Corporate Bond Portfolios: Bond-Specific Information and Macroeconomic Uncertainty*

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Abstract

We propose an approach to optimally select corporate bond portfolios based on bond-specific characteristics (maturity, credit rating, coupon, illiquidity, past performance, and issue size) and macroeconomic conditions (recessions and macroeconomic uncertainty measures). The approach relies on a parametric specification of the portfolio weights and allows us to consider a large cross-section of corporate bonds. We find that in periods of low macroeconomic uncertainty, the optimal corporate bond portfolio is tilted toward bonds with longer maturity and higher credit rating (high ex-ante default risk), relative to the benchmark. By contrast, in high macroeconomic uncertainty regimes, the optimal strategy exhibits a flight-to-safety aspect and favors short maturity and relatively low-credit-rating bonds. In all regimes, corporate bonds with high coupons, high past performance, and small size of issuance lead to higher certainty equivalent returns. Overall, we find that the characteristics used in the corporate bond pricing literature to proxy for various sources of risk are also useful in forming corporate bond portfolios. Conditioning on these characteristics and macroeconomic variables leads to a significant improvement in portfolio performance, with the certainty equivalent increasing about 5% per annum after conservative transaction costs. The gain in performance is evenly divided between high and low macroeconomic uncertainty regimes and is not exclusively concentrated in high-yield bonds.

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1 Introduction

The value of US corporate debt outstanding has grown steadily from $460 billion in 1980 to more than $8 trillion in 2015. From an investor's perspective, corporate bonds now constitute one of the largest asset classes, along with public equities and Treasuries.[1] A large literature studies corporate yield spreads and, specifically, to what extent their cross sectional and time series variation can be explained by proxies for credit risk, illiquidity, preference for high-coupon paying bonds ("reaching for yield"), momentum, downside risk, and fluctuations in macroeconomic conditions.[2] While we now have a better understanding of how to price corporate debt, the complementary and equally important issue of how investors should choose a portfolio of corporate bonds has received almost no attention.

In this paper, we ask whether bond-specific characteristics – such as maturity, credit ratings, coupon rate, illiquidity measures, past performance, and size of issue – can be used to select a portfolio of corporate bonds whose returns are, relative to a benchmark and after transaction costs, of economic significance? If so, what is the tilt of the optimal corporate bond portfolio, i.e. what characteristics are to be emphasized and in what direction? And how do macroeconomic fluctuations impact the composition and performance of the optimal allocation? These questions have received no attention in the empirical portfolio choice literature which has focused, almost exclusively, on equities (Brandt (2010)). Addressing them will further our understanding of how investors should optimally allocate resources in the over-the-counter (OTC) corporate bonds market, which is fundamentally different from the centralized stock market and is significantly under-studied. These questions are also of practical relevance as actively-managed corporate bond funds have attracted large inflows over the last several years. Failure to properly manage these portfolios might result not only

[1]The market value of the all publicly traded stocks in the U.S. (NYSE/AMEX/NASDAQ) was about $20 trillion at the end of 2015. The value of outstanding Treasury debt at the end of 2015 was $12.8 trillion.

[2]The corporate bond pricing literature is voluminous and we cannot do it justice in a footnote. Important papers in that literature include Elton et al. (2001), Longstaff, Mithal, and Neis (2005), and Huang and Huang (2012) (credit risk); Bao, Pan, and Wang (2011), Lin, Wang, and Wu (2011), Schestag, Schuster, and Uhrig-Homburg (2016) (illiquidity); Becker and Ivashina (2015) (reaching for yield), Jostova et al. (2013) (past performance); Bai, Bali, and Wen (2016)(downside risk); He and Xiong (2012) (rollover and credit risk);Chen, Collin-Dufresne, and Goldstein (2009), Bhamra, Kuehn, and Strebulaev (2010), and Chen (2010) (macroeconomic conditions and credit risk) and Chen et al. (2016) (liquidity and default risk over the business cycle).

in an inefficient allocation of resources, but also in sudden outflows, and increased odds of instability in that industry (Feroli et al. (2014) and Goldstein, Jiang, and Ng (2016)).

The construction of an optimal corporate bonds portfolio presents interesting conceptual challenges. The traditional mean-variance framework of Markowitz (1952) is the usual starting point for creating portfolios of stocks or broad asset classes (Campbell and Viceira (2002)). With individual corporate bonds, however, this approach is hard to implement as it involves estimating bond expected returns, and their variances and co-variances with a short time-series, large cross-section, and an unbalanced dataset.[3] Given the relatively short historical data of corporate bond returns, it is clear that the mean-variance approach is econometrically daunting, to say the least. Incorporating conditioning information–either bond-specific characteristics or time-variation of macroeconomic conditions–adds another layer of intractability. Finally, it is not clear that mean-variance is the right utility framework, given that the distribution of corporate bond returns is non-normal.

We propose an approach for choosing a portfolio of corporate bonds based of bond-specific characteristics and macroeconomic regimes. We use a modification of Brandt, Santa-Clara, and Valkanov's (2009) approach of directly parameterizing the portfolio weights of each asset as a function of its characteristics and macroeconomic variables. The main conceptual advantage of this approach is to sidestep the ancillary, yet very challenging, step of modeling the joint distribution of returns and characteristics and instead focus directly on the object of interest: the portfolio weights. We use a novel functional form of the weights that accommodates the extreme heterogeneity in corporate bond returns and characteristics. With the initial specification as a starting point, we modify the weights to capture some of the peculiarities of corporate bonds trading. Unlike equities, corporate bond trading occurs in OTC markets, and involves high transaction costs (Edwards, Harris, and Piwowar (2007), Dick-Nielsen, Feldhutter, and Lando (2012), Bessembinder et al. (2016)) and costly short selling (Asquith et al. (2013)). Moreover, turnover in corporate bond portfolios is fairly large

[3]The maturity of corporate bonds rarely exceeds 15 years which implies that the well-known difficulties of estimating a large number of the first two moments of returns and of ensuring the positive definiteness of the covariance matrix (e.g., Brandt (2010)) are even more severe than in the case of stocks. 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 or is paid off.

when compared to equities, even for passive benchmark portfolios.[4] We therefore estimate weight specifications that account for transaction costs, reduce the turnover, and penalize short selling.

The parameters of the weights are estimated by maximizing the average utility a representative investor would have obtained by implementing the policy over the historical sample period. By framing the portfolio optimization as a statistical estimation problem with an expected utility objective function implies that the estimation of the weights takes into account the relation between the bond-specific and macroeconomic characteristics and expected returns, variances, covariances, and even higher-order moments of corporate bond returns, to the extent that they affect the distribution of the optimized portfolios returns, and therefore the investors expected utility. In the empirical implementation, we assume a constant relative risk aversion (CRRA) utility which is simple and yet implies that the investor cares about all moments of the distribution of the corporate bond portfolio returns, not only means and variances. This parametric approach is parsimonious in the number of parameters to estimate, is simple to implement, and allows us to consider a large cross-section of bonds (on average, we have 966 bonds in a given month) and several characteristics.

We estimate the portfolio weights using monthly individual bond returns from TRACE, spanning the period January 2005 until September 2015. The bond characteristics that we consider – time to maturity (TTM), credit rating (RAT), coupon yield (COUP), a measure of illiquidity (ILLIQ), a measure of performance over the past six months (a.k.a. momentum, MOM), and size of the issue (SIZE)– are either from MERGENT FISD or are computed from the bond returns. We start off with a specification of the weights that is solely a function of bond-specific characteristics. Transaction costs values are taken from the recent literature (Edwards, Harris, and Piwowar (2007), Dick-Nielsen, Feldhutter, and Lando (2012), Bessembinder et al. (2016)). Moreover, we introduce a variation of the weights that allows the investor to lower her transaction costs and turnover by trading only partially to the op-

[4]For instance, the average total (round-trip) turnover of PIMCO Total Return Fund (PTTAX), Schwab Total Bond Market Fund (SWLBX), and Vanguard Intermediate-Term Bond Index (VBIIX) is 521%, 266%, and 127%, respectively, over the last five years. The high turnover is partly mechanical, due to the fact that a sizeable fraction of bonds expire every periods and the funds have to be re-invested.

timal weights. This smoothed version of the trading strategy is motivated by recent work by Garleanu and Pedersen (2013) who show that, in the presence of predictable components of asset returns and transaction costs, the optimal investment strategy is a linear combination of a hold portfolio and an actively traded portfolio.

Our results show that bond-specific characteristics are important in selecting corporate bond portfolios. The optimal allocation places significantly more weight on bonds with lower maturity, higher credit ratings, higher coupons, higher momentum, and lower size of issuance. The sign of the characteristics is consistent with the interpretation that, on average, the optimal portfolio is tilted toward variables that are often used to proxy for risk premia in the corporate bonds market. For instance, the tilt toward higher credit-risk bonds is in line with Longstaff, Mithal, and Neis (2005) who find a strong link between corporate yield spreads and credit risk. A tilt toward high-coupon-paying bonds can be interpreted as a "reaching for yield" behavior described in Becker and Ivashina (2015). The only exception is maturity for which, as we see below, the tilt is heavily dependent on the state of the macroeconomy. We find that smoothing the optimal trading strategy reduces significantly the turnover of the optimal portfolio.

We measure the economic importance of the characteristics by comparing the certainty equivalent return of the optimal portfolio to that of a value-weighted or equal weighted benchmark. The smooth version of the weights yields certainty equivalent returns of 2.6% per annum for the most conservative one-way transaction costs of 75 basis points (1.5% round-trip) and a constant risk aversion coefficient γ of 7. For the more empirically defensible values of 50 basis points transaction costs, the certainty equivalent is 5% per year. These results are likely understating the overall potential gains from the parametric approach, as they obtain purely in the cross section without factoring in macroeconomic fluctuations into the portfolio decision.[5]

Next, we introduce macroeconomic regimes into the weight functions. Specifically, we interact bond characteristics with the following index variables that capture the states of the

[5] While the characteristics are allowed to change across corporate bonds and over time, their impact on the weights is constant in this specification.

economy: NBER recessions, the macroeconomic uncertainty index of Jurado, Ludvigson, and Ng (2015), and a downside measure of risk, based on the cross-sectional distribution of corporate bond returns. We find that the optimal corporate bond weights depend significantly on the state of the economy. In expansions and low macroeconomic uncertainty, the optimal portfolio is tilted toward long maturity and high credit rating bonds. In these periods, the optimal strategy is to invest in characteristics that proxy for various sources of risk. During recessions and periods of high macroeconomic uncertainty, the coefficients on maturity and credit rating are negative, implying that the optimal strategy is to invest is low maturity and low credit risk bonds. This is essentially a flight-to-safety strategy. The certainty equivalent return of the optimal portfolio is between 4.7% (macroeconomic uncertainty) and 5.3% (NBER recessions) higher than the value-weighted benchmark. Overall, we find that macroeconomic regimes play an sizeable role in the optimal allocation of corporate debt. Our results complement recent work by Chen, Collin-Dufresne, and Goldstein (2009), Bhamra, Kuehn, and Strebulaev (2010), Chen (2010), He and Xiong (2012), and Chen et al. (2016) who argue that macroeconomic fluctuations have implications for the pricing of corporate debt.

Various extensions of the portfolio weights confirm our main findings. For instance, adding short selling costs lowers somewhat the coefficient estimates but does not drive away the portfolio performance results. Moreover, the trading patterns that we document are not exclusively concentrated in high-yield bonds. Finally, additional moment-based characteristics of bond returns, such as bond-specific volatility and skewness, only magnify the performance gains of the optimal portfolio but also lead to significant increase in turnover.

In contrast to the large literature on the pricing of corporate debt, there is very little corresponding work on the portfolio choice of corporate bonds. The closest paper to ours is Bai, Bali, and Wen (2016) who investigate the cross-sectional determinants of corporate bond returns. They find that downside risk is an important predictor of future bond returns and illustrate the economic significance of downside risk in a mean-Value-at-Risk portfolio timing framework. Their approach is completely different from ours and so are the empirical results. However, much like us, they emphasize the significance of taking into account the non-normality of corporate bond returns.

The remainder of the paper proceeds as follows. We describe the basic approach and its various extensions in Section 2. The corporate bond data is described in Section 3. The empirical results are presented in Section 4. We conclude in Section 5.

2 Methodology

Our starting point is the parametric portfolio framework of Brandt, Santa-Clara, and Valkanov (2009). We introduce a functional form of the weights that is suitable for corporate bonds data and accommodates both bond-specific characteristics and macroeconomic conditions. We pay particular attention to transaction costs, which are large in the corporate bonds market, and consider several variations of the weights, one that reduces turnover and is similar in spirit to recent work by Garleanu and Pedersen (2013), and another that incorporates costly short-selling.

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 $x_{i,t}$ that are observed by investors at time t. For example, the characteristics can be the bond's maturity (or duration), credit rating, coupon rate, and measures of illiquidity. The characteristics can also include the past six-month return, past (or forecasted) volatility and skewness, which investors estimate at time t. 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 that 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 bonds characteristics:

$$w_{i,t} = \bar{w}_{i,t} + g(\frac{1}{N_t}\theta' x_{i,t}), \tag{2}$$

where $\bar{w}_{i,t}$ are the weights in a benchmark portfolio, such as a value-weighted or other index portfolio. In the empirical section, we consider several benchmarks that are relevant for corporate bond portfolios.

The function $g(\frac{1}{N_t}\theta' x_{i,t})$ 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. For instance, Brandt, Santa-Clara, and Valkanov (2009), Parroso and Santa-Clara (2016), and Ghysels, Plazzi, and Valkanov (2016) use a linear specification to form equity or currency portfolios.[6] The linearity of $g(\cdot)$ is appealing from a tractability standpoint and produces reasonable weights when the characteristics are relatively "smooth" and do not exhibit significant variability over time (e.g. firm size). Corporate bonds characteristics, however, are prone to large changes which in turn implies significant variation in the weights and a high turnover. High turnover is undesirable particularly when trading corporate bonds which have significantly larger transaction costs and lower liquidity than stocks or currencies.

2.1.1 Logistic Parametric Portfolios

For bond portfolios, we specify the weights to be a logistic function of the characteristics:

$$\begin{aligned} w_{i,t} &= \bar{w}_{i,t} + (h(\frac{1}{N_t}\theta' x_{i,t}) - \bar{h}_t) && (3) \\ h(\frac{1}{N_t}\theta' x_{i,t}) &= \frac{1}{1+e^{-\frac{1}{N_t}\theta' x_{i,t}}}, && (4) \end{aligned}$$

[6] Specifically, Brandt, Santa-Clara, and Valkanov (2009) use $g(\theta' x_{i,t}) = \theta' (x_{i,t} - \bar{x}_t)/N_t$, where $x_{i,t} = \tilde{x}_{i,t}/\sigma_{x,t}$ are characteristics, standardized by their cross-sectional variances $\sigma_{x,t}$ and demeaned by the cross-sectional average, $\bar{x}_t = \frac{1}{N_t}\Sigma_{i=1}^{N_t} x_{i,t}$. In that linear specification, it is clear that the deviations from the benchmark portfolio sum to zero, $\Sigma_{i=1}^{N_t} g(x_{i,t}|\theta) = 0$, and therefore the portfolio weights some up to one, $\Sigma_{i=1}^{N_t} w_{i,t} = 1$.

where $\bar{h}_t = (\Sigma_{i=1}^{N_t} h(\frac{1}{N_t}\theta' x_{i,t}))/N_t$ is the cross-sectional average of $h(\frac{1}{N_t}\theta' x_{i,t})$ at time t. The logistic specification (4) effectively attenuates the impact of extreme fluctuations of $x_{i,t}$ on the weights. We demean $h(\frac{1}{N_t}\theta' x_{i,t})$ by its cross-sectional average to insure that deviations from the benchmark weights sum up to zero. The weights in (3-4) are a specific functional form of expression (2), where $g(\frac{1}{N_t}\theta' x_{i,t}) = (h(\frac{1}{N_t}\theta' x_{i,t}) - \bar{h}_t)$, so that $\Sigma_{i=1}^{N_t} g(\frac{1}{N_t}\theta' x_{i,t}) = 0$ and $\Sigma_{i=1}^{N_t} w_{i,t} = 1$.

There are alternative ways of specifying $g(\cdot)$ such that it is robust to extreme realizations of $x_{i,t}$. For instance, one can truncate extreme values of $x_{i,t}$. The advantage of the logistic transformation is its smoothness and well-known properties. The characteristics are standardized to have unit standard deviation by $x_{i,t} = \tilde{x}_{i,t}/\sigma_{x,t}$, where $\sigma_{x,t}$ is the cross-sectional variance of the raw characteristics $\tilde{x}_{i,t}$. The standardization allows us to compare the magnitudes of the coefficients θ across characteristics.

The term $1/N_t$ is a normalization that allows the portfolio weight function to be applied to an arbitrary and time-varying number of bonds. Without this normalization, doubling the number of bonds without otherwise changing the cross-sectional distribution of the characteristics results in twice as aggressive allocations, even though the investment opportunities are fundamentally unchanged.

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 characteristics fully capture all aspects of the joint distribution of bond returns that are relevant for forming optimal portfolios. This allows us to reduce the parameter space but it also implies that misspecification of the variables in $x_{i,t}$ will lead to misspecification in the portfolio weight. The choice of conditioning information $x_{i,t}$ is important as it is in any estimation problem.

2.1.2 Estimation

For a given functional form of the utility (e.g., CRRA or quadratic) and the weights in either (3-4), we estimate the parameters θ by maximizing the sample analogue of expression (1) with respect to these parameters

$$\max_{\theta} \frac{1}{T} \sum_{t=1}^{T} (u(\sum_{i=1}^{N_t} w_{i,t} r_{i,t+1})). \tag{5}$$

As bond returns are negatively skewed, in this paper we use a CRRA specification of the utility. 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.

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 are spelled out in Appendix B.

2.2 Transaction-Cost-Adjusted Returns

Investors in the corporate bonds market face significant transaction costs which might render some highly volatile strategies unprofitable. 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

$$r_{p,t} = \sum_{i=1}^{N_t} w_{i,t} r_{i,t+1} - cT_t, \tag{6}$$

where $T_t = \sum_{i=1}^{N_t} |w_{i,t} - w_{i,t-1}|$ is the overall portfolio turnover between period $t-1$ and t and c is the one-way trading cost, averaged across bonds and over time. As transaction costs penalize proportionately large weight fluctuations, the characteristics in the policy function (3-4) will improve the portfolio performance only if they generate significant after-transaction-cost returns. We use expression (6) as a starting point for incorporating transaction costs in the optimal portfolio decision.

There is considerable evidence that transaction costs vary over time and across bonds (Edwards, Harris, and Piwowar (2007), Dick-Nielsen, Feldhutter, and Lando (2012), Bessembinder et al. (2016)). We therefore allow transaction costs to vary in the cross-section and over time, $c_{i,t}$, and write the after-transaction-cost return as:

$$r_{p,t} = \sum_{i=1}^{N_t} w_{i,t} r_{i,t+1} - \sum_{i=1}^{N_t} c_{i,t} |w_{i,t} - w_{i,t-1}|. \tag{7}$$

In the empirical implementation, in addition to the constant-transaction-costs specification (6), we will use transaction costs that vary over time (c_t) and also across bonds ($c_{i,t}$).

A more involved question is whether, in the presence of transaction costs, it is optimal to trade every period to the optimum allocation. A large literature studies optimal selection with trading costs proportional to the bid-ask spread.[7] In a recent paper, Garleanu and Pedersen (2013) consider a case when trading costs are proportional to the amount of risk in the economy and expected returns are predictable. For a mean-variance investor, they show that the optimal trading strategy is a linear combination of last period's "hold" portfolio and the current optimal allocation. Importantly, their strategy involves constant trading toward, but not all the way to the optimal portfolio. In the next section, we consider a parametric version of Garleanu and Pedersen's (2013) solution and investigate whether the economic intuition of their model holds more generally.

2.3 Reducing the Turnover in Corporate Bond Portfolios

Specification (3-4) implies that investors trade every period all the way to the optimal allocation. However, in the presence of trading costs and time variation in investment opportunities, such a strategy will be very costly, especially in the context of corporate bond

[7]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 (2000), Lo, Mamaysky, and Wang (2004), Liu (2004), Garleanu (2009), Acharya and Pedersen (2005).

trading. An alternative strategy is to trade partially toward the optimum weights. A partial adjustment has two important advantages. It keeps current transaction costs low, as we are not trading all the way to the optimal weights. And future transaction costs will be low as the partial adjustments will target the new weights, which are expected to change predictably with the characteristics.

We modify the portfolio specification to accommodate partial adjustments. Each period, we have a target portfolio which is specified as:

$$w^t_{i,t} = \bar{w}_{i,t} + g(\frac{1}{N_t}\theta' x_{i,t}). \tag{8}$$

This is the portfolio policy (3) of an investor who trades all the way to the optimum. However, in the presence of transaction costs, investors can choose to re-balance only partially from their previous portfolio allocation, if the increase in portfolio performance associated with the new allocation is not sufficient to cover the transaction costs.

We define the optimal portfolio to be a weighted average of the target portfolio and a "hold" portfolio:

$$w_{i,t} = \alpha w^h_{i,t} + (1-\alpha) w^t_{i,t} \tag{9}$$

where $0 \leq \alpha < 1$. The hold portfolio at time t is

$$w^h_{i,t} = \eta_{i,t} w_{i,t-1} \tag{10}$$

and $\eta_{i,t} = \frac{1+r_{i,t}}{1+r_{p,t}}$. The hold portfolio at t is the same as the portfolio at $t-1$ with the weights changed by the returns.

The parameter α captures the degree of smoothing on the target portfolio weights. As α increases from zero to 1, more weight is placed on the hold portfolio and the turnover decreases accordingly. The combination of the hold and target portfolios effectively attenuates the effect of the characteristics on the weights. This is easiest to see if $\eta_{i,t} = 1$, i.e. the returns of asset i are equal to the portfolio return. In that case, $w^h_{i,t} = w_{i,t-1}$ and the optimal weights can be expressed as an exponentially decaying function of the signal in $w_{i,t}^t$.[8] The attenuation holds more generally, as long as $|\alpha\eta_{i,t}| < 1$.

There are a few ways to motivate the partial adjustment strategy (9). In the presence of predictable components of asset returns and transaction costs, Garleanu and Pedersen (2013) show formally that the the optimal investment strategy is a linear combination of a hold portfolio and an actively traded portfolio. The intuition of their result is very much along the lines of the discussing above: high transaction costs lead investors to trade only partially toward the optimal solution and when they do trade, they do so anticipating that the optimal allocation will change. Garleanu and Pedersen (2013) show that α is a function of the investor's risk aversion and transaction costs. While their solution obtains for a mean-variance utility and a specific modeling of transaction costs, the gist of their idea ought to hold more generally. We will map out the dependence between α, the risk aversion coefficient, and transaction costs of a CRRA investor to see whether the our results are consistent with the intuition in Garleanu and Pedersen (2013).

We can also view specification (9) as a parsimonious way to capture the dynamics of the weights. If $\eta_{i,t} = 1$, we can express the weights as $w_{i,t} = \alpha w_{i,t-1} + (1-\alpha)w_{i,t}^t$. In this autoregressive structure, the restriction is that all weights have the same autoregressive parameter. Finally, the partial adjustment specification can be thought of as a shrinkage of the target weights toward the hold weights.

We could let α be time varying as in Brandt, Santa-Clara, and Valkanov (2009). In their specification, α_t is determined essentially by the volatility of the characteristics relative to the magnitude of an exogenously specified no-trade region. Hence, in their approach α_t is calibrated (rather than estimated) for a given value of the no-trade region. We will estimate α from the data without relying on calibrating assumptions about the size of the no-trade region. We use the same approach outlined in Section 2.1.2 to estimate the smoothed version of the weights.

[8] Specifically, $w_{i,t} = \alpha \sum_{k=0}^{t-1} \alpha^j w_{i,t-k}^t + w_{i,0}$.

2.4 Macroeconomic Fluctuations

While the bond-specific characteristics in expression (4) vary over time, their impact on the optimal weights, θ, is constant. It is reasonable, however, to conjecture that changes in the overall economy might lead to different optimal corporate bond allocations. Indeed, evidence from the corporate bond pricing literature suggests that default and liquidity risk have a larger effect on corporate bond yields during economic downturns (Edwards, Harris, and Piwowar (2007), Bao, Pan, and Wang (2011), Dick-Nielsen, Feldhutter, and Lando (2012), and Friewald, Jankowitsch, and Subrahmanyam (2012)). Chen et al. (2016) provide a compelling model that captures the interaction of default and credit risk over the business cycle.

We use the parametric approach to estimate the optimal allocation of corporate bonds during macroeconomic regimes. Specifically, suppose that we are interested in whether the optimal allocation is different during the recent financial crisis of 2007-2009 versus the non-crisis period. Let Z_t be a variable that captures the state of the economy, such that Z_t equals to 1 during the crisis period and zero, otherwise. Then, the interaction $x_{i,t} \times Z_t$ captures the bond characteristics during the financial crisis. By including $x_{i,t} \times Z_t$ and $x_{i,t} \times (1 - Z_t)$ in expression (3), we have two sets of θ parameters, for the crisis and non-crisis periods. This is the parametric portfolio analogue to running regressions with regime dummy variables.

We aim to answer the following three questions by interacting macroeconomic regimes with the other characteristics. First, does the effect of the characteristics change with the regimes? Second, would the performance of the portfolio improve once we account for the changes in macroeconomic regimes? Finally, is the improvement in portfolio performance clustered in any particular regime? We will see in the empirical section that our approach provides clear answers to these questions.

2.5 Costly Short-Selling

Positive and negative weights in expression (7) are treated symmetrically which implies that shorting corporate bonds does not involve additional costs. However, there is a significant literature on short sales and their impact on asset values.[9] That literature has almost exclusively focused on equities, with two exceptions: Nashikkar and Pedersen (2007) and Asquith et al. (2013). Given that borrowing and shorting of bonds takes place in the OTC market, whereas in the stock market borrowing is OTC and short-selling takes place on an exchange, it is reasonable to conjecture that the costs of shorting bonds is larger than for equities.

Asquith et al. (2013) provide a thorough description of how corporate bonds are borrowed and shorted. Using a proprietary dataset, they estimate that the costs of shorting corporate bonds is 10 to 20 basis points. However, as the source of their data is a major depository institution, their estimates do not take into account additional search costs that corporate bond investors might face (Duffie, Garleanu, and Pedersen (2005)). While search frictions are hard to quantify, we take the Asquith et al. (2013) estimates as a lower bound of the total borrowing costs faced by investors in that market.

We capture costly shorting of corporate bonds by modifying the portfolio return as

$$r_{p,t} = \sum_{i=1}^{N_t} w_{i,t} r_{i,t+1} - \sum_{i=1}^{N_t} c_{i,t} |w_{i,t} - w_{i,t-1}| - \sum_{i=1}^{N_t} d_{i,t} |w_{i,t}| I_{w_{i,t}<0}, \tag{11}$$

where $I_{w_{i,t}<0}$ is an index variable that equals to one if weight $w_{i,t}$ is negative and zero, otherwise. The cost of shorting a bond during a period is $d_{i,t}$ and the total cost of all short positions is $\sum_{i=1}^{N_t} d_{i,t}|w_{i,t}|I_{w_{i,t}<0}$. Investors who have large costs of borrowing bonds (i.e. large $d_{i,t}$) will effectively be facing a no-short sale constraint.[10] By varying the magnitude of $d_{i,t}$, we can map out the impact borrowing costs have on the optimal portfolio. For simplicity, we will assume that $d_{i,t}$ is either constant across bonds and time, d, or that the cost of borrowing

[9] Papers that document the borrowing and shorting costs in the equity market are D'Avolio (2002), Geczy, Musto, and Reed (2002), Jones and Lamont (2002), Ofek, Richardson, and Whitelaw (2004), and Kolasinski, Reed, and Ringgenberg (2013).

[10] An alternative way of imposing a no-short sales constraint is to specify the optimal policy so that the weights are non-negative, as in Brandt, Santa-Clara, and Valkanov (2009)).

is higher during periods of high macroeconomic uncertainty.

2.6 Benchmark Portfolios

The benchmark portfolio, $\bar{w}_{i,t}$, 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 value-weighted or equal weighted portfolio which are transparent, investable (feasible), and fairly passive in the sense that they involve little turnover.

With corporate bonds, we use the following two benchmarks. The first benchmark sets the portfolio weights equal to the issuing amount of a bond relative to the issuing 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 value of the bond's issue size. Its weights change when bonds exit the sample (maturity, default, etc.) or new issues enter the sample. It differs from the value-weighted portfolio in the equity literature as monthly price fluctuations do not result in portfolio changes and need for re-balancing. This portfolio captures the spirit of a value-weighted index while keeping turnover low.

The second benchmark is equal weighted and assigns the same weight to all bonds. Similarly to the value-weighted portfolio, its turnover is low as weights change only when bonds exit or enter the sample. The equal weighted portfolio puts more weight, relative to the value-weighted, on small issues. We show in the empirical section that the returns of the value- and equal weighted portfolios are highly correlated with the returns of widely-used bond indices, such as the Bloomberg-FINRA Corporate Bond Index, and are therefore suitable benchmarks for our analysis.

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, it is practically difficult to implement a true hold strategy, because the universe of corporate bonds changes significantly from period to period. On average, about 36% of bonds mature in any given year and drop out from 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 value- and equal weighted portfolios that we consider change little and are very close in spirit to a passive hold portfolio.

The turnover that is empirically observed in corporate bond mutual funds is sizeable, partly due to the periodic re-balancing related to the maturity of the assets. As an example, the Vanguard Intermediate-Term Bond Index fund, which aims deliberately to reduce turnover and trading costs, reports an average annual turnover of 127% for the 2012-2015 period. Funds that trade more actively have a much higher turnover. For instance, the average annual turnover of PIMCO's Total Return Fund, one of the most widely held bond funds, is approximately 490% over the 2012-2015 period.[11] Edwards, Harris, and Piwowar (2007) note in their study of corporate bonds trading that "the most surprising statistic is that of the high sample turnover", which they report is 119% annually, during their 2003-2005 period.

3 Data

3.1 Sample Construction

We use two main sources of data for our analysis. From MERGENT FISD, we obtain information on bond characteristics, and TRACE is the source of US corporate bonds transaction prices that we use to compute returns. Our sample spans January 2005 until September 2015, covering roughly 10 years of data.[12] In TRACE, we follow standard data cleansing procedures described by Dick-Nielsen (2009).[13] Furthermore, we implement the price filters used in Edwards, Harris, and Piwowar (2007) and Friewald, Jankowitsch, and Subrahmanyam (2012).[14] We consider only straight (simple callable and puttable) bonds, thus excluding

[11]The turnover data for the Vanguard Intermediate-Term Bond Index fund (VBIIX) and Pimco's Total Return Fund (PTTAX) are from Morningstar: `http://www.morningstar.com/`.

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

[13]We delete duplicates, trade corrections, and trade cancelations on the same day. Moreover, we delete reversals, which are errors detected not on the same day they occurred.

[14]We adopt a median and a reversal filter. The median filter eliminates any transaction where the price deviates by more than 10% from the daily median or from a nine-trading-day median, which is centered at the trading day. The reversal filter eliminates any transaction with an absolute price change that deviates at the same time by at least 10% from the price of the

bonds with complex structures.

We compute the return of bond i in month t as:

$$R_{i,t} = \frac{(P_{i,t} + AI_{i,t} + C_{i,t}) - (P_{i,t-1} + AI_{i,t-1})}{(P_{i,t-1} + AI_{i,t-1})} \tag{12}$$

where $P_{i,t}$ is the volume-weighted average price of bond i on the last trading day of month t on which at least one trade occurs, P_{t-1} is the same price estimate in the previous month and $AI_{i,t}$ is the accrued interest of the bond. $C_{i,t}$ is the coupon paid between month-ends $t-1$ and t.[15] This is a standard definition of corporate bond returns (see e.g. Lin, Wang, and Wu (2011)).

We re-balance the portfolio on the last trading day of each month. To prevent stale prices from entering the returns 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.[16] Bonds are included in the sample one month after issuance and excluded two months before maturity to guarantee tradeable prices.

3.2 Bond Characteristics

The bond-specific characteristics we use as conditioning variables in our portfolio optimization are time to maturity (TTM), credit rating (RAT), coupon (COUP), illiquidity (ILLIQ), momentum (MOM), and the size of the bond offering (SIZE). TTM, RAT, COUP, and SIZE are directly available from MERGENT, while the remaining characteristics are estimated with transaction data from TRACE.

TTM is the difference in years between the maturity date of the bond and the day on which the monthly return is calculated.[17] RAT is the mean of credit ratings from Moody's, Standard and Poor's, and Fitch. We assign integer values to the different rating grades, with

transaction before, the transaction after and the average between the two.

[15] The accrued interest is calculated according to Morningstar (2013).

[16] This measure is based on Bessembinder et al. (2009) and allows to have a better estimate of the price, given that it takes into account the transaction volume. Moreover, it guarantees more powerful statistical tests on bond returns.

[17] We prefer TTM over bond duration (DUR) since calculating the latter requires the bond yield, which is not always available in TRACE and, when present, is not always precise. Our results hold if we use DUR instead of TTM.

1 being the highest and 21 the lowest credit score. Hence, bonds with high RAT score 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. We compute ILLIQ using the illiquidity measure of Bao, Pan, and Wang (2011). On trading day d, the measure is given by the auto-covariance $\gamma_d = -Cov(\Delta p_{t+1}, \Delta p_t)$, where Δp_{t+1} is the log transaction price of the bond. We implement the measure by taking into account the covariance of trades during the previous 20 working days, which translates into a rolling window of approximately one month.[18] The momentum variable MOM is computed as the monthly compounded return between months $t-7$ and $t-1$, following Jostova et al. (2013). SIZE is the dollar value of the offering amount of the respective bond issue.

To analyze the impact of the second and third moment of bond returns on optimal portfolio weights, we compute the volatility (VOL) and skewness (SKEW) of corporate bond returns. These additional bond-specific characteristics are estimated with the whole return history of a specific bond, i.e. from the time the bond enters our sample until $t-1$. The expanding window procedure allows us to include as much information as possible when computing these characteristics.

We leave a one-month lag between bond-specific characteristics and monthly returns 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.[19] We consider the logarithm of TTM, ILLIQ, and SIZE to normalize the cross-sectional distributions of those characteristics.

[18]The choice of the rolling window size is largely arbitrary. Our choice is similar to Dick-Nielsen, Feldhutter, and Lando (2012), and driven by the fact that we rebalance our portfolio every month. Results are similar by using a rolling window of one week. In order to avoid extreme outliers, we winsorize the illiquidity measure at the 0.5% level. As an alternative, we analyze the price dispersion measure based on Jankowitsch, Nashikkar, and Subrahmanyam (2011). The results are similar and available upon request.

[19]Given our definition of MOM, this implies that we drop observations without a full 6 month lagged return history. This as well ensures that the characteristics VOL and SKEW are not based on old information.

3.3 Macroeconomic Conditions

To investigate whether different macroeconomic conditions affect the optimal allocation of bonds, we use three variables to proxy for the state of the economy. The first variable is based on NBER's official dates of recessions and expansions (National Bureau of Economic Research (2010)). We define a dummy variable, CRISIS, that equals to one during a recession, and zero otherwise. In our sample, the recession period coincides with the financial crisis between December 2007 and June 2009. The second variable is based on Jurado, Ludvigson, and Ng's (2015) comprehensive index of macroeconomic uncertainty. We create a dummy variable, MU, which equals one when the index D12 is more than one standard deviation above its mean and zero otherwise.[20] The third variable, DOWN, captures the downside risk in the corporate bond market during our sample period. We first create a monthly proxy for downside risk by taking the lowest 10% quantile of corporate bond returns in each month. Second, we sort the monthly downside risk measure and consider the lowest 25% as distress months. DOWN is equal to one in month t if at least 3 out of the previous 5 months were distress months.[21]

The three macroeconomic variables – CRISIS, MU, and DOWN – capture significant changes, or regime shifts, in the economy. The CRISIS variable is constructed ex-post, after the NBER publishes official start and end dates of U.S. recessions. MU and DOWN however are forecasts of future economic uncertainty and are available to the investor at time $t-1$ to build a trading strategy.

3.4 Summary Statistics

Table 1 reports basic summary statistics of our bond sample, of selected benchmark indices, and of the bond characteristics. Panel A focuses on the composition of the sample used in the estimation which, by construction, includes only the most tradeable part of the TRACE universe. Our sample consists of 966 bonds per month on average, with a minimum of 667

[20] This period of extreme macroeconomic uncertainty fully overlaps with the NBER recession period and includes additional non-recession months.

[21] Note that our measure is robust to alternative definition of downside risk quantiles (e.g. 2%, 5%, or 15%).

bonds during the crisis period (March and April 2009) and a maximum of 1206 in March 2006. In total, 4,491 bonds appear at least once in our sample, amounting to approximately \$2 trillion of outstanding debt. These numbers are similar to studies that use a comparable sample of traded bonds, such as Bao, Pan, and Wang (2011) and Israel, Palhares, and Richardson (2016).[22]

As bonds mature and new bonds are issued, our sample changes monthly. We therefore report statistics on the number and outstanding value of bonds coming in and dropping out of the sample each month, mainly because of new issuances or maturity. On average, about 6% $((28 + 29)/966)$ of the bonds enter or exit the sample every month, resulting in an annualized (equal weighted) turnover of 72%. In value terms, this "automatic" turnover is 3.7% $((13 + 9)/597)$ of the debt outstanding in our sample, or about 13.3% annualized. The changing composition of the sample implies that even a passive corporate bond portfolio involves a significant amount of re-balancing.

Panel B reports correlations and summary statistics of the equal and value-weighted (EW and VW) portfolios in our sample of bonds. We will use these portfolios as benchmarks in the assessment of our optimal trading strategy. In addition, we report summary statistics for other widely used corporate bond indices, which are the one-month secondary market T-bill (TBill) and the FINRA-Bloomberg Investment-Grade (CorpIG) and High-Yield (CorpHY) total return corporate bond indices.[23] We also consider a weighted average of the two indices (CorpMix), based on the relative amount of investment and speculative grade bonds in our sample each month. Finally, as a reference, we include the S&P 500 total return index.

The correlation of the EW and VW portfolio returns is 97.5%. The EW and VW returns are also very highly correlated with the FINRA-Bloomberg index returns, which are commonly used in the industry as benchmarks. The correlations range from 78% for the CorpHY index to 95% for our CorpMix index, the latter of which better reflects the composition of

[22]In comparable years of the respective samples, Bao, Pan, and Wang (2011) (Israel, Palhares, and Richardson (2016)) have on average 698 bonds (1297 bonds), and \$ 715 billion (\$ 647 billion) outstanding debt per year, which compares to our 1458 bonds (1457 bonds) \$ 548 billion (\$ 718 billion) of outstanding amount. The sample periods that we use for this comparison are 2005-2008 for Bao, Pan, and Wang (2011) and 2005-2015 for Israel, Palhares, and Richardson (2016).

[23]We choose the FINRA-Bloomberg corporate bond indices because they are based on the most frequently traded part of TRACE, similar to our bond sample. Moreover, they are among the most widely used indices when it comes to US corporate bonds. See `https://www.finra.org/sites/default/files/AppSupportDoc/p015158.pdf` for further details.

our sample. The Sharpe ratio (SR) of the VW (EW) index is 0.603 (0.595) and lies between that of the CorpHY and CorpIG indices, which have Sharpe ratios of 0.394 and 0.716, respectively, and is similar to the SR of the CorpMix index, at 0.675. These summary statistics suggest that the VW and EW portfolios are very comparable to the FINRA-Bloomberg benchmarks and are suitable for evaluating active corporate bond strategies.

In Panel C, we present summary statistics of bond-specific characteristics without transformations in order to preserve economic magnitudes. The median bond in our sample has a time to maturity of 5.384 years, a modified duration of 4.5, a rating score of 6.333 (which corresponds to an A rating), a coupon of 5.750% of face value, and an issuing amount of about USD$400 million. The median illiquidity measure is 0.328 and the median momentum is 2.6%. As expected, the correlation between TTM and DUR is high, while the other variables have comparably lower correlations. The variable that exhibits the most correlation with the other characteristics is COUP, but it is never above 0.4. In our sample, bonds with high coupons tend to be of longer maturity and higher credit rating (i.e higher ex ante default risk). MOM is positively correlated with RAT, consistently with the findings of Avramov et al. (2007): momentum is stronger among low-rated assets. SIZE is slightly negatively correlated with all other variables, RAT in particular.

4 Results

We present results for several parameterizations of the optimal portfolio weights of a CRRA investor with risk aversion $\gamma = 7$, unless stated otherwise. In all cases, the benchmark is either the value- or equal weighted portfolio. We begin with cases in which the investor takes into account only bond-specific characteristics and faces transaction costs. Second, we introduce a smoothing of optimal weights as a way of reducing the portfolio turnover. Third, we test the sensitivity of our analysis to different benchmarks and combinations of characteristics. Fourth, we estimate optimal portfolios that explicitly account for macroeconomic regimes. Fifth, we examine how the optimal portfolio allocations change in the presence of costly short-selling. Finally, we present important extensions such as dividing the sample into investment grade and high-yield bonds as well as introducing volatility and skewness as additional characteristics (Bai, Bali, and Wen (2016)).

4.1 Optimal Corporate Bond Parametric Portfolios

In Table 2, we display results for the case in which the portfolio weights are a function of the following characteristics: TTM, RAT, COUP, ILLIQ, MOM, and SIZE. The parameters of the optimal weights are estimated for a grid of one-way fixed transaction costs (10*bp*, 25*bp*, 50*bp*, and 75*bp*), for time-varying transaction costs (TS), as well as cross-sectional and time-varying (CS-TS) transaction costs. One-way transaction cost estimates in the literature range from 25*bp* to 50*bp*. We include 75*bp* as conservative trading costs (Edwards, Harris, and Piwowar (2007)).[24] The table is divided in three sets of rows, describing (1) the impact of individual characteristics on the optimal weights and their standard errors, (2) average portfolio weight statistics, and (3) annualized performance measures of the optimal portfolios, respectively.

The first set of rows displays the marginal impact of the characteristics on the optimal portfolio weights, in basis points, and the p-values of estimated θs in parentheses, based on bootstrapped standard errors.[25] For all transaction costs specifications, the investor optimally tilts towards bonds with a shorter time to maturity, higher credit rating (higher ex ante default risk), higher coupon, higher illiquidity, stronger momentum, and smaller issue size. As expected, higher transaction costs penalize active trading and hence reduce the overall impact of the characteristics. In most of the discussion below, we focus on the results with the one-way 75*bp* transaction cost as it is the most conservative.

To understand the economic magnitude in Table 2, it is useful to discuss the results

[24]One-way transaction costs of 75*bp* are, strictly speaking, applicable for very small bond issues at the beginning of our sample. For details on the choice of the level of transaction costs see Appendix A.

[25]The non-linearity of $g(\cdot)$ implies that the parameters θ cannot be interpreted as the marginal impact of changes in $x_{i,t}$ on the optimal weights. The θs capture the marginal impact only if $g(\cdot)$ is linear in the characteristics, as in Brandt, Santa-Clara, and Valkanov (2009). Hence, we evaluate 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. Appendix C contains the exact steps of the computation.

in more details. The marginal impact of RAT, for instance, is about $3bp$, for the $75bp$ transaction costs case. The average bond in our sample has an average rating of about 7.3 (A- rating) and a standard deviation of 3.7 (Table 1). Take two bonds, one with a RAT one standard deviation above the mean (11 or BB+) and another with a RAT one standard deviation below the mean (3.6 or AA). Everything else equal, the weight on the first bond will be $3bp$ higher than the average, whereas the weight on second bond will be lower by the same amount. Similarly, if we consider COUP and its impact of $10.988bp$, a one-standard deviation increase (decrease) of the coupon rate of an average bond from about 5.5% to 7.2% (3.8%) implies that the weight will increase (decrease) by about $11bp$. As these are numbers for individual bonds, they seem reasonable. If we aggregate over the entire cross-section of about 988 bonds per month (Table 1), or even a fraction thereof, we observe that the overall impact of the characteristics on the weight is extremely economically significant. The underlying coefficients θ are estimated quite precisely, given the large cross-section of bonds.

The second set of rows summarizes the distribution of the optimal portfolio weights. The VW and EW benchmarks in the first two columns account for fixed transaction costs of $75bp$, which is also the focus of the discussion below. The average weight in a single bond is 0.166% which is close to the one of the benchmarks (0.11%). The average maximum and minimum weights of the optimal portfolios are reasonable, -0.586% and 1.261%, respectively, and are not extreme even for low transaction costs. They are in line with the min and max values of the VW benchmark: 0.002% and 1.090%, respectively. Our optimal portfolio has an overall short position of 29.1%, which not not extreme, but increases significantly with lower transaction costs. The yearly portfolio turnover of 535%, which is significantly higher than that of the benchmark, is in line with turnover levels of widely held corporate bond mutual funds, as discussed in Section 2.6. The turnover also increases significantly when we lower transaction costs. The results for the time-varying and cross-sectional transaction costs, in the last two columns, are comparable to our reference specification. Overall, these results show that, for reasonable transaction costs, the optimal portfolios do not rely on extreme bets to achieve the performance levels that we turn to next.

The last set of rows in Table 2 report annualized performance measures of the optimal portfolios. The benchmark portfolios have a certainty equivalent (CE) return of about 3%. The optimal portfolio delivers a CE return of between 4.4% to 13.6%, depending on transaction costs. As expected, there is a monotonic negative relation between CE returns and transaction costs. Even for the conservative 75*bp* transaction cost case, we observe more than 40% increase in the CE return per annum.[26] For more realistic transaction costs, such as 50*bp*, the CE return is 6.4%, an increase of more than 100% per year. These numbers are highly statistically and economically significant. The reference optimal portfolio exhibits a higher return than the benchmarks but a similar volatility, which translates into a Sharpe ratio of 0.64 compared to 0.55 for the benchmark. Interestingly, the optimal portfolio has higher skewness, which validates our earlier claim that taking into account higher moments of corporate bond returns might be beneficial. The performance of the TS and CS-TS portfolios are, once again, comparable to the performance of the 75*bp* reference specification. The portfolio performance improves with decreasing transaction costs, yielding Sharpe ratios of up to 1.325 that are mostly driven by a significant increase in average returns.

An interesting parallel emerge between our results and findings in the corporate bond pricing literature. Namely, the optimal portfolios in Table 2 are tilted toward characteristics that proxy for various sources of risk. For instance, bonds with higher default risk (high RAT) have higher weights. Longstaff, Mithal, and Neis (2005) find a strong link between default risk and corporate yield spreads. Similarly, bonds with high coupons have higher weights. This finding can be reconciled with the "reaching for yield" behavior described in Becker and Ivashina (2015). For moderate transaction costs, we find that illiquid bonds (high ILLIQ) have higher weights. Lin, Wang, and Wu (2011) use the same measure and find that illiquid corporate bonds have higher average returns than liquid ones. Bonds with high past return performance (high MOM) have higher weights. Jostova et al. (2013) document momentum mostly in non-investment-grade corporate bond returns. From that perspective, the only characteristic with an unexpected sign is TTM. We will see in Section

[26]Note that ΔCE in Table 2 is calculated on the basis of a benchmark with the same level of transaction costs of the respective optimal portfolio.

4.4 that the sign on TTM is entirely driven by the recent financial crisis. Specifically, the coefficient of TTM is different across macroeconomic regimes. All characteristics turn out to be statistically significant, except for illiquidity for high transaction costs. This result is easy to understand as high transaction costs penalize illiquid bonds particularly severely and make them less desirable from the investor's perspective.

We also tried zero transaction costs and low-transaction costs specifications. The coefficients that we obtain are extremely large, and so is the CE return. For the no-transaction cost case, we obtain a CE return of 25% per year and a turnover of about $7,000\%$ per year. In the absence of transaction costs penalty and given the heterogeneity in characteristics, the optimizer is essentially looking for extreme portfolio weights. The max and min portfolio weights are also extreme and so is the short position of this portfolio. These results confirm our prior that transaction costs have to be taken into account in a corporate bond portfolio allocation.

4.2 Reducing the Turnover by Smoothing the Weight Adjustments

Table 3 displays estimates of the smoothing parameter α for different levels of transaction costs and risk aversion. We present results for fixed transaction costs of $50bp$ and $75bp$ and a risk aversion coefficient of $\gamma = 5$ and 7.[27] The smoothing parameter is estimated following a two-step procedure. First, we estimate the optimal coefficients θ of the bond-specific characteristics and, second, we optimize α given the estimated values of θ from the first step. The table contains the optimal α along with the characteristics' marginal impact and their bootstrapped p-values in the first set of rows. The second and third set of rows show average weight statistics and annualized performance measures, respectively.

The estimated α is always significant and lies between 0.5 and 0.56 in all portfolio specifications. This means that the investor optimally trades half-way from the previous (hold) position toward the target. Consistent with the theoretical results of Garleanu and Pedersen

[27] Results for a larger grid of cs and γs are available upon request.

(2013), the trading rate increases (and therefore α decreases) when transaction costs are low and risk aversion is high. The intuition is as follows. When transaction costs are high, the investor trades less aggressively. If risk aversion is high, the utility cost of deviating from the optimal trade portfolio is larger and, therefore, the investor trades more closely towards the target.

We now focus on the $\gamma = 7$ results which are exactly comparable to those in Table 2. Allowing the investor to smooth his trading yields significant benefits in terms of portfolio turnover and performance. The average annualized turnover drops approximately by half for transaction cost levels of $50bp$ (569% vs. 1082%) as well as $75bp$ (264% vs. 531%). At the same time, the percentage gains in CE return are considerable with respect to the parametric portfolios without smoothing: 151.5% vs. 93.9% for transaction costs of $50bp$ and 83.9% vs. 41.9% for transaction costs of $75bp$. Overall, allowing the investor to trade only partially toward the target portfolio leads to a significant improvement of the optimal portfolio allocation as it reduces turnover significantly.

4.3 Variable Selection

Once we have established that the set of characteristics TTM, RAT, COUP, ILLIQ, MOM, and SIZE significantly improve the portfolio performance, in Table 4 we investigate the sensitivity of our approach to various combinations of these characteristics. We present both a value-weighted (VW) benchmark, together with the optimal portfolios for different combinations of the characteristics. For each combination, we display portfolios with and without smoothing.

There is a clear difference among optimal portfolios that rely on TTM, RAT, and COUP with respect to those that include all characteristics. While TTM, RAT, and COUP do not seem to significantly improve the performance with respect to the passive benchmarks, the inclusion of ILLIQ, MOM, and SIZE leads to a sizable increase of the performance. Consistently, turnover increases when including these three bond-characteristics. In line with these results, the smoothing plays a role only once ILLIQ, MOM and TTM are included, leading to an higher CE return and to a turnover which is almost half (263% vs 540%) of that in the portfolio without α. Interestingly, the sign of RAT changes when not taking into account ILLIQ, MOM, and SIZE. These findings are surprising and are worth further investigation. We will see that once we condition on macroeconomic regimes, the parameter on RAT changes with the regime.

4.4 Macroeconomic Conditions

In tables 5 and 6, we introduce variables proxying for macroeconomic conditions. Each bond-specific characteristics is interacted with a dummy that equals one in economic downturns and zero otherwise. The estimations in these tables take into account transaction costs of 75*bp*. We offer three alternative definitions of economic regimes. In table 5, we use the National Bureau of Economic Research (2010) timing of recessions and expansions, while table 6 presents results based on the macroeconomic uncertainty measured by the H12 index of Jurado, Ludvigson, and Ng (2015) and a downside risk measure based on the cross-sectional distribution of corporate bond returns.[28] We interact the bond-specific characteristics with these macro variables and present results both with an without smoothing. Additionally, in table 5, we include different variable combinations along the lines of table 4. The tables are divided in five sets of rows, displaying the marginal impact and p-values of bond-specific characteristics during the non-crisis period, marginal impact and p-values during economic downturns or macroeconomic uncertainty, optimal α when applicable, average weight statistics, and annualized performance measures. We first discuss the results in table 5 for the NBER recession/expansion periods. We then briefly compare our findings with the two alternative macroeconomic measures in table 6, which contains very similar results.

When we condition our portfolio on the NBER dummies, the results are striking: the coefficients on the bond characteristics during expansions are very different from those during recessions. In expansions, the optimal portfolio tilts towards bonds with longer time to maturity, worse rating, higher coupon, higher past momentum and smaller issue size. These

[28]For exact definitions of the three measures, see Section 3.3.

are all characteristics used to proxy for various sources of risk in corporate bonds. In recessions, the optimal portfolios favors safer bonds, those with shorter time to maturity and better credit rating. The marginal impact on COUP and MOM, while of similar sign in both regimes, is much larger during crises periods. The only characteristic that does not exhibit significant changes across macroeconomic regimes is the size of the issue (SIZE). Moreover, the difference in regimes is observed in all columns of the table. The signs of the characteristics do not change across the different specifications and variations in marginal impact are relatively small. Interestingly, the magnitude of the marginal impact coefficients is in general higher for the recession period, reflecting the higher volatility in the returns observed in the last financial crisis. In line with the results presented in table 2, all coefficients are statically significant except for illiquidity. The portfolio strategy that emerges from table 5 is that, in expansion, it is optimal to tilt generally toward riskier bonds while, in crisis situations, it is optimal to adopt a flight-to-safety strategy and to favor bonds with shorter time to maturity, lower default risk, high coupons, and higher momentum.

The average sum of negative weights (short position of the portfolio), which ranges from 28% to 41.7%, is close to that observed in Table 2 for the specification with transaction costs of 75*bp*. The turnover however is significantly lower than in Table 2, where the annualized turnover is 535%. Conditioning on the state of the economy leads to a significant reduction in annualized turnover that drops to 416% in the full model and to 269% when excluding MOM.[29]

The third set of rows contains the portfolio performance statistics. Conditioning on NBER dummies leads to significant improvement in performance, relative to the specification in Table 2. The percentage gain in CE return is 170% (vs. 41%), the average annualized return is 13.5% (vs. 6.8%), and the Sharpe ratio is 1.06 (vs. 0.64). Interestingly, once we only include TTM, RAT, and COUP, the CE return percentage gain also improves significantly compared to the standard specification in Table 4 (148% vs. 9.7%). This is due to the fact that TTM and RAT have very different coefficients in the two regimes. If we consider

[29]Momentum is typically a short-term factor and intuitively should lead to less trading once it is not taken into account.

the full period alone, we are averaging over this time variation, which leads to the weaker performance. Interestingly, once we account for macroeconomic conditions, the effect of smoothing through α becomes marginal: the CE return increases from 8.4% to 8.5% and turnover decreases slightly from 416% to 372.6%.

In Table 6, the results using alternative macroeconomic proxies are qualitatively similar. The optimal portfolio based on the economic uncertainty index of Jurado, Ludvigson, and Ng (2015) is closest to the one with NBER dummies. The portfolio based on downside risk in the corporate bond market has slightly lower CE return and Sharpe ratio, which is perhaps due to the fact that this measure is noisier and takes into account only the uncertainty present in the corporate bond market instead of the whole economy. Smoothing through α seems to have a stronger impact when using downside risk, while it leads only to marginal improvements when adopting the economic uncertainty index.

Overall, our results show that macroeconomic variables have an important role in explaining corporate bond returns. Taking them into account when choosing an optimal portfolio significantly improves the risk-adjusted performance. To the best of our knowledge, we are the first to explicitly condition on macroeconomic regimes when forming corporate bond portfolios. While our approach simply distinguishes between economic up- and downturns, the results are extremely encouraging and can be seen as a useful starting point for future research in this direction.

4.5 Costly Short Selling

Table 7 shows optimal portfolios with different levels of short selling penalization, which is defined separately for economic up- and downturns. All portfolios are based on a fixed transaction cost of $75bp$ and take into consideration the NBER recession period from December 2007 till June 2009. The column names indicate the level of short selling penalization in basis points that is applied to the non-crisis and crisis period, respectively. We display in four separate sets of rows: (1)-(2) the marginal impact and p-values for both economic regimes, (3) average weight statistics, and (4) annualized performance measures.

We find that a stronger penalization of short selling leads to lower coefficients and slightly lower significance for some of the bond-specific characteristics, as it is the case for higher levels of transaction costs. However, except for coupon that gets close to zero, all characteristics keep the original sign, and their economic interpretation is identical to that discussed in Section 4.4 before. When looking at average weight statistics, introducing costly short selling significantly impacts the short positions of the optimal portfolios, as expected. While about 63% of the portfolio is invested in short positions when no penalization is applied, this amount decreases to less than one fourth (13.5%) when using conservative short selling costs of 40*bp* (non-crisis) and 80*bp* (crisis), respectively. Additionally, higher costs lead to optimal portfolios with less extreme weights overall.

The effectiveness of the short selling penalization is strongly supported by the performance measures. Even under the most conservative short selling costs (40*bp* / 80*bp*), the gain in CE return of 106.5% with respect to the value-weighted benchmark is still remarkable.

The short selling penalization demonstrates to be a parsimonious, yet effective way to decrease the short positions in an optimal parametric portfolio, without excessively decreasing the performance.

4.6 Investment Grade and High-Yield Bonds

In this section, we present optimal portfolios exclusively based on either investment grade (IG) or high-yield bonds (HY). The overall sample of 116,932 bond-month observations (4,491 single bonds) is divided in a subsample of 93,659 bond-month observations (3,994 single bonds) for IG and 23,273 bond-month observations (1,049 single bonds) for HY. This division is especially interesting as many mutual bond funds only invest in one of the two rating categories.

We estimate optimal bond portfolios for a wide range of transaction costs, assuming them to be lower (higher) for IG (HY) bonds than in our 75*bp* reference case.[30]. Table 8 reports in four separate sets of rows: marginal impact and p-values for both economic regimes, average

[30]For details on the choice of transaction cost levels, see Appendix A

weight statistics and annualized performance measures. The results are presented in Table 8.

The marginal impact of bond-specific characteristics for portfolios based on the IG subsample is similar to the one for the full cross-section of corporate bonds (Table 5). The investor tilts towards safer assets in economic downturns and chases after risk premia in normal periods. However, there are few differences from the full sample. The characteristic SIZE flips the sign during the crisis period, i.e. the optimal portfolios are tilted towards bigger (and potentially safer) bond issues. This is consistent with the fact that investors tend to invest into safer assets during economic downturns. Second, RAT is positive in general and changes sign when decreasing transaction costs in the non-crisis period. This suggests that the strong cut-off in the pricing of default risk is given by the investment-speculative grade threshold, and that once a bond is IG, the rating factor has less importance.[31] Third, MOM seems to have a minor impact compared to the full sample, being insignificant during downturns and of lower magnitude outside of the crisis. This is consistent with Avramov et al. (2007) and Jostova et al. (2013), who find momentum to be particularly strong for firms with high credit risk: a group that is missing in a sample composed of IG bonds.

As before, the turnover drops significantly with increasing transaction costs, from 878% to 464%. The annualized performance is lower than for the full sample, but the CE return still increases significantly by up to 108.8% for the transaction costs of 30*bp*.

As for the IG subsample, the portfolios based on HY bonds show evidence of a flight to safety behavior during the crisis period. As expected, momentum is positive and significant outside of the crisis. Note that the marginal impact of MOM for HY is comparable to IG in absolute terms, but relatively much higher given the large differences in transaction costs among the two subsamples.

Annual turnover turns out to be higher for portfolios based on HY bonds, decreasing from 800% to 761% with increasing transaction costs. The performance of such portfolios, measured by the increase in CE return, is intuitively higher than for portfolios based on IG

[31] Among institutional investors, many have restrictions in investing in HY bonds, while there are no particular boundaries for IG securities.

bonds, being between 215.5% and 194.2%.[32]

4.7 Volatility and Skewness

Table 9 presents optimal portfolios taking into account VOL and SKEW in addition to the previously discussed bond-specific characteristics. For ease of interpretation, only the marginal impact and p-value of VOL and SKEW are shown, along with average weight statistics and annualized performance measures.

We find that the optimal portfolios consistently and significantly tilt toward bonds with lower volatility and positive skewness. The investor therefore dislikes bonds which showed high return variability in the past and invests in bonds whose distribution is skewed towards positive returns. It is not surprising that volatility and skewness have little meaning during the crisis period (lower coefficients and marginal significance). Strong market movements in this period are different from the long-term distribution of returns, making it irrelevant to condition optimal weights on these past moments.

The inclusion of volatility and skewness improves the performance of the portfolios at the expense of more trading. When looking at the specification with transaction costs of 75*bp*, the overall gain in CE return of 258.1% is higher than the gain of 171% for the optimal portfolio without VOL and SKEW (Table 5). The Sharpe ratio and average return are higher as well: 1.221 vs. 1.062 and 19.9% vs. 13.5%, respectively. This improvement comes at the expense of higher trading, with overall turnover going from 416% to 1196%.

Overall, volatility and skewness seem to have an impact on optimal corporate bond portfolios, but generate variations in the portfolio weights and turnover that are hardly tradeable.

[32]The astonishing performance is likely to be partially driven by extreme market movements during the crisis years.

4.8 Additional Robustness Checks

We briefly summarize the results of various additional robustness checks.[33] First, we estimate the portfolio weights for various levels of risk aversion of 1, 3, 5, and 10, which complement the original $\gamma = 7$ results for our main specification (Table 2, 75bp transaction costs). As risk aversion decreases, the economic and statistical impact of the characteristics increases. The performance of the optimal portfolio also increases, as less risk-averse investors are more aggressive in their use of cross-sectional and time-series variation in the characteristics. Hence, our portfolio results are even more significant for lower levels of γ.

Second, we investigate whether our findings are driven by individual but frequent bond issuers. In our sample, three companies, General Motors (GM), General Electric (GE), and Bank of America (BoA), issue about 11.7%, 10.2%, and 6.4% of the bonds, respectively. We re-run our estimation by omitting from the sample each one of these borrowers, one at a time. The results are unchanged.

Third, we specify the cross-sectional variation in transaction costs to be a function of illiquidity, rather than size of issuance, as assumed in the last columm of Table 2. In other words, more illiquid stocks have larger transaction costs. Here again, the results are very similar to the original specification.

5 Conclusion

We present an empirical approach to optimally select corporate bond portfolios based on bond-specific characteristics and macroeconomic regimes. We find that cross-sectional characteristics are useful to construct portfolios that have significantly higher certainty equivalent returns and Sharpe ratios, even after adjusting conservatively for transaction costs and costly short selling. We also document that the optimal corporate bond portfolio strategy depends on the state of the economy. In periods of high (low) macroeconomic uncertainty, the optimal portfolio allocation is tilted away from (toward) long-maturity and high-credit rating

[33] The full set of tables from the robustness specifications can be found in the Internet Appendix at the end of the paper.

bonds. An interpretation of this result is that, during economic downturns, a flight-to-safety strategy is optimal. A main finding of this paper is that characteristics used extensively by the corporate bond pricing literature to proxy for various sources of risk are also useful in forming corporate bond portfolios.

The results that we present are admittedly in-sample. However, given the large certainty equivalent gains, the large cross-section of bonds used in the estimation, and the robustness of the parametric weights, we believe that our main results will hold out-of-sample. Unfortunately, we cannot verify that claim as the corporate bond data does not span a long enough period.[34]

Various extensions to our results are possible. First, one can test whether more complex bond structures, such as callability, redeemable, make-whole, cross-acceleration, cross-default and others, have an effect on the optimal portfolio. Second, we can use utility functions other than CARRA in the estimation of the weights provided that they can be written in closed form. Finally, this parametric portfolio approach can be applied to other OTC markets, as long as they are liquid enough, such as municipal bonds, or agency mortgage backed securities.

[34] Hansen and Timmermann (2016) show that out-of-sample tests do no necessarily lead to better inference, especially for short datasets, as their power is significantly reduced.

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Table 1: **Summary Statistics**

This table displays summary statistics of the data used in our study. All statistics are for the sample August 2005 until September 2015. In Panel A, we report average monthly statistics of the sample of bonds that are included in our portfolio. In Panel A, we report the number of bonds, the amount of outstanding debt, and the number of bonds that come in and out of the sample. The column *Total* shows the number and amount of outstanding debt of all bonds that are present at least once in our sample. The column *TRACE* reports average monthly figures of the raw TRACE sample during our sample period. Panel B reports a correlation matrix and summary statistics for benchmark returns and comparable market indices. *EW* and *VW* are our equal and value-weighted benchmarks, respectively. *T-Bill* is the secondary market one month US Treasury bill. *IG* and *HY* are the Bloomberg-FINRA Investment Grade and High Yield total return corporate bond indices, respectively. *Mix* is a monthly weighted average of *IG* and *HY*, depending on the amount of IG and HY bonds in our sample in that month. *S&P500* is the Standard & Poor's 500 total index return. Panel C reports a correlation matrix and summary statistics for bond-specific characteristics used as conditioning variables in the portfolio optimization. TTM is the bond's time to maturity, DUR is its modified duration. RAT is the average rating of the bond across the three main rating agencies (Standard & Poor's, Moody's, and Fitch). ILLIQ is an illiquidity measure in the spirit of Bao, Pan, and Wang (2011). MOM is the monthly compounded return between months $t-7$ and $t-1$, following Jostova et al. (2013). SIZE is the bond offering amount at issuance in billions of USD.

Panel A: Bond Sample							
	Mean	**Std.**	**Min**	**Median**	**Max**	**Total**	**TRACE**
# Bonds	966	135	667	976	1206	4491	14065
# Bonds In	28	14	8	25	79	-	-
# Bonds Out	29	12	6	29	70	-	-
Outst. Debt	597	141	420	604	888	1984	4384
Outst. Debt In	13	8	1	12	53	-	-
Outst. Debt Out	9	6	1	8	34	-	-
Panel B: Bond Indexes							
	EW	**VW**	**T-Bill**	**IG**	**HY**	**Mix**	**S&P500**
Mean	0.073	0.062	0.012	0.047	0.063	0.051	0.080
Std	0.101	0.082	0.005	0.049	0.127	0.057	0.148
Skew	1.310	-0.039	1.188	-0.865	0.553	-0.109	-0.805
SR	0.595	0.603	–	0.716	0.394	0.675	0.455
EW	1.000	0.975	-0.089	0.846	0.827	0.922	0.401
VW		1.000	-0.090	0.920	0.786	0.951	0.406
T-Bill			1.000	-0.084	-0.063	-0.069	-0.040
IG				1.000	0.651	0.945	0.367
HY					1.000	0.852	0.654
Mix						1.000	0.520
S&P500							1.000
Panel C: Bond Characteristics							
	TTM	**DUR**	**RAT**	**COUP**	**ILLIQ**	**MOM**	**SIZE**
Mean	8.328	5.444	7.328	5.497	0.902	0.041	0.618
Median	5.384	4.500	6.333	5.750	0.328	0.026	0.400
Std	8.175	3.967	3.754	1.695	1.491	0.144	0.766
Min	0.247	0.032	1.000	0.000	0.000	-0.864	0.010
Max	94.266	22.984	23.000	14.250	10.755	4.625	15.000
TTM	1.000	0.943	-0.034	0.277	0.330	0.041	-0.083
DUR		1.000	-0.087	0.234	0.303	0.057	-0.087
RAT			1.000	0.383	0.224	0.202	-0.162
ILLIQ				1.000	0.210	0.092	-0.109
COUP					1.000	-0.002	-0.240
MOM						1.000	-0.042
SIZE							1.000

Table 2: **Optimal Corporate Bonds Portfolios - Various Transaction Costs**

This table shows estimates of the optimal portfolio policy for the following bond-specific characteristics: time to maturity (TTM), credit rating (RAT), coupon (COUP), illiquidity (ILLIQ), momentum (MOM), and size (SIZE). The parameters are estimated with a power utility with $\gamma = 7$. Our sample period is from August 2005 until September 2015 and includes 116,932 bond-month observations. The column VW (EW) refers to the value-weighted (equal weighted) portfolio benchmark with fixed transaction costs of 75bp. The columns display optimal parametric portfolio policies with different fixed transaction costs levels of 10bp, 25bp, 50bp, and 75bp, time-varying transaction costs TS, and transaction costs that vary both over time and cross-sectionally CS-TS (see Appendix A). The first set of rows presents the marginal impact of the characteristics and bootstrapped p-values. The second set of rows shows average absolute portfolio weight, average minimum and maximum portfolio weights, average sum of negative weights, and annual turnover of the portfolio. The last set of rows reports the (annualized) performance of the optimal portfolio, displaying its certainty equivalent, certainty equivalent delta with respect to the corresponding benchmark, its mean, standard deviation, skewness and Sharpe ratio.

	VW	**EW**	**CBPP**					
			10bp	**25bp**	**50bp**	**75bp**	**TS**	**CS-TS**
TTM	-	-	-40.049	-15.557	-11.200	-10.074	-10.519	-10.234
	-	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RAT	-	-	16.628	19.696	10.613	2.953	5.239	3.707
	-	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
COUP	-	-	18.343	3.877	8.487	10.988	10.649	11.148
	-	-	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ILLIQ	-	-	32.656	6.984	0.891	-0.115	0.109	-0.024
	-	-	(0.001)	(0.001)	(0.070)	(0.675)	(0.737)	(0.930)
MOM	-	-	52.357	36.918	21.341	9.983	13.476	11.150
	-	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SIZE	-	-	-11.245	-11.718	-8.224	-5.461	-6.229	-5.490
	-	-	(0.063)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\lvert w_i \rvert \times 100$	0.106	0.106	0.537	0.348	0.231	0.166	0.185	0.174
$\max\ w_i \times 100$	1.090	0.106	4.178	2.952	1.878	1.261	1.422	1.316
$\min\ w_i \times 100$	0.002	0.106	-2.480	-1.604	-0.970	-0.586	-0.700	-0.628
$\sum w_i I(w_i < 0)$	0.000	0.000	-2.071	-1.169	-0.602	-0.291	-0.381	-0.326
$\sum \lvert (w_{i,t} - w_{i,t-1}) \rvert$	0.551	0.746	33.027	18.946	10.819	5.310	6.994	5.875
CE	0.031	0.030	0.136	0.100	0.064	0.044	0.049	0.046
	-	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
%ΔCE	-	-	2.886	1.941	0.939	0.419	0.531	0.438
$\bar{r}$	0.058	0.067	0.276	0.186	0.105	0.068	0.077	0.071
$\sigma(r)$	0.082	0.101	0.197	0.158	0.112	0.086	0.092	0.088
Skew	-0.068	1.292	1.833	2.040	2.564	3.304	3.036	3.163
SR	0.551	0.538	1.325	1.088	0.820	0.640	0.692	0.659

Table 3: **Optimal Corporate Bonds Portfolios - Smoothing Fluctuations and Reducing Turnover**

This table displays estimates of the smoothing parameter α for different transaction costs and risk aversion γ of a CRRA investor. The parameter α is estimated conditional on the optimal portfolio based on the following bond-specific characteristics: time to maturity (TTM), credit rating (RAT), coupon (COUP), illiquidity (ILLIQ), momentum (MOM), and size (SIZE). Our sample period is from August 2005 until September 2015 and includes 116,932 bond-month observations. The columns *VW* refer to the value-weighted benchmark with transaction costs of 75bp. We present optimal portfolios for risk aversion of 5 and 7, and for transaction costs of 50*bp* and 75*bp*. The first set of rows presents the marginal impact of the characteristics and bootstrapped p-values. The second set of rows shows the optimal α and bootstrapped p-values. The third set of rows shows average absolute portfolio weight, average minimum and maximum portfolio weights, average sum of negative weights, and annual turnover of the portfolio. The last set of rows reports the (annualized) performance of the optimal portfolio, displaying its certainty equivalent, certainty equivalent delta with respect to the corresponding benchmark, its mean, standard deviation, skewness and Sharpe ratio.

	VW	**CBPP ($\gamma = 5$)**		**VW**	**CBPP ($\gamma = 7$)**	
		50bp	**75bp**		**50bp**	**75bp**
TTM	-	-8.712	-7.523	-	-11.200	-10.074
	-	(0.001)	(0.001)	-	(0.001)	(0.001)
RAT	-	17.744	6.695	-	10.613	2.953
	-	(0.001)	(0.001)	-	(0.001)	(0.001)
COUP	-	6.655	10.032	-	8.487	10.988
	-	(0.001)	(0.001)	-	(0.001)	(0.001)
ILLIQ	-	1.301	-0.081	-	0.891	-0.115
	-	(0.005)	(0.734)	-	(0.070)	(0.675)
MOM	-	28.194	11.880	-	21.341	9.983
	-	(0.001)	(0.001)	-	(0.001)	(0.001)
SIZE	-	-9.762	-6.137	-	-8.224	-5.461
	-	(0.001)	(0.001)	-	(0.001)	(0.001)
α	-	0.498	0.564	-	0.497	0.555
	-	(0.001)	(0.001)	-	(0.001)	(0.001)
$\lvert w_i \rvert \times 100$	0.106	0.262	0.164	0.106	0.213	0.158
$\max\ w_i \times 100$	1.090	2.010	1.253	1.090	1.610	1.175
$\min\ w_i \times 100$	0.002	-1.006	-0.518	0.002	-0.812	-0.512
$\sum w_i I(w_i < 0)$	0.000	-0.758	-0.284	0.000	-0.520	-0.251
$\sum \lvert(w_{i,t} - w_{i,t-1})\rvert$	0.551	7.438	2.997	0.551	5.694	2.642
CE	0.039	0.102	0.067	0.031	0.083	0.057
	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
%ΔCE	-	1.550	0.718	-	1.515	0.839
$\bar{r}$	0.058	0.145	0.092	0.058	0.116	0.079
$\sigma(r)$	0.082	0.124	0.097	0.082	0.093	0.076
Skew	-0.068	1.559	2.106	-0.068	1.615	2.009
SR	0.551	1.059	0.812	0.551	1.103	0.859

Table 4: **Optimal Corporate Bonds Portfolios - Variables Selection**
This table displays estimates for different variable specifications of the optimal policy. The bond-specific characteristics that we consider are: time to maturity (TTM), credit rating (RAT), coupon (COUP), illiquidity (ILLIQ), momentum (MOM), and size (SIZE). The parameters are estimated with a power utility with risk aversion of 7 and fixed transaction costs of 75*bp*. Our sample period is from August 2005 until September 2015 and includes 116,932 bond-month observations. For each of the specifications, we present results with and without smoothing parameter α, which is estimated following the procedure described in Section 2.3. The column VW refers to the value-weighted benchmark without characteristics. The first set of rows presents the marginal impact of the characteristics and bootstrapped p-values. The second set of rows shows the optimal α and bootstrapped p-values, whenever applicable. The third set of rows shows average absolute portfolio weight, average minimum and maximum portfolio weights, average sum of negative weights, and annual turnover of the portfolio. The last set of rows reports the (annualized) performance of the optimal portfolio, displaying its certainty equivalent, certainty equivalent delta with respect to the corresponding benchmark, its mean, standard deviation, skewness and Sharpe ratio.

	VW	**CBPP (75bp)**					
		(1)	(2)	(3)	(4)	(5)	(6)
TTM	-	-3.423		-7.512		-10.074	
	-	(0.001)		(0.001)		(0.001)	
RAT	-	-		-2.019		2.953	
	-	-		(0.001)		(0.001)	
COUP	-	-		10.059		10.988	
	-	-		(0.001)		(0.001)	
ILLIQ	-	-		-		-0.115	
	-	-		-		(0.675)	
MOM	-	-		-		9.983	
	-	-		-		(0.001)	
SIZE	-	-		-		-5.461	
	-	-		-		(0.001)	
α	-	-	0.023	-	0.028	-	0.557
	-	-	(0.232)	-	(0.293)	-	(0.001)
$\lvert w_i\rvert \times 100$	0.106	0.116	0.116	0.137	0.137	0.166	0.158
$\max\ w_i \times 100$	1.090	1.086	1.086	1.177	1.177	1.261	1.175
$\min\ w_i \times 100$	0.002	-0.051	-0.051	-0.374	-0.374	-0.586	-0.511
$\sum w_i I(w_i < 0)$	0.000	-0.047	-0.047	-0.151	-0.150	-0.291	-0.251
$\sum \lvert(w_{i,t} - w_{i,t-1})\rvert$	0.551	0.644	0.635	0.942	0.926	5.400	2.633
CE	0.031	0.032	0.032	0.034	0.034	0.044	0.057
	-	(0.393)	(0.391)	(0.179)	(0.177)	(0.001)	(0.001)
%ΔCE	-	0.032	0.032	0.097	0.097	0.419	0.839
$\bar{r}$	0.058	0.054	0.054	0.057	0.057	0.068	0.079
$\sigma(r)$	0.082	0.075	0.075	0.080	0.080	0.086	0.076
Skew	-0.068	0.044	0.027	1.800	1.752	3.304	2.003
SR	0.551	0.556	0.556	0.553	0.554	0.640	0.859

Table 5: **Optimal Corporate Bond Portfolios With Macroeconomic Fluctuations**
This table presents estimates of the optimal portfolio policy conditioning on two macroeconomic regimes (no crisis and crisis) and different combinations of bond-specific characteristics, defined in Table 2. We use an NBER recession dummy variable, interacted with the bond-specific characteristics, to proxy for macroeconomic regimes. The regime-specific parameters are estimated for a power utility with risk aversion $\gamma = 7$ and fixed transaction costs of $75bp$. Our sample period covers August 2005 until September 2015 and includes 116,932 bond-month observations. For the full specification, we present results with and without the smoothing parameter α. The column VW refers to the corresponding value-weighted benchmark. The first two sets of rows present the marginal impact of the characteristics in both regimes and bootstrapped p-values. The third set of rows shows the optimal α and bootstrapped p-values, whenever applicable. The fourth set of rows shows the average sum of negative weights and annual turnover of the portfolio. The last set of rows reports the (annualized) performance of the optimal portfolio, displaying its certainty equivalent, certainty equivalent delta with respect to the corresponding benchmark, its mean, standard deviation, skewness and Sharpe ratio.

	VW	**CBPP (75bp) and NBER Recessions**				
		(1)	(2)	(3)	(4)	(5)
$\text{TTM}_{no\ crisis}$	-	13.519	5.704	4.005	4.761	
	-	(0.001)	(0.001)	(0.001)	(0.001)	
$\text{RAT}_{no\ crisis}$	-	-	23.306	19.615	21.104	
	-	-	(0.001)	(0.001)	(0.001)	
$\text{COUP}_{no\ crisis}$	-	-	3.825	1.699	2.058	
	-	-	(0.001)	(0.001)	(0.001)	
$\text{ILLIQ}_{no\ crisis}$	-	-	-	0.028	0.108	
	-	-	-	(0.733)	(0.221)	
$\text{MOM}_{no\ crisis}$	-	-	-	-	3.352	
	-	-	-	-	(0.001)	
$\text{SIZE}_{no\ crisis}$	-	-	-	-10.694	-11.523	
	-	-	-	(0.001)	(0.001)	
TTM_{crisis}	-	-34.546	-50.902	-52.694	-49.988	
	-	(0.001)	(0.001)	(0.001)	(0.001)	
RAT_{crisis}	-	-	-16.851	-19.868	-11.227	
	-	-	(0.001)	(0.001)	(0.001)	
COUP_{crisis}	-	-	51.945	50.069	43.446	
	-	-	(0.001)	(0.001)	(0.001)	
ILLIQ_{crisis}	-	-	-	-2.133	-1.658	
	-	-	-	(0.616)	(0.623)	
MOM_{crisis}	-	-	-	-	10.223	
	-	-	-	-	(0.001)	
SIZE_{crisis}	-	-	-	-10.852	-11.571	
	-	-	-	(0.001)	(0.001)	
α	-	-	-	-	-	0.137
	-	-	-	-	-	(0.001)
$\sum w_i I(w_i < 0)$	0.000	-0.344	-0.702	-0.541	-0.632	-0.622
$\sum \lvert(w_{i,t} - w_{i,t-1})\rvert$	0.551	2.188	3.096	2.969	4.160	3.726
CE	0.031	0.050	0.077	0.079	0.084	0.085
	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
%ΔCE	-	0.613	1.484	1.548	1.710	1.742
$\bar{r}$	0.058	0.074	0.122	0.126	0.135	0.134
$\sigma(r)$	0.082	0.080	0.108	0.111	0.114	0.112
Skew	-0.068	0.653	0.539	0.848	0.640	0.602
SR	0.551	0.767	1.004	1.015	1.062	1.080

Table 6: **Optimal Corporate Bond Portfolios - Alternative Definitions of Macroeconomic Fluctuations**

The table presents estimates of the optimal portfolio policy conditioning on the following two alternative definitions of macroeconomic regimes: the index of macroeconomic uncertainty of Jurado, Ludvigson, and Ng (2015) (MU) and extreme cross sectional dispersion of bond returns to capture downside risk (DOWN) (Section 3.3). The regimes are introduced through an interaction of bond-specific characteristics, defined in Table 2, with a dummy variable that equals one in economic downturns. The regime-specific parameters are estimated for a power utility with $\gamma = 7$ and fixed transaction costs of $75bp$. Our sample period covers August 2005 until September 2015 and includes 116,932 bond-month observations. We present results with and without the smoothing parameter α. The first two sets of rows display the marginal impact the characteristics in both regimes, the estimate of *alpha*, and bootstrapped p-values. The third set of rows shows the optimal α, whenever applicable. The fourth set of rows shows the average sum of negative weights and annual turnover of the portfolio. The last set of rows reports the (annualized) performance of the optimal portfolio, displaying its certainty equivalent, certainty equivalent delta with respect to the corresponding benchmark, its mean, standard deviation, skewness and Sharpe ratio.

	VW	**CBPP (75bp)**		**VW**	**CBPP (75bp)**	
		MU			**DOWN**	
		(1)	(2)		(3)	(4)
$\text{TTM}_{no\ crisis}$	-	3.595		-	-1.518	
	-	(0.001)		-	(0.001)	
$\text{RAT}_{no\ crisis}$	-	15.980		-	14.327	
	-	(0.001)		-	(0.001)	
$\text{COUP}_{no\ crisis}$	-	4.311		-	10.085	
	-	(0.001)		-	(0.001)	
$\text{ILLIQ}_{no\ crisis}$	-	0.053		-	0.083	
	-	(0.510)		-	(0.397)	
$\text{MOM}_{no\ crisis}$	-	1.862		-	6.952	
	-	(0.001)		-	(0.001)	
$\text{SIZE}_{no\ crisis}$	-	-10.012		-	-8.772	
	-	(0.001)		-	(0.001)	
TTM_{crisis}	-	-37.142		-	-27.686	
	-	(0.001)		-	(0.001)	
RAT_{crisis}	-	9.003		-	-7.506	
	-	(0.001)		-	(0.001)	
COUP_{crisis}	-	17.985		-	24.588	
	-	(0.001)		-	(0.001)	
ILLIQ_{crisis}	-	1.016		-	-0.643	
	-	(0.756)		-	(0.700)	
MOM_{crisis}	-	26.288		-	6.405	
	-	(0.001)		-	(0.001)	
SIZE_{crisis}	-	-9.106		-	-13.096	
	-	(0.001)		-	(0.001)	
α	-	-	0.263	-	-	0.431
	-	-	(0.001)	-	-	(0.001)
$\sum w_i I(w_i < 0)$	0.000	-0.488	-0.470	0.000	-0.505	-0.463
$\sum \lvert (w_{i,t} - w_{i,t-1}) \rvert$	0.551	4.094	3.248	0.551	5.675	3.766
CE	0.031	0.078	0.081	0.031	0.057	0.071
	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
%ΔCE	-	1.516	1.613	-	0.839	1.290
$\bar{r}$	0.058	0.122	0.120	0.058	0.090	0.100
$\sigma(r)$	0.082	0.106	0.099	0.082	0.097	0.087
Skew	-0.068	0.676	0.432	-0.068	1.784	1.233
SR	0.551	1.018	1.074	0.551	0.794	0.997

Table 7: **Optimal Corporate Bond Portfolios - Costly Short Selling**

This table displays estimates of the optimal portfolio policy for various costs of borrowing and shorting corporate bonds (see Asquith et al. (2013)). The policy is a function of NBER regimes interacted with bond-specific characteristics, which defined in Table 2. The regime-specific parameters are estimated for a power utility with $\gamma = 7$ and fixed transaction costs of $75bp$. Our sample period covers August 2005 until September 2015 and includes 116,932 bond-month observations. The column VW refers to the value-weighted portfolio benchmark. The header of the remaining columns display the level of short-selling penalization applied in the non-crisis and crisis period, respectively. The first two sets of rows display the marginal impact the characteristics in both regimes and bootstrapped p-values. The third set of rows shows the average sum of negative weights and annual turnover of the portfolio. The last set of rows reports the (annualized) performance of the optimal portfolio, displaying its certainty equivalent, certainty equivalent delta with respect to the corresponding benchmark, its mean, standard deviation, skewness and Sharpe ratio.

	VW	**CBPP (75bp)**				
		0bp/0bp	**10bp/10bp**	**20bp/20bp**	**20bp/40bp**	**40bp/80bp**
$\text{TTM}_{no\ crisis}$	-	4.761	3.024	1.834	1.865	0.742
	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\text{RAT}_{no\ crisis}$	-	21.104	17.034	13.742	13.626	9.492
	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\text{COUP}_{no\ crisis}$	-	2.058	-0.381	-0.668	-0.693	-0.376
	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\text{ILLIQ}_{no\ crisis}$	-	0.108	0.118	0.114	0.114	0.106
	-	(0.221)	(0.179)	(0.198)	(0.196)	(0.229)
$\text{MOM}_{no\ crisis}$	-	3.352	2.134	1.511	1.498	0.992
	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\text{SIZE}_{no\ crisis}$	-	-11.523	-11.735	-11.233	-11.205	-10.661
	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
TTM_{crisis}	-	-49.988	-45.058	-40.479	-33.623	-24.272
	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RAT_{crisis}	-	-11.227	-8.963	-7.059	-4.790	-3.148
	-	(0.001)	(0.001)	(0.001)	(0.012)	(0.055)
COUP_{crisis}	-	43.446	35.561	30.153	22.241	14.267
	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ILLIQ_{crisis}	-	-1.658	-2.092	-2.485	-2.970	-3.287
	-	(0.646)	(0.551)	(0.467)	(0.327)	(0.177)
MOM_{crisis}	-	10.223	10.293	10.307	10.262	9.447
	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SIZE_{crisis}	-	-11.571	-12.016	-11.371	-11.506	-11.423
	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\sum w_i I(w_i < 0)$	0.000	-0.632	-0.426	-0.301	-0.269	-0.135
$\sum \lvert (w_{i,t} - w_{i,t-1}) \rvert$	0.551	4.160	3.382	2.917	2.781	2.236
CE	0.031	0.084	0.078	0.073	0.071	0.064
	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
%ΔCE	-	1.710	1.516	1.355	1.290	1.065
$\bar{r}$	0.058	0.135	0.116	0.104	0.100	0.086
$\sigma(r)$	0.082	0.114	0.100	0.089	0.087	0.077
Skew	-0.068	0.640	0.772	0.906	0.936	1.235
SR	0.551	1.062	1.033	1.021	0.993	0.955

Table 8: **Optimal Portfolios - Investment Grade and High-Yield Bonds**
The table displays estimates of the optimal portfolio policy estimated for two subsamples of bonds: investment grade (93,659 bond-month observations) and high-yield (23,273 bond-month observations) bonds. The policy is a function of NBER regimes interacted with bond-specific characteristics, which are defined in Table 2. The regime-specific parameters are estimated for a power utility with $\gamma = 7$. Our sample period covers August 2005 until September 2015. We present results with fixed transaction costs of 30*bp*, 40*bp*, and 50*bp* (100*bp*, 110*bp*, and 120*bp*) for the investment grade (high-yield) subsample. The first two sets of rows display the marginal impact the characteristics in both regimes and bootstrapped p-values. The third set of rows shows the average sum of negative weights and annual turnover of the portfolio. The last set of rows reports the (annualized) performance of the optimal portfolio, displaying its certainty equivalent, certainty equivalent delta with respect to the corresponding benchmark, its mean, standard deviation, skewness and Sharpe ratio.

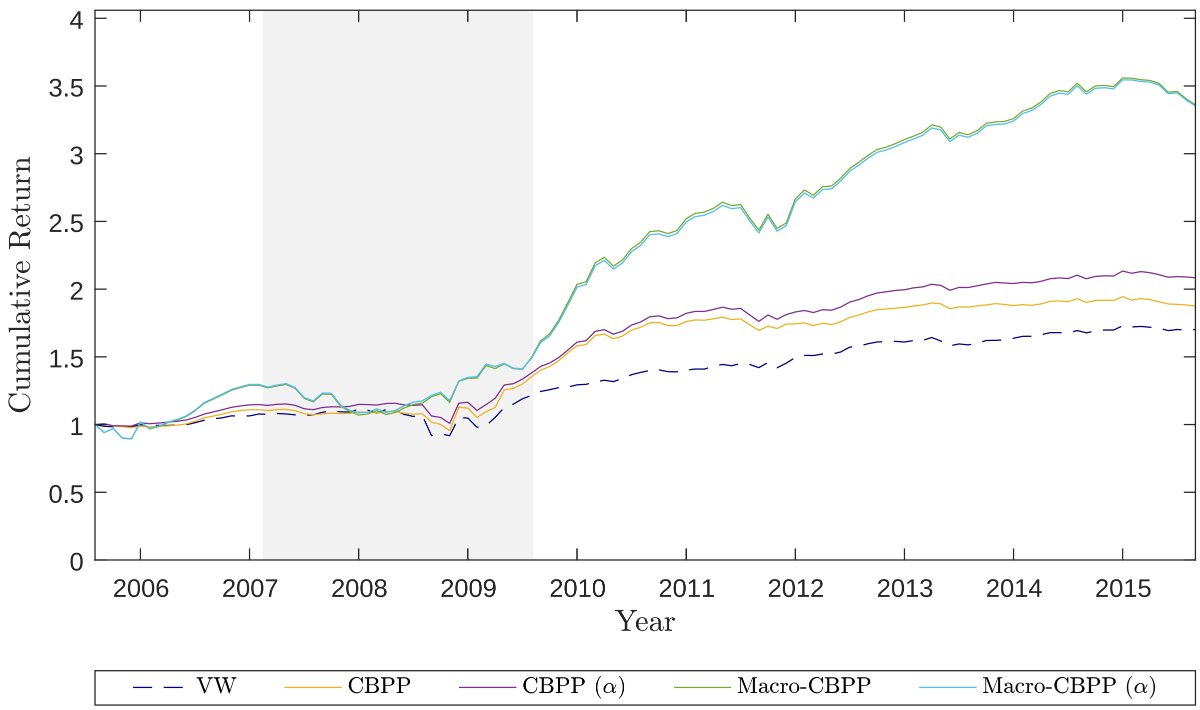
	CBPP - IG			**CBPP - HY**		
	30bp	**40bp**	**50bp**	**100bp**	**110bp**	**120bp**
$\text{TTM}_{no\ crisis}$	28.634	24.318	20.292	27.072	27.540	28.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\text{RAT}_{no\ crisis}$	-5.554	-0.571	1.784	219.318	217.660	216.194
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\text{COUP}_{no\ crisis}$	15.245	12.363	11.342	-39.598	-33.025	-27.857
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\text{ILLIQ}_{no\ crisis}$	0.642	0.314	0.209	0.514	0.352	0.204
	(0.004)	(0.040)	(0.076)	(0.561)	(0.661)	(0.779)
$\text{MOM}_{no\ crisis}$	4.019	1.593	0.873	3.216	3.090	3.101
	(0.001)	(0.001)	(0.001)	(0.016)	(0.010)	(0.004)
$\text{SIZE}_{no\ crisis}$	-35.131	-24.620	-18.187	-128.637	-122.392	-120.060
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
TTM_{crisis}	-65.329	-65.802	-62.445	-230.625	-225.491	-219.500
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RAT_{crisis}	69.630	54.340	44.363	96.462	94.290	91.722
	(0.001)	(0.001)	(0.001)	(0.012)	(0.007)	(0.004)
COUP_{crisis}	173.499	147.318	124.038	90.978	89.973	88.738
	(0.001)	(0.001)	(0.001)	(0.082)	(0.056)	(0.040)
ILLIQ_{crisis}	-32.678	-14.483	-7.544	11.324	9.719	8.562
	(0.095)	(0.175)	(0.215)	(0.870)	(0.872)	(0.872)
MOM_{crisis}	-15.264	-6.539	-2.587	34.812	34.104	33.800
	(0.128)	(0.249)	(0.484)	(0.379)	(0.345)	(0.305)
SIZE_{crisis}	34.814	26.235	16.895	16.719	17.043	17.739
	(0.001)	(0.001)	(0.001)	(0.527)	(0.482)	(0.433)
$\sum w_i I(w_i < 0)$	-1.628	-1.201	-0.928	-1.124	-1.09	-1.064
$\sum \lvert(w_{i,t} - w_{i,t-1})\rvert$	8.788	5.999	4.644	8.043	7.801	7.609
CE	0.071	0.064	0.059	0.097	0.089	0.081
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
%ΔCE	1.088	0.939	0.788	2.155	2.047	1.942
$\bar{r}$	0.108	0.093	0.082	0.232	0.219	0.207
$\sigma(r)$	0.097	0.086	0.078	0.193	0.190	0.187
Skew	0.105	0.034	0.030	1.315	1.250	1.199
SR	0.972	0.922	0.885	1.123	1.077	1.031

Table 9: **Optimal Corporate Bond Portfolios – Volatility and Skewness**
This table shows estimates of the optimal portfolio policy conditioning on individual bond return volatility (VOL) and skewness (SKEW) in addition to other bond-specific characteristics, which are defined in Table 2. All characteristics are interacted with the NBER regime dummy. For brevity, we only display the VOL and SKEW parameters, which are estimated for a power utility with $\gamma = 7$. In the columns, we present results for different fixed transaction costs levels of 10*bp*, 25*bp*, 50*bp*, and 75*bp*, for time-varying transaction costs TS, and transaction costs that vary both over time and cross-sectionally *CS-TS* (see Appendix A). The first two sets of rows present the marginal impact of bond-specific volatility (VOL) and skewness (SKEW) and the bootstrapped p-values in normal periods and during economic downturns, respectively. The third set of rows shows the average sum of negative weights and annual turnover of the portfolio. The last set of rows reports the (annualized) performance of the optimal portfolio, displaying its certainty equivalent, certainty equivalent delta with respect to the corresponding benchmark, its mean, standard deviation, skewness and Sharpe ratio.

	CBPP					
	10bp	**25bp**	**50bp**	**75bp**	**TS**	**CS-TS**
VOL$_{no\ crisis}$	-111.721	-107.726	-83.850	-54.525	-64.142	-59.177
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SKEW$_{no\ crisis}$	148.132	119.768	83.158	53.207	60.677	56.101
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
VOL$_{crisis}$	46.563	31.541	17.648	9.216	9.382	7.824
	(0.443)	(0.068)	(0.017)	(0.029)	(0.011)	(0.018)
SKEW$_{crisis}$	15.932	11.982	11.569	9.796	9.021	8.647
	(0.701)	(0.308)	(0.007)	(0.001)	(0.001)	(0.001)
$\sum w_i I(w_i < 0)$	-8.576	-6.613	-4.363	-2.678	-3.142	-2.871
$\sum \lvert(w_{i,t} - w_{i,t-1})\rvert$	40.757	28.766	18.835	11.961	13.922	12.712
CE	0.262	0.210	0.150	0.111	0.121	0.114
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
%ΔCE	6.486	5.176	3.545	2.581	2.781	2.563
$\bar{r}$	0.621	0.458	0.294	0.199	0.223	0.208
$\sigma(r)$	0.283	0.241	0.190	0.151	0.162	0.156
Skew	1.179	1.090	0.999	0.907	0.951	0.928
SR	2.128	1.828	1.466	1.221	1.280	1.238

Figure 1: **Cumulative Portfolio Returns**

This figure presents cumulative returns over the sample period from August 2005 until September 2015 (116,932 bond-month observations) for the value-weighted benchmark portfolio (VW) and four different specification of optimal parametric portfolios. We show results for portfolios whose weights are conditioned on bond-specific characteristics (CBPP) as well as on bond-specific characteristics and a proxy for macroeconomic conditions (Macro-CBPP). The proxy for different macroeconomic regimes is the NBER recession period from December 2007 till June 2009, which is presented as a gray area in the figure. Both portfolios are additionally presented taking into account smoothing of portfolio weights (CBPP (α) and Macro-CBPP (α)), as discussed under 2.3.



A Transaction Costs Magnitude

Since the dissemination of TRACE, an extensive literature on transaction costs in OTC markets has grown.[35] Transaction costs have been estimated overall as well as conditional on credit rating, time period, bond offering amount, and trade size. There is a wide range of popular transaction cost measures. We choose the Roll measure (see Roll (1984)) to be our benchmark, which is among the best performers when it comes to measure transaction costs in bond markets, as shown by Schestag, Schuster, and Uhrig-Homburg (2016).

In this paper, we take a conservative approach and consider the higher cost estimates found in previous research. Our main specification relies on flat transaction costs of $75bp$. This number relates to estimates based on the full TRACE database by Friewald, Jankowitsch, and Subrahmanyam (2012), Bao, Pan, and Wang (2011), and Schestag, Schuster, and Uhrig-Homburg (2016).[36] Our choice of transaction costs that vary over time and cross-sectionally starts from the flat $75bp$ estimate and incorporates patterns documented in the literature. Specifically, we rely on the findings of Friewald, Jankowitsch, and Subrahmanyam (2012), Schestag, Schuster, and Uhrig-Homburg (2016), and Bessembinder et al. (2016), who show that transaction costs are particularly high in times of economic uncertainty (e.g. during the last financial crisis) and for bonds with a small offering amount. Table A.1 shows in detail the transaction cost values adopted for the specifications with time-varying (TS) costs and those with transaction costs varying both in time and cross-sectionally ($CS - TS$).

We believe that our choice of transaction costs is the most reasonable compromise, taking into account different estimates in the literature. However, our approach is flexible and allows for any desired level of transaction costs, varying both over time and across assets.

[35] See e.g. Bessembinder, Maxwell, and Venkataraman (2006), Hotchkiss and Jostova (2007), Bao, Pan, and Wang (2011), Dick-Nielsen, Feldhutter, and Lando (2012), and Friewald, Jankowitsch, and Subrahmanyam (2012) among others.

[36] See Table 4, Panel B in Friewald, Jankowitsch, and Subrahmanyam (2012), Table 7 in Bao, Pan, and Wang (2011), and Table 2 in Schestag, Schuster, and Uhrig-Homburg (2016).

Table A.1: **Time and Cross-Sectional Varying Transaction Costs**

This table shows the level of transaction costs adopted in the specifications where we allow for their variation in the time series and in the cross-section (TS and $CS - TS$). The numbers are all in basis-points. We consider three time periods: pre-crisis (January 2005-November 2007), crisis (December 2007-June 2009), and post-crisis (July 2009-September 2015). For the cross-section, we instead sort the bonds by offering amount in each month, and then divide the sample in terciles. The bonds in the highest, medium and lowest tercile are defined to be large, medium and small, respectively.

	PRE CRISIS			**CRISIS**			**POST CRISIS**		
	SMALL	**MEDIUM**	**LARGE**	**SMALL**	**MEDIUM**	**LARGE**	**SMALL**	**MEDIUM**	**LARGE**
TS	70	70	70	85	85	85	60	60	60
CS-TS	80	80	60	100	95	80	70	70	50

B Estimation Details

B.1 Covariance Matrix of Coefficients

We estimate the covariance matrix of coefficients $\Sigma_{\hat{\theta}}$ by bootstrap. For that, we generate $1,000$ samples of returns and characteristics 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 estimate the coefficients of the optimal portfolio policy and compute the covariance matrix of the coefficients across all bootstrapped samples. This approach has the advantage of not relying on asymptotic results, and takes into account the potentially nonnormal features of the data.

The resulting estimate of the covariance matrix of the coefficients $\Sigma_{\hat{\theta}}$ can be used to test hypotheses about the elements of θ. These tests address the economic question of whether a given characteristic is related to the moments of returns in such a way that the investor finds it optimal to deviate from the benchmark portfolio weights according to the realization of the characteristic for each stock.

It is important to recognize that this is not equivalent to testing whether a characteristic is cross-sectionally related to the conditional moments of stock returns for at least two reasons. First, the benchmark portfolio weights may already reflect an exposure to the characteristics, and it may not be optimal to change that exposure. Second, a given characteristic may be correlated with first and second moments in an offsetting way, such that the conditionally optimal portfolio weights are independent of the characteristic.

B.2 Variance of 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.

C Marginal Impact Calculation

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

$$w_{i,t} = \bar{w}_{i,t} + g\left(\frac{1}{N_t}\theta' x_{i,t}\right)$$

implies that the parameters θ cannot be interpreted as the marginal impact of changes in $x_{i,t}$ on the optimal weights. Hence, we evaluate 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.

We compute the average values of the conditioning variables $\bar{\bar{x}}$ by first taking cross-sectional means of $x_{i,t}$ across bonds i for each t and second taking the time-series average of these values across t. Based on these quantities, we compute the marginal impact of characteristic $\bar{\bar{x}}_j$ on optimal weights, evaluated at the average of the other characteristics $\bar{\bar{x}}_{\char`~j}$ as

$$\frac{\mathrm{d}w}{\mathrm{d}x_j} = g\left(\frac{1}{N_t}\hat{\theta}'\left(\bar{\bar{x}}_j + 1\right)|\bar{\bar{x}}_{\sim j}\right) - g\left(\frac{1}{N_t}\hat{\theta}'\bar{\bar{x}}_j|\bar{\bar{x}}_{\sim j}\right). \tag{13}$$

Note that the benchmark weights $\bar{w}_{i,t}$ drop out when taking the first derivative of the optimal weights with respect to the conditioning variables. Furthermore, (13) is simplified due to the fact that characteristics are standardized to have a cross-sectional standard deviation of 1 in each t.

When conditioning on macroeconomic regime changes, the average characteristics and thus the marginal impact are calculated separately for the different periods.

Marginal Impact Involving Smoothing Parameter α

To smooth trading, the investor does not trade fully towards the optimal target portfolio, but towards an average between the portfolio he holds ("hold" portfolio) and the target portfolio. The weights of his optimal portfolio are

$$w_{i,t} = \alpha w_{i,t}^{h} + (1-\alpha)\, w_{i,t}^{t},$$

with

$$w_{i,t}^{h} = \eta_{i,t} w_{i,t-1} = \eta_{i,t}\left(\alpha w_{i,t-1}^{h} + (1-\alpha)\, w_{i,t-1}^{t}\right)$$

being the hold portfolio, i.e. the optimal portfolio from the period before with the weights changed by the returns $\eta_{i,t} = \frac{1+r_{i,t}}{1+r_{p,t}}$, and

$$w_{i,t}^{t} = \bar{w}_{i,t} + g\left(\frac{1}{N_t}\theta' x_{i,t}\right)$$

being the target portfolio.

Corporate bonds are issued and mature regularly, thus the investors portfolio changes even in the absence of deliberate trading. In the passive hold portfolio, we set weights of newly issued bonds coming into the sample to zero, as we have no information about how to optimally invest into them. The net-weights left by maturing bonds that drop out of the sample are distributed equally among remaining long positions. Plugging the definition of the hold portfolio into the specification of optimal portfolio weights, we can see that they follow the iterative process

$$w_{i,t} = \eta_{i,t}\left(\alpha^2 w_{i,t-1}^{h} + \alpha\,(1-\alpha)\, w_{i,t-1}^{t}\right) + (1-\alpha)\, w_{i,t}^{t}.$$

There exists no hold portfolio in the first period, as the investor has to build up his positions. Thus, he trades fully towards the target portfolio $w_{i,1}^{t}$. Furthermore, we set

$\eta_{i,t} = 1$, i.e. the return of our average asset i is equal to the portfolio return. We compute the marginal impact of characteristic $\bar{\bar{x}}_j$ on optimal weights, evaluated at the average of the other characteristics $\bar{\bar{x}}_{\text{~}j}$ as

$$\begin{aligned}
\frac{\mathrm{d}w}{\mathrm{d}x_j} &= \alpha^2 \frac{\mathrm{d}w^h_{i,t-1}}{\mathrm{d}x_j} + \alpha\left(1-\alpha\right)\frac{\mathrm{d}w^t_{i,t-1}}{\mathrm{d}x_j} + \left(1-\alpha\right)\frac{\mathrm{d}w^t_{i,t}}{\mathrm{d}x_j} \\
&= \alpha^t \frac{\mathrm{d}w^t_{i,t-t+1}}{\mathrm{d}x_j} + \alpha(L)\left(1-\alpha\right)\frac{\mathrm{d}g(\cdot)}{\mathrm{d}x_j} \\
&= \alpha^t \frac{\mathrm{d}g(\cdot)}{\mathrm{d}x_j} + \alpha(L)\left(1-\alpha\right)\frac{\mathrm{d}g(\cdot)}{\mathrm{d}x_j} \\
&= \frac{\mathrm{d}g(\cdot)}{\mathrm{d}x_j} = g\left(\frac{1}{N_t}\hat{\theta}'\left(\bar{\bar{x}}_j + 1\right)|\bar{\bar{x}}_{\text{~}j}\right) - g\left(\frac{1}{N_t}\hat{\theta}'\bar{\bar{x}}_j|\bar{\bar{x}}_{\text{~}j}\right)
\end{aligned}$$

with

$$\alpha(L) = \left(1 + \alpha L + \alpha L^2 + \ldots + \alpha L^{t-1}\right)$$

Note that the benchmark weights $\bar{w}_{i,t}$ drop out when taking the first derivative of the target weights with respect to the conditioning variables. Thus, an approximation of the true marginal impact (abstracting from bonds coming into and dropping out of the sample) follows the computation set out before under (13).

INTERNET APPENDIX

Corporate Bond Portfolios: Bond-Specific Information and Macroeconomic Uncertainty

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In this internet appendix we include additional specifications of our corporate bond parametric portfolios (CBPP) that are not included in the paper. In Table 1 we display corporate bond parametric portfolios with different levels of risk aversion γ. In Table 2 we present specifications where we independently exclude each of the top three issuers in our sample (General Motors, General Electric, and Bank of America). In Table 3 we present specifications where we allow transaction costs to vary over time and cross-sectionally, depending either on bond issue amount or on the bond-specific illiquidity. Specifically, we sort the bonds by offering amount (illiquidity) each month and divide the sorted sample in terciles. Bonds with the smallest issue amount (highest illiquidity) are assigned the highest level of transaction costs, according to the values shown in Appendix A in the paper.

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Table 1: **Optimal Corporate Bonds Portfolios - Different Levels of Risk Aversion**
This table shows estimates of the optimal portfolio policy for the following bond-specific characteristics: time to maturity (TTM), credit rating (RAT), coupon (COUP), illiquidity (ILLIQ), momentum (MOM), and size (SIZE). The parameters are estimated with a power utility. Our sample period is from August 2005 until September 2015. In each of the specifications we present a different level of risk aversion γ. The columns display optimal parametric portfolio policies with fixed transaction costs levels of $75bp$. The first set of rows presents the marginal impact of the characteristics and bootstrapped p-values. The second set of rows shows average absolute portfolio weight, average minimum and maximum portfolio weights, average sum of negative weights, and annual turnover of the portfolio. The last set of rows reports the (annualized) performance of the optimal portfolio, displaying its certainty equivalent, certainty equivalent delta with respect to the corresponding benchmark, its mean, standard deviation, skewness and Sharpe ratio.

	$\gamma = \mathbf{1}$	$\gamma = \mathbf{3}$	$\gamma = \mathbf{5}$	$\gamma = \mathbf{7}$	$\gamma = \mathbf{10}$
TTM	10.161	-3.305	-7.523	-10.074	-12.688
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RAT	48.296	14.675	6.695	2.953	-0.260
	(0.001)	(0.001)	(0.001)	(0.001)	(0.138)
COUP	10.895	9.582	10.032	10.988	12.319
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ILLIQ	0.126	-0.046	-0.081	-0.115	-0.146
	(0.599)	(0.835)	(0.734)	(0.675)	(0.665)
MOM	36.577	16.318	11.880	9.983	8.591
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SIZE	-22.181	-8.448	-6.137	-5.461	-5.604
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\lvert w_i\rvert \times 100$	0.573	0.223	0.175	0.166	0.167
$\max\ w_i \times 100$	3.813	1.738	1.380	1.261	1.189
$\min\ w_i \times 100$	-1.704	-0.741	-0.606	-0.586	-0.606
$\sum w_i I(w_i < 0)$	-2.262	-0.567	-0.333	-0.291	-0.293
$\sum I(w_i \leq 0)/N_t$	0.517	0.397	0.328	0.306	0.304
$\sum \lvert(w_{i,t} - w_{i,t-1})\rvert$	19.671	8.479	6.212	5.310	4.705
CE	0.126	0.066	0.051	0.044	0.038
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\%\Delta$CE	1.377	0.435	0.308	0.419	1.111
$\bar{r}$	0.232	0.108	0.080	0.068	0.058
$\sigma(r)$	0.444	0.172	0.112	0.086	0.068
Skew	3.020	3.238	3.294	3.304	3.329
SR	0.489	0.553	0.604	0.640	0.673

Table 2: **Optimal Corporate Bonds Portfolios - Exclusion of Most Frequent Issuers**
This table shows estimates of the optimal portfolio policy for the following bond-specific characteristics: time to maturity (TTM), credit rating (RAT), coupon (COUP), illiquidity (ILLIQ), momentum (MOM), and size (SIZE). The parameters are estimated with a power utility with $\gamma = 7$. Our sample period is from August 2005 until September 2015. In each of the specifications we exclude one of the top three issuers in our sample: General Motors (NO GM), General Electric (NO GE), and Bank of America (NO BofA). The columns display optimal parametric portfolio policies with fixed transaction costs levels of 50*bp* and 75*bp*. The first set of rows presents the marginal impact of the characteristics and bootstrapped p-values. The second set of rows shows average absolute portfolio weight, average minimum and maximum portfolio weights, average sum of negative weights, and annual turnover of the portfolio. The last set of rows reports the (annualized) performance of the optimal portfolio, displaying its certainty equivalent, certainty equivalent delta with respect to the corresponding benchmark, its mean, standard deviation, skewness and Sharpe ratio.

	NO GM		**NO GE**		**NO BofA**	
	50bp	**75bp**	**50bp**	**75bp**	**50bp**	**75bp**
TTM	-12.956	-9.686	-11.320	-11.256	-10.783	-10.359
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RAT	6.087	4.386	13.802	5.129	11.978	3.669
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
COUP	23.499	16.917	5.732	10.022	6.314	11.566
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ILLIQ	-0.248	-0.115	1.021	-0.152	1.060	-0.068
	(0.516)	(0.639)	(0.095)	(0.661)	(0.067)	(0.834)
MOM	3.450	1.105	24.995	13.028	25.577	13.099
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SIZE	-7.315	-5.837	-7.175	-5.596	-11.431	-7.214
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\lvert w_i \rvert \times 100$	0.225	0.179	0.263	0.192	0.253	0.185
max $w_i \times 100$	1.499	1.292	2.122	1.452	2.105	1.406
min $w_i \times 100$	-0.856	-0.607	-1.065	-0.656	-1.119	-0.705
$\sum w_i I(w_i < 0)$	-0.437	-0.245	-0.621	-0.316	-0.630	-0.321
$\sum \lvert (w_{i,t} - w_{i,t-1}) \rvert$	2.558	1.479	11.203	6.054	11.911	6.316
CE	0.045	0.040	0.067	0.046	0.070	0.048
	(0.001)	(0.013)	(0.001)	(0.001)	(0.001)	(0.001)
%ΔCE	0.286	0.212	1.233	0.586	1.188	0.548
$\bar{r}$	0.068	0.063	0.113	0.073	0.120	0.075
$\sigma(r)$	0.080	0.079	0.120	0.093	0.124	0.093
Skew	1.236	0.817	2.574	3.335	2.639	3.354
SR	0.685	0.635	0.836	0.646	0.859	0.669

Table 3: **Optimal Corporate Bonds Portfolios - Cross-Sectional Varying T-Costs**
This table shows estimates of the optimal portfolio policy for the following bond-specific characteristics: time to maturity (TTM), credit rating (RAT), coupon (COUP), illiquidity (ILLIQ), momentum (MOM), and size (SIZE). The parameters are estimated with a power utility with $\gamma = 7$. Our sample period is from August 2005 until September 2015 and includes 116,932 bond-month observations. All columns refer to portfolios with transaction costs that vary both over time and cross-sectionally *CS-TS* (see Appendix **??**). In the first (last) two columns, transaction costs vary cross-sectionally depending on the bond issue amount (illiquidity). The columns *VW* refer to the respective value-weighted bond portfolio benchmarks. The first set of rows presents the marginal impact of the characteristics and bootstrapped p-values. The second set of rows shows average absolute portfolio weight, average minimum and maximum portfolio weights, average sum of negative weights, and annual turnover of the portfolio. The last set of rows reports the (annualized) performance of the optimal portfolio, displaying its certainty equivalent, certainty equivalent delta with respect to the corresponding benchmark, its mean, standard deviation, skewness and Sharpe ratio.

	Sort by SIZE		**Sort by ILLIQ**	
	VW	**CS-TS**	**VW**	**CS-TS**
TTM	-	-10.234	-	-10.763
	-	(0.001)	-	(0.001)
RAT	-	3.707	-	3.143
	-	(0.001)	-	(0.001)
COUP	-	11.148	-	11.921
	-	(0.001)	-	(0.001)
ILLIQ	-	-0.024	-	-0.042
	-	(0.930)	-	(0.885)
MOM	-	11.150	-	10.800
	-	(0.001)	-	(0.001)
SIZE	-	-5.490	-	-5.804
	-	(0.001)	-	(0.001)
$\lvert w_i \rvert \times 100$	0.106	0.174	0.106	0.175
$\max\ w_i \times 100$	1.090	1.316	1.090	1.301
$\min\ w_i \times 100$	0.002	-0.628	0.002	-0.638
$\sum w_i I(w_i < 0)$	0.000	-0.326	0.000	-0.330
$\sum \lvert(w_{i,t} - w_{i,t-1})\rvert$	0.551	5.875	0.551	5.728
CE	0.032	0.046	0.031	0.046
	-	(0.001)	-	(0.001)
$\%\Delta$CE	-	0.438	-	0.484
$\bar{r}$	0.058	0.071	0.058	0.070
$\sigma(r)$	0.082	0.088	0.082	0.088
Skew	-0.081	3.163	-0.085	3.271
SR	0.559	0.659	0.554	0.654