low levels of turnover and short positions. The optimal portfolio predicts various measures of economic activity above and beyond the information content of yield spreads, meaning it provides a superior hedge against undesirable states of the economy.

The key message of our paper is that the cross-section of bond characteristics contains a wealth of information that empirical methods can use in forming corporate bond portfolios. However, incorporating this information is more complex than previously thought. Multiple characteristics that have predictive power over bond returns do not lead to superior performance when incorporated in portfolios that take into account real transaction costs and keep a reasonable level of short positions and turnover. Further, narrow investment mandates among active bond fund managers seem to limit them from holding and optimal portfolio. Our paper only a first step understanding how to approach portfolio allocation in corporate bond markets, and opens the door to exciting possibilities for further research. For example, more work is needed to understand whether representative agent models are suitable for corporate bond investors, given the heterogeneous nature of their mandates (see for example Bretscher et al. (2020)). Also, much needs be done to shed light on the implications of the fact that not all characteristics are easily tradeable.

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Table 1: **Summary Statistics**

This table displays summary statistics of the corporate bond data used in our study. Our dataset includes 266,851 bond-month observations between September 1993 and December 2017. Panel A shows average monthly statistics of our sample of corporate bonds. First, we show monthly statistics for the number of bonds and outstanding debt (in billion USD) for all bonds in our sample, for bonds coming in our sample each month, and for those dropping out of our sample in each month. The column Total shows the number and the amount of outstanding debt of all bonds that are present at least once in our sample. Panel B shows summary statistics and correlations for bond-specific characteristics. TTM is the bond's time to maturity in years, RAT is the average rating of the bond across the three main rating agencies (Standard & Poor's, Moody's, and Fitch), COUP is the bond's coupon, and SIZE is the bond's outstanding amount in billion USD.

Panel A: Corporate Bond Sample

	Mean	**SD**	**Q25**	**Median**	**Q75**	**Total**
# Bonds	914	599	615	763	918	6084
# Bonds In	20	44	8	14	19	-
# Bonds Out	17	80	2	12	18	-
Debt Outst.	456	349	79	438	718	3317
Debt Outst. In	11	21	1	6	14	-
Debt Outst. Out	7	15	0	4	8	-

Panel B: Corporate Bond Characteristics

	TTM	**RAT**	**COUP**	**SIZE**
Mean	9.239	6.694	6.064	0.499
SD	9.411	3.015	1.984	0.796
Min	0.236	1.000	0.000	0.000
Median	6.044	6.000	6.500	0.250
Max	99.578	25.000	15.500	15.000
TTM	1.000	0.017	0.239	-0.062
RAT	0.017	1.000	0.220	-0.042
COUP	0.239	0.220	1.000	-0.290
SIZE	-0.062	-0.042	-0.290	1.000

Table 2: **Parametric Corporate Bond Portfolios – Smooth Maximum α**
This table displays optimal parametric corporate bond portfolios based on the bond-specific characteristics time to maturity (TTM), credit rating (RAT), coupon (COUP), and size (SIZE). Our dataset includes 266,851 bond-month observations between September 1993 and December 2017. The parameters are estimated for a power utility function with $\gamma = 5$, taking into account transaction costs. The column VW (EW) refers to the value-weighted (equal-weighted) benchmark portfolio for α=300. The other columns display optimal portfolios for different levels of the smooth maximum parameter α, starting from a value-weighted benchmark. The first set of rows shows the marginal impact of the characteristics and bootstrapped p-values for the corresponding coefficients. The second set of rows shows (annualized) performance measures and portfolio statistics, displaying certainty equivalent return (CE) and bootstrapped p-value, percentage increase in CE with respect to the corresponding benchmark, the mean (total, for the passive benchmark, and for active portfolio tilts) and standard deviation of portfolio returns, Sharpe ratio, average short positions, and annual turnover.

	VW	**EW**	**CBPP**			
			$\alpha = 0$	$\alpha = 150$	$\alpha = 300$	$\alpha = 750$
TTM			0.023	0.476	0.330	1.075
			(0.001)	(0.001)	(0.001)	(0.001)
RAT			0.194	1.230	1.128	3.245
			(0.001)	(0.001)	(0.001)	(0.001)
COUP			0.368	0.044	0.020	0.031
			(0.001)	(0.001)	(0.001)	(0.001)
SIZE			−0.341	−0.038	−0.047	0.095
			(0.001)	(0.001)	(0.001)	(0.001)
CE(r)	0.055	0.058	0.094	0.096	0.091	0.086
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
%ΔCE	0.000	0.000	0.709	0.745	0.655	0.564
$\bar{r}$	0.066	0.068	0.151	0.137	0.127	0.119
$\bar{r}_{passive}$	0.066	0.068	0.066	0.066	0.066	0.066
$\bar{r}_{active}$	0.000	0.000	0.085	0.071	0.061	0.053
$\sigma(r)$	0.060	0.054	0.135	0.114	0.107	0.101
SR	0.678	0.788	0.908	0.963	0.935	0.906
$\sum w_i I(w_i < 0)$	0.000	0.000	−1.482	−0.225	−0.116	−0.004
$\sum \lvert (w_{i,t} - w_{i,t-1}) \rvert$	0.654	0.648	3.347	1.342	1.161	0.983

Table 3: **Parametric Corporate Bond Portfolios – Out-of-Sample Performance**
This table displays out-of sample portfolio statistics for the value-weighted benchmark and different specifications of the parametric corporate bond portfolio, based on the bond-specific characteristics time to maturity (TTM), credit rating (RAT), coupon (COUP), and size (SIZE). Our dataset includes 266,851 bond-month observations between September 1993 and December 2017. The parameters are estimated for a power utility function with $\gamma = 5$, taking into account transaction costs. Optimal tilts are applied out-of-sample from January 2002 until December 2017, using an expanding window estimation. The column VW (EW) refers to the value-weighted (equal-weighted) benchmark portfolio for α=300. The other columns display out-of-sample portfolios for different levels of the smooth maximum parameter α, starting from a value-weighted benchmark. In particular, we report (annualized) performance measures and portfolio statistics, displaying certainty equivalent return (CE) and bootstrapped p-value, percentage increase in CE with respect to the corresponding benchmark, the mean and standard deviation of portfolio returns, Sharpe ratio, average short positions, and annual turnover. The out-of-sample period includes 212,061 bond-month observations.

	VW	**EW**	**CBPP**			
			$\alpha = 0$	$\alpha = 150$	$\alpha = 300$	$\alpha = 750$
CE(r)	0.051	0.055	−0.418	0.085	0.082	0.075
%ΔCE	0.000	0.000	−9.171	0.682	0.621	0.481
$\bar{r}$	0.065	0.066	0.187	0.129	0.116	0.104
$\bar{r}_{passive}$	0.065	0.066	0.065	0.065	0.065	0.065
$\bar{r}_{active}$	0.000	0.000	0.122	0.064	0.051	0.039
$\sigma(r)$	0.069	0.059	0.344	0.114	0.100	0.093
SR	0.755	0.900	0.504	1.015	1.028	0.979
$\sum w_i I(w_i < 0)$	0.000	0.000	−4.966	−0.240	−0.115	−0.010
$\sum \lvert(w_{i,t} - w_{i,t-1})\rvert$	0.602	0.627	19.640	2.228	1.553	1.352

Table 4: **Univariate Portfolio Sorts for Bond Characteristics**
This table displays results for univariate corporate bond portfolio sorts, conditional on bond-specific characteristics. Our dataset includes 266,851 bond-month observations between September 1993 and December 2017. For each month, corporate bonds are sorted into quintile portfolios based on either time to maturity (TTM), rating (RAT), coupon (COUP), or size (SIZE). Value-weighted returns are calculated for each portfolio during the following month. P1 contains bonds in the lowest quintile with respect to a given sorting variable, P5 those in the highest. P5−P1 presents results for a hedge portfolio that is long in P5 and short in P1. Panel A reports annualized excess returns in percentage points and certainty equivalent returns (CE) for a power utility function with $\gamma = 5$. The last two columns report long-short hedge portfolio returns and certainty equivalent returns, accounting for transaction costs. Panel B displays correlations of long-short hedge portfolio returns, accounting for transaction costs. Robust two-tailed p-values following Newey and West (1987, 1994) are reported in parentheses.

Panel A: Performance

	w/o t-costs		**w/ t-costs**	
	P5−P1	**CE**	**P5−P1**	**CE**
TTM	0.034	0.021	0.029	0.016
	(0.023)		(0.052)	
RAT	0.048	0.022	0.042	0.016
	(0.035)		(0.058)	
COUP	0.034	0.023	0.029	0.018
	(0.003)		(0.010)	
SIZE	0.002	−0.003	−0.003	−0.008
	(0.773)		(0.646)	

Panel B: Correlations

	TTM	**RAT**	**COUP**	**SIZE**
TTM	1.000	0.037	0.344	−0.290
RAT	0.037	1.000	0.767	−0.487
COUP	0.344	0.767	1.000	−0.611
SIZE	−0.290	−0.487	−0.611	1.000

Table 5: **Parametric Corporate Bond Portfolios and Macro Predictability**
This table displays results for forecasting future realized GDP growth and consumption growth with returns of the optimal parametric corporate bond portfolio, decomposed into its passive and active part. The optimal portfolio returns are based on a value-weighted corporate bond benchmark. We use a specification with $\alpha = 300$, and take into account the bond-specific characteristics time to maturity (TTM), credit rating (RAT), coupon (COUP), and size (SIZE). The parameters are estimated for a power utility function with $\gamma = 5$, taking into account transaction costs. Our dataset includes 266,851 bond-month observations between September 1993 and December 2017, the forecasts are estimated beginning in January 2002. Optimal portfolios are estimated using an expanding window that ends before the period over which changes in the macroeconomic variables are calculated. The portfolio return during the final month of each estimation period is used to forecast the macroeconomic variables. We take into account growth in macroeconomic variables over the next quarter (GDP_{Q1} and CONS_{3M}) and over the next year (GDP_{Q4} and CONS_{12M}). We furthermore control for the GZ credit spread index from Gilchrist and Zakrajšek (2012) (GZ) and include a lagged (non-overlapping) value of the dependent variable (AR(1)). Our regression sample ends in August 2016 due to the availability of GZ. Robust two-tailed p-values following Newey and West (1987) for three and twelve lags, according to the horizon of the dependent variable, are reported in parentheses. All variables are standardized and demeaned.

	$\mathbf{GDP}_{Q1}$		$\mathbf{GDP}_{Q4}$		$\mathbf{CONS}_{3M}$		$\mathbf{CONS}_{12M}$	
$r_{passive}$		0.302		0.298		0.321		0.193
		(0.001)		(0.001)		(0.003)		(0.001)
r_{active}		0.178		0.489		0.160		0.275
		(0.047)		(0.001)		(0.029)		(0.002)
GZ	−0.616	−0.674	−0.518	−0.509	−0.439	−0.479	−0.440	−0.379
	(0.004)	(0.001)	(0.002)	(0.001)	(0.010)	(0.001)	(0.077)	(0.052)
AR(1)	0.031	0.066	0.012	0.202	0.024	0.044	0.004	0.146
	(0.864)	(0.650)	(0.965)	(0.294)	(0.813)	(0.658)	(0.988)	(0.478)
Obs.	59	59	56	56	177	177	168	168
Adj. R2	0.400	0.522	0.264	0.618	0.204	0.339	0.191	0.304

Table 6: **Parametric Corporate Bond Portfolios and Credit Spread Predictability**
This table displays results for forecasting future realized values of the GZ credit spread index from Gilchrist and Zakrajšek (2012) (GZ) and its changes over time (ΔGZ) with returns of the optimal parametric corporate bond portfolio, decomposed into its passive and active part. The optimal portfolio returns are based on a value-weighted corporate bond benchmark. We use a specification with $\alpha = 300$, and take into account the bond-specific characteristics time to maturity (TTM), credit rating (RAT), coupon (COUP), and size (SIZE). The parameters are estimated for a power utility function with $\gamma = 5$, taking into account transaction costs. Our dataset includes 266,851 bond-month observations between September 1993 and December 2017, the forecasts are estimated beginning in January 2002. Optimal portfolios are estimated using an expanding window that ends before the period over which changes in GZ are calculated. The portfolio return during the final month of each estimation period is used to forecast GZ or ΔGZ. Our regression sample ends in August 2016 due to the availability of GZ. We take into account macroeconomic variables over the next quarter (GZ_{3M} and ΔGZ_{3M}) and over the next year (GZ_{12M} and ΔGZ_{12M}). We control for a lagged (non-overlapping) value of the dependent variable (AR(1)). Robust two-tailed p-values following Newey and West (1987) for three and twelve lags, according to the horizon of the dependent variable, are reported in parentheses. All variables are standardized and demeaned.

	$\mathbf{GZ}_{3M}$		$\mathbf{GZ}_{12M}$		$\Delta\mathbf{GZ}_{3M}$		$\Delta\mathbf{GZ}_{12M}$	
$r_{passive}$		−0.186		−0.050		−0.254		−0.061
		(0.027)		(0.046)		(0.000)		(0.280)
r_{active}		−0.156		−0.234		−0.239		−0.210
		(0.008)		(0.108)		(0.003)		(0.022)
AR(1)	0.803	0.835	0.195	0.212	0.151	0.017	0.004	−0.057
	(0.000)	(0.000)	(0.140)	(0.077)	(0.168)	(0.850)	(0.984)	(0.773)
Obs.	174	174	156	156	174	174	156	156
Adj. R2	0.645	0.709	0.038	0.087	0.023	0.131	0.000	0.036

Table 7: **Parametric Corporate Bond Portfolios and Bond Funds Holdings**
This table displays statistics for average bond characteristics for our benchmark portfolios, the optimal parametric portfolio, and US corporate bond mutual funds. We report average bond characteristics for the equal-weighted (EW) and value-weighted (VW) corporate bond benchmarks, for the out-of-sample parametric corporate bond portfolio (CBPP, for the reference specification with α=300, estimated for a power utility function with $\gamma = 5$, accounting for transaction costs), and of index funds, actively managed funds, and all US corporate bond mutual funds. Finally, we show the difference in average bond characteristics between the out-of-sample parametric corporate bond portfolio and actively managed funds. Two-sample two-tailed p-values are reported in parentheses. Our dataset includes 266,851 bond-month observations between September 1993 and December 2017. The out-of-sample returns are obtained by applying optimal tilts out-of-sample from January 2002 until December 2017, using an expanding window estimation. We get information about mutual fund holdings from Morningstar.

	TTM	**RAT**	**COUP**	**SIZE**
EW	7.564	6.974	5.359	0.776
VW	8.041	6.461	5.261	1.982
CBPP	9.977	13.029	6.775	0.806
Active Funds	8.531	10.803	6.360	0.971
Passive Funds	9.613	6.920	5.155	1.207
All Funds	8.642	10.417	6.234	0.992
CBPP-Active	1.446	2.226	0.415	−0.165
	(0.001)	(0.001)	(0.001)	(0.001)

Table 8: **Parametric Corporate Bond Portfolios and Bond Funds Performance**
This table displays results for forecasting monthly out-of-sample parametric corporate bond portfolio returns in excess of active US bond fund returns with the distance in characteristics between the two portfolios. The parametric corporate bond portfolio returns are based on a value-weighted corporate bond benchmark. We use a specification with $\alpha = 300$, and take into account the bond-specific characteristics time to maturity (TTM), credit rating (RAT), coupon (COUP), and size (SIZE). The parameters are estimated for a power utility function with $\gamma = 5$, taking into account transaction costs. Our dataset includes 266,851 bond-month observations between September 1993 and December 2017. The out-of-sample returns are obtained by applying optimal tilts out-of-sample from January 2002 until December 2017, using an expanding window estimation. We control for a lagged (non-overlapping) value of the dependent variable (AR(1)). Robust two-tailed p-values following Newey and West (1987) are reported in parentheses. All right-hand side variables are standardized and demeaned.

	$r_{CBPP,t+1} - r_{ACT,t+1}$				
$\Delta CHARS_t$	0.423				
	(0.002)				
ΔTTM_t		−0.361			
		(0.104)			
ΔRAT_t			0.242		
			(0.078)		
$\Delta COUP_t$				0.411	
				(0.023)	
$\Delta SIZE_t$					0.462
					(0.001)
AR(1)	−0.003	−0.038	−0.011	0.009	−0.043
	(0.993)	(0.880)	(0.970)	(0.974)	(0.876)
Constant	0.484	0.480	0.482	0.484	0.482
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Obs.	179	179	179	179	179
Adj. R2	0.020	0.015	0.001	0.023	0.032

Table 9: **Parametric Corporate Bond Portfolios – Downside Risk**
This table displays optimal parametric corporate bond portfolios based on the bond-specific characteristics time to maturity (TTM), credit rating (RAT), coupon (COUP), size (SIZE), and downside risk (DSIDE). We show performance statistics for both in-sample and out-of-sample portfolios. Our dataset includes 186,062 bond-month observations between September 1993 and December 2017. The parameters are estimated for a power utility function with $\gamma = 5$, using α=300, and taking into account transaction costs. Optimal tilts are applied out-of-sample from January 2002 until December 2017, using an expanding window estimation. The column VW refers to the value-weighted benchmark portfolio. The other columns display optimal and out-of-sample portfolios with (CH+D) and without downside risk (CH). The first set of rows shows the marginal impact of the characteristics and bootstrapped p-values for the corresponding coefficients. The second set of rows shows (annualized) performance measures and portfolio statistics, displaying certainty equivalent return (CE) and bootstrapped p-value, percentage increase in CE with respect to the corresponding benchmark, the mean (total, for the passive benchmark, and for active portfolio tilts) and standard deviation of portfolio returns, Sharpe ratio, average short positions, and annual turnover.

	In Sample			**Out-of-Sample**		
	VW	**CBPP**		**VW**	**CBPP**	
		CH	CH+D		CH	CH+D
TTM		0.539	0.539			
		(0.001)	(0.001)			
RAT		1.737	1.708			
		(0.001)	(0.001)			
COUP		0.095	0.092			
		(0.001)	(0.001)			
SIZE		−0.144	−0.137			
		(0.001)	(0.001)			
DSIDE			−0.027			
			(0.001)			
CE(r)	0.057	0.091	0.091	0.056	0.077	0.076
	(0.001)	(0.001)	(0.001)			
%ΔCE	0.000	0.596	0.596	0.000	0.372	0.349
$\bar{r}$	0.068	0.126	0.126	0.070	0.107	0.105
$\bar{r}_{passive}$	0.068	0.068	0.068	0.070	0.070	0.070
$\bar{r}_{active}$	0.000	0.058	0.058	0.000	0.037	0.035
$\sigma(r)$	0.059	0.104	0.104	0.069	0.094	0.091
SR	0.719	0.950	0.952	0.836	1.000	1.005
$\sum w_i I(w_i < 0)$	0.000	−0.063	−0.065	0.000	−0.058	−0.060
$\sum \lvert(w_{i,t} - w_{i,t-1})\rvert$	0.750	1.130	1.134	0.774	1.627	1.880

Table 10: **Parametric Corporate Bond Portfolios – Stock Characteristics**
This table displays optimal parametric corporate bond portfolios based on the bond-specific characteristics time to maturity (TTM), credit rating (RAT), coupon (COUP), and size (SIZE), as well as on the stock-specific characteristics size (ME), book-to-market (BTM), momentum (MOM), idiosyncratic volatility (IVOL), CAPM beta (BETA), and skewness (SKEW). We show performance statistics for both in-sample and out-of-sample portfolios. Our dataset includes 135,070 bond-month observations between September 1993 and December 2017. The parameters are estimated for a power utility function with $\gamma = 5$, using α=300, and taking into account transaction costs. Optimal tilts are applied out-of-sample from January 2002 until December 2017, using an expanding window estimation. The column VW refers to the value-weighted benchmark portfolio. The other columns display optimal and out-of-sample portfolios with bond (B), stock (S), and both (B+S). The first set of rows shows the marginal impact of the characteristics and bootstrapped p-values for the corresponding coefficients. The second set of rows shows (annualized) performance measures and portfolio statistics, displaying certainty equivalent return (CE) and bootstrapped p-value, percentage increase in CE with respect to the corresponding benchmark, the mean (total, for the passive benchmark, and for active portfolio tilts) and standard deviation of portfolio returns, Sharpe ratio, average short positions, and annual turnover.

	In Sample				Out-of-Sample			
	VW	**CBPP**			**VW**	**CBPP**		
		B	S	B+S		B	S	B+S
TTM		0.542		0.497				
		(0.001)		(0.001)				
RAT		1.100		1.029				
		(0.001)		(0.001)				
COUP		−0.062		−0.032				
		(0.001)		(0.001)				
SIZE		−0.281		−0.241				
		(0.001)		(0.001)				
ME			−0.198	−0.167				
			(0.001)	(0.001)				
BTM			5.770	−0.035				
			(0.001)	(0.001)				
MOM			1.746	0.006				
			(0.001)	(0.037)				
IVOL			−0.062	0.007				
			(0.001)	(0.145)				
BETA			−0.206	−0.047				
			(0.001)	(0.001)				
SKEW			−0.226	−0.025				
			(0.001)	(0.001)				
CE(r)	0.059	0.078	0.069	0.078	0.053	0.062	0.048	0.060
	(0.001)	(0.001)	(0.001)	(0.001)				
%ΔCE	0.000	0.322	0.169	0.322	0.000	0.172	−0.083	0.131
$\bar{r}$	0.069	0.100	0.080	0.099	0.065	0.082	0.057	0.075
$\bar{r}_{passive}$	0.069	0.069	0.069	0.069	0.065	0.065	0.065	0.065
$\bar{r}_{active}$	0.000	0.031	0.011	0.030	0.000	0.017	−0.008	0.010
$\sigma(r)$	0.056	0.086	0.058	0.084	0.065	0.083	0.054	0.070
SR	0.738	0.830	0.903	0.844	0.795	0.824	0.807	0.865
$\sum w_i I(w_i < 0)$	0.000	−0.078	−0.001	−0.077	0.000	−0.107	−0.012	−0.096
$\sum \lvert(w_{i,t} w_{i,t-1})\rvert$	0.682	1.285	1.546	1.306	0.697	2.235	3.019	2.202

Table 11: **Parametric Corporate Bond Portfolios – IG and HY Bonds**
This table displays optimal parametric corporate bond portfolios based on the bond-specific characteristics time to maturity (TTM), credit rating (RAT), coupon (COUP), and size (SIZE) for two subsamples: investment grade (IG) and high-yield (HY) bonds. We show performance statistics for both in-sample and out-of-sample portfolios. Our dataset includes 266,851 bond-month observations between September 1993 and December 2017. The parameters are estimated for a power utility function with $\gamma = 5$, using α=300, and taking into account transaction costs. Optimal tilts are applied out-of-sample from January 2002 until December 2017, using an expanding window estimation. The column VW refers to the value-weighted benchmark portfolio. The other columns display optimal and out-of-sample portfolios for the two subsamples. The first set of rows shows the marginal impact of the characteristics and bootstrapped p-values for the corresponding coefficients. The second set of rows shows (annualized) performance measures and portfolio statistics, displaying certainty equivalent return (CE) and bootstrapped p-value, percentage increase in CE with respect to the corresponding benchmark, the mean (total, for the passive benchmark, and for active portfolio tilts) and standard deviation of portfolio returns, Sharpe ratio, average short positions, and annual turnover.

	In Sample				**Out-of-Sample**			
	IG		**HY**		**IG**		**HY**	
	VW	**CBPP**	**VW**	**CBPP**	**VW**	**CBPP**	**VW**	**CBPP**
TTM		0.359		−0.054				
		(0.001)		(0.798)				
RAT		0.623		7.200				
		(0.001)		(0.001)				
COUP		0.302		−1.084				
		(0.001)		(0.001)				
SIZE		−0.139		−1.653				
		(0.001)		(0.001)				
CE(r)	0.050	0.064	0.074	0.137	0.038	0.049	0.045	0.077
	(0.001)	(0.001)	(0.001)	(0.001)				
%ΔCE	0.000	0.280	0.000	0.851	0.000	0.273	0.000	0.711
$\bar{r}$	0.059	0.079	0.129	0.234	0.050	0.057	0.131	0.202
$\bar{r}_{passive}$	0.059	0.059	0.129	0.129	0.050	0.050	0.131	0.131
$\bar{r}_{active}$	0.000	0.020	0.000	0.105	0.000	0.006	0.000	0.072
$\sigma(r)$	0.055	0.068	0.135	0.167	0.063	0.051	0.171	0.195
SR	0.623	0.782	0.758	1.227	0.599	0.867	0.684	0.964
$\sum w_i I(w_i < 0)$	0.000	−0.112	0.000	−0.002	0.000	−0.063	0.000	−0.003
$\sum \lvert(w_{i,t} - w_{i,t-1})\rvert$	0.660	1.058	1.141	1.681	0.623	1.910	0.985	1.894

Figure 1: **Monthly One-way Transaction costs**. This figure displays the time series of the average transaction costs we apply to the bonds in our sample. We plot average transaction costs for the full sample and separately for the investment grade and high-yield subsamples. Our dataset includes 266,851 bond-month observations between September 1993 and December 2017.

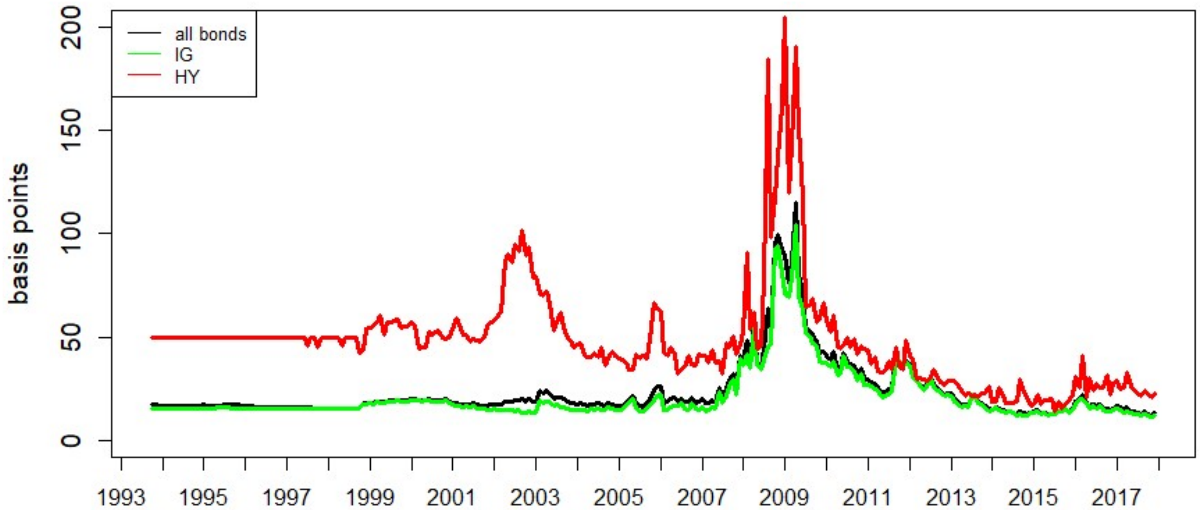
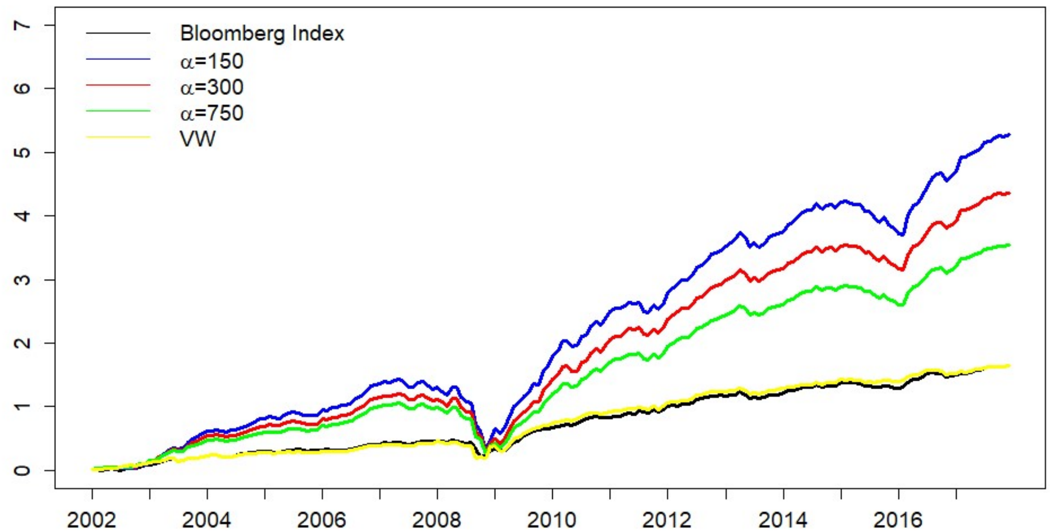
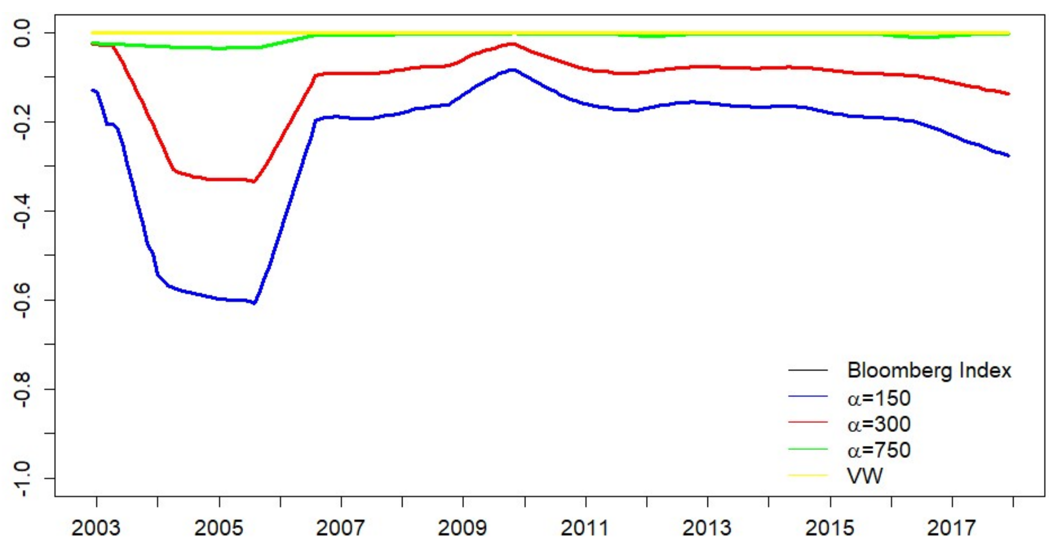


Figure 2: **Out-of-Sample Performance**. This figure displays the time series of cumulative returns and short positions (12-months moving average) of out-of sample portfolios for different values of smooth maximum parameter α, based on the bond-specific characteristics time to maturity (TTM), credit rating (RAT), coupon (COUP), and size (SIZE). Our dataset includes 266,851 bond-month observations between September 1993 and December 2017. The parameters are estimated for a power utility function with $\gamma = 5$, taking into account transaction costs. Optimal tilts are applied out-of-sample from January 2002 until December 2017, using an expanding window estimation.

(a) Cumulative Returns



(b) Short Positions



Appendix A Magnitude of transaction costs

In our optimization, we apply bond specific transaction costs by exploiting information from Datastream and TRACE. First, following among others Schestag, Schuster, and Uhrig-Homburg (2016), we calculate round-trip transaction costs of bond i at month-end t with the bid-ask spread:

$$bidask_{i,t} = \frac{P_t^{buy} - P_t^{sell}}{0.5 \cdot (P_t^{buy} + P_t^{sell})} \tag{10}$$

where P_t^{buy} is the price at which an investor can buy the bond from the dealer and P_t^{sell} is the price at which the investor can sell the bond to the dealer. P_t^{buy} and P_t^{sell} are based on month-end prices for the Datastream sample.[23] In the TRACE sample, we exploit the richness of the transaction-level data and estimate P_t^{buy} and P_t^{sell} by averaging daily bid-ask spreads over the month t.[24] As we are considering one-way transaction costs in our optimization, the final transaction cost that we apply is given by $TC_{i,t} = \frac{bidask_{i,t}}{2}$. Consistent with Bessembinder et al. (2018), the one-way transaction cost is as half the difference between the price at which dealers will sell a bond and the price at which they will purchase the bond. Taking a conservative approach, whenever in the sample we observe a bid-ask spread that is zero or negative, we nevertheless assign a transaction cost level of 10bps.

[23] For the vast majority of bonds from September 1993 until September 1998, Datastream only provides mid-prices. In that period, we apply the average transaction cost observed in the rest of the Datastream sample, dividing between IG (15bps) and HY bonds (50bps).

[24] We consider days where both buy and sell prices are available. To avoid retail transactions driving our estimates, we consider only institutional trades, defined following Bessembinder et al. (2009) as those with a trading volume of at least \$100,000. If in a month a bond has not days with both buys and sell prices, or no transactions of at least \$100,000, we assign the average transaction cost across bonds in that month, distinguishing between IG and HY bonds.

Appendix B Estimation details

B.1 Bootstrapping the coefficients

We follow the bootstrap procedure outlined in Brandt, Santa-Clara, and Valkanov (2009, pp. 3419-3420) to estimate the covariance matrix of coefficients $\Sigma_{\hat{\theta}}$. Our original data set consists of monthly observations of bond returns and bond-specific characteristics. We randomly draw - with replacement - $1,000$ samples from this data set. As the original sample period covers different economic regimes, we maintain the time-series dependence of the data by separately drawing randomly each month. Thus, each of the bootstrapped samples covers the period of our original sample, which goes from September 1993 till September 2015. For each bootstrapped sample, we follow the procedure described in Section 2 and estimate optimal portfolio weights. We retain the coefficients $\hat{\theta}$ and in a final step compute the covariance matrix $\Sigma_{\hat{\theta}}$. We estimate the covariance matrix separately for each portfolio specification (e.g., for different levels of transaction costs or when accounting for short-sale costs).

We use the bootstrapped covariance matrix to test whether the coefficients $\hat{\theta}$, which are estimated for the original sample, are significantly different from zero. Brandt, Santa-Clara, and Valkanov (2009) discuss that this test of statistical significance does not automatically allows for a statement about whether a given bond-specific characteristic is cross-sectionally related to conditional bond returns. They argue that the passive benchmark weights $\bar{w}_{i,t}$ may already reflect a tilt toward some characteristics (e.g., a positive tilt for SIZE for a value-weighted benchmark). It might not be optimal for an investor to change this exposure and the corresponding $\hat{\theta}$ will be indistinguishable from zero.

B.2 Bootstrapping the certainty equivalent return

We estimate the variance of the certainty equivalent return (CE) σ^2_{CE} by bootstrap. For that, we estimate the distribution of the CE under the null hypothesis that our parameter vector θ is zero and that bond-specific characteristics have no impact on optimal portfolio weights.

We generate $1,000$ samples of returns by randomly drawing monthly observations from the original data set (with replacement). As our sample period covers different economic regimes, we maintain the time-series dependence of the data by separately drawing randomly each month. For each of these bootstrapped samples, we compute the CE of the portfolio while keeping $\theta = 0$. Finally, we compute σ^2_{CE} across all bootstrapped samples.

The resulting estimate of σ^2_{CE} can be used to test hypotheses about the CE (e.g., whether the CE of portfolios conditioned on bond-specific characteristics is larger than the CE of an equally or value-weighted benchmark).

Appendix C Calculation of marginal impact

The non-linearity of $g(\cdot)$ in our parametric portfolio weight specification

$$w_{i,t} = g(\bar{w}_{i,t}; x_{i,t}; \theta)$$

implies that the parameters θ cannot be interpreted as the marginal impact of changes in $x_{i,t}$ on the optimal portfolio weights. Hence, we evaluate the marginal impact by computing changes in $w_{i,t}$ that result for a one-standard-deviation change in each of the conditioning variables $x_{i,t}$, evaluated at the average value of the other characteristics and at the estimated θ. This is the standard approach used to measure economic impact in non-linear models.

As the characteristics are normalized to have a cross-sectional mean of zero and a standard deviation of one in each month t, the calculation of the marginal impact simplifies to the difference between the average weight of a bond with characteristic x^j being set to one, while all other characteristics $x^{\tilde{}j}$ are kept at zero (w^{x^j}), and the average weight of the benchmark portfolio (w^0), given by

$$\begin{aligned} w^{x^j} &= g(\bar{w}; x^j = 1; x^{\tilde{}j} = 0; \theta) \text{ and} && (11) \\ w^0 &= g(\bar{w}; x = 0; \theta), && (12) \end{aligned}$$

with $\bar{w}$ being the average benchmark weight in the sample.[25] The marginal impact of characteristic x^j on the optimal portfolio weights, taking into account the re-scaling of weights such that they sum up to one, can then be calculated as

[25]The normalization applied in $h(\cdot)$ in (4) is done by using $\bar{N}$, the average number of bonds in the portfolio in each month t.

$$\frac{\mathrm{d}w}{\mathrm{d}x^j} = \frac{\frac{w^{x^j}}{w^{x^j}+w^0*\left(\bar{N}-1\right)} - \frac{w^0}{w^0*\bar{N}}}{1-0} \tag{13}$$

$$= \frac{w^{x^j}}{w^{x^j}+w^0*\left(\bar{N}-1\right)} - \frac{1}{\bar{N}}. \tag{14}$$

Appendix D Calculation of stock characteristics

We get monthly returns for common stocks (share code 10 and 11) from CRSP and match them to our sample of corporate bonds, taking care of mergers, acquisitions and spin offs. We merge our matched sample with Compustat to get accounting variables for all stocks in our sample. All accounting variables from Compustat are lagged by six months to make sure they are observable at the time of portfolio formation. Our final sample consists of 135,070 bond-month observations between September 1993 and December 2017.

We calculate the market capitalization (ME) of a firm by multiplying the share price from the end of the past fiscal year by shares outstanding from the monthly CRSP file. The book-to-market ratio (BTM) is calculated by dividing a firm's book equity by ME. Book equity is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit, minus the book value of preferred stock, following Davis, Fama, and French (2002). A stock's momentum (MOM) is calculated following Jegadeesh and Titman (1993) and Carhart (1997) as the one year cumulative return spanning month $t-12$ till $t-1$. Over the same time period, a firm's exposure to the market portfolio (BETA) as well as sample skewness (SKEW) is calculated, using daily stock return data from CRSP. The idiosyncratic volatility of a stock (IVOL) is calculated following Ang et al. (2006) as the volatility of a stock's daily residual return during month $t-1$, after controlling for exposure to the market portfolio as well as Fama and French's (1993) SMB and HML factors.[26]

[25] This is done using the Bond-CRSP linking table provided by WRDS for the period 2003-2017, and manually for the period 1993-2003.

[26] We thank Kenneth French to make those factors available on his website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Internet Appendix for

Implementable Corporate Bond Portfolios

Table IA1: **Parametric Corporate Bond Portfolios – Single Characteristics**
This table displays optimal parametric corporate bond portfolios based on the bond-specific characteristics time to maturity (TTM), credit rating (RAT), coupon (COUP), and size (SIZE). Our dataset includes 266,851 bond-month observations between September 1993 and December 2017. The parameters are estimated for a power utility function with $\gamma = 5$, using α=300, and taking into account transaction costs. The column VW refers to the value-weighted benchmark portfolio. The first set of rows shows the marginal impact of the characteristics and bootstrapped p-values for the corresponding coefficients. The second set of rows shows (annualized) performance measures and portfolio statistics, displaying certainty equivalent return (CE) and bootstrapped p-value, percentage increase in CE with respect to the corresponding benchmark, the mean (total, for the passive benchmark, and for active portfolio tilts) and standard deviation of portfolio returns, Sharpe ratio, average short positions, and annual turnover.

	VW	**CBPP**			
TTM		1.166			
		(0.001)			
RAT			1.479		
			(0.001)		
COUP				1.306	
				(0.001)	
SIZE					−0.248
					(0.001)
CE(r)	0.055	0.065	0.088	0.070	0.061
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
%ΔCE		0.182	0.600	0.273	0.109
$\bar{r}$	0.066	0.085	0.128	0.084	0.073
$\bar{r}_{passive}$	0.066	0.066	0.066	0.066	0.066
$\bar{r}_{active}$	0.000	0.019	0.062	0.018	0.007
$\sigma(r)$	0.060	0.080	0.112	0.068	0.062
SR	0.678	0.729	0.900	0.849	0.769
$\sum w_i I(w_i < 0)$	0.000	−0.105	−0.110	−0.090	−0.135
$\sum \lvert(w_{i,t} - w_{i,t-1})\rvert$	0.654	0.951	1.139	0.752	1.062

Table IA2: **Parametric Corporate Bond Portfolios – Single Characteristics – Out-of-Sample Performance**

This table displays out-of sample portfolio statistics for the value-weighted benchmark and different specifications of the parametric corporate bond portfolio, based on the bond-specific characteristics time to maturity (TTM), credit rating (RAT), coupon (COUP), and size (SIZE). Our dataset includes 266,851 bond-month observations between September 1993 and December 2017. The parameters are estimated for a power utility function with $\gamma = 5$, using α=300, and taking into account transaction costs. Optimal tilts are applied out-of-sample from January 2002 until December 2017, using an expanding window estimation. The column VW refers to the value-weighted benchmark portfolio. The other columns display out-of-sample portfolios. In particular, we report (annualized) performance measures and portfolio statistics, displaying certainty equivalent return (CE) and bootstrapped p-value, percentage increase in CE with respect to the corresponding benchmark, the mean and standard deviation of portfolio returns, Sharpe ratio, average short positions, and annual turnover. For the out-of-sample period, the sample includes 212,061 bond-month observations.

	VW	**CBPP**			
		TTM	RAT	COUP	SIZE
CE(r)	0.051	0.051	0.073	0.068	0.053
%ΔCE	0.000	0.011	0.439	0.347	0.036
$\bar{r}$	0.065	0.070	0.116	0.087	0.064
$\bar{r}_{passive}$	0.065	0.065	0.065	0.065	0.065
$\bar{r}_{active}$	0.000	0.004	0.050	0.022	−0.002
$\sigma(r)$	0.069	0.077	0.111	0.079	0.058
SR	0.755	0.737	0.926	0.929	0.874
$\sum w_i I(w_i < 0)$	0.000	−0.095	−0.115	−0.069	−0.063
$\sum \lvert(w_{i,t} - w_{i,t-1})\rvert$	0.602	2.063	1.422	0.905	1.475

Table IA3: **Parametric Corporate Bond Portfolios and Macro Predictability – Industrial Production Growth and Changes in the Unemployment Rate**
This table displays results for forecasting future realized industrial production growth and changes in the unemployment rate with returns of the optimal parametric corporate bond portfolio, decomposed into its passive and active part. The optimal portfolio returns are based on a value-weighted corporate bond benchmark. We use a specification with $\alpha = 300$, and take into account the bond-specific characteristics time to maturity (TTM), credit rating (RAT), coupon (COUP), and size (SIZE). The parameters are estimated for a power utility function with $\gamma = 5$, taking into account transaction costs. Our dataset includes 266,851 bond-month observations between September 1993 and December 2017, the forecasts are estimated beginning in January 2002. Optimal portfolios are estimated using an expanding window that ends before the period over which changes in the macroeconomic variables are calculated. The portfolio return during the final month of each estimation period is used to forecast the macroeconomic variables. We take into account growth in macroeconomic variables over the next quarter (IPG_{3M} and UNRATE_{3M}) and over the next year (IPG_{12M} and UNRATE_{12M}). We control for the GZ credit spread index from Gilchrist and Zakrajšek (2012) (GZ) and include a lagged (non-overlapping) value of the dependent variable (AR(1)). Our regression sample ends in August 2016 due to the availability of GZ. Robust two-tailed p-values following Newey and West (1987) for three and twelve lags, according to the horizon of the dependent variable, are reported in parentheses. All variables are standardized and demeaned.

	$\textbf{IPG}_{3M}$		$\textbf{IPG}_{12M}$		$\textbf{UNRATE}_{3M}$		$\textbf{UNRATE}_{12M}$	
$r_{passive}$		0.095		0.171		−0.130		−0.168
		(0.360)		(0.001)		(0.054)		(0.001)
r_{active}		0.283		0.323		−0.025		−0.250
		(0.001)		(0.001)		(0.610)		(0.039)
GZ	−0.365	−0.416	−0.527	−0.488	0.639	0.667	0.432	0.350
	(0.004)	(0.001)	(0.023)	(0.006)	(0.001)	(0.001)	(0.003)	(0.015)
AR(1)	0.344	0.300	−0.391	−0.284	0.101	0.092	0.109	0.265
	(0.004)	(0.018)	(0.117)	(0.136)	(0.389)	(0.408)	(0.621)	(0.294)
Obs.	177	177	168	168	177	177	168	168
Adj. R2	0.421	0.512	0.132	0.272	0.510	0.523	0.265	0.352

Table IA4: **Parametric Corporate Bond Portfolios – Illiquidity**

This table displays optimal parametric corporate bond portfolios based on the bond-specific characteristics time to maturity (TTM), credit rating (RAT), coupon (COUP), size (SIZE), and illiquidity (ILLIQ). We show performance statistics for both in-sample and out-of-sample portfolios. Our dataset includes 266,851 bond-month observations between September 1993 and December 2017. The parameters are estimated for a power utility function with $\gamma = 5$, using α=300, and taking into account transaction costs. Optimal tilts are applied out-of-sample from January 2002 until December 2017, using an expanding window estimation. The column VW refers to the value-weighted benchmark portfolio. The other columns display optimal and out-of-sample portfolios with (CH+ILLIQ) and without (CH) illiquidity. The first set of rows shows the marginal impact of the characteristics and bootstrapped p-values for the corresponding coefficients. The second set of rows shows (annualized) performance measures and portfolio statistics, displaying certainty equivalent return (CE) and bootstrapped p-value, percentage increase in CE with respect to the corresponding benchmark, the mean (total, for the passive benchmark, and for active portfolio tilts) and standard deviation of portfolio returns, Sharpe ratio, average short positions, and annual turnover.

	In Sample			**Out-of-Sample**		
	VW	**CBPP**		**VW**	**CBPP**	
		CH	CH+ILLIQ		CH	CH+ILLIQ
TTM		0.539	2.178			
		(0.001)	(0.001)			
RAT		1.737	6.270			
		(0.001)	(0.001)			
COUP		0.095	0.157			
		(0.001)	(0.001)			
SIZE		−0.144	−0.395			
		(0.001)	(0.001)			
ILLIQ			0.016			
			(0.189)			
CE(r)	0.055	0.091	0.091	0.051	0.082	0.078
	(0.001)	(0.001)	(0.001)			
%ΔCE	0.000	0.655	0.655	0.000	0.621	0.537
$\bar{r}$	0.066	0.126	0.127	0.065	0.116	0.114
$\bar{r}_{passive}$	0.066	0.055	0.055	0.065	0.065	0.065
$\bar{r}_{active}$	0.000	0.071	0.072	0.000	0.051	0.048
$\sigma(r)$	0.060	0.104	0.107	0.069	0.100	0.104
SR	0.678	0.950	0.935	0.755	1.028	0.963
$\sum w_i I(w_i < 0)$	0.000	−0.063	−0.116	0.000	−0.115	−0.120
$\sum \lvert(w_{i,t} - w_{i,t-1})\rvert$	0.654	1.130	1.162	0.602	1.553	2.789

Table IA5: **Parametric Corporate Bond Portfolios – Momentum**
This table displays optimal parametric corporate bond portfolios based on the bond-specific characteristics time to maturity (TTM), credit rating (RAT), coupon (COUP), size (SIZE), and bond momentum (MOM). We show performance statistics for both in-sample and out-of-sample portfolios. Our dataset includes 254,880 bond-month observations between September 1993 and December 2017. The parameters are estimated for a power utility function with $\gamma = 5$, using α=300, and taking into account transaction costs. Optimal tilts are applied out-of-sample from January 2002 until December 2017, using an expanding window estimation. The column VW refers to the value-weighted benchmark portfolio. The other columns display optimal and out-of-sample portfolios with (CH+MOM) and without (CH) bond momentum. The first set of rows shows the marginal impact of the characteristics and bootstrapped p-values for the corresponding coefficients. The second set of rows shows (annualized) performance measures and portfolio statistics, displaying certainty equivalent return (CE) and bootstrapped p-value, percentage increase in CE with respect to the corresponding benchmark, the mean (total, for the passive benchmark, and for active portfolio tilts) and standard deviation of portfolio returns, Sharpe ratio, average short positions, and annual turnover.

	In Sample			**Out-of-Sample**		
	VW	**CBPP**		**VW**	**CBPP**	
		CH	CH+MOM		CH	CH+MOM
TTM		2.334	2.312			
		(0.001)	(0.001)			
RAT		5.775	5.771			
		(0.001)	(0.001)			
COUP		0.233	0.225			
		(0.001)	(0.001)			
SIZE		−0.417	−0.438			
		(0.001)	(0.001)			
MOM			0.070			
			(0.379)			
CE(r)	0.055	0.088	0.088	0.052	0.076	0.075
	(0.001)	(0.001)	(0.001)			
%ΔCE	0.000	0.600	0.600	0.000	0.466	0.456
$\bar{r}$	0.066	0.123	0.123	0.066	0.108	0.102
$\bar{r}_{passive}$	0.066	0.066	0.066	0.066	0.066	0.066
$\bar{r}_{active}$	0.000	0.057	0.057	(0.001)	0.042	0.035
$\sigma(r)$	0.060	0.106	0.106	0.069	0.098	0.090
Skew	−0.235	0.262	0.276	−0.235	−2.016	−1.382
SR	0.670	0.903	0.903	0.767	0.970	0.984
$\sum w_i I(w_i < 0)$	0.000	−0.113	−0.113	0.000	−0.114	−0.097
$\sum \lvert(w_{i,t} - w_{i,t-1})\rvert$	0.656	1.155	1.168	0.574	1.684	3.250