Cross-Predictability in Corporate Bonds

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Abstract

This paper develops an optimizing framework to forecast corporate bond returns using lagged returns from both the same and other bonds. The method exploits the autocovariance and cross-autocovariance structure of returns to construct dynamic, self-financing portfolios with closed-form solutions. Applied to ICE and TRACE data, our strategies generate high out-of-sample Sharpe ratios—exceeding 1.2 for portfolios sorted by credit risk and trading frictions. Predictability remains robust after risk adjustments and across market conditions. The results suggest that cross-bond return spillovers may play an important role in corporate bond markets and offer a useful perspective for bond pricing and portfolio construction.

Keywords: Corporate Bonds, Return Predictability, Asset Pricing, Portfolio Construction, Cross-bond Spillover, Autocovariance Structure, TRACE, ICE.

JEL Classification: C1, G11, G12, G14.

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1 Introduction

Do corporate bonds exhibit predictable returns? This question lies at the heart of asset pricing but remains far less explored than in equities. While decades of research have uncovered a wide range of equity return predictors, our understanding of return dynamics in corporate bond markets is limited. Several challenges help explain this disparity: bond trading is often infrequent, data have historically been fragmented, and market frictions—such as illiquidity, price dispersion, and dealer intermediation—complicate empirical analysis. Yet the gap is consequential. The U.S. corporate bond market amounts to about $11.4 trillion and is characterized by rich heterogeneity in credit risk, liquidity, and issuer fundamentals.[1]

Early studies found little evidence of momentum in investment-grade bonds (Gebhardt, Hvidkjaer, and Swaminathan, 2005), in contrast to the pronounced return continuation observed in equities (Jegadeesh and Titman, 1993). Subsequent work identified significant momentum in high-yield bonds and underscored the importance of credit risk and trading frictions (Bao, Pan, and Wang, 2011; Jostova, Nikolova, Philipov, and Stahel, 2013). More recent studies have examined bond- and issuer-level characteristics and employed machine learning to extract predictive structure (Lin, Wu, and Zhou, 2018; Israel, Palhares, and Richardson, 2018; Bartram, Grinblatt, and Nozawa, 2025). Despite these advances, however, existing approaches have yet to capture the dynamic cross-asset interactions that shape bond returns.

This paper develops a framework that systematically uncovers both self-

[1] As of the first quarter of 2025, according to SIFMA, www.sifma.org/resources/research/statistics/us-corporate-bonds-statistics/.

and cross-predictability in corporate bonds—capturing not only how a bond's own past returns forecast its future performance, but also how past returns of other bonds influence it. At the core of this framework is an optimizing procedure that constructs dynamic, self-financing portfolios from lagged returns. The approach delivers analytical solutions for the optimal portfolio weights and expected profitability, fully leveraging the autocovariance and cross-autocovariance structure of bond returns.

To ensure tractability and mitigate estimation noise in high-dimensional settings, we impose structure on the mapping from lagged returns to portfolio positions. We consider both unrestricted strategies, which rely directly on expected return estimates, and restricted variants that impose a uniform expected return across assets, thereby isolating the role of return dependencies. The restricted formulation serves as an intertemporal analog of the global minimum variance portfolio (GMVP): just as the GMVP assigns greater weight to assets with lower average correlations with others, our strategy favors bonds with lower or even negative average cross-autocovariances. This setup provides an intuitive and analytically tractable link between dynamic return interactions and optimal portfolio construction. In addition, the framework supports decompositions of the autocovariance matrix—such as separating its upper and lower triangular components—to reveal potential lead–lag structures and asymmetric return spillovers across bonds.

We implement the methodology using two broad corporate bond datasets—ICE and TRACE—which differ in pricing mechanisms, coverage, and construction. We consider 82 predictive characteristics, spanning bond-specific variables such as yield, duration, option-adjusted spread (OAS), and liquidity,

as well as equity-based firm characteristics such as size, value, momentum, and profitability. For each characteristic, bonds are sorted into 30 portfolios on cross-sectional signal values, and the strategy is applied to the resulting portfolio return series. This design produces a panel of 82 characteristic-specific strategy returns, which forms the basis for subsequent aggregation, performance attribution, and robustness analyses.

The results reveal strong and persistent bond return predictability. When the strategy is applied to portfolios sorted on credit-related characteristics—such as yield, price, and OAS—it delivers average monthly returns of 120 to 150 basis points, with Sharpe ratios between 1.14 and 1.27. When applied to portfolios sorted on trading-friction variables—such as bid–ask spreads and return volatility—average returns are lower (60–90 basis points), but Sharpe ratios are even higher, reaching up to 1.37. By contrast, portfolios sorted on interest-rate risk characteristics (e.g., duration, convexity) consistently perform poorly, while those sorted on equity-style variables exhibit only moderate, and often negligible, predictability.

To synthesize information across signals, we construct a tangency portfolio that combines the 82 strategy returns using mean–variance optimization. The resulting portfolios deliver high out-of-sample Sharpe ratios, exceeding one in both ICE and TRACE. We also examine a constrained version of the tangency portfolio that excludes expected return inputs and relies solely on dynamic autocovariances. This strategy generates average monthly returns of more than 80 basis points in ICE and 70 in TRACE, highlighting the economic value of intertemporal dependencies.

To further understand the drivers of predictability, we decompose prof-

itability into own- and cross-bond components. The cross component—capturing return spillovers across securities—consistently dominates. In ICE, for example, the cross-driven strategy delivers 115 basis points per month with a Sharpe ratio of 1.17, while the own-only strategy yields just 38 basis points and a Sharpe ratio of 0.72. These results highlight the central role of cross-bond dynamics in shaping predictable variation in corporate bond returns.

Our contribution is twofold. First, we develop a tractable and interpretable method for extracting and exploiting dynamic structure in corporate bond returns. Methodologically, our approach complements recent advances in dynamic factor modeling and portfolio optimization (e.g., Kelly, Malamud, and Pedersen, 2023), but uniquely emphasizes intertemporal dependencies rather than latent contemporaneous factors. Second, our findings provide a new perspective on corporate bond factor modeling. By grounding signal construction in the autocovariance structure of returns, we uncover persistent components—especially those linked to credit risk and trading frictions.

The remainder of the paper is organized as follows. Section 2 presents the methodology and derives the optimal trading strategy. Section 3 describes the ICE and TRACE datasets and the construction of bond and stock characteristics. Section 4 reports the empirical results, including profitability decomposition, factor-based strategy performance, and alpha estimation. Section 5 concludes.

2 Methodology

This section presents the modeling framework that underlies our empirical analysis. The model leverages the intertemporal structure of corporate bond returns to derive an optimal trading strategy that incorporates both own- and cross-autocovariances. We begin by outlining a general framework for cross predictability in corporate bond returns based on lagged returns, and then derive explicit solutions for the resulting optimal trading strategies and their expected profitability.

2.1 Leveraging Predictability from Past Returns

At each time t, a hypothetical investor constructs a zero-cost trading strategy involving N corporate bonds, using past returns as predictive signals. The strategy reflects the belief that a bond's return can be forecasted not only from its own lagged returns but also from the lagged returns of other bonds. Our empirical analysis applies to portfolios of corporate bonds, so N is fixed. However, the framework can be readily adapted to settings in which the number of investable assets varies over time.

Let R_t denote an N-dimensional vector of realized returns on corporate bonds at time t, and let R_s denote the return vector at a future time $s = t+K$, where $K \geq 1$. For example, $K = 1$ corresponds to a short-term horizon, while $K = 6$ reflects an intermediate-term strategy. The auto-covariance matrix between R_s and R_t is denoted by Ω, and Ω' represents the auto-covariance between R_t and R_s. The mean return vector is denoted by μ, an N-vector.

We assume that both μ and Ω remain constant within each estimation

window. However, as the model is estimated using a rolling sample, the estimates of μ and Ω evolve over time as the window shifts, thereby adapting to changing market conditions.

The trading strategy builds on Kelly, Malamud, and Pedersen (2023), with some modifications. It is given by

$$\begin{aligned} w_t' &= R_t' L - \frac{1}{N} R_t' L A, \\ &= R_t' L \Phi, \\ &= R_t' \Psi, \end{aligned} \tag{1}$$

where L is an $N \times N$ matrix chosen to optimize investment performance, A is an $N \times N$ matrix of ones, and $\Phi = I_N - \frac{1}{N} A$ is a projection matrix that enforces the zero-cost condition. Here, I_N denotes the $N \times N$ identity matrix, and $\Psi = L\Phi$ is the effective position matrix that maps past returns into portfolio weights while ensuring the self-financing constraint. In particular, the strategy satisfies $w_t' \iota_N = 0$, where ι_N is an N-dimensional vector of ones.

The proposed investment nests standard cross-sectional momentum as a special case. In particular, when the restriction $\Psi = \frac{1}{N}\Phi$ (equivalently, $L = \frac{1}{N} I_N$) is imposed, the strategy simplifies to the momentum of Lo and MacKinlay (1990) and Lewellen (2002).[2] However, by relaxing this restriction, we allow for richer dynamics that exploit both auto-covariances and cross-autocovariances in returns.

Let $\pi_s = w_t' R_s$ denote the realized return on the strategy. Its expected

[2]While the traditional momentum of Jegadeesh and Titman (1993) constructs equally weighted portfolios of extreme deciles only, Lo and MacKinlay (1990) and Lewellen (2002) apply past return-based weights to the whole cross-section.

value is given by:

$$E(\pi_s) = (\mu \otimes \mu + \text{vec}(\Omega))' \, \text{vec}(\Psi), \tag{2}$$

where $\otimes$ denotes the Kronecker product and vec is the vectorization operator.[3]

The expected-value decomposition highlights two distinct sources of profitability. The first term, $\mu \otimes \mu$, captures the interaction structure of expected returns across assets. In particular, it aggregates all pairwise products of expected returns, rewarding strategies that emphasize co-aligned return expectations. The second term, $\text{vec}(\Omega)$, reflects dynamic return dependencies through own- and cross-autocovariances. Thus, equation (2) provides a transparent decomposition of expected profitability into static and dynamic components.

It is essential to note that the matrix Ψ is constructed to satisfy the self-financing constraint. Therefore, optimization focuses on identifying the optimal matrix L, from which $\Psi = L\Phi$ is subsequently computed.

The investor maximizes expected profitability by choosing the optimal matrix L, subject to a Frobenius norm constraint $\|L\|_F = \kappa$. The parameter κ is calibrated so that the total absolute value of long and short positions across the corporate bond cross-section equals two, ensuring economic interpretability and consistency with standard factor construction practices.[4]

Imposing the Frobenius norm constraint offers several advantages. First,

[3]To see this, write $\pi_s = w_t' R_s = R_t' \Psi R_s$. Then $E(\pi_s) = \mathbb{E}[R_t' \Psi R_s] = \text{tr}(\Psi \mathbb{E}[R_s R_t']) = \mu' \Psi \mu + \text{tr}(\Psi \Omega)$, where tr denotes the trace operator. Using the identities $\text{vec}(XYZ) = (Z' \otimes X)\text{vec}(Y)$ and $\text{tr}(X'Y) = \text{vec}(X)'\text{vec}(Y)$, we obtain equation (2).

[4]Short positions total -1 and long positions 1.

it ensures that the resulting strategy remains balanced and scalable. Second, it enables an explicit expression for both the strategy and its expected profitability in terms of the components of the vector μ and the matrix Ω. Third, the norm constraint acts as a form of regularization, similar to ridge-type shrinkage, which helps mitigate overfitting. From a Bayesian perspective, imposing the norm constraint is equivalent to placing a *zero-mean Gaussian prior* on $\mathrm{vec}(L)$, so that the optimization yields a maximum a posteriori estimate that shrinks the position matrix toward zero.

Having established the structure of the trading strategy and the associated constraints, we now formulate the corresponding optimization problem. Specifically, we seek to maximize the expected profitability with respect to the matrix L, subject to the Frobenius norm constraint.

The Lagrangian is given by:

$$\mathcal{L} = \mu' L \Phi \mu + \mathrm{tr}(L \Phi \Omega) + \lambda \left(\kappa - \sqrt{\sum_{i=1}^{N} \sum_{j=1}^{N} L_{ij}^2} \right), \tag{3}$$

where λ denotes the Lagrange multiplier and L_{ij} is the (i, j)-th entry of the matrix L.

The first-order condition associated with equation (3) is

$$\frac{\partial \mathcal{L}}{\partial L} = \left[\mu \mu' + \Omega' \right] \Phi - \frac{1}{\kappa} \lambda L = 0. \tag{4}$$

This yields a system of N^2+1 equations—corresponding to the N^2 elements of L and the scalar Lagrange multiplier λ—which jointly determine the optimal solution.

To solve the optimization problem, we define the adjusted prediction matrix as

$$\Pi_A = \Phi E(R_s R_t'). \tag{5}$$

Under this specification, the Lagrange multiplier is given by

$$\lambda = \sqrt{\text{tr}(\Pi_A' \Pi_A)}, \tag{6}$$

and the optimal matrix L takes the form

$$L = \kappa \left(\text{tr}(\Pi_A' \Pi_A)\right)^{-1/2} \Pi_A'. \tag{7}$$

from which the effective position matrix Ψ follows.

The expression in equation (7) represents a modification of the approach introduced by Kelly, Malamud, and Pedersen (2023). In their Principal Portfolios framework, the solution takes the form

$$L = (\Pi'\Pi)^{-1/2}\Pi', \tag{8}$$

where $\Pi = E(R_s R_t')$. This solution arises from imposing a spectral norm constraint, which restricts the largest singular value of the position matrix to one.

To understand our distinct solution for the position matrix, note that we impose a Euclidean norm constraint on $\text{vec}(L)$, which is equivalent to a Frobenius norm constraint on L. This choice facilitates an analytical expression for both the strategy weights and their associated profitability in terms of the components of the mean vector and the auto- and cross-covariance ma-

trix. We calibrate the scaling parameter κ and apply the projection matrix Φ to ensure that the absolute values of the long and short positions sum to one, yielding a zero-cost spread portfolio. Importantly, the analytical structure of our solution also allows for an alternative formulation of the trading strategy that depends solely on autocovariances and cross-autocovariances, thereby mitigating sensitivity to estimation errors in expected returns.

2.2 Trading Strategies

We present an explicit expression for the trading strategy. In particular, the (i, j)-th element of Ψ can be written as

$$\Psi_{i,j} = \frac{1}{\zeta} \sum_{k=1}^{N} (\mu_i \mu_k + \omega_{k,i}) \left(\delta_{kj} - \frac{1}{N} \right), \tag{9}$$

where $\zeta = \frac{\lambda}{\kappa}$, $\omega_{i,j}$ is the (i, j)-th component of Ω, and δ_{kj} is the Kronecker delta which is equal to 1 if $k = j$ and zero otherwise. The time t trading strategy is then expressed as $w_t = \Psi' R_t$.

Two remarks about ζ are warranted. First, both the ex-ante and out-of-sample Sharpe ratios of the zero-cost strategy are invariant to the choice of ζ; varying ζ scales both the expected return and volatility proportionally, leaving their ratio unchanged. Second, ζ is a well-defined parameter, determined by the norm constraint κ and the optimized Lagrange multiplier λ. As noted earlier, we calibrate κ such that the total absolute value of long and short positions sums to two. Given this calibration, the value of ζ follows directly.

Having determined the components of Ψ, we can now express the position

in corporate bond (or portfolio of corporate bonds) i at time t as follows:

$$w_{i,t} = \frac{1}{\zeta} \sum_{j=1}^{N} r_{j,t} \left[\sum_{k=1}^{N} (\mu_i \mu_k + \omega_{k,i}) \left(\delta_{k,j} - \frac{1}{N} \right) \right], \tag{10}$$

where $r_{j,t}$ denotes the return on bond j at time t.

To improve the transparency of the trading strategy, we consider a simplified scenario with only two corporate bonds, having means denoted by μ_1 and μ_2, and realized returns at time t given by $r_{1,t}$ and $r_{2,t}$, respectively.

The position in the first bond can be expressed as: $w_{1,t} = \frac{1}{2\zeta} (\phi_1 r_{1,t} + \phi_2 r_{2,t})$, with $w_{2,t} = -w_{1,t}$. Here, $\phi_1 = (\mu_1 - \mu_2)\mu_1 + (\omega_{1,1} - \omega_{2,1})$, and $\phi_2 = (\mu_1 - \mu_2)\mu_2 - (\omega_{2,2} - \omega_{1,2})$.

This formulation highlights two key forces that shape portfolio weights. First, it emphasizes the role of the expected return difference $(\mu_1 - \mu_2)$, where a larger gap implies a stronger signal for portfolio positioning. Second, it draws attention to the distinction between a bond's own autocovariance and its cross-autocovariances with other bonds. While the first force is intuitive, the second is essential for understanding the mechanics of the trading strategy. This distinction becomes particularly salient when expected return differences are normalized away—that is, under the assumption of equal expected returns across bonds.

To mitigate potential estimation errors in the mean return vector μ, we therefore consider a setting in which all assets are assumed to have identical expected returns. This restriction enables the construction of an optimal portfolio that relies solely on autocovariances and cross-autocovariances, as captured by the matrix Ω.

The resulting structure is analogous to the Global Minimum Variance Portfolio (GMVP), which similarly avoids reliance on expected return estimates. However, unlike the GMVP—which is based on the covariance matrix of contemporaneous returns and minimizes variance—our strategy leverages the auto- and cross-autocovariance matrix of lagged returns to maximize profit, thereby capturing intertemporal return predictability.

The unified-mean trading strategy is modified to

$$w_{i,t} = \frac{1}{\zeta} \sum_{j=1}^{N} r_{j,t} \left[\sum_{k=1}^{N} \omega_{k,i} \left(\delta_{k,j} - \frac{1}{N} \right) \right]. \tag{11}$$

Notice that the expression within the square brackets on the right side of the equation signifies the difference between (i) $\omega_{j,i}$ and (ii) the average cross-autocovariance of all bonds but j with bond i. Let us denote that difference as $\omega^e_{j,i} = \frac{N-1}{N} \left[\omega_{j,i} - \frac{1}{N-1} \left(\omega_{1,i} + \omega_{2,i} + \ldots + \omega_{N,i} \right) \right]$, where the sum of cross-autocovariances does not include $\omega_{j,i}$, while $\omega_{i,i}$ is included. Then, it follows that $w_{i,t} = \frac{1}{\zeta} \sum_j \omega^e_{j,i} r_{j,t}$.

The derived portfolio in equation (11) shares similarities with the Global Minimum Variance Portfolio (GMVP), which relies solely on the return covariance matrix. In deriving the GMVP, an asset appears more attractive if its average correlation with the other assets is low. Likewise, in our setting, an asset becomes more appealing for investment if it exhibits low autocovariances with other assets.

2.3 Profitability

We now shift our focus to analyzing the strategy's profitability. Substituting the optimal matrix Ψ into equation (2), the expected profitability can be expressed as:

$$E(\pi_s) = \frac{1}{\zeta}\left[\operatorname{tr}(\Omega'\Phi\Omega) + N^2\sigma_\mu^2\left(\sigma_\mu^2 + \mu_m^2\right) + 2\sum_{i=1}^{N}\mu_i\left(\sum_{j=1}^{N}\omega_{j,i}(\mu_j - \mu_m)\right)\right], \tag{12}$$

where $\mu_m = \frac{1}{N}\sum_{i=1}^{N}\mu_i$ denotes the average expected return across all bonds, and $\sigma_\mu^2 = \frac{1}{N}\sum_{i=1}^{N}(\mu_i - \mu_m)^2$ represents the cross-sectional variance of expected returns.

The second term in equation (12) illustrates how profitability increases with the dispersion in expected returns. The third term can be rewritten as $2N\sum_{i=1}^{N}\mu_i \operatorname{cov}(\omega_{j,i}, \mu_j)$, indicating that profitability is enhanced when a bond's autocovariance and cross-autocovariances are positively correlated with the expected returns of other bonds. We analyze the first term in detail below.

In particular, consider the case where expected returns are identical across all bonds, so that $\mu_i = \mu_m$ for all i. Under this restriction, the last two terms in equation (12) vanish, and expected profitability simplifies to (dropping ζ for notational ease):

$$\begin{aligned} E(\pi_s) &= \operatorname{tr}(\Omega'\Phi\Omega) \\ &= \sum_{i=1}^{N}\sum_{j=1}^{N}\omega_{ji}\omega_{ij} - \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N}\left(\sum_{k=1}^{N}\omega_{ki}\omega_{kj}\right). \end{aligned} \tag{13}$$

In this case, expected profitability is nonnegative, as it equals the trace of the positive semidefinite matrix $\Omega'\Phi\Omega$. It becomes strictly positive under mild conditions—specifically, when Ω varies beyond the constant vector. This highlights the central role of cross-autocovariances in driving profitability, especially given their overwhelming prevalence relative to autocovariances.

The empirical analysis evaluates the investment performance of two approaches: the unrestricted strategy in equation (10), and the constrained variant in equation (11), which imposes a uniform expected return across assets. Their ex-ante profitability is characterized by equations (12) and (13), respectively. Our primary focus, however, is on the realized out-of-sample performance of portfolios of corporate bonds.

3 Corporate Bond Data

The empirical analysis draws on corporate bond return data from two major sources: ICE (Intercontinental Exchange, also known as the ICE Bank of America [BofA] Corporate Bond Database) and TRACE (FINRA's Trade Reporting and Compliance Engine).

3.1 ICE Data

ICE provides daily and monthly corporate bond prices used in the valuation of Bank of America corporate bond indexes. When purchasing ICE data, researchers must specify both the corporate bond index of interest and the desired data frequency. ICE maintains over 6,000 standard fixed income indexes, covering approximately 56,000 investment-grade and 7,000 high-

yield corporate debt issues across global bond markets.[5]

Our ICE dataset contains monthly prices for the constituents of the two most comprehensive U.S. corporate bond indexes: *C0A0*, ICE BofA US investment grade corporate index, and *H0A0*, ICE BofA high yield index. The sample includes 2,404,789 monthly bond-level return observations from December 1996 through June 2024, corresponding to a monthly average of 7,279 individual bond returns and a total of 48,373 distinct bonds.

ICE Data Services offers "Continuous Evaluated Pricing (CEPTM)".[6] These evaluated prices are market-based estimates generated by a rules-based pricing engine and represent ICE's good-faith determination of the price at which a bond could be transacted in an orderly institutional round-lot trade ($1 million or more) under current market conditions. The evaluation process applies standard asset-class-specific valuation techniques and prioritizes the use of observable market inputs, such as quoted prices for comparable securities, benchmark yield curves, and corroborated market data.

Evaluations are continuously updated as new market information becomes available, including dealer quotes and transaction data. TRACE execution data are also incorporated as inputs. Additional sources may include dealer runs, information from electronic communication networks (ECNs), transaction reporting services, and unstructured data (e.g., emails) from market participants.

In summary, the ICE dataset offers a long time span, extensive bond-level coverage, and vendor-applied quality controls. It includes both total

[5]See www.ice.com/fixed-income-data-services/data-and-analytics/pricing/evaluated-pricing.

[6]Source: "Continuous Evaluated Pricing (CEPTM) for Fixed Income Methodology," Intercontinental Exchange, ©2024 ICE Data Pricing & Reference Data, LLC.

and excess returns and provides a reliable foundation for studying the long-term behavior of corporate bond returns.

3.2 TRACE Data

TRACE, available through Wharton Research Data Services (WRDS), is the most widely used trade-based data source for U.S. corporate bonds. Since July 2002, dealers have been required to report all trades in eligible securities to TRACE. Initially, only trades in large investment-grade (IG) bonds were disseminated, followed by smaller IG bonds and eventually non-investment-grade (NIG) bonds.

Standard TRACE provides timely information on all disseminated trades but caps reported trade sizes at $5 million for IG bonds and $1 million for NIG bonds. In contrast, *Enhanced TRACE* provides, with a six-month lag, both disseminated and non-disseminated trades without caps on trade sizes.

We collect prices from both *Standard TRACE* and *Enhanced TRACE* over their full coverage period. Because *Enhanced TRACE* offers more complete trade-level information, we use it as our primary data source from July 2002 to December 2022. For January 2023 to June 2023, we supplement it with *Standard TRACE*. We employ WRDS-provided SAS programs for pre-cleaning both versions of TRACE.[7] These programs apply corrections, cancellations, and reversals reported by dealers and remove duplicate inter-dealer trades.

[7] See wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/wrds-bond-return/cleaning-trace-data/wrds-clean-trace-enhanced-file/ and wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/wrds-bond-return/cleaning-trace-data/wrds-clean-standard-trace-file/, dated October 2017.

We construct corporate bond returns using the WRDS production SAS program.[8] Daily prices are estimated as trade-size-weighted averages of intraday prices, excluding commissions and trades with negative prices. The program generates three month-end prices: `PRICE_LDM` (last trading day of the month), `PRICE_L5M` (last daily price within the month's last five trading days), and `PRICE_EOM` (last daily price of the calendar month). We adopt the return based on the last five trading days, `RET_L5M`, as our baseline monthly return measure.

Returns are winsorized at 100%.[9] The program also adjusts returns in the month of default. It aggregates the returns of defaulted IG (NIG) bonds over the month before, of, and after default, and assigns the average to all default-month returns: -20.779% for IG and -22.488% for NIG/unrated bonds in our sample. These values are not adjusted for "flat trading," and post-default returns are excluded from the sample.

The final dataset includes 1,426,930 bond-month return observations from July 2002 to June 2023. This constitutes the standard WRDS Bond Returns Database.[10]

In summary, TRACE offers high-frequency, trade-level data with granular details on transaction size and dissemination. Enhanced TRACE in particular provides a more complete view of the market, especially post-2002, and is therefore our primary source for analyzing trade-based return dynamics in

[8]The program is available at wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/wrds-bond-return/sas-code-behind-the-scene/sas-code-behind-the-scene/. It merges *Standard TRACE* and *Enhanced TRACE* with FISD and excludes convertible, non-U.S., Rule 144A, and other ineligible bonds.

[9]The WRDS production programs were updated in August 2024 to apply revised filters and outlier treatments.

[10]See, for example, Bai, Bali, and Wen (2023), among others.

more recent years.

3.3 Descriptive Statistics

Table 1 reports descriptive statistics for individual corporate bond returns from ICE and TRACE. The ICE returns span January 1997 to June 2024, with an average of 7,287 individual bond returns per month. The ICE dataset provides both raw total returns and excess returns, the latter computed relative to a comparable-maturity Treasury security. ICE data are subject to vendor-applied quality controls, including expert-driven outlier screening. Nevertheless, the maximum total return in ICE, reported in Panel A, is 8,575%. Upon inspection, this observation lacks a corresponding price in the preceding month and is therefore treated as a data error. After removing cases with missing lagged prices, the maximum return is 679%.

Based on 2.4 million bond-month observations, the average total return in ICE is 43 basis points per month (bpm), with 98% of returns falling within the range of -11% to 9.6%. The average excess return is 18 bpm. The standard deviation of total (excess) returns is 4.28% (4.13%) per month.

Since our analysis utilizes portfolios, extreme individual bond return outliers have less influence. Table 2 reports summary statistics for portfolios of ICE bond returns, while Table 3 reports analogous statistics for TRACE return portfolios. These portfolios are constructed using bond characteristics from ICE or TRACE, as well as stock and firm characteristics from CRSP and COMPUSTAT. We form 82 sets of 30 portfolios: 26 sets based on bond characteristics and 56 on stock characteristics grouped into six anomaly categories following Hou, Xue, and Zhang (2015). The bond characteristics rep-

resent the union of available variables from the ICE and TRACE databases. The majority of characteristics are found in both databases. However, there are three different prices and returns available in TRACE, as explained earlier. TRACE also offers trading volumes and bid-ask spreads that are not available in ICE. ICE, on the other hand, offers bond analytics such as OAS, convexity, fair market value, and various alternative calculations of duration and attribution returns (e.g. price return, amortization return, and coupon return).

For the ICE portfolios in Table 2, average excess returns range from 8 to 21 bpm depending on the availability of characteristics and the number of eligible bonds in each period. For instance, portfolios sorted on TRACE yield data are only available from July 2002, while ICE yields are available from December 1996. Fewer bonds are matched with stock characteristics than with bond characteristics because stock variables are limited to public firms, which constitute roughly half of bond issuers, and many stock variables are sparsely populated.

Portfolios based on stock characteristics exhibit average excess returns of about 12 bpm, while those based on ICE and TRACE bond characteristics average 15 bpm and 20 bpm, respectively. The table reports both the overall standard deviation of returns within each characteristic group (SD) and the average of 30 portfolio standard deviations in each characteristic-based cross-section (Ave SD). These average around 1.9% and 1.8% per month, respectively, with overall standard deviations ranging from 1.68% to 2.39% per month.

The table also reports the minimum and maximum standard deviation

for each portfolio cross-section. Some portfolios exhibit monthly volatility as low as 0.35%, while others reach up to 7.66%. Portfolio returns exhibit far smaller outliers than individual bonds in Table 1. For example, individual bond excess returns from ICE can fall below −100% (implying total default and shortfall against the risk-free rate) or exceed 600% in a month, while portfolio losses rarely exceed −20% and never surpass −40%. Maximum portfolio returns are always below 40%, and typically below 20%.

Table 2 also shows the minimum and maximum number of bonds per portfolio and the number of periods in each series. Stock-based portfolios tend to be more unevenly populated, with 20–30 bonds in some portfolios and over 200 in others. In contrast, bond-characteristic portfolios more consistently include at least 100 bonds, and some exceed 200.

Table 3 presents similar statistics for TRACE portfolios, based on raw returns computed using WRDS production scripts. The TRACE time series is shorter than that of ICE, and time coverage is less restricted by characteristic availability. WRDS offers three end-of-month return calculations: (1) based on the last available trade (any day), (2) using the last trading day's price, and (3) based on trades from the last five trading days. We adopt the third measure.[11]

TRACE portfolios have an average monthly return of approximately 45 bpm. Their standard deviations are slightly higher than ICE portfolios, both overall and cross-sectionally. Minimum and maximum values are somewhat more dispersed, but overall the return distributions are broadly comparable. Portfolio sizes vary more in TRACE, and tend to be smaller than ICE

[11] See Jostova, Nikolova, and Philipov (2024) for a discussion of the different TRACE return methodologies.

portfolios, due to the transaction-based nature of TRACE and the greater prevalence of missing observations. While TRACE includes all corporate bond issues, ICE focuses on index constituents, which are more stable and complete.

In summary, the descriptive statistics reveal substantial heterogeneity in bond returns across the sample. While average monthly returns are modest, the distribution exhibits considerable skewness and kurtosis, reflecting occasional extreme outcomes. The ICE dataset shows a wide range of returns due to its broader historical span and coverage, whereas TRACE data exhibit tighter dispersion. After removing a handful of clearly erroneous or missing-price observations, the data appear robust for empirical analysis.

4 Cross predictability in corporate bonds

We begin by illustrating our methodology using a prominent and economically meaningful example: yield-based return predictability. This characteristic not only serves as a compelling proof of concept but also offers a transparent window into the mechanics of our strategy and the distinct contributions of self- versus cross-predictability.

We sort corporate bonds into 30 portfolios based on effective yield ($N = 30$) and apply our return-predictability strategy to the resulting return series. Table 4 reports a decomposition of strategy profitability into self-predictability (captured by the diagonal elements of the autocovariance matrix Ω) and cross-predictability (off-diagonal elements), using both the ICE and TRACE datasets.

In the ICE sample, a strategy that excludes both the mean return vector and the diagonal of Ω—thus isolating pure cross-predictability—yields an average monthly return of 107 basis points. Self-predictability contributes 57 basis points, while cross-predictability accounts for the remaining 50. In TRACE, the total strategy return is 96 basis points, with 89 basis points driven by cross-predictability and only 7 by self-predictability.

To facilitate direct comparison, we normalize the position vectors in each component strategy such that long and short positions each sum to one. Under this scaling, the pure cross-predictability strategy—based on a zero-diagonal Ω—delivers 77 basis points per month in ICE and 83 in TRACE. The self-predictability strategy, which uses only the diagonal of Ω, yields even higher average returns: 150 basis points in ICE and 138 in TRACE.

This example demonstrates that dynamic return dependencies, especially those across assets, can generate economically meaningful profitability. Motivated by these findings, we now turn to a systematic implementation of the strategy across a wide range of bond- and stock-level characteristics.

We implement the analysis across 82 predictive signals: 26 bond-level characteristics (e.g., yield, duration, OAS, liquidity) and 56 firm-level equity characteristics (e.g., size, value, momentum, investment). For each characteristic, we sort corporate bonds into 30 portfolios based on the cross-sectional values of that signal and apply our return-predictability framework to the resulting time series. This yields 82 strategy-specific return series, each representing a dynamic, zero-cost portfolio constructed using one-month lagged returns.

To capture the structure of return dynamics, we estimate several vari-

ants of the autocovariance matrix Ω, each designed to highlight a different component of predictability. Our six optimization approaches include: (1) an unconstrained strategy based on Π, which incorporates expected return differences; (2) a restricted variant based on Ω, which assumes equal means across portfolios; (3–4) decompositions into the diagonal (Ω^{d}) and off-diagonal ($\Omega^{\emptyset d}$) components of Ω; and (5–6) triangular decompositions of Ω to examine lead-lag asymmetries.

Table 5 reports results using ICE data. Strategies based on bond characteristics yield consistently high and statistically significant returns. Approximately 70% of these strategies are significant at the 5% level, with several producing monthly profits exceeding 100 basis points—even though the average underlying portfolio-level return is only 14 basis points.[12]

The equal-mean strategy (Ω) remains highly profitable, indicating that autocovariances alone capture substantial structure. While Π strategies slightly outperform Ω, the margin is narrow, suggesting that the marginal value of incorporating expected return differences is modest—possibly due to estimation noise or the dominance of dynamic terms.

The decomposition of Ω reveals that both self- and cross-predictability are relevant. The diagonal component (Ω^{d}) is often dominant, but the off-diagonal component ($\Omega^{\emptyset d}$) remains economically meaningful. Lower and upper triangle restrictions further highlight that high-yielding and low-price bonds are especially predictive, depending on the ordering of portfolios.

TRACE data, reported in Table 6, yield qualitatively similar results. Bond-based signals remain strong, though average profits are modestly lower.

[12]The results for yield (`ixRxIeYLD`) match those in Table 4.

Interestingly, the Ω-based strategy now outperforms Π more clearly—especially when ICE-based predictors are used on TRACE portfolios—suggesting that mean return estimation is noisier in trade-level data, amplifying the value of autocovariance-driven designs.

Stock-based predictors yield more mixed results. In ICE, value-versus-growth and volatility-related trading frictions perform well; others, including momentum and investment, are less robust. In TRACE, stock-based strategies perform somewhat better, particularly for intangibles and investment. Amihud illiquidity stands out, doubling its ICE-based return.

Taken together, Table 5 and Table 6 highlight that return predictability in corporate bonds is widespread, persistent, and economically meaningful—especially for characteristics linked to credit risk and trading frictions. The presence of both autocorrelations and cross-autocorrelations aligns with findings in equity markets (Avramov, Cheng, Schreiber, and Shemer, 2017) and underscores the importance of dynamic structure in bond pricing.

In the next stage, we treat the 82 characteristic-based strategy return series as investable assets and construct tangency portfolios via mean-variance optimization. This aggregation yields portfolios that maximize the Sharpe ratio and summarize the benefits of diversifying across signal-based strategies.

We benchmark these tangency portfolios against several passive alternatives. An equally weighted bond market portfolio constructed from ICE excess returns achieves an annualized Sharpe ratio of 0.32, while its TRACE-

based counterpart reaches 0.44.[13] A value-weighted bond market portfolio using ICE data (weighted by fair market value) delivers a Sharpe ratio of 0.44, compared to 0.39 using TRACE data (weighted by amount outstanding).

To better understand the drivers of performance, we form tangency portfolios within grouped subsets of the 82 strategies. Specifically, we construct tangency portfolios (i) separately for bond- and stock-based strategies, and (ii) across ten finer subgroups: three bond-related (credit risk, interest rate risk, and trading frictions/others) and seven stock-related (six following the Hou, Xue, and Zhang (2015) classification and one miscellaneous group). This allows us to evaluate which signal types contribute most to return predictability when optimally combined.

Table 7 reports out-of-sample tangency portfolio statistics using ICE data. Panel A shows that bond-based tangency portfolios deliver annualized Sharpe ratios between 1.14 and 1.35—roughly three times higher than passive market benchmarks. The highest Sharpe ratios are achieved under the zero-diagonal Ω specification, which isolates cross-predictability. Stock-based tangency portfolios are less profitable, with Sharpe ratios ranging from 0.14 to 0.38, but again reach their peak under the cross-predictability-only variant. Notably, while the bond Ω^d (autocovariance-only) tangency portfolio produces the highest raw return (46 basis points per month), its elevated volatility lowers its risk-adjusted performance relative to the $\Omega^{\emptyset d}$ (cross-covariance-only) specification. In untabulated results, combining bond and stock signals yields Sharpe ratios between 0.80 and 1.14, suggesting meaningful complementarity

[13]The ICE Sharpe ratio is based on reported excess returns. Since TRACE does not provide excess returns, we subtract the Fama-French risk-free rate—available from WRDS and Prof. Ken French's website—from total returns.

between the two sources.

Panel B provides further granularity across the ten subgroups. Among bond-based predictors, trading frictions generate the highest Sharpe ratios (0.94 to 1.14), suggesting these signals are especially effective in reducing portfolio volatility. Credit risk portfolios rank next (0.80 to 0.87), while interest rate characteristics underperform (Sharpe ratio: 0.48). Among stock subgroups, miscellaneous characteristics lead with Sharpe ratios up to 0.76, followed by value-versus-growth (0.59 to 0.73) and momentum. Profitability-based portfolios follow, while stock trading frictions underperform due to the mixed performance of volatility (strong) and skewness (weak) signals.

To assess the impact of short-sale constraints, the final three columns of Table 7 report results without these restrictions. In the unconstrained case, portfolio weights can become extreme, leading to elevated volatility and reduced Sharpe ratios. Only strategies based on bond trading frictions remain stable under unconstrained optimization, and only when cross-covariances are included. Under the diagonal-only (Ω^d) specification, unconstrained optimization proves highly unstable.

Table 8 presents analogous results using TRACE data. Broad patterns mirror those in ICE, though stock-based tangency portfolios perform markedly better. In Panel A, stock-based portfolios achieve Sharpe ratios up to 0.87. Bond-based portfolios again dominate, peaking at 1.21 under the cross-predictability-only specification. In contrast, profitability declines significantly under the zero-off-diagonal specification, confirming the importance of cross-predictability. In Panel B, trading friction strategies once again lead (Sharpe ratio up to 1.28), while interest rate portfolios remain the weakest.

Among stock signals, value-versus-growth stands out, with Sharpe ratios up to 1.11, driven by high average returns.

Overall, these findings underscore that cross-bond return predictability can be harnessed to construct portfolios with substantially higher returns than passive benchmarks. While interest rate risk contributes little to portfolio profitability, trading frictions and credit risk characteristics consistently deliver the strongest performance.

We next examine whether the superior performance of our characteristic-based portfolios can be explained by exposure to a bond market risk factor. To do so, we regress strategy returns on the value-weighted bond market portfolio.

Figure 1 displays the resulting alphas for ICE data. Portfolios based on credit risk characteristics generate alphas as high as 1.25% per month under the diagonal-only Ω specification. However, these high alphas often come with elevated volatility. The Ω triangle decomposition indicates that high credit risk values—lower triangle for yield and spreads, upper triangle for price—are key drivers.

Stock-based predictors generally yield smaller alphas. Only trading frictions (e.g., volatility) and value-versus-growth characteristics deliver statistically and economically significant alphas; most other stock characteristics are statistically indistinguishable from zero.

Figure 2 confirms these patterns using TRACE data. The bond market portfolio here is computed using TRACE returns weighted by amount outstanding, and excess returns are net of the Fama-French risk-free rate. As in the ICE sample, the highest alphas are associated with credit risk and

trading friction signals, while interest rate variables remain uninformative.

Having established that market risk does not account for profitability, we next examine the strategy's performance across different market environments. Specifically, we explore how profitability varies between recessions and expansions, and how it is affected by investor sentiment. To this end, we augment the CAPM regressions with two additional controls: a recession dummy (equal to one during NBER-defined recession months) and a low-sentiment dummy (equal to one if the University of Michigan Consumer Sentiment Index is below its sample median).[14]

The environment-adjusted alphas are reported in Figure 3 for ICE and in Figure 4 for TRACE. These graphs reproduce the original alpha figures but include two columns of plus/minus signs indicating the estimated effects of the recession and low-sentiment dummies. A green plus in the first column indicates that profitability is higher during recessions; a red minus denotes lower profitability. The second column reports the sign of the sentiment dummy.

We observe mostly green pluses in the first column, indicating that strategy profitability tends to increase during recessions. This may reflect the methodology's ability to extract value from noisy signals in volatile or dislocated markets. The impact of low sentiment is more mixed: neutral to mildly negative for ICE-based bond strategies, and clearly negative in TRACE data, particularly for stock characteristics. As many of these stock characteristics reflect pricing anomalies, the TRACE findings are consistent with Stam-

[14]The dummies are included as intercept shifts rather than interactions, since our focus is on their direct effect on profitability. We obtain the recession indicator from the Federal Reserve Bank of St. Louis (fred.stlouisfed.org/series/USREC) and sentiment data from Bloomberg.

baugh, Yu, and Yuan (2012), who find that anomaly profits are amplified in high-sentiment environments.

Although alpha magnitudes remain economically large after controlling for recessions and sentiment, statistical significance is somewhat attenuated. Still, credit-based portfolios continue to exhibit strong and robust performance across market conditions, underscoring the persistent predictive power of credit risk. Among stock-side signals, trading frictions—particularly volatility—exhibit improved risk-adjusted performance once macroeconomic conditions are taken into account.[15]

In contrast, bond return strategies that rely solely on autocovariances tend to lose significance when controlling for macro conditions, while those based on cross-autocovariances retain their predictive strength. This distinction highlights the importance of cross-asset dependencies, especially in uncertain economic environments.

A particularly notable result within the TRACE sample concerns momentum. When controlling for recessions and sentiment, momentum-based strategies—on both bond and stock sides—achieve their highest profitability, but only when based on autocovariances. In this case, cross-asset dependencies appear to play a more limited role.

In summary, the profitability of predictive strategies varies with the market environment. Higher returns are observed during recessions, while periods of low investor sentiment—particularly in TRACE—are associated with weaker performance. Although statistical significance may diminish after accounting for macro conditions, strategies linked to credit risk in bonds and

[15]When the alpha during recessions exceeds the original CAPM alpha, this suggests that gains in recession periods outweigh losses in general downturns.

volatility in equities remain robust and economically meaningful.

5 Conclusion

This paper develops an analytically tractable framework for uncovering return predictability in corporate bond markets. We construct zero-cost trading strategies by exploiting the dynamic structure of past returns—specifically, autocovariances and cross-autocovariances—among portfolios formed on bond and stock characteristics. The method yields closed-form solutions for optimal portfolio weights and expected profitability under a self-financing constraint.

Our empirical implementation spans 82 characteristics and two comprehensive datasets—ICE and TRACE. We find strong, persistent, and economically meaningful predictability in the lagged return dynamics of characteristic-sorted portfolios. The most profitable strategies are those constructed from past returns of portfolios sorted by credit risk and trading friction characteristics, such as yield, price, OAS, and volatility. These signals consistently deliver out-of-sample Sharpe ratios exceeding 1.2 and substantially outperform passive bond benchmarks.

A central insight is the importance of cross-bond predictability. Strategies that exploit return spillovers across portfolios dominate those based solely on own-bond autocorrelations. This highlights the economic value of cross-sectional return interactions and the need to move beyond traditional models that assume independence across assets.

Methodologically, our framework contributes to the literature on high-

dimensional portfolio optimization by providing a tractable, interpretable, and robust approach to dynamic strategy construction. It complements recent work on factor momentum and latent portfolio design by grounding dynamic factors in the autocovariance structure of returns. In doing so, it offers a new foundation for bond pricing, factor discovery, and return forecasting—particularly in environments where expected return estimation is noisy.

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Table 1. Descriptive statistics of individual bond returns

The table reports descriptive statistics of the returns of individual corporate bonds from ICE and TRACE (see section 3 for data details). The ICE sample spans the period from January 1997 to June 2024 and has a monthly average of 7,287 individual bond returns. The TRACE sample contains a monthly average of 5,685 bond returns over the August 2002 to June 2023 period. Panel A provides descriptive statistics across all bond-month observations, giving equal weight to each bond-month. For the left (right) block of Panel B, we first compute mean and SD statistics for each bond (month) and then averages across bonds (months). All returns are in percent per month.

Panel A: Averages across all bond-month observations.

Sample	Total obs	Bond return statistics										
		Mean (%)	SD (%)	Skew	Kurt	Min (%)	1st (%)	25th (%)	50th (%)	75th (%)	99th (%)	Max
ICE–Excess return	2404789	0.18	4.13	9	948	-101.0	-11.0	-0.3	0.1	0.8	9.6	679
ICE–Excess return ($\leq$ 100%)	2404606	0.17	3.83	-1	108	-101.0	-11.0	-0.3	0.1	0.8	9.5	100
ICE–Total return	2392889	0.44	7.06	752	909716	-99.8	-10.4	-0.5	0.4	1.4	10.5	8575
ICE–Total return (excluding 8575% return)	2392888	0.44	4.37	11	1354	-99.8	-10.4	-0.5	0.4	1.4	10.5	741
ICE–Total return (nonmissing price)	2386025	0.43	4.28	7	774	-99.8	-10.3	-0.5	0.4	1.4	10.5	679
ICE–Total return ($\leq$ 100%)	2392703	0.42	4.02	-1	89	-99.8	-10.4	-0.5	0.4	1.4	10.5	100
TRACE–Total return ($\leq$ 100%)	1426930	0.43	4.29	2	110	-100.0	-10.6	-0.5	0.3	1.4	11.1	100

Panel B: Average statistics per bond (left) or per month (right)

	Statistics per bond				Statistics per month			
	Mean	Mean SD	Min SD	Max SD	Mean	Mean SD	Min SD	Max SD
ICE–Excess return	0.13	2.48	0	137	0.16	3.18	0.95	16.56
ICE–Excess return ($\leq$ 100%)	0.11	2.43	0	54	0.15	3.00	0.95	12.70
ICE–Total return	0.38	2.89	0	1592	0.50	3.69	0.98	117.39
ICE–Total return (excluding 8575% return)	0.37	2.85	0	186	0.50	3.37	0.98	16.64
ICE–Total return (nonmissing price)	0.38	2.84	0	137	0.49	3.30	0.98	16.65
ICE–Total return ($\leq$ 100%)	0.35	2.79	0	54	0.48	3.15	0.98	13.23
TRACE–Total return ($\leq$ 100%)	0.41	2.84	0	111	0.48	3.57	1.13	13.38

Table 2. Portfolio summaries using ICE excess returns

The table reports descriptive statistics of the excess returns of 82 sets of 30 portfolios formed by sorting on bond and stock characteristics. The mean S.D. is the cross-sectional average of the portfolios standard deviations, the min and max S.D. are the cross-sectional minimum and maximum standard deviations, S.D., max and min are the standard deviation, minimum and maximum of all portfolio returns in each set. The first three letters in the variable name refer to excess returns from ICE, and the last part of the name is the code of the characteristic. An I before the bond characteristic code indicates it was obtained from ICE, a W—from TRACE via WRDS. Stock codes match Hou, Xue, and Zhang (2015). All variable codes are described in Appendix A.

	Mean	Ave SD	Min SD	Max SD	SD	Min	Max	Min N	Max N	T
ixRxWYLD	0.21	1.95	0.40	7.20	2.39	-36.82	32.94	109	216	252
ixRxWPRC	0.21	2.00	1.32	7.66	2.35	-39.99	37.77	103	218	252
ixRxWDUR	0.21	1.96	1.29	2.51	1.98	-20.49	14.76	109	216	252
ixRxWTDVol	0.22	1.92	1.65	2.17	1.92	-15.29	14.08	106	218	252
ixRxIConv	0.15	1.80	1.10	2.41	1.83	-19.41	13.12	101	239	328
ixRxIFMV	0.15	1.80	1.43	4.84	1.91	-22.61	30.45	112	223	328
ixRxIOAS	0.15	1.81	0.47	6.73	2.21	-36.54	35.58	78	286	328
ixRxImDur	0.15	1.80	1.07	2.36	1.83	-19.68	12.46	111	224	328
ixRxIpR3m	0.15	1.88	1.26	6.46	2.15	-33.04	39.22	75	221	327
ixRxIbeYTM	0.15	1.81	0.35	6.75	2.24	-36.12	35.55	107	229	328
ixRxIeDur	0.15	1.81	1.17	2.31	1.83	-19.98	14.54	111	224	328
ixRxIeConv	0.15	1.81	1.33	2.40	1.83	-19.84	14.65	104	236	328
ixRxIeYLD	0.15	1.81	0.36	6.80	2.25	-36.93	35.55	109	231	328
ixRxIPrice	0.15	1.85	1.23	7.24	2.20	-39.54	37.48	99	223	328
ixRxIspDur	0.15	1.81	1.18	2.31	1.83	-19.95	14.57	111	224	328
ixRxIamrtR	0.20	1.94	0.90	6.04	2.18	-34.16	29.73	84	275	269
ixRxItR3m	0.15	1.88	1.28	6.30	2.13	-32.14	39.42	18	220	327
ixRxItR12m	0.17	1.95	1.32	7.16	2.27	-34.21	39.27	91	201	318
ixRxIpR12m	0.17	1.94	1.30	7.40	2.28	-35.25	39.44	91	202	318
ixRxIcoupR	0.20	1.92	0.69	6.69	2.26	-28.55	34.00	99	253	269
ixRxIxsret	0.15	1.86	1.16	5.77	2.08	-37.98	34.28	32	378	328
ixRxIMtrty	0.15	1.77	0.77	2.44	1.83	-19.57	14.19	94	241	328
ixRxWTSprd	0.23	1.95	1.26	4.72	2.06	-27.23	31.07	70	212	252
ixRxWRETEOM	0.21	1.97	1.34	5.81	2.18	-38.02	35.50	108	218	251
ixRxWMtrty	0.21	1.92	0.87	2.61	1.98	-19.66	13.63	92	234	252
ixRxIAccInt	0.15	1.71	1.28	2.82	1.73	-20.64	16.08	2	460	328
ixRxiaci	0.12	1.85	1.36	3.04	1.89	-19.85	26.71	21	183	323
ixRxidPia	0.12	1.86	1.39	2.87	1.89	-20.30	22.11	26	188	323
ixRxinoa	0.12	1.80	1.49	2.48	1.81	-17.67	17.76	33	210	323
ixRxidNoa	0.12	1.79	1.37	2.37	1.81	-17.38	19.01	28	221	323
ixRxidLno	0.12	1.80	1.39	2.52	1.82	-18.03	23.93	32	201	323
ixRxiig	0.12	1.86	1.34	3.17	1.90	-19.02	20.75	22	184	323
ixRxitwoig	0.12	1.87	1.44	3.16	1.93	-22.62	28.36	24	187	323
ixRxinsi	0.12	1.85	1.25	3.45	1.90	-19.16	21.22	23	226	323
ixRxiivg	0.12	1.82	1.37	2.91	1.85	-22.96	24.58	22	168	323
ixRxita	0.11	1.85	1.48	2.33	1.86	-22.67	16.03	21	181	323
ixRxinOL	0.12	1.87	1.31	2.87	1.90	-22.93	20.10	26	187	323
ixRxinOlq	0.12	1.80	1.40	2.68	1.82	-18.63	19.28	32	192	323
ixRxindSi	0.12	1.81	1.36	3.17	1.85	-21.52	25.44	22	166	323
ixRxindSa	0.12	1.87	1.44	3.40	1.92	-26.59	23.56	26	165	323
ixRxindGs	0.12	1.85	1.27	3.55	1.91	-32.81	20.70	25	169	323

ixRxindSs	0.13	1.97	1.40	4.27	2.07	-34.75	31.45	13	127	323
ixRxinAla	0.12	1.78	1.46	2.83	1.81	-19.58	16.56	32	199	323
ixRxmabr	0.12	1.79	1.38	3.60	1.84	-19.62	21.02	31	214	323
ixRxmre	0.12	1.77	1.22	4.66	1.93	-25.91	23.60	19	208	323
ixRxmr11	0.12	1.78	1.20	5.87	2.00	-32.91	30.03	35	209	323
ixRxmrs	0.12	1.79	1.50	2.35	1.79	-19.91	19.67	31	195	323
ixRxmtes	0.12	1.78	1.46	2.30	1.79	-19.25	20.91	32	210	323
ixRxme06	0.12	1.79	1.54	2.12	1.79	-17.65	16.66	30	200	323
ixRxme12	0.13	1.78	1.48	2.32	1.78	-17.76	16.04	29	214	323
ixRxproe	0.08	1.76	1.08	5.40	1.96	-21.38	30.75	31	171	229
ixRxpdRoe	0.08	1.77	1.26	4.71	1.90	-19.13	33.89	29	175	229
ixRxproa	0.08	1.82	1.18	4.16	1.92	-21.20	22.41	34	185	229
ixRxpdRoa	0.08	1.83	1.26	3.47	1.89	-22.20	23.31	24	171	229
ixRxpcto	0.12	1.88	1.38	2.96	1.91	-17.94	23.42	22	186	323
ixRxpgla	0.08	1.82	1.20	3.10	1.87	-16.29	24.36	29	180	229
ixRxpglaq	0.12	1.80	1.27	3.36	1.84	-20.24	20.52	29	202	323
ixRxpZ	0.11	1.81	1.02	3.98	1.92	-23.82	22.66	18	166	323
ixRxpbl	0.12	1.78	1.47	2.40	1.80	-18.56	18.13	29	194	323
ixRxtIvff	0.12	1.78	1.09	5.26	1.98	-31.95	29.23	29	206	323
ixRxtIvc	0.12	1.78	1.13	5.28	1.99	-32.15	29.30	32	207	323
ixRxtIvq	0.10	1.66	0.96	5.14	1.88	-18.89	28.87	33	184	276
ixRxtTv	0.12	1.80	1.14	5.31	1.99	-31.91	28.41	29	209	323
ixRxtPps	0.12	1.78	1.12	5.33	2.00	-30.56	29.18	27	209	323
ixRxtMdr	0.12	1.80	1.22	4.54	1.94	-22.43	31.75	27	199	323
ixRxtTs	0.12	1.79	1.46	2.52	1.80	-18.21	18.83	30	204	323
ixRxtIsc	0.12	1.78	1.56	2.11	1.79	-18.30	19.03	32	232	323
ixRxtIsff	0.12	1.78	1.51	2.19	1.78	-16.90	17.92	22	209	323
ixRxtIsq	0.10	1.68	1.32	2.17	1.69	-16.14	17.71	32	182	276
ixRxvgbm	0.12	1.77	1.27	3.48	1.83	-27.35	21.47	31	187	323
ixRxvgjunbm	0.12	1.75	1.18	3.89	1.83	-29.05	20.35	31	192	323
ixRxvgbmq	0.12	1.73	1.05	3.94	1.83	-27.73	20.90	32	187	323
ixRxvgdm	0.12	1.79	1.01	3.31	1.87	-25.26	19.73	34	206	323
ixRxvgdmq	0.12	1.77	1.02	3.58	1.87	-26.29	20.32	29	201	323
ixRxvgam	0.12	1.80	1.01	3.34	1.88	-24.68	29.17	34	218	323
ixRxvgamq	0.12	1.79	1.02	3.56	1.89	-24.53	24.39	29	210	323
ixRxvgepq	0.12	1.79	1.26	5.14	1.94	-24.29	24.68	32	209	323
ixRxvgcp	0.12	1.79	1.23	3.64	1.89	-26.54	19.34	31	198	323
ixRxAmihud	0.12	1.82	1.09	4.33	1.93	-29.40	23.94	31	204	323
ixRxcr6m	0.12	1.78	1.26	5.61	1.98	-35.19	23.94	34	209	323
ixRxIOR	0.13	1.78	1.38	2.87	1.81	-18.88	18.84	34	215	323
ixRxTobin	0.12	1.78	1.05	3.68	1.85	-28.73	20.07	26	186	323

Table 3. Portfolio descriptive statistics using TRACE returns

The table reports descriptive statistics of the returns of 82 sets of 30 portfolios formed by sorting on bond and stock characteristics. The mean S.D. is the cross-sectional average of the portfolios standard deviations, the min and max S.D. are the cross-sectional minimum and maximum standard deviations, S.D., max and min are the standard deviation, minimum and maximum of all portfolio returns in each set. The first two letters in the variable name (wR) refer to returns from TRACE via WRDS, and the last part of the name is the code of the characteristic. An I before the bond characteristic code indicates it was obtained from ICE, a W—from TRACE via WRDS. Stock codes match Hou, Xue, and Zhang (2015). All codes are described in Appendix A.

	Mean	Ave SD	Max SD	Min SD	SD	Min	Max	Min N	Max N	T
wRxWYLD	0.47	2.05	0.51	6.78	2.43	-39.44	31.15	89	264	250
wRxWPRC	0.47	2.04	1.23	5.98	2.37	-38.65	38.10	87	265	250
wRxWDUR	0.47	1.96	0.78	3.43	2.06	-13.84	18.33	89	264	250
wRxWTDVol	0.47	1.82	1.67	2.41	1.83	-10.75	12.87	90	265	250
wRxIConv	0.47	2.10	1.11	3.54	2.18	-14.12	20.30	60	211	250
wRxIFMV	0.47	2.06	1.73	5.36	2.16	-20.10	32.83	62	202	250
wRxIOAS	0.47	2.21	0.86	7.12	2.52	-34.47	36.82	53	235	250
wRxImDur	0.47	2.10	0.99	3.54	2.19	-13.52	19.97	62	202	250
wRxIpR3m	0.48	2.21	1.60	6.71	2.45	-30.45	41.00	60	199	250
wRxIbeYTM	0.47	2.20	0.57	7.16	2.55	-33.71	36.82	61	205	250
wRxIeDur	0.47	2.11	1.07	3.55	2.19	-15.09	19.94	62	202	250
wRxIeConv	0.47	2.10	1.24	3.55	2.19	-14.65	20.45	59	207	250
wRxIeYLD	0.47	2.19	0.55	7.19	2.56	-34.22	36.82	62	206	250
wRxIPrice	0.47	2.17	1.43	7.74	2.51	-37.35	38.76	56	202	250
wRxIspDur	0.47	2.11	1.10	3.55	2.20	-15.08	19.96	62	203	250
wRxIamrtR	0.47	2.17	1.12	6.22	2.36	-31.99	30.93	53	232	250
wRxItR3m	0.48	2.21	1.60	6.53	2.43	-29.60	41.17	59	198	250
wRxItR12m	0.46	2.24	1.54	7.46	2.54	-34.68	40.89	53	181	250
wRxIpR12m	0.46	2.23	1.50	7.66	2.56	-35.40	40.99	53	180	250
wRxIcoupR	0.46	2.16	0.81	6.86	2.44	-26.28	36.37	58	222	250
wRxIxsret	0.47	2.14	1.50	5.98	2.34	-34.24	36.65	62	206	250
wRxIMtrty	0.47	2.04	0.85	3.44	2.16	-13.27	18.14	58	220	250
wRxWTSprd	0.47	1.86	1.08	4.45	1.99	-25.69	26.26	85	259	250
wRxWRETEOM	0.47	1.99	1.31	6.18	2.25	-38.10	32.33	90	265	250
wRxWMtrty	0.47	1.91	0.65	3.39	2.05	-14.01	17.30	81	278	250
wRxIAccInt	0.46	1.94	1.60	3.07	1.96	-17.63	16.84	1	427	250
wRxiaci	0.45	1.95	1.67	3.39	1.98	-14.37	30.91	10	185	250
wRxidPia	0.45	2.03	1.59	3.87	2.09	-29.10	34.84	15	217	250
wRxinoa	0.44	1.91	1.60	2.55	1.93	-21.98	20.59	9	237	250
wRxidNoa	0.44	1.90	1.56	3.00	1.92	-27.43	23.33	9	215	250
wRxidLno	0.45	1.92	1.58	2.98	1.94	-22.27	23.67	7	223	250
wRxiig	0.44	1.96	1.60	3.66	2.00	-17.47	28.22	2	182	250
wRxitwoig	0.45	1.95	1.61	3.74	2.00	-19.74	29.30	11	195	250
wRxinsi	0.45	1.93	1.56	3.54	1.97	-16.84	24.13	8	230	250
wRxiivg	0.45	1.98	1.52	3.65	2.04	-31.98	27.43	2	195	250
wRxita	0.45	1.91	1.68	2.25	1.92	-14.65	14.46	11	192	250
wRxinOL	0.45	1.94	1.44	3.45	1.97	-17.88	28.29	13	172	250
wRxinOlq	0.44	1.92	1.61	2.48	1.93	-21.00	21.97	8	241	250
wRxindSi	0.44	1.92	1.62	2.88	1.95	-20.07	26.06	10	169	250
wRxindSa	0.45	1.96	1.54	3.22	2.00	-25.36	25.14	12	175	250
wRxindGs	0.45	1.96	1.52	3.46	2.03	-32.77	27.43	19	186	250
wRxindSs	0.46	2.02	1.48	3.99	2.10	-30.88	27.67	8	138	250

wRxinAla	0.44	1.92	1.49	3.69	1.96	-23.23	34.22	21	214	250
wRxmabr	0.44	1.93	1.55	3.41	1.97	-21.55	21.37	15	227	250
wRxmre	0.44	1.94	1.44	4.80	2.06	-27.39	22.84	4	201	250
wRxmr11	0.45	1.97	1.50	5.61	2.13	-35.78	28.79	11	234	250
wRxmrs	0.45	1.93	1.57	2.78	1.95	-27.06	24.55	25	223	250
wRxmtes	0.44	1.91	1.54	2.91	1.93	-26.63	24.98	16	218	250
wRxme06	0.45	1.91	1.59	2.29	1.91	-18.61	21.15	14	222	250
wRxme12	0.44	1.91	1.57	2.49	1.92	-22.87	24.49	16	233	250
wRxproe	0.56	1.85	1.21	5.60	2.05	-20.23	32.16	19	214	163
wRxpdRoe	0.56	1.85	1.32	5.07	2.00	-22.63	32.21	10	217	163
wRxproa	0.56	1.87	1.25	3.79	1.97	-24.28	26.51	2	200	163
wRxpdRoa	0.56	1.91	1.36	3.49	1.97	-26.27	26.15	5	207	163
wRxpcto	0.45	1.93	1.43	3.24	1.96	-15.82	26.60	15	177	250
wRxpgla	0.56	1.85	1.31	3.55	1.91	-20.31	17.99	20	212	163
wRxpglaq	0.44	1.93	1.45	3.48	1.97	-21.92	25.12	14	228	250
wRxpZ	0.44	1.91	1.44	3.87	1.97	-25.93	19.97	8	172	250
wRxpbl	0.45	1.93	1.66	3.24	1.95	-23.93	25.51	6	209	250
wRxtIvff	0.45	1.97	1.40	5.37	2.12	-35.56	25.75	21	224	250
wRxtIvc	0.45	1.97	1.46	5.07	2.11	-31.10	28.54	4	219	250
wRxtIvq	0.55	1.77	1.15	4.69	1.93	-21.24	24.75	10	218	210
wRxtTv	0.45	1.99	1.44	5.06	2.13	-30.49	26.75	10	226	250
wRxtPps	0.45	1.98	1.44	5.42	2.17	-32.84	33.17	13	224	250
wRxtMdr	0.45	1.97	1.49	4.45	2.08	-29.38	26.71	18	243	250
wRxtTs	0.45	1.93	1.58	2.64	1.95	-22.76	24.15	3	220	250
wRxtIsc	0.44	1.91	1.57	2.46	1.91	-22.74	25.64	18	223	250
wRxtIsff	0.45	1.91	1.60	2.35	1.92	-21.94	25.71	16	215	250
wRxtIsq	0.55	1.71	1.31	2.67	1.73	-22.49	24.89	14	209	210
wRxvgbm	0.45	1.92	1.40	3.54	1.98	-27.74	23.41	9	212	250
wRxvgjunbm	0.45	1.92	1.40	3.90	1.98	-23.59	22.78	16	216	250
wRxvgbmq	0.44	1.90	1.43	4.08	1.97	-26.91	18.50	13	232	250
wRxvgdm	0.45	1.97	1.47	3.70	2.05	-24.78	29.86	7	238	250
wRxvgdmq	0.44	1.95	1.48	3.77	2.03	-28.40	19.15	13	215	250
wRxvgam	0.45	1.98	1.44	3.29	2.04	-24.14	26.68	11	235	250
wRxvgamq	0.45	1.98	1.47	4.03	2.06	-25.29	30.93	14	233	250
wRxvgepq	0.45	1.96	1.47	5.19	2.08	-24.03	26.41	20	229	250
wRxvgcp	0.45	1.95	1.45	3.99	2.05	-28.41	27.81	20	221	250
wRxAmihud	0.44	2.00	1.43	4.46	2.08	-28.49	28.96	7	231	250
wRxcr6m	0.45	1.99	1.53	5.05	2.13	-35.48	30.13	21	229	250
wRxIOR	0.45	1.90	1.54	3.02	1.93	-18.28	22.92	21	227	250
wRxTobin	0.44	1.95	1.45	3.73	2.01	-28.00	28.99	15	219	250

Table 4. Decomposition of weights between auto-covariances and cross-covariances

Ω is split in two components, Ω^d which only contains the diagonal elements of Ω, with all off-diagonal elements set to zero, and $\Omega^{\emptyset d}$ sets the diagonal to zero and retains all off-diagonal elements. $\Omega = \Omega^d + \Omega^{\emptyset d}$. And the Omega-weights are then sum of two components:

$$w^d = R_t \times \Psi^d$$
$$w^{\emptyset d} = R_t \times \Psi^{\emptyset d}$$

where $\Psi^d = trace\left((\Phi\Omega^d)'(\Phi\Omega^d)\right)^{-0.5}(\Omega^d)'\Phi'$, with Φ being the self-financing matrix.
Likewise, $\Psi^{\emptyset d} = trace((\Phi\Omega^{\emptyset d})'(\Phi\Omega^{\emptyset d}))^{-0.5}(\Omega^{\emptyset d})'\Phi'$ The signals for the weights are past returns. The table represents different cases for the weights. When unscaled, $w = w^d + w^{\emptyset d}$. When scaled, both w^d and $w^{\emptyset d}$ separately sum up to 0, their short side to -1 and their long sides to 1. The first three letters in the variable name, ixRxIeYLD, refer to excess returns from ICE, and the last part of the name (eYLD) is the code of the bond characteristic, described in Appendix A. An I before the bond characteristic code indicates it was obtained from ICE. The first two letters in wRxWYLD stand for (raw) returns obtained from TRACE via WRDS, the last three for the name of the characteristic (YLD), and W that it was obtained from TRACE via WRDS.

	Ω	$\Omega^{\emptyset d}$unscaled	Ω^dunscaled	$\Omega^{\emptyset d}$scaled	Ω^dscaled
ixRxIeYLD	1.07	0.50	0.57	0.77	1.50
	(**4.64**)	(**2.77**)	(**4.69**)	(**3.84**)	(**4.97**)
wRxWYLD	0.96	0.89	0.07	0.83	1.38
	(**3.68**)	(**2.75**)	(0.26)	(**3.41**)	(**3.47**)

Table 5. Portfolio profits using ICE excess returns

Each set contains 30 portfolios based on 26 bond and 56 stock characteristics. The signals for the weights are past returns.

	Π	Ω	$\Omega^{\emptyset d}$	Ω^{d}	0-U	0-L
Bond characteristics						
ixRxWYLD	0.94	0.92	0.60	1.63	0.77	0.26
	(**2.97**)	(**2.89**)	(**2.21**)	(**3.94**)	(**2.15**)	(**2.25**)
ixRxWPRC	0.97	0.91	0.41	1.54	-0.08	0.83
	(**2.93**)	(**2.71**)	(1.63)	(**3.34**)	(-0.70)	(**2.12**)
ixRxWDUR	0.11	0.11	0.10	0.10	0.17	-0.07
	(1.81)	(1.77)	(1.76)	(1.23)	(1.85)	(-0.99)
ixRxWTDVol	0.28	0.28	0.28	0.12	-0.20	0.28
	(**4.73**)	(**4.73**)	(**4.73**)	(**2.21**)	(**-3.34**)	(**4.58**)
ixRxIConv	0.12	0.11	0.11	0.15	0.15	-0.04
	(**2.37**)	(**2.30**)	(**2.23**)	(**2.50**)	(**2.17**)	(-0.72)
ixRxIFMV	0.55	0.55	0.47	0.86	-0.10	0.59
	(**4.01**)	(**4.02**)	(**4.06**)	(**4.71**)	(-1.70)	(**4.39**)
ixRxIOAS	1.06	1.08	0.75	1.51	0.96	0.20
	(**4.71**)	(**4.85**)	(**3.97**)	(**5.04**)	(**3.53**)	(**2.26**)
ixRxImDur	0.13	0.13	0.13	0.14	0.16	-0.04
	(**2.73**)	(**2.62**)	(**2.60**)	(**2.25**)	(**2.38**)	(-0.78)
ixRxIpR3m	0.26	0.23	0.10	0.65	0.30	-0.03
	(1.43)	(1.31)	(0.75)	(**2.43**)	(**2.64**)	(-0.16)
ixRxIbeYTM	1.14	1.14	0.79	1.53	0.97	0.18
	(**4.75**)	(**4.79**)	(**3.95**)	(**4.93**)	(**3.50**)	(**2.01**)
ixRxIeDur	0.09	0.09	0.08	0.14	0.12	-0.05
	(1.95)	(1.86)	(1.75)	(**2.32**)	(1.68)	(-0.81)
ixRxIeConv	0.10	0.09	0.08	0.14	0.13	-0.04
	(**2.23**)	(**2.08**)	(1.90)	(**2.35**)	(1.91)	(-0.74)
ixRxIeYLD	1.07	1.07	0.77	1.50	0.95	0.21
	(**4.60**)	(**4.64**)	(**3.84**)	(**4.97**)	(**3.48**)	(**2.18**)
ixRxIPrice	1.01	1.00	0.62	1.41	0.08	0.97
	(**4.24**)	(**4.19**)	(**3.54**)	(**4.34**)	(0.96)	(**3.25**)
ixRxIspDur	0.12	0.11	0.11	0.15	0.16	-0.07
	(**2.11**)	(**2.02**)	(**2.03**)	(**2.48**)	(**2.17**)	(-1.36)
ixRxIamrtR	0.96	0.96	0.56	1.20	0.82	-0.04
	(**4.05**)	(**4.05**)	(**3.00**)	(**4.08**)	(**3.24**)	(-0.45)
ixRxItR3m	0.27	0.23	0.11	0.66	0.33	-0.14
	(1.52)	(1.36)	(0.81)	(**2.55**)	(**2.90**)	(-0.74)
ixRxItR12m	0.62	0.61	0.27	1.01	0.03	0.60
	(**2.94**)	(**2.88**)	(1.95)	(**3.21**)	(0.36)	(**2.16**)
ixRxIpR12m	0.77	0.76	0.36	1.13	0.04	0.70
	(**3.51**)	(**3.45**)	(**2.47**)	(**3.50**)	(0.42)	(**2.40**)
ixRxIcoupR	1.09	1.10	0.77	1.45	0.90	0.10
	(**4.21**)	(**4.28**)	(**3.52**)	(**4.21**)	(**3.07**)	(0.89)
ixRxIxsret	0.27	0.24	0.15	0.44	0.27	0.12
	(1.82)	(1.62)	(1.29)	(**1.97**)	(**2.38**)	(0.69)
ixRxIMtrty	0.10	0.10	0.11	0.12	0.14	-0.04
	(1.61)	(1.56)	(1.77)	(1.75)	(**2.02**)	(-1.10)
ixRxWTSprd	0.57	0.57	0.49	0.85	0.55	0.04
	(**3.35**)	(**3.33**)	(**3.52**)	(**3.56**)	(**2.86**)	(0.47)
ixRxWRETEOM	0.28	0.27	0.17	0.58	0.26	0.08
	(1.44)	(1.42)	(1.19)	(**1.99**)	(**2.49**)	(0.30)
ixRxWMtrty	0.13	0.13	0.13	0.11	0.15	-0.04
	(1.54)	(1.52)	(1.59)	(1.20)	(1.52)	(-0.82)
ixRxIAccInt	0.17	0.17	0.13	0.30	0.15	-0.01
	(**2.51**)	(**2.60**)	(**2.37**)	(**2.79**)	(**2.57**)	(-0.33)

HXZ anomalies, Investment

ixRxiaci	0.11	0.11	0.12	0.26	-0.00	0.19
	(1.48)	(1.42)	(1.85)	(**2.17**)	(-0.02)	(**2.68**)
ixRxidPia	0.10	0.09	0.06	0.21	-0.01	0.09
	(1.73)	(1.66)	(1.09)	(**2.69**)	(-0.15)	(**2.10**)
ixRxinoa	0.03	0.03	0.02	0.04	-0.03	0.08
	(0.77)	(0.78)	(0.54)	(0.64)	(-0.68)	(1.94)
ixRxidNoa	0.05	0.05	0.04	0.04	-0.03	0.10
	(1.30)	(1.16)	(1.10)	(0.94)	(-1.00)	(**2.75**)
ixRxidLno	0.01	0.01	-0.01	0.10	-0.06	0.05
	(0.26)	(0.24)	(-0.21)	(1.55)	(-1.44)	(1.12)
ixRxiig	0.12	0.11	0.09	0.23	-0.03	0.12
	(**1.96**)	(1.77)	(1.72)	(**2.71**)	(-0.72)	(**2.01**)
ixRxitwoig	0.09	0.08	0.08	0.32	-0.08	0.16
	(1.31)	(1.14)	(1.09)	(**2.34**)	(-1.63)	(**2.58**)
ixRxinsi	0.01	0.00	0.01	0.09	0.01	-0.06
	(0.28)	(0.05)	(0.17)	(1.03)	(0.20)	(-1.59)
ixRxiivg	-0.01	-0.01	0.01	0.04	-0.08	0.09
	(-0.16)	(-0.12)	(0.11)	(0.54)	(-1.82)	(**2.43**)
ixRxita	0.07	0.06	0.06	0.09	0.03	0.03
	(1.53)	(1.47)	(1.44)	(1.54)	(0.85)	(0.89)

HXZ anomalies, Intangibles

ixRxinOL	0.06	0.06	0.03	0.15	0.06	-0.03
	(1.04)	(1.00)	(0.56)	(1.68)	(1.33)	(-0.38)
ixRxinOlq	0.04	0.04	0.03	0.11	0.06	-0.02
	(0.87)	(0.81)	(0.67)	(**2.46**)	(1.20)	(-0.45)
ixRxindSi	0.06	0.06	0.04	0.16	0.06	0.00
	(0.86)	(0.87)	(0.56)	(1.51)	(1.12)	(0.06)
ixRxindSa	0.07	0.08	0.08	0.09	0.11	-0.00
	(1.12)	(1.14)	(1.18)	(0.95)	(1.73)	(-0.10)
ixRxindGs	0.18	0.18	0.12	0.41	0.07	0.16
	(**2.32**)	(**2.29**)	(1.62)	(**3.45**)	(1.07)	(**2.59**)
ixRxindSs	0.12	0.11	0.11	0.21	0.08	0.11
	(1.18)	(1.11)	(1.41)	(1.19)	(0.70)	(**2.54**)
ixRxinAla	0.00	0.01	0.00	0.06	0.00	0.00
	(0.02)	(0.13)	(0.06)	(0.74)	(0.02)	(0.12)
ixRxmabr	0.11	0.10	0.06	0.25	-0.03	0.12
	(**2.02**)	(1.94)	(1.26)	(**3.08**)	(-0.56)	(1.82)

HXZ anomalies, Momentum

ixRxmre	0.25	0.24	0.13	0.44	0.04	0.26
	(**2.37**)	(**2.31**)	(1.47)	(**2.62**)	(0.77)	(**2.09**)
ixRxmr11	0.41	0.35	0.05	0.77	-0.06	0.23
	(**2.63**)	(**2.37**)	(0.48)	(**3.54**)	(-0.72)	(1.32)
ixRxmrs	-0.00	0.00	0.00	0.01	-0.00	0.02
	(-0.01)	(0.14)	(0.05)	(0.12)	(-0.02)	(0.60)
ixRxmtes	-0.01	-0.00	-0.01	0.06	-0.01	0.01
	(-0.13)	(-0.09)	(-0.17)	(1.05)	(-0.44)	(0.26)
ixRxme06	-0.02	-0.01	-0.02	0.08	-0.02	-0.00
	(-0.84)	(-0.70)	(-1.13)	(**2.59**)	(-0.90)	(-0.01)
ixRxme12	-0.02	-0.01	-0.02	0.02	0.02	-0.03
	(-0.51)	(-0.50)	(-0.74)	(0.43)	(0.61)	(-1.77)

HXZ anomalies, Profitability

ixRxproe	0.28	0.27	0.04	0.74	-0.07	0.12
	(1.72)	(1.72)	(0.30)	(**2.76**)	(-0.73)	(0.55)
ixRxpdRoe	0.13	0.13	0.05	0.30	-0.02	0.08
	(1.34)	(1.35)	(0.58)	(1.84)	(-0.29)	(0.58)
ixRxproa	0.03	0.03	-0.07	0.34	-0.12	0.13
	(0.29)	(0.30)	(-0.72)	(**1.99**)	(-1.45)	(1.15)
ixRxpdRoa	-0.05	-0.06	-0.07	0.16	-0.05	-0.01
	(-0.48)	(-0.58)	(-1.37)	(0.85)	(-0.97)	(-0.10)

ixRxpcto	0.03	0.03	0.04	0.05	-0.02	0.03
	(0.49)	(0.40)	(0.48)	(0.61)	(-0.31)	(0.76)
ixRxpgla	0.08	0.06	-0.00	0.28	-0.10	0.13
	(1.35)	(1.09)	(-0.00)	(**2.68**)	(-1.47)	(1.65)
ixRxpglaq	0.11	0.11	0.03	0.31	-0.04	0.12
	(1.85)	(1.74)	(0.64)	(**2.47**)	(-0.83)	(1.85)
ixRxpZ	0.21	0.21	0.15	0.40	-0.02	0.26
	(**2.37**)	(**2.32**)	(1.93)	(**2.93**)	(-0.45)	(**2.65**)
ixRxpbl	0.00	0.00	-0.01	0.06	0.02	-0.02
	(0.01)	(0.01)	(-0.33)	(0.81)	(0.38)	(-0.35)
HXZ anomalies, Trading Frictions						
ixRxtIvff	0.57	0.58	0.38	0.89	0.69	-0.00
	(**3.73**)	(**3.86**)	(**3.92**)	(**4.28**)	(**3.77**)	(-0.02)
ixRxtIvc	0.53	0.53	0.30	0.94	0.63	-0.03
	(**3.44**)	(**3.47**)	(**3.00**)	(**4.47**)	(**3.65**)	(-0.52)
ixRxtIvq	0.43	0.42	0.16	0.78	0.43	-0.11
	(**2.84**)	(**2.88**)	(1.72)	(**3.57**)	(**2.64**)	(-1.36)
ixRxtTv	0.47	0.46	0.20	0.84	0.52	-0.05
	(**3.25**)	(**3.20**)	(**2.05**)	(**4.01**)	(**3.19**)	(-0.80)
ixRxtPps	0.49	0.49	0.35	0.84	-0.12	0.65
	(**3.36**)	(**3.39**)	(**3.19**)	(**3.85**)	(-1.68)	(**3.68**)
ixRxtMdr	0.39	0.38	0.21	0.72	0.41	-0.05
	(**3.98**)	(**3.91**)	(**2.85**)	(**4.69**)	(**3.23**)	(-0.72)
ixRxtTs	0.01	0.01	0.00	0.05	0.06	-0.05
	(0.22)	(0.26)	(0.03)	(1.50)	(1.83)	(-1.23)
ixRxtIsc	-0.00	-0.00	-0.01	0.02	0.02	-0.00
	(-0.08)	(-0.16)	(-0.48)	(0.82)	(0.66)	(-0.21)
ixRxtIsff	-0.01	-0.01	-0.02	0.05	0.01	-0.01
	(-0.44)	(-0.32)	(-0.65)	(1.68)	(0.29)	(-0.62)
ixRxtIsq	-0.00	-0.01	-0.01	-0.03	0.00	-0.01
	(-0.19)	(-0.26)	(-0.33)	(-1.11)	(0.03)	(-0.35)
HXZ anomalies, Value vs Growth						
ixRxvgbm	0.20	0.19	0.10	0.45	0.22	-0.04
	(**2.78**)	(**2.69**)	(1.70)	(**3.92**)	(**2.47**)	(-1.05)
ixRxvgjunbm	0.18	0.18	0.11	0.40	0.25	-0.01
	(**2.41**)	(**2.38**)	(**1.98**)	(**2.76**)	(**2.91**)	(-0.20)
ixRxvgbmq	0.16	0.16	0.11	0.33	0.20	0.01
	(1.95)	(**2.01**)	(1.85)	(**2.10**)	(**2.16**)	(0.19)
ixRxvgdm	0.18	0.18	0.10	0.34	0.21	-0.05
	(**2.61**)	(**2.58**)	(1.61)	(**3.03**)	(**2.55**)	(-0.68)
ixRxvgdmq	0.22	0.22	0.15	0.42	0.25	0.02
	(**2.89**)	(**2.82**)	(**2.23**)	(**3.00**)	(**2.87**)	(0.30)
ixRxvgam	0.19	0.20	0.10	0.55	0.18	-0.01
	(**2.52**)	(**2.54**)	(1.41)	(**3.33**)	(**2.05**)	(-0.19)
ixRxvgamq	0.25	0.25	0.18	0.42	0.23	0.04
	(**2.96**)	(**2.91**)	(**2.57**)	(**3.05**)	(**2.62**)	(0.52)
ixRxvgepq	0.47	0.45	0.25	0.75	-0.07	0.58
	(**3.56**)	(**3.49**)	(**2.89**)	(**3.59**)	(-1.48)	(**3.83**)
ixRxvgcp	0.33	0.32	0.20	0.52	0.14	0.17
	(**3.84**)	(**3.79**)	(**2.50**)	(**4.51**)	(1.70)	(**2.25**)
Other stock characteristics						
ixRxAmihud	0.39	0.39	0.34	0.60	0.49	-0.06
	(**3.65**)	(**3.66**)	(**3.75**)	(**4.01**)	(**3.81**)	(-1.32)
ixRxcr6m	0.12	0.10	-0.07	0.37	0.02	0.02
	(0.93)	(0.82)	(-0.72)	(1.87)	(0.20)	(0.14)
ixRxIOR	0.08	0.08	0.06	0.17	0.03	0.06
	(**2.10**)	(**2.04**)	(1.72)	(**2.41**)	(0.78)	(1.26)
ixRxTobin	0.12	0.13	0.08	0.31	-0.02	0.20
	(1.23)	(1.28)	(1.33)	(**2.17**)	(-0.44)	(**2.23**)

Table 6. Portfolio profits using TRACE returns

Each set contains 30 portfolios based on 26 bond and 56 stock characteristics. The signals for the weights are past returns.

	Π	Ω	0-diag	0-offdiag	0-U	0-L
Bond characteristics						
wRxWYLD	0.96	0.96	0.83	1.38	1.20	0.41
	(**3.66**)	(**3.68**)	(**3.41**)	(**3.47**)	(**3.76**)	(**2.86**)
wRxWPRC	0.84	0.79	0.65	1.15	0.32	0.89
	(**3.31**)	(**3.11**)	(**2.78**)	(**3.55**)	(**2.04**)	(**3.20**)
wRxWDUR	-0.01	-0.00	-0.02	0.06	0.17	-0.15
	(-0.08)	(-0.03)	(-0.19)	(0.44)	(1.22)	(-1.49)
wRxWTDVol	0.32	0.28	0.29	0.04	-0.13	0.32
	(**4.94**)	(**4.69**)	(**4.85**)	(0.70)	(**-3.53**)	(**5.91**)
wRxIConv	0.04	0.04	0.02	0.05	0.16	-0.14
	(0.33)	(0.35)	(0.13)	(0.40)	(1.19)	(-1.32)
wRxIFMV	0.71	0.77	0.68	0.94	0.25	0.86
	(**4.06**)	(**4.24**)	(**3.29**)	(**3.05**)	(**3.18**)	(**3.72**)
wRxIOAS	0.88	1.06	0.91	1.41	1.12	0.50
	(**2.96**)	(**3.58**)	(**3.19**)	(**3.32**)	(**3.20**)	(**3.14**)
wRxImDur	0.05	0.05	0.02	0.06	0.16	-0.12
	(0.40)	(0.37)	(0.14)	(0.47)	(1.21)	(-1.15)
wRxIpR3m	0.30	0.35	0.22	0.58	0.34	0.18
	(1.48)	(1.51)	(1.01)	(1.47)	(**2.13**)	(0.61)
wRxIbeYTM	0.94	1.09	0.88	1.42	1.10	0.46
	(**3.41**)	(**3.63**)	(**3.13**)	(**3.33**)	(**3.28**)	(**2.98**)
wRxIeDur	0.00	0.00	-0.02	0.03	0.15	-0.14
	(0.01)	(0.00)	(-0.13)	(0.22)	(1.08)	(-1.28)
wRxIeConv	-0.00	-0.01	-0.04	0.05	0.14	-0.17
	(-0.04)	(-0.08)	(-0.33)	(0.40)	(1.02)	(-1.57)
wRxIeYLD	0.97	1.10	0.91	1.43	1.10	0.47
	(**3.49**)	(**3.67**)	(**3.21**)	(**3.36**)	(**3.29**)	(**3.01**)
wRxIPrice	0.97	1.01	0.73	1.07	0.25	1.14
	(**3.02**)	(**2.94**)	(**2.35**)	(**2.27**)	(1.55)	(**3.08**)
wRxIspDur	-0.00	-0.00	-0.02	0.02	0.14	-0.14
	(-0.00)	(-0.03)	(-0.17)	(0.16)	(1.03)	(-1.33)
wRxIamrtR	0.82	0.88	0.67	1.07	0.86	0.26
	(**3.35**)	(**3.22**)	(**2.64**)	(**2.97**)	(**2.78**)	(**2.32**)
wRxItR3m	0.23	0.30	0.16	0.51	0.36	0.07
	(1.29)	(1.39)	(0.75)	(1.34)	(**2.15**)	(0.24)
wRxItR12m	0.83	0.90	0.54	1.19	0.16	0.87
	(**2.86**)	(**2.92**)	(1.81)	(**2.72**)	(1.10)	(**2.31**)
wRxIpR12m	0.86	0.92	0.60	1.07	0.21	0.92
	(**2.92**)	(**2.94**)	(**1.99**)	(**2.37**)	(1.36)	(**2.42**)
wRxIcoupR	0.99	1.17	1.00	1.41	1.24	0.49
	(**3.34**)	(**3.82**)	(**3.49**)	(**3.47**)	(**3.69**)	(**2.93**)
wRxIxsret	0.38	0.37	0.27	0.44	0.32	0.08
	(**2.43**)	(**2.06**)	(1.41)	(1.43)	(**2.52**)	(0.31)
wRxIMtrty	0.10	0.09	0.04	0.08	0.09	-0.07
	(0.80)	(0.70)	(0.36)	(0.58)	(0.62)	(-0.73)
wRxWTSprd	0.73	0.72	0.65	0.67	0.76	0.00
	(**4.36**)	(**4.26**)	(**3.97**)	(**2.98**)	(**4.01**)	(0.04)
wRxWRETEOM	0.62	0.50	0.40	0.78	0.15	0.51
	(**3.14**)	(**2.71**)	(**2.11**)	(**2.38**)	(1.11)	(1.94)
wRxWMtrty	0.05	0.06	-0.00	0.09	0.10	-0.10
	(0.37)	(0.45)	(-0.01)	(0.68)	(0.68)	(-1.21)
wRxIAccInt	0.02	0.07	0.08	-0.13	0.02	0.05
	(0.07)	(0.34)	(0.39)	(-0.82)	(0.10)	(0.56)

HXZ anomalies, Investment						
wRxiaci	0.26	0.27	0.21	0.20	0.12	0.26
	(**3.05**)	(**2.96**)	(**2.32**)	(1.19)	(**2.99**)	(**2.28**)
wRxidPia	0.23	0.25	0.27	0.22	0.17	0.26
	(**2.09**)	(**2.19**)	(**2.31**)	(1.15)	(**2.01**)	(1.90)
wRxinoa	0.12	0.11	0.12	0.05	0.04	0.20
	(**2.39**)	(**2.21**)	(**2.20**)	(0.50)	(0.71)	(**3.88**)
wRxidNoa	0.12	0.11	0.11	0.09	0.05	0.13
	(**2.92**)	(**2.60**)	(**2.33**)	(1.11)	(1.12)	(**2.89**)
wRxidLno	0.06	0.06	0.10	-0.08	0.05	0.12
	(1.39)	(1.34)	(1.74)	(-0.68)	(0.90)	(**2.30**)
wRxiig	0.06	0.06	0.10	-0.00	0.08	0.11
	(0.60)	(0.60)	(1.03)	(-0.02)	(1.13)	(0.93)
wRxitwoig	0.19	0.22	0.21	0.23	0.01	0.36
	(**2.13**)	(**2.28**)	(**2.04**)	(1.27)	(0.29)	(**3.06**)
wRxinsi	0.08	0.07	0.13	0.22	0.15	-0.02
	(0.77)	(0.67)	(1.17)	(1.06)	(1.09)	(-0.40)
wRxiivg	-0.00	0.00	0.10	-0.00	0.11	0.03
	(-0.01)	(0.03)	(0.66)	(-0.01)	(1.00)	(0.18)
wRxita	0.12	0.12	0.12	0.12	0.09	0.11
	(**2.28**)	(**2.25**)	(**2.08**)	(1.89)	(1.60)	(**2.57**)
HXZ anomalies, Intangibles						
wRxinOL	0.08	0.09	0.11	0.14	0.17	0.06
	(1.04)	(1.14)	(1.14)	(0.92)	(**2.25**)	(0.65)
wRxinOlq	0.11	0.11	0.14	-0.06	0.16	0.01
	(**2.37**)	(**2.48**)	(**2.75**)	(-0.55)	(**3.09**)	(0.26)
wRxindSi	0.07	0.06	0.04	0.23	0.08	0.07
	(0.97)	(0.83)	(0.59)	(1.77)	(0.95)	(1.42)
wRxindSa	0.13	0.12	0.12	0.04	0.16	0.10
	(1.76)	(1.57)	(1.25)	(0.28)	(1.63)	(1.61)
wRxindGs	0.29	0.34	0.28	0.51	0.09	0.40
	(**2.43**)	(**2.75**)	(**2.69**)	(**2.37**)	(1.14)	(**3.56**)
wRxindSs	0.28	0.31	0.23	0.40	0.19	0.19
	(**2.03**)	(**2.23**)	(**2.10**)	(**2.09**)	(1.24)	(**3.33**)
wRxinAla	-0.01	-0.00	0.11	-0.04	0.02	0.17
	(-0.11)	(-0.05)	(1.07)	(-0.20)	(0.21)	(**2.16**)
HXZ anomalies, Momentum						
wRxmabr	0.04	0.06	0.04	0.29	0.03	0.08
	(0.60)	(0.91)	(0.47)	(**2.63**)	(0.63)	(1.10)
wRxmre	0.15	0.14	0.02	0.44	0.23	-0.10
	(0.76)	(0.71)	(0.09)	(1.72)	(1.94)	(-0.44)
wRxmr11	0.60	0.61	0.34	1.06	0.22	0.55
	(**2.61**)	(**2.58**)	(1.94)	(**3.40**)	(**2.28**)	(**2.17**)
wRxmrs	0.02	-0.02	0.02	-0.15	0.10	-0.08
	(0.45)	(-0.35)	(0.31)	(-1.13)	(**2.44**)	(-1.28)
wRxmtes	0.04	0.02	0.02	-0.01	0.12	-0.01
	(0.89)	(0.47)	(0.45)	(-0.07)	(**2.95**)	(-0.09)
wRxme06	0.04	0.04	0.03	0.05	0.09	-0.03
	(1.31)	(1.32)	(1.03)	(1.32)	(**2.68**)	(-0.73)
wRxme12	0.02	0.01	0.03	-0.06	0.03	0.04
	(0.38)	(0.32)	(0.71)	(-1.10)	(0.99)	(0.85)
HXZ anomalies, Profitability						
wRxproe	0.40	0.45	0.54	0.15	0.19	0.66
	(1.86)	(1.93)	(**2.19**)	(0.39)	(1.57)	(**2.04**)
wRxpdRoe	0.21	0.24	0.30	0.15	0.23	0.38
	(1.67)	(1.82)	(**2.01**)	(0.39)	(**2.39**)	(1.55)
wRxproa	0.22	0.19	0.17	0.24	0.01	0.33
	(1.57)	(1.29)	(1.08)	(1.27)	(0.11)	(1.80)
wRxpdRoa	0.20	0.14	0.20	-0.21	0.07	0.24
	(1.37)	(0.97)	(1.11)	(-0.60)	(0.42)	(1.49)

wRxpcto	0.11	0.12	0.17	0.06	0.09	0.16
	(1.92)	(**2.06**)	(**2.96**)	(0.62)	(1.80)	(**3.18**)
wRxpgla	0.27	0.24	0.24	0.16	0.11	0.30
	(**2.78**)	(**2.74**)	(**2.52**)	(1.02)	(1.07)	(**2.68**)
wRxpglaq	0.17	0.16	0.07	0.44	0.10	0.12
	(**2.27**)	(**2.11**)	(1.02)	(**2.95**)	(**1.96**)	(1.35)
wRxpZ	0.40	0.43	0.35	0.55	0.20	0.37
	(**3.08**)	(**3.22**)	(**2.86**)	(**2.92**)	(**3.48**)	(**2.59**)
wRxpbl	-0.03	-0.05	-0.03	-0.13	-0.05	0.02
	(-0.59)	(-1.01)	(-0.50)	(-0.92)	(-0.70)	(0.33)
HXZ anomalies, Trading Frictions						
wRxtIvff	0.59	0.63	0.39	0.79	0.60	0.20
	(**2.99**)	(**3.01**)	(**2.17**)	(**2.68**)	(**2.75**)	(**2.83**)
wRxtIvc	0.60	0.63	0.43	0.67	0.63	0.23
	(**3.13**)	(**3.08**)	(**2.28**)	(**2.32**)	(**2.65**)	(**3.00**)
wRxtIvq	0.31	0.36	0.26	0.49	0.52	0.04
	(1.70)	(1.77)	(1.27)	(1.81)	(**2.19**)	(0.42)
wRxtTv	0.51	0.55	0.35	0.69	0.51	0.24
	(**2.63**)	(**2.67**)	(1.88)	(**2.54**)	(**2.25**)	(**2.96**)
wRxtPps	0.76	0.78	0.58	0.82	0.24	0.87
	(**3.54**)	(**3.56**)	(**3.18**)	(**3.03**)	(**3.06**)	(**3.38**)
wRxtMdr	0.40	0.43	0.33	0.80	0.46	0.19
	(**2.66**)	(**2.79**)	(**2.33**)	(**4.10**)	(**2.65**)	(**2.66**)
wRxtTs	-0.02	-0.02	-0.03	0.08	0.03	-0.04
	(-0.55)	(-0.44)	(-0.70)	(1.38)	(0.57)	(-1.08)
wRxtIsc	-0.03	-0.03	-0.02	-0.03	0.01	-0.02
	(-0.61)	(-0.69)	(-0.39)	(-0.62)	(0.26)	(-0.39)
wRxtIsff	0.02	0.01	0.02	-0.07	0.05	0.00
	(0.61)	(0.21)	(0.41)	(**-2.14**)	(1.08)	(0.09)
wRxtIsq	0.03	0.03	0.01	0.08	0.02	0.01
	(0.69)	(0.63)	(0.35)	(1.23)	(0.51)	(0.31)
HXZ anomalies, Value vs Growth						
wRxvgbm	0.25	0.28	0.18	0.27	0.26	0.11
	(**2.52**)	(**2.81**)	(1.80)	(1.43)	(**2.25**)	(1.94)
wRxvgjunbm	0.32	0.35	0.23	0.40	0.36	0.11
	(**3.60**)	(**3.54**)	(**2.14**)	(**2.26**)	(**2.80**)	(1.63)
wRxvgbmq	0.27	0.30	0.21	0.36	0.27	0.12
	(**2.60**)	(**2.53**)	(1.94)	(1.84)	(1.90)	(1.68)
wRxvgdm	0.13	0.10	0.07	0.18	0.15	0.11
	(1.12)	(0.84)	(0.56)	(0.83)	(1.07)	(1.36)
wRxvgdmq	0.18	0.19	0.08	0.39	0.22	0.14
	(1.53)	(1.50)	(0.66)	(**2.05**)	(1.67)	(1.60)
wRxvgam	0.25	0.22	0.16	0.20	0.26	0.13
	(**2.61**)	(**2.01**)	(1.20)	(1.12)	(1.76)	(1.57)
wRxvgamq	0.28	0.30	0.19	0.32	0.33	0.13
	(**3.05**)	(**2.93**)	(1.65)	(1.76)	(**2.19**)	(1.47)
wRxvgepq	0.57	0.63	0.44	0.73	0.11	0.75
	(**3.21**)	(**3.26**)	(**2.54**)	(**2.85**)	(1.71)	(**3.31**)
wRxvgcp	0.35	0.39	0.37	0.41	0.33	0.34
	(**2.47**)	(**2.70**)	(**2.85**)	(1.93)	(**2.15**)	(**3.22**)
Other stock characteristics						
wRxAmihud	0.77	0.83	0.70	0.96	0.84	0.32
	(**3.57**)	(**3.66**)	(**3.38**)	(**3.18**)	(**3.27**)	(**3.09**)
wRxcr6m	0.28	0.26	0.09	0.66	0.17	0.10
	(1.49)	(1.32)	(0.58)	(**2.18**)	(1.71)	(0.44)
wRxIOR	0.15	0.14	0.12	0.10	0.02	0.25
	(**2.14**)	(**2.06**)	(1.62)	(0.88)	(0.31)	(**3.29**)
wRxTobin	0.28	0.33	0.24	0.52	0.16	0.30
	(**2.44**)	(**2.59**)	(**2.05**)	(**2.48**)	(**2.21**)	(**2.03**)

Table 7. Tangency portfolio summaries using ICE excess returns

Each month we perform the cross-predictability portfolio strategy. With a 60 month out-of-sample window of optimal portfolio returns we estimate tangency weights based on constrained and unconstrained Markowitz optimization. The reported monthly Sharpe ratios are based on next period returns. Portfolio groups are named in each row. Darker color indicates higher constrained Sharpe ratio.

		No short sales			Unconstrained		
		Mean	S.D.	Sharpe ratio	Mean	S.D.	Sharpe ratio
Panel A. Sharpe ratios across bonds and stocks							
Π	Bond	0.29	0.89	0.33	0.14	2.29	0.06
Π	Stock	0.02	0.39	0.04	-1.09	12.24	-0.09
Ω	Bond	0.31	0.93	0.33	1.71	23.97	0.07
Ω	Stock	0.02	0.38	0.05	5.57	84.28	0.07
$\Omega^{\emptyset d}$	Bond	0.31	0.79	0.39	3.15	29.02	0.11
$\Omega^{\emptyset d}$	Stock	0.05	0.48	0.11	-1.01	11.76	-0.09
Ω^{d}	Bond	0.46	1.42	0.33	7.02	137.08	0.05
Ω^{d}	Stock	0.06	0.62	0.10	1.20	15.06	0.08
Panel B. Sharpe ratios by bond and stock categories							
Π	Bond Credit Risk	0.81	3.17	0.25	-1.29	21.05	-0.06
Π	Bond Interest Risk	0.12	0.87	0.14	-0.50	13.23	-0.04
Π	Bond Trading costs	0.30	0.90	0.33	0.60	2.26	0.27
Π	Stock Investments	0.06	0.89	0.07	0.19	5.10	0.04
Π	Stock Intantibles	0.06	0.91	0.07	-0.96	10.36	-0.09
Π	Stock Momentum	0.18	1.14	0.16	-1.26	22.43	-0.06
Π	Stock Profitability	0.17	1.31	0.13	-0.43	52.28	-0.01
Π	Stock Frictions	0.08	0.64	0.12	1.81	25.42	0.07
Π	Stock Value-Growth	0.23	1.37	0.17	-1.64	20.55	-0.08
Π	Stock Other	0.39	1.86	0.21	0.30	11.53	0.03
Ω	Bond Credit Risk	0.80	3.34	0.24	0.45	31.31	0.01
Ω	Bond Interest Risk	0.12	0.88	0.14	0.60	13.08	0.05
Ω	Bond Trading costs	0.29	0.89	0.33	0.59	2.29	0.26
Ω	Stock Investments	0.06	0.87	0.07	0.05	10.43	0.01
Ω	Stock Intantibles	0.06	0.89	0.07	-0.13	8.16	-0.02
Ω	Stock Momentum	0.19	1.22	0.15	-0.09	1.77	-0.05
Ω	Stock Profitability	0.17	1.36	0.12	-4.98	83.47	-0.06
Ω	Stock Frictions	0.07	0.64	0.11	0.31	3.16	0.10
Ω	Stock Value-Growth	0.25	1.39	0.18	8.48	85.64	0.10
Ω	Stock Other	0.40	1.83	0.22	-2.84	35.54	-0.08
$\Omega^{\emptyset d}$	Bond Credit Risk	0.65	2.85	0.23	0.32	10.92	0.03
$\Omega^{\emptyset d}$	Bond Interest Risk	0.13	0.87	0.14	1.41	20.68	0.07
$\Omega^{\emptyset d}$	Bond Trading costs	0.31	1.05	0.29	0.50	1.86	0.27
$\Omega^{\emptyset d}$	Stock Investments	0.10	0.96	0.10	0.07	12.86	0.01
$\Omega^{\emptyset d}$	Stock Intantibles	0.05	0.92	0.06	-0.79	11.14	-0.07
$\Omega^{\emptyset d}$	Stock Momentum	0.06	0.82	0.07	-32.29	470.80	-0.07
$\Omega^{\emptyset d}$	Stock Profitability	0.15	1.47	0.10	-0.45	3.95	-0.11
$\Omega^{\emptyset d}$	Stock Frictions	0.14	0.83	0.17	5.64	89.88	0.06
$\Omega^{\emptyset d}$	Stock Value-Growth	0.23	1.32	0.17	-1.78	18.20	-0.10
$\Omega^{\emptyset d}$	Stock Other	0.40	1.83	0.22	0.47	10.13	0.05
Ω^{d}	Bond Credit Risk	0.89	3.71	0.24	-9.98	155.01	-0.06
Ω^{d}	Bond Interest Risk	0.13	0.91	0.14	-0.10	15.82	-0.01
Ω^{d}	Bond Trading costs	0.47	1.70	0.27	-51.69	707.78	-0.07
Ω^{d}	Stock Investments	0.08	0.78	0.11	0.86	27.77	0.03
Ω^{d}	Stock Intantibles	0.11	0.85	0.13	2.05	22.29	0.09
Ω^{d}	Stock Momentum	0.05	0.54	0.10	0.39	4.32	0.09
Ω^{d}	Stock Profitability	0.17	1.13	0.15	-0.58	9.44	-0.06
Ω^{d}	Stock Frictions	0.05	0.43	0.11	1.17	13.06	0.09
Ω^{d}	Stock Value-Growth	0.38	1.84	0.21	3.49	44.02	0.08
Ω^{d}	Stock Other	0.26	1.76	0.14	6.68	97.14	0.07

Table 8. Tangency portfolio summaries using TRACE returns

Using a 60-month moving window of prior data, each month we perform the cross-predictability portfolio strategy. We apply the strategy portfolio weights out of sample to the next period. Then we group the strategy optimal portfolios in eight groups based on their underlying characteristics. Using another 60-window rolling window of out of sample grouped portfolio returns, we estimate tangency portfolio weights using constrained (no short sales) and unconstrained optimization.

		No short sales			Unconstrained		
		Mean	S.D.	Sharpe ratio	Mean	S.D.	Sharpe ratio
Panel A. Sharpe ratios across bonds and stocks							
Π	Bond	0.23	0.85	0.27	0.48	4.20	0.12
Π	Stock	0.09	0.37	0.24	0.17	4.09	0.04
Ω	Bond	0.24	0.80	0.29	0.96	3.72	0.26
Ω	Stock	0.09	0.39	0.23	-0.10	18.21	-0.01
$\Omega^{\emptyset d}$	Bond	0.27	0.79	0.35	0.51	2.30	0.22
$\Omega^{\emptyset d}$	Stock	0.08	0.43	0.18	0.92	9.33	0.10
Ω^{d}	Bond	0.16	1.31	0.12	0.30	10.72	0.03
Ω^{d}	Stock	0.14	0.68	0.20	11.39	129.59	0.09
Panel B. Sharpe ratios by bond and stock categories							
Π	Bond Credit Risk	0.65	2.22	0.29	0.15	2.75	0.05
Π	Bond Interest Risk	-0.13	1.75	-0.07	13.74	155.64	0.09
Π	Bond Trading costs	0.38	1.06	0.36	0.41	1.39	0.30
Π	Stock Investments	0.15	0.69	0.22	-8.12	96.29	-0.08
Π	Stock Intantibles	0.10	0.60	0.16	0.33	5.97	0.05
Π	Stock Momentum	0.43	2.69	0.16	-0.86	8.52	-0.10
Π	Stock Profitability	0.16	0.68	0.24	0.12	14.06	0.01
Π	Stock Frictions	0.26	1.14	0.23	2.24	24.00	0.09
Π	Stock Value-Growth	0.41	1.32	0.31	0.17	9.19	0.02
Π	Stock Other	0.21	1.04	0.20	0.53	5.17	0.10
Ω	Bond Credit Risk	0.68	2.27	0.30	0.36	2.18	0.16
Ω	Bond Interest Risk	-0.14	1.74	-0.08	2.09	24.59	0.08
Ω	Bond Trading costs	0.37	1.02	0.37	0.50	1.41	0.36
Ω	Stock Investments	0.17	0.73	0.23	1.01	16.86	0.06
Ω	Stock Intantibles	0.11	0.59	0.19	1.54	10.00	0.15
Ω	Stock Momentum	0.39	2.28	0.17	-0.20	11.14	-0.02
Ω	Stock Profitability	0.19	0.75	0.25	11.11	147.20	0.08
Ω	Stock Frictions	0.24	1.01	0.24	12.40	133.37	0.09
Ω	Stock Value-Growth	0.46	1.54	0.30	-2.82	26.99	-0.10
Ω	Stock Other	0.22	1.05	0.21	-0.54	6.82	-0.08
$\Omega^{\emptyset d}$	Bond Credit Risk	0.69	2.59	0.27	0.40	2.92	0.14
$\Omega^{\emptyset d}$	Bond Interest Risk	-0.14	1.78	-0.08	-0.13	9.51	-0.01
$\Omega^{\emptyset d}$	Bond Trading costs	0.38	1.01	0.37	0.47	1.49	0.32
$\Omega^{\emptyset d}$	Stock Investments	0.22	1.02	0.21	0.77	14.07	0.06
$\Omega^{\emptyset d}$	Stock Intantibles	0.11	0.62	0.18	-2.76	35.33	-0.08
$\Omega^{\emptyset d}$	Stock Momentum	0.23	1.51	0.15	-16.00	110.87	-0.14
$\Omega^{\emptyset d}$	Stock Profitability	0.17	0.88	0.19	0.66	6.60	0.10
$\Omega^{\emptyset d}$	Stock Frictions	0.28	1.11	0.25	3.38	42.75	0.08
$\Omega^{\emptyset d}$	Stock Value-Growth	0.49	1.77	0.28	0.18	4.00	0.05
$\Omega^{\emptyset d}$	Stock Other	0.26	1.23	0.22	-0.01	3.77	-0.00
Ω^{d}	Bond Credit Risk	0.79	2.85	0.28	2.69	12.94	0.21
Ω^{d}	Bond Interest Risk	-0.13	1.72	-0.07	0.42	5.26	0.08
Ω^{d}	Bond Trading costs	0.62	2.24	0.27	0.57	3.30	0.17
Ω^{d}	Stock Investments	0.28	1.16	0.24	0.01	3.76	0.00
Ω^{d}	Stock Intantibles	0.26	1.04	0.25	-0.52	11.46	-0.05
Ω^{d}	Stock Momentum	0.48	1.93	0.25	-2.70	57.57	-0.05
Ω^{d}	Stock Profitability	0.29	1.39	0.21	1.34	4.83	0.28
Ω^{d}	Stock Frictions	0.10	0.75	0.14	-0.08	2.47	-0.03
Ω^{d}	Stock Value-Growth	0.74	2.33	0.32	2.10	10.20	0.21
Ω^{d}	Stock Other	0.50	2.14	0.24	0.71	14.95	0.05

Figure 1. Portfolio profit alphas using ICE returns

The figure reports the profits of the cross-predictability strategy from Table 5 risk-adjusted with the value-weighted bond market factor. Bond market returns are computed as a weighted average, with fair-market value (provided by the vendor) as weights, of the cross-section of available individual bond excess returns in ICE. Darker bars indicate statistical significance at 5%.

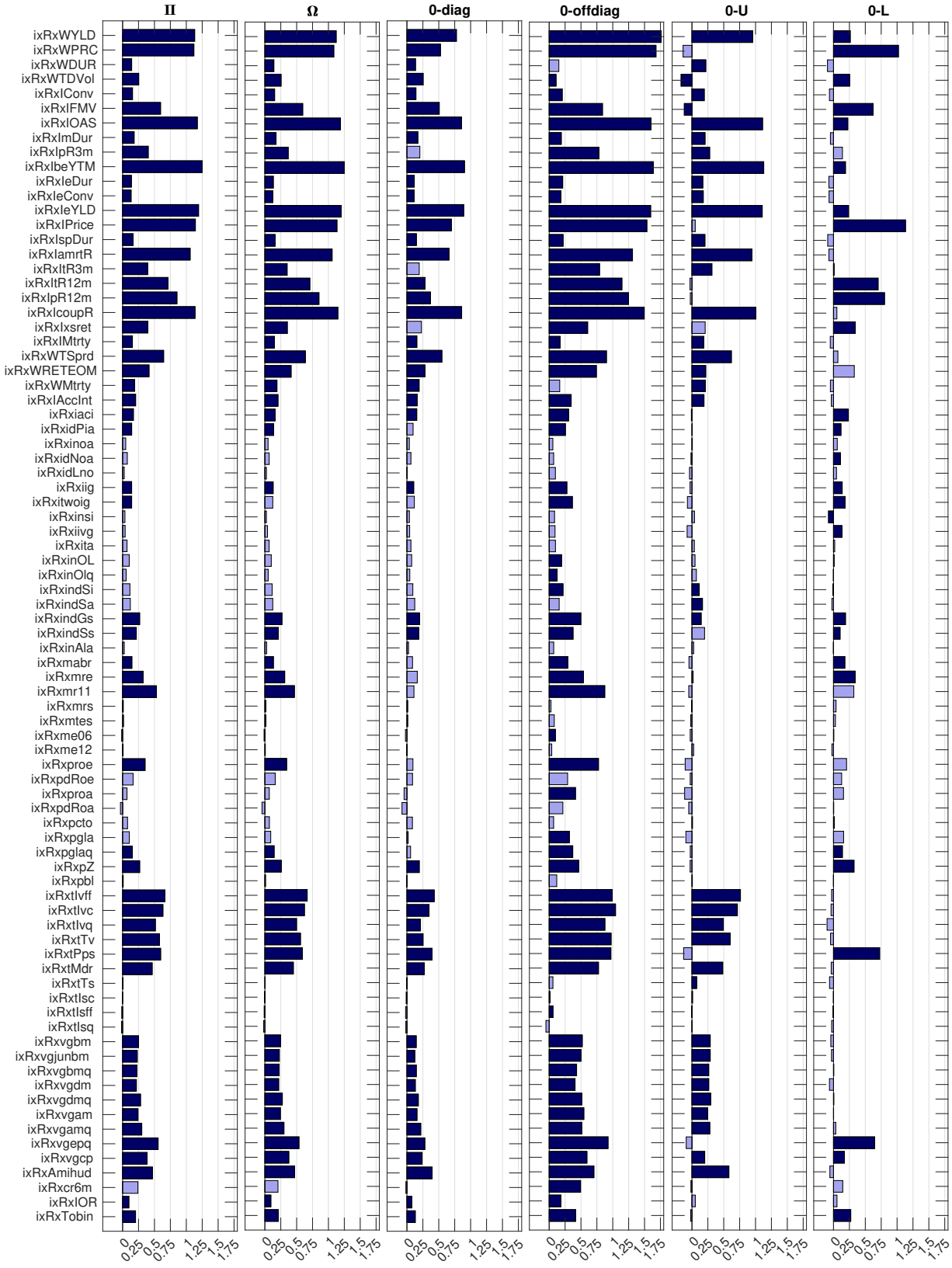


Figure 2. Portfolio profit alphas using TRACE returns

The alphas on the figure are the risk-adjusted returns from Table 6. The bond market returns are computed as a weighted average, with weights amount outstanding, of the cross-section of available individual bond returns in TRACE each period. Darker bars indicate statistical significance at 5%.

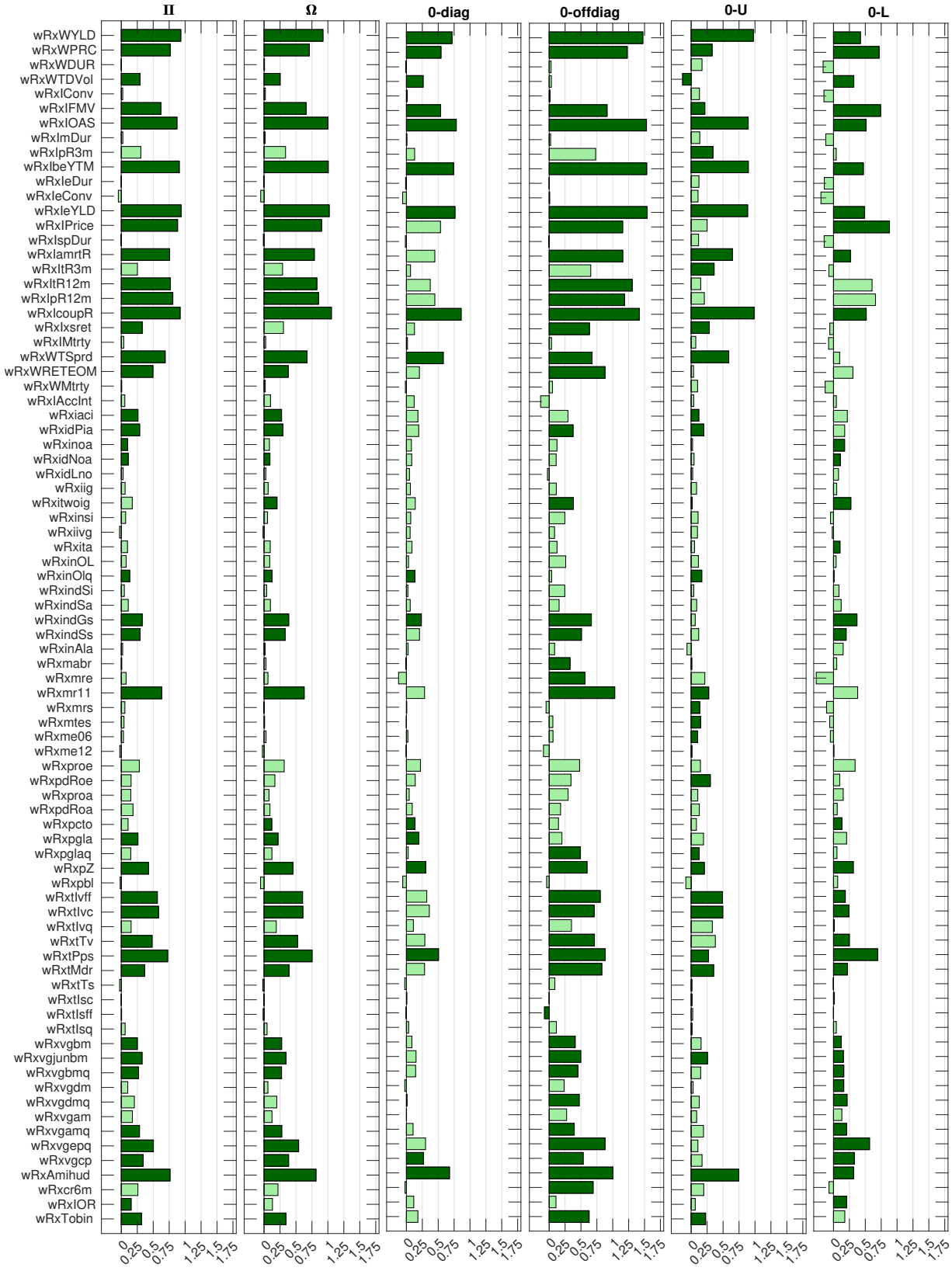


Figure 3. ICE portfolio alphas with recessions and sentiment

We risk-adjust profits by regressing on the value-weighted bond market factor. In the same regression we include dummies for recession and low sentiment (below the median). Darker bars indicate statistical significance at 5%. Two columns of pluses and minuses in each plot reflect positive or negative effect on profitability of recessions and low sentiment.

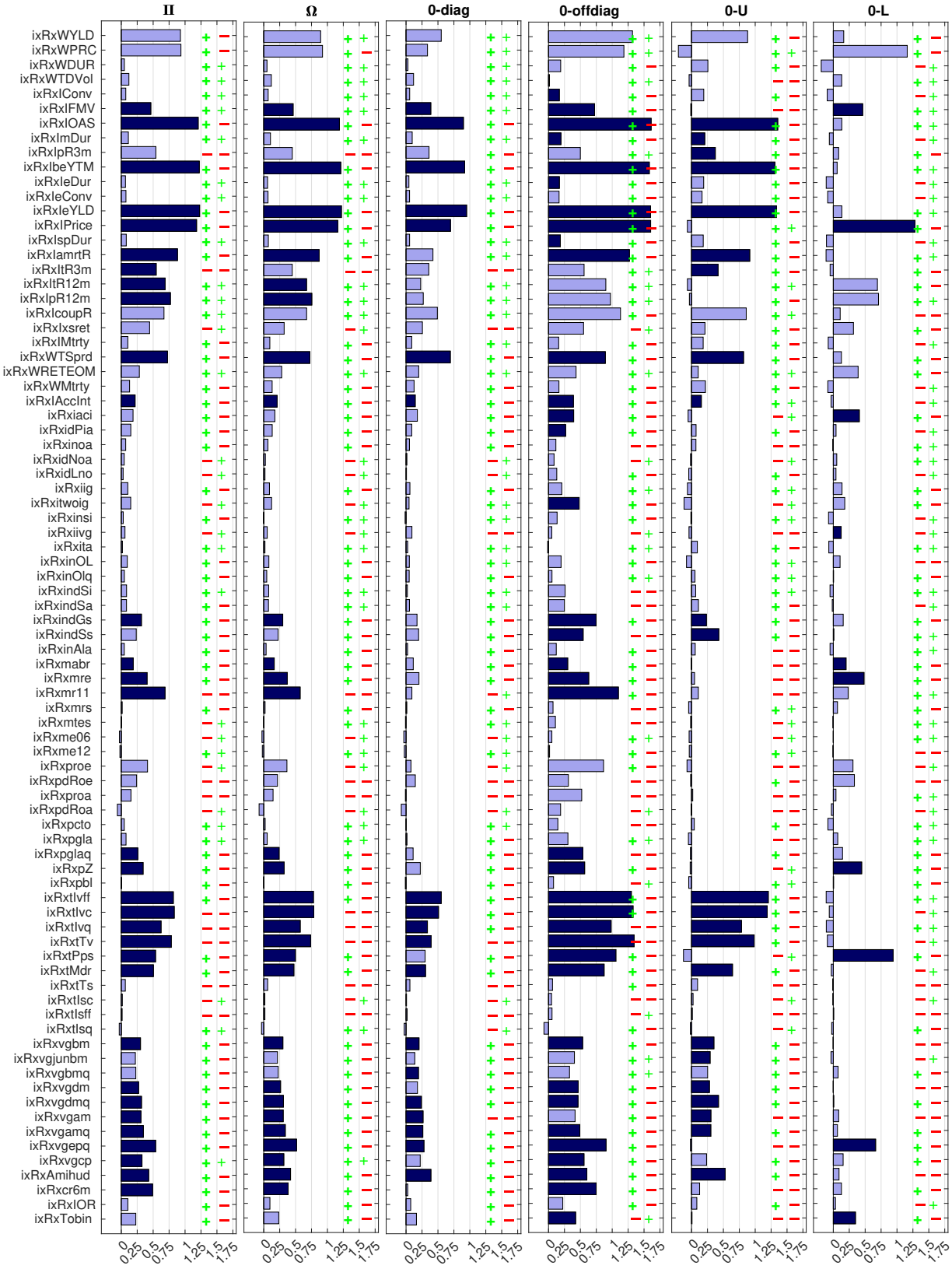
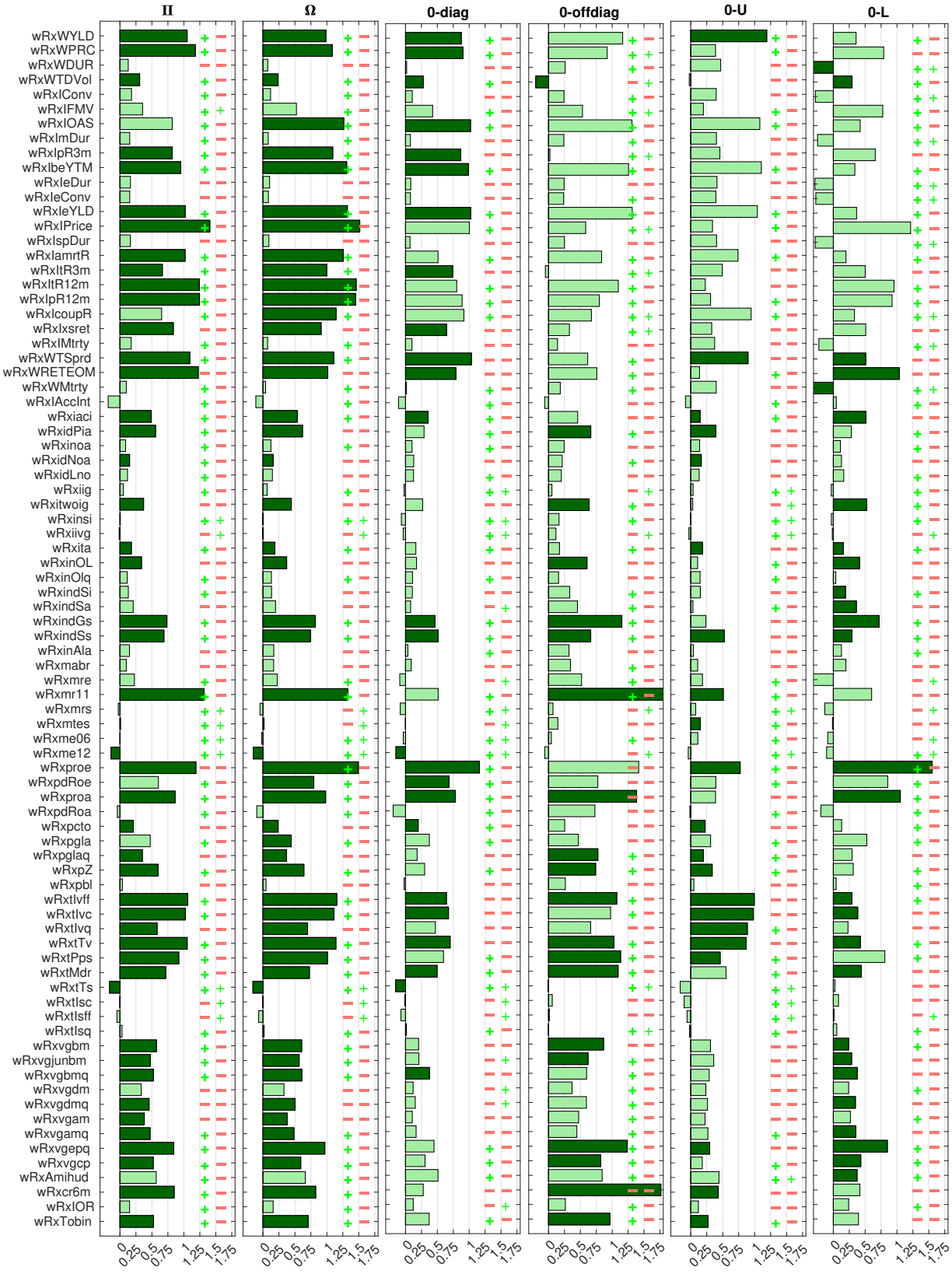


Figure 4. TRACE portfolio alphas with recessions and sentiment

We risk-adjust profits by regressing on the value-weighted bond market factor. In the same regression we include dummies for recession and low (below the median) sentiment. Darker bars indicate statistical significance at 5%. Two columns of pluses and minuses in each plot reflect positive or negative effect on profitability of recessions and low sentiment.



Appendix A. Variable Description

Variable	Description
Bond characteristics	
ixR	Excess bond return from the ICE database: "The total return percentage of a bond minus the total return percentage of a risk-matched basket of governments. The government basket is comprised of synthetic securities derived from the fair value government yield curve corresponding to the currency of denomination of the bond. The hedge basket is key rate duration-matched to the bond at six nodes: 6-month, 2-year, 5-year, 10-year, 20-year and 30-year. The excess return of an Index is equal to the average of its constituent security excess returns, weighted by their full market values as of the beginning of the period."[16] "Excess return is a measure of relative value that neutralizes the interest rate and yield curve risk of a bond, thereby isolating that portion of its performance that is attributed solely to credit and optionality risks."[17]
wR	Bond return from TRACE based on last 5 trading days of the month
WYLD	Yield from the TRACE database
WPRC	Price based on last 5 trading days from TRACE
WDUR	Duration from TRACE
WTDVol	Trading dollar volumen from TRACE
IConv	Bond convexity from ICE
IFMV	Fair market value from ICE
IOAS	Option adjusted spread from ICE
ImDur	Modified duration from ICE
IpR3m	Price cumulative return over three months from ICE
IbeYTM	Bond-equivalent yield to maturity from ICE
IeDur	Effective duration from ICE
IeConv	Effective convexity from ICE
IeYLD	Effective yield from ICE
IPrice	Price from ICE
IspDur	Spread duration from ICE
IamrtR	Amortization return from ICE
ItR3m	Total return over 3 months from ICE
ItR12m	Total return over 12 months from ICE
IpR12m	Price return over 12 months from ICE
IcoupR	Coupon return from ICE
Ixsret	Excess return from ICE, same variable as ixR
IMtrty	Maturity from ICE
WTSprd	Average bid-ask spread from TRACE
WRETEOM	End-of-month return (any day of month) from TRACE
WMtrty	Maturity from TRACE
IAccInt	Accrued interest from ICE

[16]Source: a file "Data Field descriptions (ICE).xls" provided by ICE upon data purchase.

[17]Source: "Bond Index Methodologies Includes ICE ESG and Climate-Related Bond Index methodologies December 6, 2023."

HXZ anomalies, Investment

i1aci	A.3.1 Abnormal corporate investment
i2dPia	A.3.4 Cnanges in PPE and inventory-to-assets
i3noa	A.3.5 Net operating assets
i4dNoa	A.3.5 Changes in net operating assets
i5dLno	A.3.6 Changes in long-term net operating assets
i6ig	A.3.7 Investment growth
i7twoig	A.3.8 Two-year investment growth
i8nsi	A.3.10 Net stock issues
i9ivg	A.3.14 Inventory growth
i10ta	A.3.17 Total accrual

HXZ anomalies, Intangibles

in1Rds	A.5.6 R&D expenses-to-sales
in2OL	A.5.8 Operating leverage
in3Olq	A.5.9 Quarterly operating leverage
in4Age	A.5.18 Age
in5dSi	A.5.20 % change in sales minus % change in inventory
in6dSa	A.5.21 % change in sales minus % change in accounts receivable
in7dGs	A.5.22 % change in gross margin minus % change in sales
in8dSs	A.5.23 % change in sales minus % change in SG&A
in9Ana	A.5.26 Analyst coverage
in10Ala	A.5.46 Asset illiquidity

HXZ anomalies, Momentum

m1abr	A.1.2 Cumulative abnormal returns around earning announcements
m2re	A.1.3 Revisions in analysts earnings forecasts
m3r11	A.1.5 Prior 11-month returns
m4rs	A.1.7 Revenue surprises
m5tes	A.1.8 Tax expense surprises
m6dEf	A.1.9 Changes in analyst earnings forecasts
m7Nei	A.1.10 The number of quarters with consecutive earnings increase
m852w	A.1.11 52-week high
m9e06	A.1.12 Six-month residual momentum
m10e12	A.1.13 11-month residual momentum

HXZ anomalies, Profitability

p1Roe	A.4.1 Return on equity
p2dRoe	A.4.2 4-quarter change in return on equity
p3Roa	A.4.3 Return on assets
p4dRoa	A.4.4 4-quarter change in return on assets
p5cto	A.4.6 Capital turnover
p6Gla	A.4.10 Gross profits-to-lagged assets
p7glaq	A.4.11 Quarterly gross profits-to-lagged assets
p8O	A.4.24 Ohlson's O-score
p9Z	A.4.26 Altman Z-score
p10bl	A.4.32 Book leverage

HXZ anomalies, Trading Frictions

t1Ivff	A.6.2 Idiosyncratic volatility per the Fama and French (1993) 3-factor model
t2Ivc	A.6.4 Idiosyncratic volatility per the CAPM
t3Ivq	A.6.5 Idiosyncratic volatility per the q-factor model
t4Tv	A.6.6 Total volatility
t5Pps	A.6.15 Share price
t6Mdr	A.6.18 Maximum daily return
t7Ts	A.6.19 Total skewness
t8Isc	A.6.20 Idiosyncratic skewness per the CAPM
t9Isff	A.6.21 Idiosyncratic skewness per the Fama and French (1993) 3-factor model
t10Isq	A.6.22 Idiosyncratic skewness per the q-factor model

HXZ anomalies, Value vs Growth

vg1bm	A.2.1 Book-to-market equity
vg2junbm	A.2.2 Book-to-June-end market equity
vg3bmq	A.2.3 Quarterly book-to-market equity
vg4dm	A.2.4 Debt-to-market
vg5dmq	A.2.5 Quarterly debt-to-market
vg6am	A.2.6 Assets-to-market
vg7amq	A.2.7 Quarterly assets-to-market
vg8ep	A.2.9 Earnings-to-price
vg9epq	A.2.10 Quarterly earnings-to-price
vg10cp	A.2.12 Cash flow-to-price

Miscellaneous stock characteristics

Amihud	Amihud illiquidity
cr6m	Past six month cumulative return
IOR	Institutions ownership ratio
Tobin	Tobin's q
grossprof	Gross profitability