WU VIENNA

MASTER THESIS

Timing Corporate Bond Factors

Author:
Jakob PERTL

Supervisor:
Prof. Josef ZECHNER

A thesis submitted in fulfillment of the requirements for the degree of Master of Science

in

Quantitative Finance

August 14, 2025

WU VIENNA

Abstract

Quantitative Finance

Master of Science

Timing Corporate Bond Factors

by Jakob PERTL

This thesis investigates whether cross-sectional risk premia in corporate bonds that fail to replicate in prior studies can be recovered through timing. The motivation is to move beyond unconditional factor portfolios and to examine whether predictable periods of elevated premia can be identified and exploited in practice. Using TRACE data from July 2002 to November 2021, I replicate 21 established corporate bond factors following Dick-Nielsen et al., 2023 and adapt the timing signal construction and evaluation framework of Neuhierl et al., 2024 to the corporate bond setting. The analysis applies 31 timing signals, including momentum, macroeconomic, and aggregation-based approaches, to assess their ability to forecast factor returns. Across all factors, short-horizon momentum signals, such as the one-month momentum measure, improved Sharpe ratios by an average of 0.11, while certain macroeconomic indicators, such as the Federal Funds Rate, improved them by 0.09. Aggregating timing signals through a simple equal-weighted average achieved an improvement of 0.13. I then extended the approach to timing multiple factors simultaneously, resulting in a timed multi-factor portfolio that produced a 0.39% monthly premium over a benchmark portfolio. Implementability tests reveal that concentrated long-only portfolios retain economically and statistically significant alphas after transaction costs, with the top-10 percent portfolio delivering a monthly alpha of 0.26%. These findings indicate that corporate bond risk premia persist in a time-varying form. When timed with suitable signals and implemented with realistic constraints, they can be harvested by investors beyond simple market exposure.

Acknowledgements

First of all, I would like to thank my supervisor, Prof. Zechner, for his continuous and engaging discussions of my work. His critical feedback and ability to challenge my ideas while guiding me toward better solutions have been invaluable for my learning and the quality of this work. I truly appreciate, and do not take for granted, the time and effort he invested to enable me to write what I hope is a good thesis.

I am also grateful to Christian Stolborg, the maintainer of the dataset used throughout this thesis. I appreciate his patience in helping me resolve replication issues, even though I was just a random master's student reaching out for assistance.

My heartfelt thanks go to my girlfriend, Anna, who took the time and effort to read and critique my thesis, despite her expertise being in medicine rather than finance.

I would also like to thank Simon Mitterhofer, who generously shared his office desk with me and should therefore be considered a major contributor.

Finally, I am deeply thankful to my parents, without whose unwavering support throughout my studies I would never have reached the point of writing acknowledgements for my thesis.

Thank you!

Contents

Chapter 1

Introduction

I believe that the clearest way to introduce the topic of my Master's thesis is to dissect its title, *Timing Corporate Bond Factors*. To begin, a *corporate bond* is a debt obligation issued by a company to raise capital. Compared with other asset classes, corporate bonds are less standardized because contracts often contain covenants and terms tailored to the specific needs of issuers and investors. This heterogeneity typically leads to low trading volumes and limited liquidity in the asset class.

This naturally raises the question of whether a general theory can explain the cross-section of corporate bonds. In equities, the literature has developed from the CAPM introduced by Sharpe, 1964, to the Size and Value factors of Fama and French, 1992, and eventually to what has been called the "factor zoo" by Cochrane, 2011 and Harvey, Liu, and Zhu, 2016. The literature on *factors*, or cross-sectional risk premia, in corporate bonds is much smaller. A seminal contribution is Fama and French, 1993, who identify two key drivers of corporate bond returns. The first is interest rate risk, which is present in virtually all debt instruments. The second is default risk, which reflects the possibility of issuer default. A corporate bond with greater exposure to either risk should, in principle, offer higher expected returns. Later studies document numerous additional risk premia, such as liquidity by Lin, Wang, and Wu, 2011, carry by Israel, Palhares, and Richardson, 2018, and value by Houweling and Zundert, 2017, among many others. At the same time, as in the equity literature, the growing number of proposed factors has led to criticism of their validity and methodology, for example by Dickerson, Mueller, and Robotti, 2023. Further, Dick-Nielsen et al., 2023 attempt to replicate many of these factors using a carefully cleaned dataset and find that reproducibility is generally low.

This brings us to the final missing word of the title, *timing*. At this point one may ask: if most corporate bond factors fail to deliver consistent premiums, why attempt to time them? The answer is that risk premia are time-varying. Even if a factor does not show a significant premium over the full sample, there may be periods when investors place a higher value on the associated risk, which can temporarily restore the premium. Timing provides a way to identify and exploit such periods, effectively "resurrecting" factors. The literature on timing individual risk premia in corporate bonds is virtually non-existent. The most relevant reference is Neuhierl et al., 2024, *Timing the Factor Zoo*, which applies timing strategies to a broad set of equity factors. This thesis takes that approach and applies it to a new asset class, corporate bonds, which makes Neuhierl et al., 2024 a central influence on the methodology. In addition, I incorporate insights from the broader time-series literature on corporate bond returns, particularly Chang and Huang, 1990 and Lin, Wu, and Zhou, 2016.

To evaluate the potential for *timing corporate bond factors*, the thesis is structured as follows. Chapter 2 replicates the cross-section of corporate bond returns and examines whether risk premia are time-varying. Chapter 3 introduces the timing signals and evaluates the results of applying each signal to each factor. Chapter 4 extends the analysis by timing multiple factors simultaneously using an aggregated timing signal. Chapter 5 addresses issues of implementability. Since factors are typically constructed as long–short portfolios with potentially high turnover, I examine a long-only version of the timed multi-factor portfolio to assess whether it can be implemented in practice without prohibitive transaction costs. Finally, additional graphs and tables are provided in Appendix A. All coding was done in the R programming language (R Core Team, 2022) and is available on GitHub in the timing_bond_factors repository.

Chapter 2

Data

2.1 TRACE

In July 2002, the Financial Industry Regulatory Authority (FINRA) launched TRACE (Trade Reporting and Compliance Engine), a system through which FINRA members and certain depository institutions report transaction data on over-the-counter (OTC) corporate bond activity. The TRACE dataset covers virtually every transaction in U.S. corporate bonds, as reporting has been mandatory since the system's inception. Since its launch, the dataset has been widely used in academic research (Financial Industry Regulatory Authority, 2024).

2.2 Cleaning Corporate Bond Prices

Despite its comprehensive coverage, the TRACE dataset contains numerous errors. Various approaches have been proposed in the academic literature to address these issues. One of the main contributors to the standardization of data preprocessing has been Dick-Nielsen, 2009; Dick-Nielsen, 2014, whose methods have seen widespread adoption.

More recently, Dick-Nielsen et al., 2023 introduced further improvements in error handling. After calculating monthly returns for each corporate bond, the authors manually reviewed the 5,000 largest return outliers (in absolute value). Interestingly, only 292 of these were identified as true errors, while 4,708 appeared to be valid returns. This represents an important contribution, as conventional cleaning methods might have removed or winsorized these influential observations, potentially discarding valuable information.

Additionally, the authors have made their cleaned dataset publicly available to facilitate further research. It can be accessed at Christian Stolborg's website (data retrieved on 17/02/2025). I have therefore chosen to use this cleaned dataset as the foundation for the empirical analysis in this thesis.

The dataset spans the period from 31/07/2002 to 30/11/2021 and contains a total of 1,625,377 observations, including 44,909 unique bonds. Each observation represents the monthly excess return of a given corporate bond.

2.3 Further Data Sources

To replicate various corporate bond factors, additional bond-specific data was required. I obtained bond issue and issuer characteristics from the Mergent Fixed

Income Securities Database (FISD) via the Wharton Research Data Services (WRDS). Furthermore, Treasury yield data was sourced through WRDS using the CRSP database. Finally, macro-level signals were collected from the Bloomberg Terminal.

Chapter 3

The Cross-Section of Corporate Bond Returns

3.1 Literature Review

The cross-section of equities has been extensively studied, beginning with the seminal paper by Fama and French, 1992, which introduced the size and value factors. Since then, the equity literature has expanded rapidly, leading to increasing criticism of the so-called "factor zoo," as noted by Cochrane, 2011 and Harvey, Liu, and Zhu, 2016.

In contrast, the cross-section of corporate bond returns has received comparatively less attention. This is partly due to the fact that corporate bonds are less frequently traded and are predominantly traded over-the-counter, resulting in lower data quality. Nevertheless, the first paper to propose a "Corporate Bond CAPM" was published relatively early by Fama and French, 1993. This seminal work decomposes the market portfolio of corporate bonds into two components: credit (*DEF*) and interest rate (*TERM*) risk.

- **DEF**: The difference between the monthly return on a value-weighted corporate bond market portfolio and a duration-matched Treasury return.
- **TERM**: The difference between a duration-matched Treasury return and a short-term Treasury return.

In recent years, the literature has shown growing interest in risk premia in corporate bonds beyond the Bond CAPM framework introduced by Fama. For instance, Houweling, Mentink, and Vorst, 2005 investigated the role of bond characteristics such as amount outstanding and age. Jostova et al., 2013 analyzed momentum-based risk premia, while Israel, Palhares, and Richardson, 2018 examined multiple factors, including carry and low-duration.

However, the increasing number of proposed "risk premia" has raised concerns about the robustness and validity of many findings. For example, Bai, Bali, and Wen, 2019 documented several new factors but had to retract their paper after Dickerson, Mueller, and Robotti, 2023 uncovered methodological flaws. Similarly, Dick-Nielsen et al., 2023 demonstrated that after thorough data cleaning and robust factor construction, most factors fail to replicate.

3.2 Methodology

The aim of this thesis is to analyze whether well-documented risk premia in corporate bonds vary over time and whether they can be timed. In the cross-sectional analysis, I treat the factor universe as exogenous. Accordingly, both the selection of factors and the methodology closely follow Dick-Nielsen et al., 2023. Their methodology is briefly summarized below.

First, all bonds are grouped into three rating categories:

1. **IG+**: Investment Grade Plus, including all bonds rated from AAA to A3 by Moody's or AAA to A- by Standard & Poor's.
2. **IG-**: Investment Grade Minus, including bonds rated from Baa1 to Baa3 by Moody's or BBB+ to BBB- by Standard & Poor's.
3. **SG**: Speculative Grade, including all bonds rated Ba1 or lower by Moody's or BB+ or lower by Standard & Poor's.

Within each rating group, bonds are sorted into quintiles to form portfolios. This constitutes the main deviation from Dick-Nielsen et al., 2023, who used tertiles. I opted for quintiles because, as discussed in Chapter 6, having smaller portfolios is more practical when analyzing implementable long-only strategies.

For a given factor i, the long-short factor return within each rating group RG at time t is computed as:

$$f_t^{i,RG} = r_t^{\text{HIGH-}i,RG} - r_t^{\text{LOW-}i,RG}$$

Finally, to aggregate across the three rating groups, the overall factor return at time t is calculated as:

$$f_t^i = \frac{1}{3}\left(f_t^{i,\text{IG+}} + f_t^{i,\text{IG-}} + f_t^{i,\text{SG}}\right)$$

3.3 Factors

In total, I construct 21 factors using the methodology described earlier. These factors can be broadly grouped into several thematic categories, which I will now discuss. For a detailed description of each factor's construction, please refer to Appendix Table A.1.

3.3.1 Familiarity Among Factors

To better understand the relationships between the factors, I examined which ones tend to group bonds into similar quintiles. Figure 3.1 shows the extent to which pairs of factors assign the same bond to the same quintile at a given time. I then applied clustering techniques to identify patterns and similarities.

Based on this analysis, the factors can be categorized into the following groups:

- **Size**: This group includes *amt_out* (amount outstanding) and *mkt_val* (market value), both of which capture size-related effects.

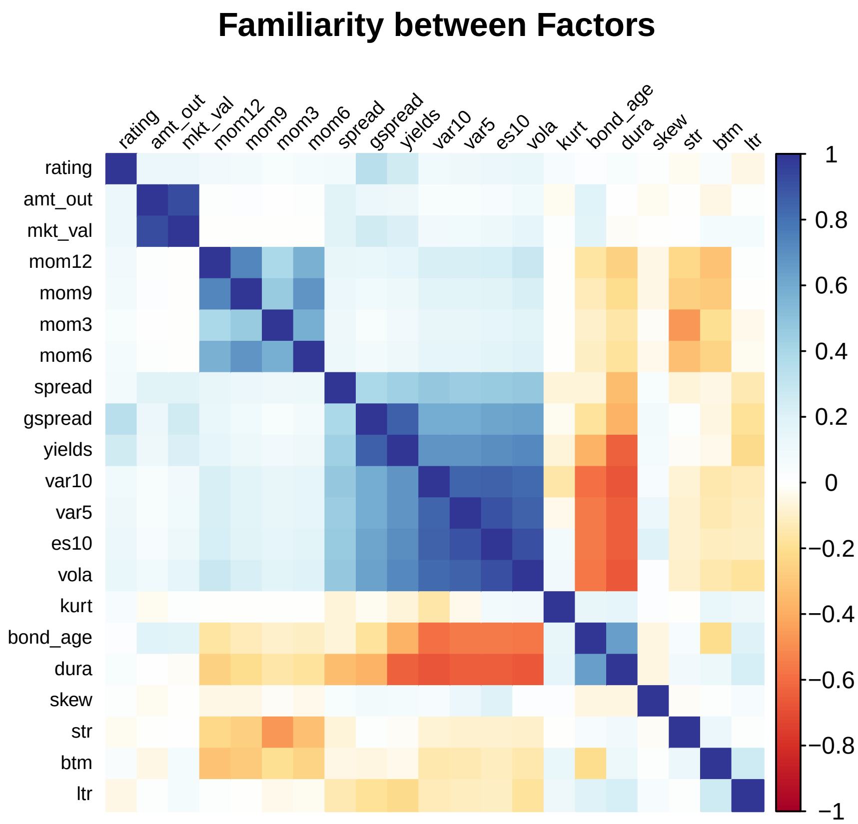

FIGURE 3.1: Factor similarity based on Spearman's rank correlation. For each pair of factors, I compute the Spearman's rho statistic between their respective bond-level quantile assignments at each time point. Factors that sort bonds similarly exhibit higher correlations and are grouped together through hierarchical clustering.

- **Momentum**: This group consists of the momentum factors *mom3* through *mom12*, which are closely correlated with one another.
- **High Credit Risk**: The largest group includes factors associated with undesirable risk characteristics. For example, *gspread* goes long bonds with high credit spreads. Other members of this group include risk-based factors such as *var5* (Value at Risk) and *vola* (volatility). Interestingly, the liquidity proxy *spread* also belongs to this cluster.
- **Low Term Risk**: This group contains *bond_age* and *dura*, both of which are clearly related to bond maturity and take on little term risk.
- **Others**: A few factors appear to be relatively uncorrelated with any others. These include the short-term reversal factor *str* and the book-to-market factor *btm*. Interestingly, the two reversal factors *str* and *ltr* do not exhibit a strong similarity.

3.3.2 Performance

Table 3.1 presents performance metrics for the constructed factors. The market portfolio, consisting of the value-weighted universe of corporate bonds, delivers an annualized excess return of 6.00% with a Sharpe ratio of 1.06.

The second panel of the table reports results for all long-short factor portfolios. It is important to note that these returns are not directly comparable to the market portfolio, as they are constructed by taking long and short positions in different corporate bonds, rather than being net of the risk-free rate.

Interestingly, many of the long-short portfolios do not generate positive excess returns. For example, the *dura* factor goes long low-duration (lower risk) bonds and short high-duration (higher risk) bonds, leading to a negative raw return. However, as will be discussed later, adjusting for risk reveals positive alphas for some of these strategies. On the other hand, the momentum-based factors appear to offer little or no evidence of persistent risk premia in this analysis.

TABLE 3.1: Performance metrics of factor portfolios. This table reports annualized excess returns, annualized volatility, maximum drawdowns, and Sharpe ratios for all factor portfolios based on monthly excess return data.

	Ann. Excess Return	Ann. Volatility	Worst Drawdown	Sharpe Ratio
market	6.00	5.65	13.07	1.06
def	2.55	5.91	23.36	0.43
term	3.21	5.25	8.19	0.61
amt_out	-0.33	3.51	10.45	-0.09
bond_age	-2.70	5.42	41.49	-0.50
btm	7.96	9.66	20.14	0.82
dura	-3.44	7.18	52.18	-0.48
gspread	10.43	11.36	22.30	0.92
mkt_val	2.47	6.43	14.69	0.39
rating	1.34	4.87	19.10	0.27
spread	3.63	6.59	17.58	0.55
yields	10.98	12.12	25.85	0.91
str	7.37	7.69	13.62	0.96
mom3	-4.70	8.08	60.82	-0.58
mom6	-3.69	8.12	52.83	-0.45
mom9	-3.79	8.57	51.51	-0.44
mom12	-3.93	8.86	53.22	-0.44
es10	5.48	10.31	29.66	0.53
kurt	2.32	4.72	9.60	0.49
skew	2.16	4.49	8.80	0.48
var10	3.82	9.57	35.83	0.40
var5	4.59	8.97	27.23	0.51
vola	4.29	10.02	31.12	0.43
ltr	0.07	4.37	15.99	0.02

3.3.3 Alphas

Next, we aim to measure the risk premia embedded in the factors beyond what is captured by the Bond CAPM. For each factor i, I estimate the following regression model:

$$f_t^i = \alpha_i + \beta_{DEF}^i \cdot \mathrm{DEF}_t + \beta_{TERM}^i \cdot \mathrm{TERM}_t + \epsilon_t^i$$

We then examine the intercept (α) to assess whether a factor carries a risk premium. This methodology allows us to control for the two main sources of risk premia TERM and DEF and identify significant positive alphas. This approach is preferable to simply evaluating significant excess returns, as those may be explained by other risk factors.

For example, consider the Value-at-Risk factor at the 5% level, *var5*. As shown in Table 3.1, it exhibits a promising excess return and Sharpe ratio. However, Table 3.2 reveals that *var5* has a negative and statistically insignificant estimate for the intercept, indicating that no risk premium can be detected. This suggests the factor likely loads heavily on credit (DEF) or duration (TERM) risk.

Another illustrative case is the low-duration factor (*dura*). While it shows a negative excess return in Table 3.1, Table 3.2 reports highly significant positive alphas. This implies the factor is short on duration (TERM) risk and that there appears to be a positive risk premium associated with low-duration bonds beyond what is explained by TERM.

TABLE 3.2: Estimated monthly alphas of factor portfolios. This table reports the intercept estimates (alphas) from regressions of factor returns on the Fama default (DEF) and term (TERM) factors, following the specification $f_t^i = \alpha_i + \beta_{DEF}^i \cdot \text{DEF}t + \beta_{TERM}^i \cdot \text{TERM}_t + \epsilon_t^i$. The "Estimate" column shows the point estimate of α_i, while "Lower" and "Upper" report the lower and upper bounds of the Newey–West adjusted 95% confidence interval. The column "p_raw" provides p-values for testing the null hypothesis $\alpha_i = 0$, and "p_fdr" reports p-values adjusted for multiple hypothesis testing using the procedure by Benjamini and Hochberg, 1995.

	Factor	Estimate	Lower	Upper	p_raw	p_fdr
1	amt_out	0.12	0.00	0.24	0.05	0.14
2	bond_age	0.22	0.12	0.32	0.00	0.00
3	btm	0.38	0.11	0.65	0.01	0.03
4	dura	0.27	0.11	0.42	0.00	0.01
5	gspread	0.35	0.09	0.62	0.01	0.04
6	mkt_val	0.18	-0.04	0.40	0.11	0.21
7	rating	0.01	-0.13	0.16	0.88	0.88
8	spread	-0.10	-0.24	0.04	0.16	0.29
9	yields	0.23	-0.03	0.48	0.08	0.19
10	str	0.48	0.20	0.77	0.00	0.01
11	mom3	-0.24	-0.51	0.04	0.09	0.19
12	mom6	-0.15	-0.42	0.12	0.26	0.39
13	mom9	-0.12	-0.38	0.15	0.39	0.48
14	mom12	-0.18	-0.47	0.11	0.22	0.36
15	es10	-0.02	-0.29	0.24	0.85	0.88
16	kurt	0.18	-0.01	0.37	0.07	0.18
17	skew	0.10	-0.08	0.27	0.29	0.40
18	var10	-0.23	-0.42	-0.04	0.02	0.06
19	var5	-0.08	-0.29	0.13	0.46	0.53
20	vola	-0.10	-0.38	0.18	0.48	0.53
21	ltr	0.09	-0.09	0.28	0.32	0.42

Table 3.2 reports the estimated α values and 95% Newey–West adjusted confidence

intervals for each factor. The column *p_raw* provides the p-value for the null hypothesis that $\alpha = 0$. The column *p_fdr* presents p-values adjusted for multiple testing using the procedure proposed by Benjamini and Hochberg, 1995, an important correction given that we are testing 21 factors.

As shown in Table 3.2, the sobering reality is that most factors do not replicate. In fact, only 5 out of 21 factors (23.81%) exhibit a statistically significant alpha after both Newey–West adjustment and multiple-testing correction: Bond Age (*bond_age*), Book-to-Market (*btm*), Low Duration (*dura*), Credit Spread (*gspread*), and Short-Term Reversal (*str*). This finding is consistent with Dick-Nielsen et al., 2023, who report that approximately 27% of factors are reproducible during the TRACE period (2002–2021).

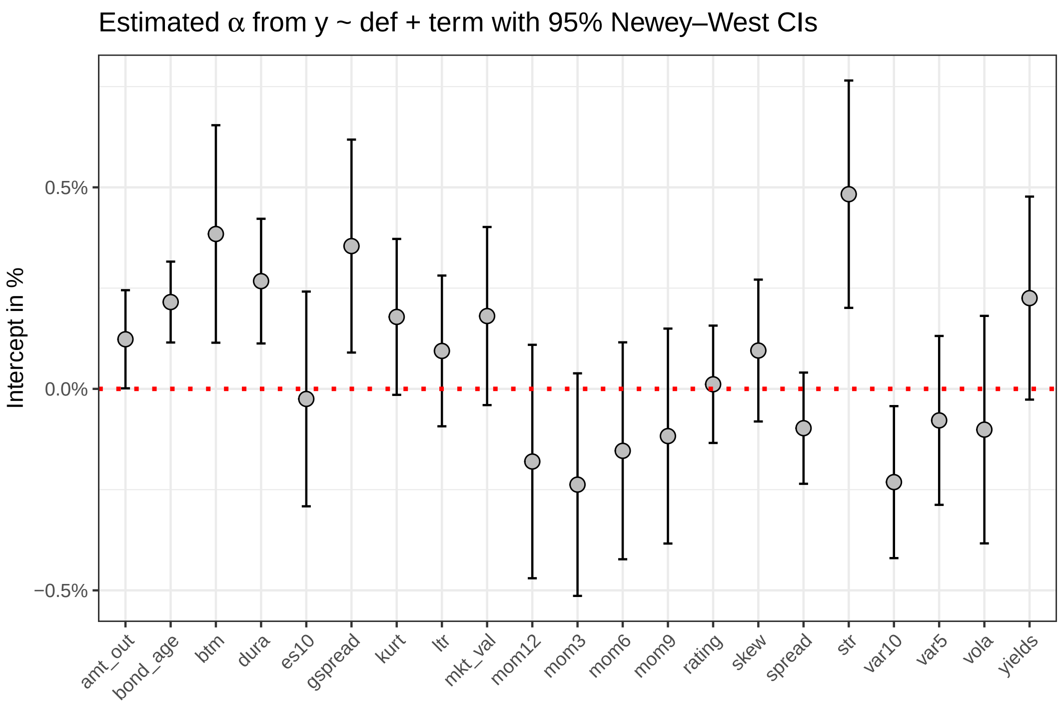

FIGURE 3.2: Estimated factor alphas with 95% confidence intervals. This figure plots the estimated intercepts (α_i) from regressions of factor returns on the Fama default (DEF) and term (TERM) factors, specified as $f_t^i = \alpha_i + \beta^i_{DEF} \cdot \mathrm{DEF}t + \beta^i_{TERM} \cdot \mathrm{TERM}_t + \epsilon^i_t$. For each factor, the point estimate of α_i is displayed along with Newey–West adjusted 95% confidence bands. The red dotted horizontal line marks the zero intercept, highlighting which factors exhibit statistically significant alphas.

Figure 3.2 visualizes the results from Table 3.2, highlighting the estimated factor alphas. While we have already identified the five reproducible factors, the figure also shows that several others come close, including Amount Outstanding (*amt_out*), Kurtosis (*kurt*), and Yield-to-Maturity (*yields*).

In conclusion, although many factors fail to reproduce, some appear to capture persistent risk premia in corporate bonds:

- **Low Term Risk**: While investors are typically rewarded for taking on more TERM risk, there appears to be a risk premium associated with bonds of shorter duration. That is, bonds nearing maturity offer excess returns after controlling for overall TERM exposure.

- **Value**: Bonds with a high book-to-market ratio, where book value is defined as the market value at issuance, tend to reward investors.
- **High Credit Risk**: Bonds with very high credit spreads seem to contain an additional risk premium, even after accounting for overall credit risk. This may be due to heightened risk aversion among investors toward high-default-risk bonds.
- **Short-Term Reversal**: This factor yields the highest estimated alpha among all, indicating a particularly strong risk premium.

Finally, it is worth noting that the factors used in this study are closely aligned with those examined by Dick-Nielsen et al., 2023, as illustrated in the appendix in Figures A.1 and A.2. The main exception lies in the momentum factors. Whereas I find slightly negative and statistically insignificant alphas, they report slightly positive but also insignificant results. I attribute this discrepancy to methodological differences in handling missing values (NAs).

3.4 Time-Varying Alphas

Having analyzed the cross-section of corporate bond returns, we now turn to their behavior over time. Before constructing time-varying factor portfolios to detect periods of outperformance, I would like to emphasize that risk premia are generally not constant. This phenomenon is well documented in the equity literature. For instance, while the value factor has historically performed well, it has delivered weak returns over the past two decades, clearly indicating that the value premium is time-varying. Some attribute this underperformance to the prolonged low interest rate environment in recent years. These observations suggest that there may be signals capable of predicting when a factor will be successful.

(A) Alpha from 24-month rolling regression of *dura* on DEF and TERM.

(B) Alpha from 24-month rolling regression of *mom3* on DEF and TERM.

FIGURE 3.3: Time-varying factor alphas from 24-month rolling regressions. This figure shows the evolution of factor alphas estimated from rolling regressions of factor returns on the Fama default (DEF) and term (TERM) factors, using a 24-month window. The regression specification is $f_t^i = \alpha_i + \beta_{DEF}^i \cdot \text{DEF}t + \beta_{TERM}^i \cdot \text{TERM}_t + \epsilon_t^i$. The plot illustrates how the estimated risk premia (α_i) fluctuate over time. Shaded bands represent Newey–West adjusted 95% confidence intervals.

To illustrate the time variation in the risk premia of the constructed corporate bond factors, I re-estimate the previous regressions of the form:

$$f_t^i = \alpha_i + \beta_{DEF}^i \cdot \mathrm{DEF}_t + \beta_{TERM}^i \cdot \mathrm{TERM}_t + \epsilon_t^i$$

using a rolling window of 24 monthly observations (i.e., two years). Figures 3.3a and 3.3b show the estimated α values over time with 95% confidence intervals.

For the momentum factor *mom3*, the overall estimated risk premium is negative, but there are periods, such as in 2017, where it becomes positive. In contrast, the *dura* factor, which captures low-term risk, shows a significant spike in 2009. This suggests that between 2007 and 2009, low-duration bonds exhibited a strong positive monthly alpha of more than 0.5%.

Chapter 4

Simple Timing

4.1 Methodology

As discussed in Chapter 2, we are unable to easily replicate the cross-sectional risk premia in corporate bonds that have been documented in the literature. This is not surprising, as similar difficulties have been reported by other authors, including Dick-Nielsen et al., 2023 and Dickerson, Robotti, and Nozawa, 2024. However, Figures 3.3a and 3.3b suggest that these risk premia are time-varying. This naturally raises the question of whether such time variation can be predicted.

To investigate this, I closely follow the methodology of Neuhierl et al., 2024. In their study, the authors attempt to *time the factor zoo*, i.e., to predict time-varying risk premia in equities. They do so by aggregating several well-established timing signals from previous research and evaluating their ability to forecast future factor returns.

The academic literature on timing individual corporate bond risk premia is virtually non-existent, which is understandable given the limited cross-sectional evidence currently available. However, some research has explored time-varying returns in the broader corporate bond market. Two early examples include Fama and French, 1989 and Chang and Huang, 1990. The latter show that lagged excess returns on 2-month Treasury bills and the excess Baa yield can predict future corporate bond portfolio returns. More recently, Lin, Wu, and Zhou, 2016 employ 27 timing signals derived from equity, Treasury, and corporate bond markets.

In constructing timing signals for this study, I incorporate both signals used to time equity risk premia, such as those employed by Neuhierl et al., 2024, and several *macro* timing signals, which capture promising time-series information for the corporate bond market as a whole.

In total, I construct 23 standalone signals and 8 aggregated signals. Each timing signal is specific to a given factor and defines the weight or exposure to that factor at each point in time. For a given factor i and timing signal j, the timed factor is constructed as:

$$\tilde{f}^{i,j}_{t+1} = w^{i,j}_t f^i_{t+1}$$

where $w^{i,j}_t$ is the timing weight for factor i and timing signal j at time t. Altogether, this results in 31 timing signals applied to 21 factors, yielding a total of 651 unique timed factor portfolios.

The signals can be grouped into the following categories. For a detailed explanation of the construction of each signal, see Table A.2 in the appendix.

- **Momentum**: Based on the idea that past factor returns are positively correlated with future returns (Ehsani and Linnainmaa, 2022; Gupta and Kelly, 2019).
- **Volatility**: High current volatility of a factor is associated with lower expected future returns (Moreira and Muir, 2017).
- **Reversal**: Past returns tend to revert, implying mean reversion in factor performance (Moskowitz, Ooi, and Pedersen, 2012).
- **Characteristic Spread**: An increase in the high-minus-low characteristic spread signals higher future returns (Huang and Shi, 2021).
- **Macro**: Macroeconomic indicators such as inflation and the VIX are used to time factor exposures, following the approach of Chang and Huang, 1990.
- **Aggregates**: Includes simple averages (e.g., *all*) and more sophisticated aggregation methods (e.g., *pls1*).

4.1.1 Macro Signals

Since the macro signals introduced in this study are novel and have not been previously implemented in this form in the literature, I will explain their construction in detail. In total, six distinct macro timing signals are considered. For each macro signal, denoted as macro_t^j, I use the absolute level of the variable rather than its changes. Although using changes is the more conventional approach, I believe that the absolute level of a macro variable contains valuable information. For instance, consider the Federal Funds Rate: a reduction from 6% to 3% and a reduction from 1% to 0.5% both represent a 50% change, yet these two scenarios are economically very different. Using only changes would ignore the information carried by the absolute level of the variable.

This choice does introduce heteroscedasticity into the regression model. However, since the model is used solely for prediction and not for inference, this is acceptable. I also experimented with using changes in macro signals, but this approach resulted in highly unstable regressions. This is because some macro variables, such as GDP, evolve very slowly, which leads to erratic behavior in the resulting timing weights. In total, six different macro timing signals are considered:

1. **fed**: The Federal Funds Rate
2. **gdp**: Real GDP Growth
3. **cpi**: Year-over-year CPI Inflation
4. **slope**: The yield spread between 10-year Treasury bonds and the Federal Funds Rate
5. **vix**: The CBOE Volatility Index (VIX)
6. **tvix**: The VIXTLT Index, a long-term Treasury equivalent of the equity VIX

For each macro signal, the corresponding timing weight is computed as follows. At each time point t, I run a rolling regression of the factor return on the lagged macro signal using a 12-month window. This setup reflects the perspective of an investor who attempts to predict the one-month-ahead return of a factor based on macroeconomic information:

$$f_t^i = \alpha_i + \beta_i \cdot \text{macro}_{t-1}^j + \epsilon_t$$

Using this simple regression model, the hypothetical investor would then forecast the future one-month return by applying the estimated coefficient β_i to the current value of the macro signal:

$$\beta_i \cdot \text{macro}_t^j$$

At this point, we obtain a return forecast for a given factor. The next step is to transform this forecast into a timing weight. Since the predicted returns from the linear model are typically small in magnitude, I scale the forecast by a factor of 10 and add a base level of 0.5. This construction ensures that the average timing weight remains positive while still providing sufficient variability to take short positions in the factor when appropriate. The choice of a base level of 0.5 and a scaling factor of 10 is motivated by the need to align these weights with the other timing weights used in this study. I experimented with alternative parameter values for the base and scaling factors and found that, while they influence the absolute level of the weights, the resulting timing performance remains relatively stable.

Thus, the final timing weight for a given factor i and macro signal j is defined as:

$$w_t^{i,j} = 10 \cdot \beta_i \cdot \text{macro}_t^j + 0.5$$

This approach simulates an investor who uses a simple 12-month rolling regression model to forecast next month's return for factor i based on macro variable j, without introducing look-ahead bias. The timing weight thus reflects the investor's updated belief, conditional on currently available macroeconomic information.

4.1.2 PLS Signals

Most of the aggregation signals I implement are relatively straightforward. The signals *mom*, *vol*, *rev*, *char*, and *macro* are computed as the simple average of all individual signals within their respective categories. The signal *all* is then calculated as the average of these five category-level aggregates. This approach ensures that each category contributes equally to the overall signal, regardless of the number of signals within each group.

The PLS (Partial Least Squares) aggregation signals, however, are more complex. In their study, Neuhierl et al., 2024 perform PLS regressions in-sample and subsequently evaluate the timing performance out-of-sample. In my case, this setup is not ideal for several reasons. First, I work with monthly data spanning only 10 years, which results in 120 observations. Splitting this into in-sample and out-of-sample sets would leave only 60 observations each, which may not be sufficient for robust estimation. Second, for consistency and comparability across signals, I aim to evaluate all timing signals over the same full sample period. Third, several of the other timing signals, particularly the *macro* signals, are constructed using rolling-window methods, which align more naturally with a similar approach for PLS. For these reasons, my implementation of PLS differs from that of the original authors.

The partial least squares (PLS) approach was introduced by Kelly and Pruitt, 2013, who applied the method to predict a general equity market index. PLS is a statistical technique that combines elements of principal component analysis and multiple regression. It is particularly useful when working with datasets that include a large number of predictor variables that are highly correlated, or when the number of predictors exceeds the number of observations. This makes it especially suitable for our setting, where each factor is associated with 31 different timing signals serving as predictors.

For a given factor i at time t, I run a 12-month rolling PLS regression of the form:

$$f_t^i = \phi(\text{signals}_{t-1}) + \epsilon_t$$

where f_t^i is the return on factor i in period t, ϕ represents the PLS regression function, and signals_{t-1} is the vector of the 23 timing signals from the previous period. Based on this regression, I generate a one-month-ahead return forecast $\hat{r}_{t+1}^{\text{PLS-}i}$ for each factor.

From this return forecast, I construct two timing weights:

- **pls1**: The sign of the predicted return, i.e., $w_t^{\text{PLS-}i} = \text{sign}(\hat{r}_{t+1}^{\text{PLS-}i})$
- **pls2**: A scaled version of the predicted return with a base adjustment, analogous to the construction of the *macro* signals:

$$w_t^{\text{PLS-}i} = 10 \cdot \hat{r}_{t+1}^{\text{PLS-}i} + 0.5$$

To ensure sufficient data availability for each regression, I adopt a robust approach: the PLS regression is executed as long as at least three timing signals are non-missing.

This approach simulates an investor who, at each point in time, collects all available signals from the past 12 months and runs a predictive PLS regression to estimate the future return of a given factor. Based on this prediction, the investor then forms portfolio weights that reflect the desired exposure to the factor.

4.2 Correlation

Before analyzing the success of the timing strategies, let us first examine the timing weights themselves. Many of the signals are clearly related and therefore may exhibit similar factor exposures. Figure 4.1 shows the correlation matrix of all timing weights. To aid interpretation, I applied a simple clustering technique to better visualize which signals tend to co-move.

Looking at the resulting clusters, we observe several expected patterns. Timing signals within the same category (such as *Reversal*) tend to co-move strongly. The *Macro* signals appear largely uncorrelated with each other, which is reasonable given that they are based on fundamentally different types of inputs.

Interestingly, while the *Char* signals form a distinct cluster, they also appear to be part of a larger block that includes the aggregated timing weights (*pls* and *all*) as well as *mom1* and *smom1*. This suggests that the two 1-month momentum signals capture dynamics different from those of the other momentum signals. Furthermore, the aggregated *all* signal, despite being a simple average of all signals, exhibits a wide range of correlations with the individual signals. Both the *all* and *pls* signals show

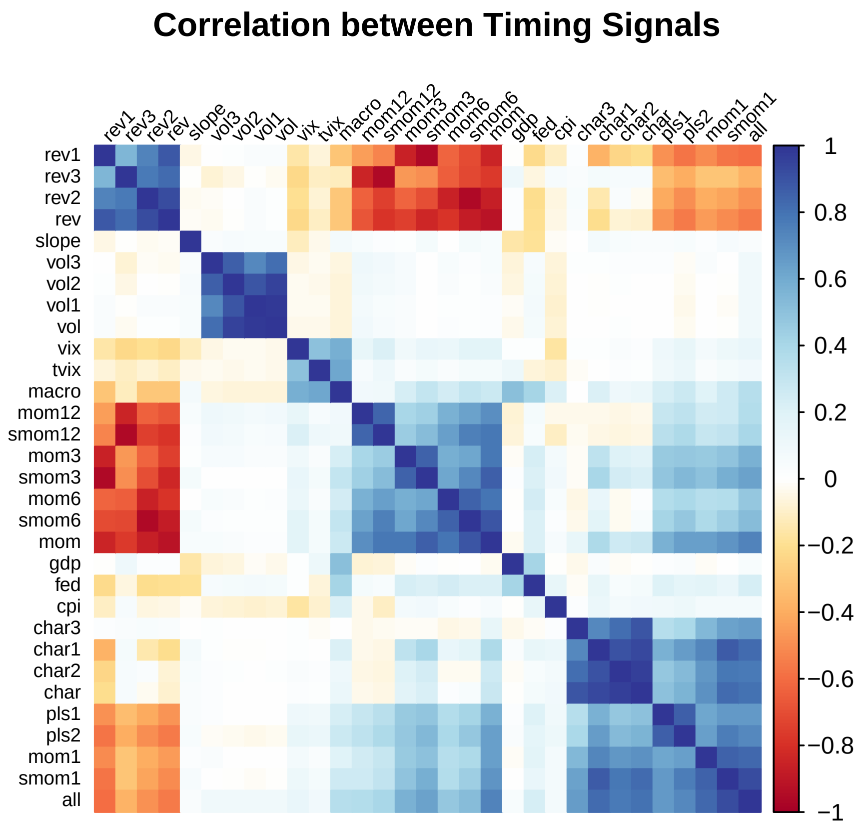

FIGURE 4.1: Spearman correlation between timing weights across signals. For each pair of timing signals j and k, I compute the Spearman rank correlation between their respective timing weights $w_t^{i,j}$ and $w_t^{i,k}$ across all factors i and time periods t. The correlation matrix visualizes how similarly different signals adjust portfolio exposures over time. To highlight patterns and groupings among signals with similar weighting behavior, hierarchical clustering is applied to reorder rows and columns.

strong positive correlations with momentum-related signals and negative correlations with the *Reversal* signals, indicating a pronounced momentum tilt.

4.3 Timing Weights

Figure 4.2 shows the average timing weight assigned to each factor by each signal, along with 5th and 95th percentiles. This figure illustrates how the timing weights are distributed across signals and time.

A clear pattern emerges across signal categories. On average, *Volatility* timing signals assign the largest weights to factors, indicating a strong and persistent long exposure. The *Reversal* signals also tend to assign relatively high weights, though to a lesser extent. A notable issue with the construction of these timing weights is that they rarely result in short positions. For most signals in these categories, even the 5th percentile of the weight distribution remains well above 0.5, meaning that the investor is almost always allocated to the factor with a positive weight. In particular, the *Reversal* signals exhibit very little variation in their timing weights, typically assigning close to a full long position (i.e., a weight of 1) with only minor deviations.

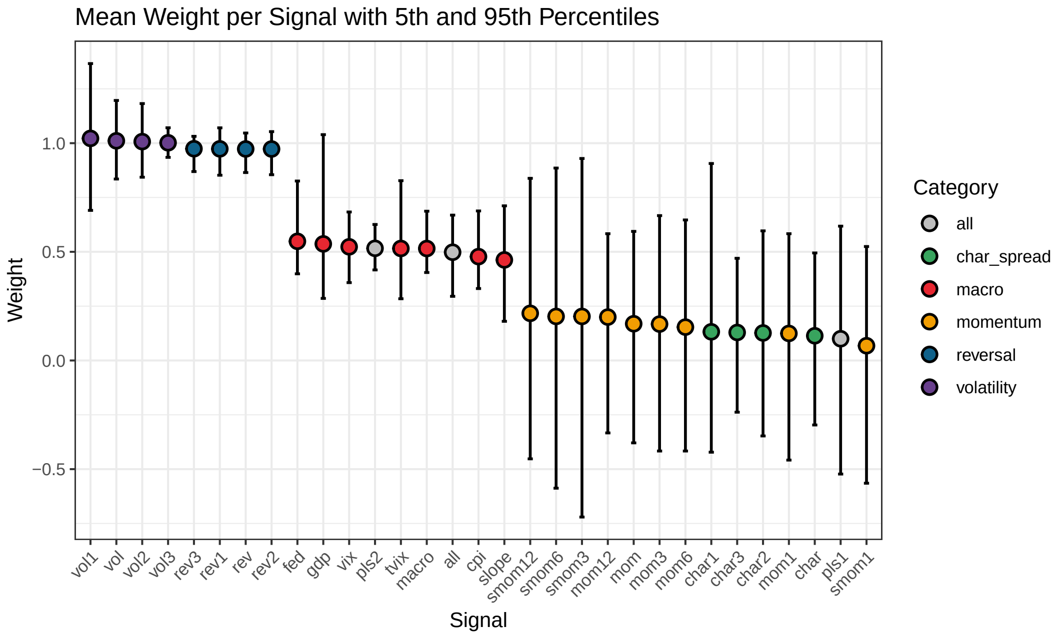

FIGURE 4.2: Distribution of timing weights across signals. For each timing signal j, this figure summarizes the distribution of timing weights $w_t^{i,j}$ across all factors i and time periods t. The point represents the average timing weight (mean), while the error bars indicate the 5th and 95th percentiles of the weight distribution. This visualization illustrates the typical factor exposures assigned by each signal over time.

This limited variability reduces their ability to adjust exposures dynamically and thus diminishes their usefulness as effective timing signals.

Although centered around 0.5 by construction, the *Macro* signals show slightly more variation, but still rarely assign short positions. In contrast, the *Momentum* and *Char* timing weights demonstrate substantial variability across factors and over time, frequently taking both long and short positions in factors.

In designing the timing weight methodology, I aimed to follow the original approach as closely as possible. However, after observing the limited variation in the weights for certain signals, I experimented with methods to increase their variance. This adjustment did not significantly affect their timing performance in terms of Sharpe ratios or alphas. Nonetheless, it is important to recognize that the specific procedure used to convert a signal into a weight can influence the results, highlighting the need for a more standardized methodology.

4.4 Alphas

To measure the timing success of a signal, I closely follow the methodology of Gupta and Kelly, 2019. For a given factor i with timing signal j, let $\tilde{f}_t^{i,j}$ denote the timed factor return from $t-1$ to t, and f_t^i the corresponding untimed factor return. The following regression is then estimated:

$$\tilde{f}_t^{i,j} = \alpha^{i,j} + \beta^{i,j} \cdot f_t^i + \epsilon_t$$

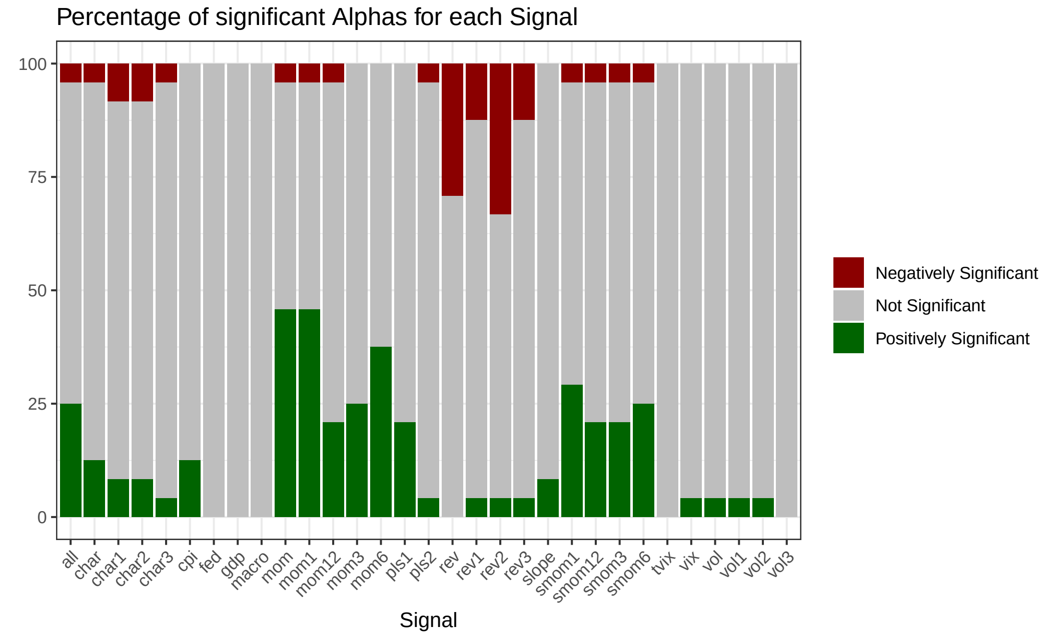

FIGURE 4.3: Proportion of statistically significant alphas across timing signals. For each factor i and timing signal j, I estimate the regression $\tilde{f}t^{i,j} = \alpha^{i,j} + \beta^{i,j} \cdot ft^i + \epsilon_t$ to assess the timing performance relative to the untimed factor return. The figure shows, for each timing signal j, the proportion of factors with statistically significant positive (green) and negative (red) alphas. The remaining share (grey) represents factors where the timing signal does not yield a statistically significant alpha. Each bar sums to 100% of the factors.

We can then examine whether a significantly positive α is obtained, which would indicate that the timed factor successfully improves upon the untimed factor. However, it is important to interpret the magnitude of α with caution, as the timing weights introduce leverage, directly affecting the size of the intercept.

Figure 4.3 displays the timing performance of each signal across all factors. The plot illustrates the proportion of significant alphas obtained from the timed vs. untimed regressions for each signal.

Overall, the results are mixed. Most alphas are not statistically significant, as indicated by the predominance of grey bars. However, a clear pattern emerges: the *Momentum* signals exhibit strong timing success. The aggregated momentum signal *mom* significantly improves the performance of 45.83% of the factors, suggesting that many factors benefit from being timed using momentum information. In addition, the aggregated signals *all* (25.00%) and *pls1* (20.83%) also significantly improve a notable portion of the factors.

In contrast, and unsurprisingly, the *Reversal* signals tend to deteriorate performance. The overall reversal signal *rev* significantly reduces returns for 29.17% of the factors. Some macroeconomic signals, such as *cpi* (12.50%) and *slope* (8.33%), show limited success in improving timing performance.

In summary, Figure 4.3 suggests that timing success is primarily observed with *Momentum* and aggregated signals, while a few *Macro* signals also show some promise.

4.5 Sharpe Ratios

Another way to evaluate timing success is by comparing Sharpe ratios. This approach is preferred over directly comparing excess returns, as it accounts for risk-adjustment. As we have seen, many timing signals often result in factor exposures below 1, leading to lower excess returns relative to their untimed counterparts. However, comparing Sharpe ratios eliminates this leverage effect, allowing for a more meaningful comparison between timed and untimed portfolios. The difference in Sharpe ratios for signal j and factor i is defined as:

$$\Delta SR_{i,j} = SR(\tilde{f}^{i,j}) - SR(f^i)$$

While we can assess timing success by directly comparing the magnitude of the Sharpe ratio differences, we can also perform a statistical test to determine whether the difference is significant. A simple test was proposed by Jobson and Korkie, 1981, which assumes that the two return series follow a bivariate normal distribution with i.i.d. observations. A more robust alternative was introduced by Ledoit and Wolf, 2008, which relaxes these assumptions to allow for heavy tails and heteroscedasticity.

In Figure 4.4, I present the average Sharpe ratio improvement for each timing signal. The results vary considerably across signals: while some enhance the Sharpe ratio notably, others have a negative impact on risk-adjusted performance. Although the overall magnitude may seem modest, it is important to note that these values represent the average improvement across all factors, meaning that individual pairings often show much larger differences.

The aggregated signals demonstrate particularly promising results. The *all* signal, which is the simple average across all category signals, improves the Sharpe ratio of a given factor by 0.13 on average. Additionally, the *pls2* and *pls1* signals enhance risk-adjusted performance by 0.07 and 0.03, respectively. Interestingly, the naïve aggregation in *all* outperforms both PLS signals as well as most other individual signals. This suggests that the 12-month rolling PLS regression is too noisy to aggregate information more effectively than a simple average. A more robust approach, such as that of Neuhierl et al., 2024, which fits the PLS model on a large sample and evaluates it out-of-sample, might improve the PLS signals aggregation performance.

We also observe clear timing success in the *momentum* and *macro* signal categories. For the momentum signals, a distinct pattern emerges: performance worsens as the look-back window increases. The *mom1* signal, which is simply the sign of the previous factor return, improves the Sharpe ratio by 0.11 on average. Similarly, the aggregated momentum signal *mom* improves performance by 0.07 on average, highlighting the benefits of aggregating signal information. In contrast, the momentum signals based on 12-month look-back windows actually reduce risk-adjusted performance. As for the *macro* signals, we see promising results from selected signals such as *fed* (Federal Funds Rate), which improves the Sharpe ratio by 0.09 on average, and the aggregated *macro* signal, which improves it by 0.05. These findings suggest that central bank policy, specifically the risk-free rate, has an influence on corporate bond risk premia.

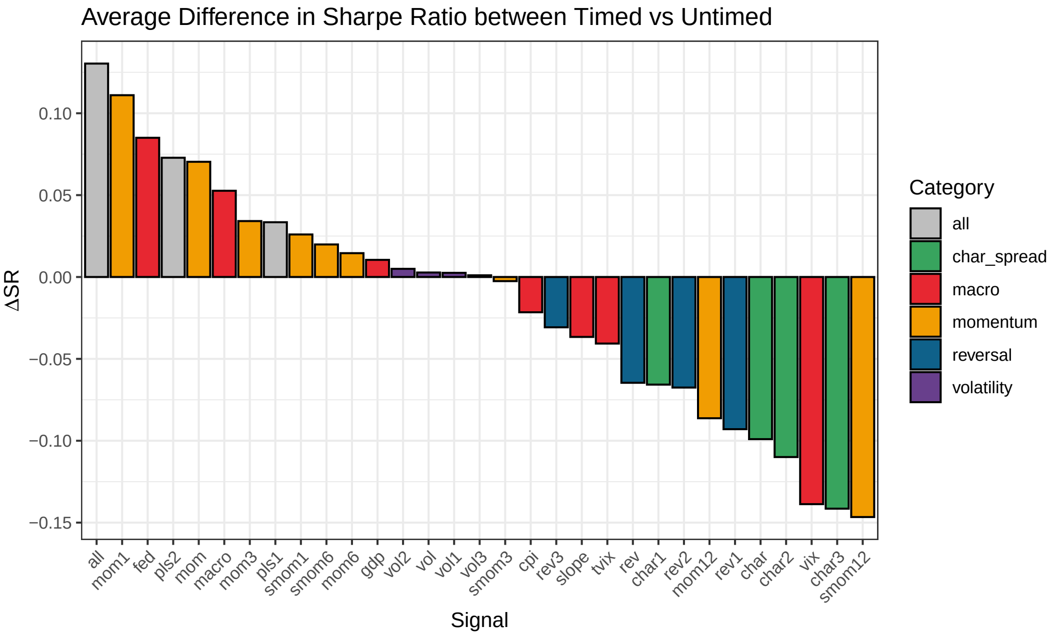

FIGURE 4.4: Average Sharpe ratio improvement across timing signals. For each factor i and timing signal j, I compute the difference in Sharpe ratios ($\Delta SR^{i,j}$) between the timed factor return $\tilde{ft}^{i,j}$ and the untimed factor return ft^i. This figure plots the average ΔSR across all factors for each timing signal j, illustrating how the application of each signal affects risk-adjusted performance on average.

Finally, many timing signals fail to improve performance, particularly those in the *Reversal* and *Characteristic Spread* categories. The aggregated signals *rev* and *char* reduce the Sharpe ratio by 0.06 and 0.09 on average, respectively.

Figure 4.5 further illustrates the Sharpe ratio improvements across timing signals. For each signal, I present the relative frequency of significant Sharpe ratio differences ΔSR.

Overall, one can see that most of the area is grey, indicating that the majority of timed factor portfolios do not significantly affect the Sharpe ratio. Interestingly, the signal with the highest average Sharpe ratio improvement, *all*, does not significantly improve the Sharpe ratio of any individual factor.

Once again, the momentum signals show strong timing performance. The *mom1* signal significantly improves 25.00% of factors, while *mom3* significantly improves 20.83%. The other momentum signals also show limited but noteworthy success. This supports the idea that time-varying risk premia in corporate bonds exhibit a degree of persistence. In other words, if a given risk premium has performed well over the past one to three months, increasing exposure to it tends to be beneficial. Moreover, since the 12-month momentum signals perform quite poorly, it seems that this persistence is relatively short-lived.

Another interesting point emerges in the *characteristic spread* signals. As seen in Figure 4.4, these signals tend to reduce the Sharpe ratio on average. However, they still manage to achieve timing success in some specific cases. The aggregated signal *char* significantly increases the Sharpe ratio in 8.33% of the factors, while also significantly decreasing it in 20.83%. This suggests that although the *characteristic spread*

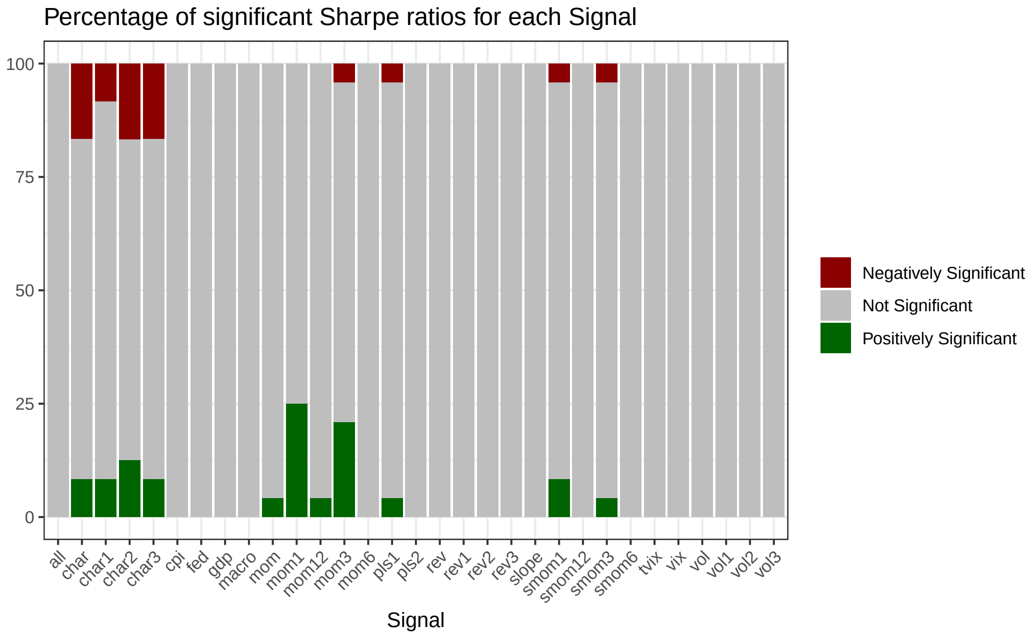

FIGURE 4.5: Proportion of statistically significant Sharpe ratio differences across timing signals. For each factor i and timing signal j, I test the difference in Sharpe ratios ($\Delta SR^{i,j}$) between the timed and untimed factor returns using the test proposed by Jobson and Korkie, 1981. The figure displays, for each timing signal j, the proportion of factors with statistically significant positive (green) and negative (red) Sharpe ratio differences. The remaining share (grey) represents factors where the Sharpe ratio difference is not statistically significant. Each bar sums to 100% of the factors.

signals generally perform poorly, they may still be effective in timing a subset of factors.

In Figure 4.6, I illustrate the difference in Sharpe ratios for each timing signal and factor pairing. I applied basic clustering to better visualize potential patterns.

Let us first consider the overall timeability of the *market* portfolio. This portfolio is a long-only, market-weighted portfolio of all bonds, representing the broad US corporate bond market. Unsurprisingly, no signal appears to time this factor successfully. Visually, the entire row is shaded red to grey, indicating that attempts to time the overall market tend to reduce the Sharpe ratio.

Next, I analyze the factors identified as carrying significant risk premia in Chapter 3:

- **btm**: The Book-to-Market factor shows little benefit from timing. Most signals have minimal to a negative effect.
- **dura**: The Duration factor exhibits strong timing potential. In particular, the *pls1* signal increases the Sharpe ratio by 0.99, and many other signals also show positive results.
- **gspread**: Similar to *btm*, the Credit Spread factor does not appear to benefit meaningfully from timing.
- **str**: The Short-Term Reversal factor is especially difficult to time. Some signals even decrease the Sharpe ratio by more than 1.

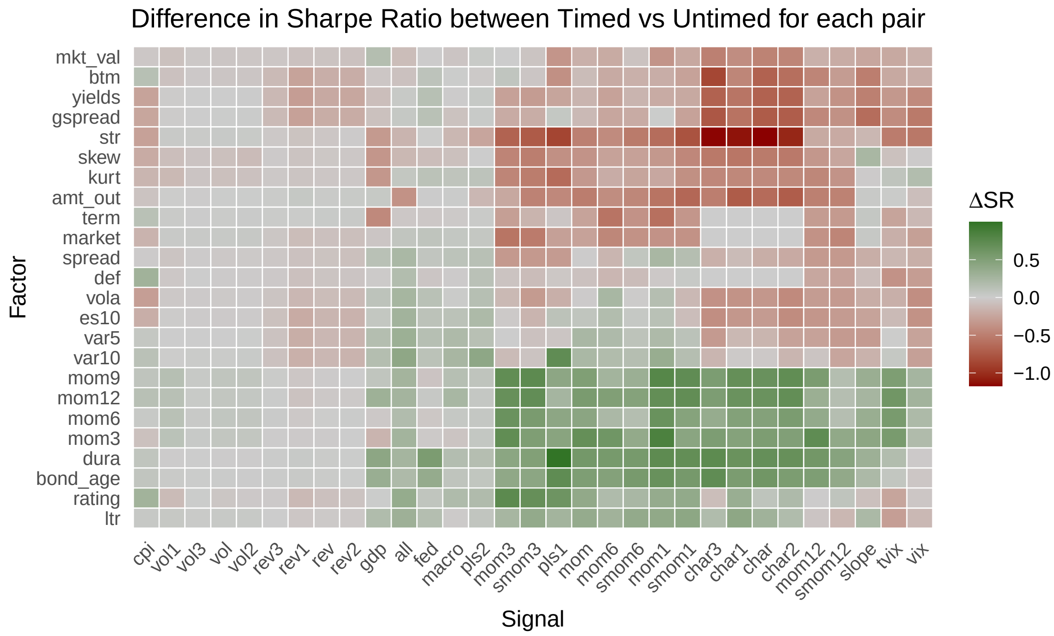

FIGURE 4.6: Sharpe ratio differences across factor-signal pairs. For each factor i and timing signal j, I compute the difference in Sharpe ratios ($\Delta SR^{i,j}$) between the timed and untimed factor returns. The figure displays these Sharpe ratio differences in a heatmap, where each cell corresponds to a specific factor-signal pair. The x-axis lists timing signals, and the y-axis lists factors. Colors range from red (negative Sharpe ratio difference) to grey (no difference) to green (positive difference), illustrating how timing performance varies across pairs. Hierarchical clustering is applied to the rows and columns to reveal patterns and groupings among factors and signals with similar timing outcomes.

In the bottom right corner of the heatmap, we can identify a cluster of factor-signal combinations that perform particularly well together. This block includes most of the *momentum* and *characteristic spread* signals, as well as some *macro* signals. Interestingly, timing momentum factors using momentum signals seems to be a promising strategy.

One column that stands out is the *all* timing signal. Although it does not produce the largest Sharpe ratio increases, it performs consistently well across nearly all factors. Specifically, it improves the Sharpe ratio in 18 out of 24 cases. Table 4.1 summarizes the distribution of ΔSR for the *all* signal. The factor *var10* sees the largest improvement, with an increase of 0.41. The median improvement is 0.19, meaning that half of the factors benefit from improvements of 0.19 or more.

Overall, while the improvements may not be statistically significant for individual factors, the consistent performance of the *all* signal across nearly all factors clearly demonstrates its effectiveness. This also explains why it performed so well in Figure 4.4, yet showed no significant improvements in Figure 4.5. Once again, we see that aggregating timing signals enhances performance across the board.

	ΔSR
Min.	-0.38
1st Qu.	0.02
Median	0.19
Mean	0.13
3rd Qu.	0.27
Max.	0.41

TABLE 4.1: Distribution of Sharpe ratio differences for the *all* timing signal. This table summarizes the distribution of Sharpe ratio differences (ΔSR) between the timed and untimed factor returns across all factors when applying the *all* timing signal. The reported statistics include the minimum, first quartile (Q1), median, third quartile (Q3), and maximum ΔSR values.

4.6 Conclusion

In this chapter, I aimed to analyze and demonstrate how individual timing signals can improve the performance of individual factors. We saw that *momentum* signals with shorter look-back windows tend to work well, as do certain *macro* signals, such as the central bank rate timing signal *fed*. This suggests that there is some degree of persistence in corporate bond risk premia, and that these premia are influenced by macroeconomic variables.

Furthermore, we observed that aggregated signals perform particularly well, especially the relatively simple *all* signal. This implies that even though many individual signals are weak or even negative on their own, they still carry valuable information about time-varying risk premia when combined.

In the next chapter, I will shift focus to timing multiple factors simultaneously using a single signal. This approach follows the methodology of Neuhierl et al., 2024, where the authors use their PLS signal for multi-factor timing. However, given the clear advantage of the *all* signal over the two PLS signals I constructed, I will use the *all* signal to build the multi-factor portfolio.

Chapter 5

Multi Timing

5.1 Methodology

In Chapter 4, we observed that simple timing strategies, where exposure to a given factor is adjusted using a timing signal, can yield promising results. This naturally raises the question of whether we can extend this approach to construct a multi-factor portfolio.

A straightforward method would be to invest equally in each timed factor using the successful *all* signal. However, this approach closely resembles an untimed multi-factor portfolio, since, as shown in Figure 4.2, the timing signal often leads to exposures that do not vary significantly over time. A more dynamic and potentially effective approach is to allow the *all* signal to guide the selection of factors to invest in. This enables the strategy to allocate capital each month to the most attractive factors, while avoiding those deemed less appealing. This approach follows the multi-factor construction of Neuhierl et al., 2024.

To construct the multi-factor portfolio, I proceed as follows: at the beginning of each month, I evaluate the *all* signal for each of the 21 individual factors. I then select the top quintile of factors based on the signal, which typically yields four factors. The portfolio takes a long position in these selected factors, weighting them equally. Formally, the return of the timed multi-factor portfolio at time t is given by:

$$\mathrm{TMF}_t = \frac{1}{|\mathrm{Q5}_{\mathrm{all}}|} \sum_{i \in \mathrm{Q5}_{\mathrm{all}}} \tilde{f}_t^{i,\mathrm{all}},$$

where TMF_t denotes the return of the multi-factor timing portfolio at time t, $\mathrm{Q5}_{\mathrm{all}}$ represents the set of factors in the top quintile according to the *all* signal, and $\tilde{f}_t^{i,\mathrm{all}}$ is the return of factor i timed using the *all* signal.

To evaluate the success of this timing strategy, it is essential to compare the performance of the multi-timed portfolio against an appropriate benchmark. Selecting a benchmark is not trivial, but a natural choice is a portfolio that equally weights all 21 untimed factor portfolios:

$$\mathrm{Bench}_t = \frac{1}{21} \sum_{i=1}^{21} f_t^i,$$

where f_t^i denotes the return of the untimed factor i at time t.

This benchmark reflects the performance of an investor who is aware of the existence of cross-sectional risk premia but does not attempt to time them. Consequently, comparing the multi-timed portfolio against this benchmark allows us to isolate and quantify the value added by the timing strategy.

5.2 Performance

Table 5.1 presents key performance metrics comparing the timed multi-factor (TMF) portfolio to the benchmark portfolio. While the TMF portfolio achieves an annualized excess return of 4.14%, this return may primarily reflect its higher volatility.

More importantly, we observe that the timing strategy improves the Sharpe ratio from 0.76 to 0.96, a notable increase of 0.20. From an economic perspective, this improvement is substantial. As previously shown in Chapter 4, the *all* signal increased the Sharpe ratio of individual factors by an average of 0.13. The fact that the Sharpe ratio improvement in the multi-factor setting is even greater (0.20) suggests that allowing the signal to select which factors to include is an effective strategy.

Perhaps most surprising is the improvement in the *Worst Drawdown* metric for the TMF portfolio. The TMF portfolio experienced a maximum drawdown of only 7.22%, compared to 8.86% for the benchmark. Given that the TMF portfolio exhibits more than twice the annualized volatility of the benchmark, this result is particularly striking. It suggests that a significant portion of the volatility stems from upward movements, and that the timing strategy may offer some degree of downside protection.

	TMF	Benchmark	Δ
Ann. Return	6.49	2.35	4.14
Ann. Volatility	6.78	3.10	3.68
Worst Drawdown	7.22	8.86	-1.64
Ann. Sharpe Ratio	0.96	0.76	0.20

TABLE 5.1: Multi-Factor Performance Metrics

In Figure 5.1, we can observe several characteristics already noted in Table 5.1. The *Benchmark* portfolio behaves similarly to a traditional corporate bond portfolio (despite being long-short). It exhibits drawdowns during the Global Financial Crisis (2007–2009), followed by a strong rebound beginning in March 2009. This pattern aligns with the broader developments in corporate bond markets at the time, where renewed investor confidence led to tightening credit spreads. Additionally, the benchmark portfolio experienced another drawdown beginning in 2015, which, albeit to a lesser extent, can also be observed in broader U.S. corporate bond indices.

In contrast, the TMF portfolio behaves quite differently. Compared to the benchmark, it underperforms during relatively "calm" periods, where it appears to consistently harvest modest risk premia. However, during periods of market stress or when the benchmark portfolio experiences drawdowns, the TMF portfolio remains largely unaffected. It seems to successfully allocate capital to the right risk premia during these times, thereby avoiding losses. When risk premia begin to recover, the TMF portfolio captures the upswing almost fully, resulting in a stair-step pattern in its cumulative performance.

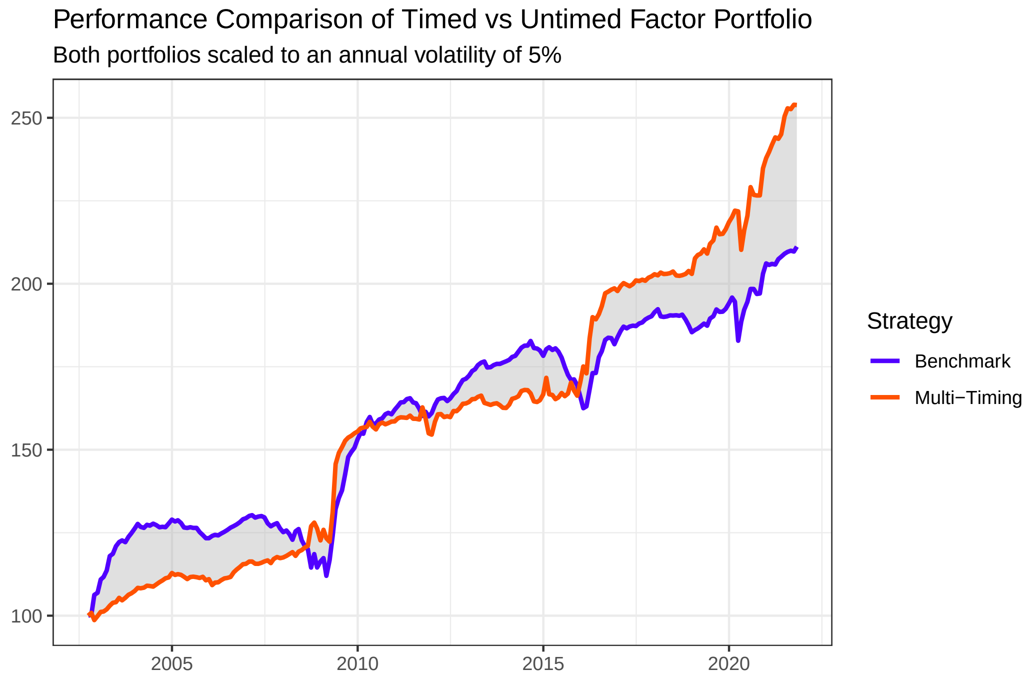

FIGURE 5.1: Performance comparison of the timed multi-factor (TMF) portfolio and the benchmark portfolio. This figure shows the cumulative return paths of the TMF portfolio and its benchmark, with both portfolios starting at a normalized value of 100. Returns are volatility-scaled such that each portfolio exhibits an annualized volatility of 5%. The plot illustrates the relative performance differences over time after adjusting for risk.

This phenomenon merits further investigation. It would be particularly interesting to analyze which risk premia the strategy selects during different periods, and whether any systematic patterns can be identified.

Although Table 5.1 shows an improvement of 0.20 in the annualized Sharpe ratio, statistical testing does not confirm this difference to be significant. As shown in Table 5.2, the improvement in the monthly Sharpe ratio is 0.06. Applying both the standard test proposed by Jobson and Korkie, 1981 and the more robust test by Ledoit and Wolf, 2008, we do not find statistical evidence of a significant increase in Sharpe ratios, with p-values of 0.55 and 0.47, respectively.

Obs.	Monthly TMF SR	Monthly Benchmark SR	Δ	LW T-Stat	LW P-Value	JK Z-Score	JK P-Value
230	0.28	0.22	0.06	0.73	0.47	0.60	0.55

TABLE 5.2: Sharpe ratio comparison of timed and untimed multi-factor portfolios. This table compares the monthly Sharpe ratios of the timed multi-factor (TMF) portfolio and the untimed benchmark portfolio. The table reports the number of observations, the Sharpe ratios of both portfolios, and the difference in Sharpe ratios. To assess statistical significance, I apply the test by Ledoit and Wolf, 2008 (LW) and the test by Jobson and Korkie, 1981 (JK). The final columns present the respective test statistics and associated p-values

5.3 Comparison to Benchmark

To statistically evaluate the timing success of the multi-factor portfolio, I estimate a linear regression of the TMF portfolio on the benchmark portfolio. Since the benchmark represents an investor who does not engage in factor timing, the intercept of this regression provides insight into the added value generated by the timing strategy.

Table 5.3 presents the results of this regression. The loading on the benchmark is statistically significant at the 10% level, but not at the 5% level. This indicates a relationship between the two portfolios, while still suggesting notable differences in their behavior, consistent with the patterns observed in Figure 5.1. The estimated coefficient is 0.78, implying that a 1 percentage point change in the benchmark is associated with a 0.78 percentage point change in the TMF portfolio. This represents a relatively high factor loading, suggesting that the TMF portfolio captures a substantial portion of the movement in cross-sectional risk premia.

More importantly, the timing success of the TMF portfolio can be assessed through the intercept. The intercept is statistically significant at the 1% level, indicating a strong and positive alpha. The estimated value of 0.39 implies that, after controlling for benchmark exposure, the TMF portfolio delivers an additional average monthly excess return of 0.39%. From an economic perspective, this represents a meaningful return enhancement attributable to the timing strategy. These results suggest that risk premia in corporate bonds are time-varying and can be effectively timed using the aggregated signal.

TABLE 5.3: Regression of timed multi-factor portfolio returns on benchmark returns. To evaluate outperformance, I regress the returns of the timed multi-factor (TMF) portfolio on the benchmark portfolio returns using the specification $\text{TMF}_t = \alpha + \beta \cdot \text{Bench}_t + \epsilon_t$. Standard errors are adjusted for heteroscedasticity and autocorrelation using Newey–West corrections with a lag length of five months. The intercept α measures the risk-adjusted excess return of the TMF portfolio relative to the benchmark.

	Dependent variable:
	TMF
Benchmark	0.777^{*}
	(0.414)
Constant	0.390^{***}
	(0.107)
Observations	230
R^2	0.126
Adjusted R^2	0.122
Residual Std. Error	1.834 (df = 228)
F Statistic	32.934^{***} (df = 1; 228)
Note:	*p<0.1; **p<0.05; ***p<0.01

5.4 Regression on *DEF* and *TERM*

To further evaluate the timing success of the timed multi-factor (TMF) portfolio, I regress both the TMF and the benchmark portfolio on the *DEF* and *TERM* factors. This regression aims to assess whether any excess returns remain after accounting for the bond market factors introduced in the Bond CAPM by Fama and French, 1993. The results are presented in Table 5.4.

TABLE 5.4: Regression of portfolio returns on Fama bond factors. This table reports the results from regressing portfolio returns on the default (DEF) and term (TERM) factors using the specification $r_t = \alpha + \beta_1 \cdot \mathrm{DEF}_t + \beta_2 \cdot \mathrm{TERM}_t + \epsilon_t$. Standard errors are corrected for heteroscedasticity and autocorrelation using the Newey–West procedure with a lag length of five months. The intercept α captures the risk-adjusted excess return unexplained by exposure to the DEF and TERM factors.

	Dependent variable:	
	TMF	Benchmark
	(1)	(2)
DEF	0.213	0.420***
	(0.277)	(0.072)
TERM	0.043	0.120*
	(0.181)	(0.063)
Constant	0.484***	0.071
	(0.137)	(0.047)
Observations	230	230
R^2	0.029	0.521
Adjusted R^2	0.021	0.517
Residual Std. Error (df = 227)	1.937	0.622
F Statistic (df = 2; 227)	3.446**	123.412***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Let us first consider the regression where the TMF portfolio is the dependent variable (1). Neither the *DEF* nor the *TERM* coefficients are statistically significant at conventional levels. Moreover, the estimates themselves are small (DEF = 0.213, TERM = 0.043), suggesting that the TMF portfolio does not exhibit meaningful exposure to default or term risk. This implies that the TMF portfolio is largely independent of systematic corporate bond market risk and successfully isolates alternative sources of risk premia. Notably, the regression intercept (α) is statistically significant at the 1% level, with an estimated value of 0.484. This indicates that, after controlling for credit risk (*DEF*) and duration risk (*TERM*), the TMF portfolio delivers an additional monthly excess return of 0.48%.

In contrast, the results for the benchmark portfolio differ substantially (2). The portfolio shows significant exposure to credit risk, with the *DEF* coefficient being both economically large and statistically significant at the 1% level. This is somewhat surprising, as the benchmark is an equal-weighted average of cross-sectional factor portfolios, which are long-short and sorted within credit rating groups. Despite this design, the benchmark appears to load primarily on credit risk. Additionally, the *TERM* coefficient is positive and significant at the 10% level, suggesting that the benchmark portfolio also picks up some exposure to duration risk. The intercept, however, is not statistically significant at any conventional level, indicating that the benchmark does not capture additional unexplained risk premia beyond those associated with credit and term risk.

The results presented in Table 5.4 further support the hypothesis that timing signals enable the capture of risk premia that would otherwise remain insignificant. Simply investing in cross-sectional factors without applying timing strategies does not lead to statistically significant outperformance. Instead, such a strategy mainly results in exposure to credit risk (*DEF*) and, to a lesser extent, duration risk (*TERM*).

In contrast, timing the factors, as implemented in the TMF portfolio, appears to eliminate exposure to both credit and duration risk, effectively removing systematic corporate bond market risk. Moreover, the TMF portfolio exhibits a statistically and economically significant excess return even after controlling for the Bond CAPM risk factors. This provides strong evidence for the effectiveness of factor timing in generating meaningful alpha.

5.5 Conclusion

Overall, this chapter has shown that applying the *all* signal to time multiple factors simultaneously can help revive the significance of cross-sectional risk premia. A key methodological choice was to allow the timed multi-factor (TMF) portfolio to invest only in a subset of factors each month, based on signal strength. Using this approach, we observed improvements in simple performance metrics.

However, the improvement in the Sharpe ratio was not found to be statistically significant. Despite this, regression analysis revealed that the TMF portfolio generates a statistically significant monthly excess return of 0.39% over the benchmark. Furthermore, when regressing both the TMF and benchmark portfolios on the *DEF* and *TERM* factors, we found that the TMF portfolio delivers a statistically and economically significant premium of 0.48% per month. In contrast, the benchmark portfolio fails to generate a positive and significant α, instead loading primarily on credit risk.

These findings support the conclusion that factor timing using aggregated signals can effectively isolate and harvest risk premia beyond those captured by traditional long-short strategies or bond market risk factors.

Chapter 6

Long-Only

6.1 Methodology

In Chapter 5, we have seen that a timed multi-factor (TMF) portfolio appears to successfully harvest risk premia in U.S. corporate bond markets. However, from an investor's standpoint, the TMF portfolio raises several important questions. Most notably: could such a portfolio actually be implemented in practice?

One major practical challenge is the large number of corporate bonds that the TMF portfolio shorts each month. While shorting is theoretically possible in corporate bond markets, in practice it is unlikely that an investor could effectively short a wide array of individual corporate bonds on a monthly basis.

To address this issue, I decided to examine the internal structure of the TMF portfolio, essentially to "look under the hood." Specifically, for each bond in each month, I calculate its net weight within the TMF. A given bond may be long in one factor and short in another, meaning that these exposures can offset each other. By aggregating and netting the weights across all factors at the bond level, we gain insight into the actual composition of the TMF portfolio.

Based on these net weights, I construct a long-only version of the portfolio (*long-only*), which includes only those bonds with a positive net weight. Each bond is weighted proportionally to its net weight in the original TMF portfolio. Despite excluding the short positions, this long-only portfolio still contains a large number of bonds. Therefore, I also examine two more concentrated portfolios: one that includes only the top 10% of bonds by net weight (*top-10%*) and another that includes only the top 1% (*top-1%*).

These three portfolios represent more realistic and potentially investable strategies for actual market participants. In this chapter, I analyze their characteristics and performance.

6.2 Characteristics

In Table 6.1, I present the characteristics of the three long-only portfolios compared to the full sample of all bonds. In terms of duration, all three portfolios appear to be broadly in line with the overall market, except at the 75th percentile, where they exhibit significantly higher duration. This may be attributable to timing effects. Additionally, there is a trend indicating that more concentrated portfolios tend to have lower median duration.

TABLE 6.1: Distribution of bond characteristics across portfolios. For each portfolio, the table reports the 5th, 25th, 50th (median), 75th, and 95th percentiles of various bond characteristics, calculated across the constituent bonds within the portfolio. The *Market* rows display the corresponding percentiles for the market portfolio, defined as the market value-weighted aggregate of all bonds in the sample.

Duration					
Portfolio	5%	25%	Median	75%	95%
Long-only	1.44	3.35	6.24	10.97	15.70
Top-10%	1.38	3.03	5.35	11.54	15.34
Top-1%	1.40	2.98	5.23	11.15	14.46
Market	1.43	3.20	5.36	8.65	14.78

Market Value (in Million $)					
Portfolio	5%	25%	Median	75%	95%
Long-only	8.91	126.95	350.22	674.08	1726.67
Top-10%	268.13	544.54	1005.84	1828.80	3543.60
Top-1%	500.69	1031.55	1990.98	3215.07	5618.64
Market	4.35	105.14	367.76	711.89	1766.11

Yield (in %)					
Portfolio	5%	25%	Median	75%	95%
Long-only	1.46	3.31	4.68	6.31	11.08
Top-10%	1.74	3.90	5.35	7.12	12.91
Top-1%	2.26	4.33	5.89	7.66	14.25
Market	1.26	2.95	4.44	6.03	9.65

With respect to market value, we observe a notable deviation from the overall market. While the *long-only* portfolio is roughly in line with, or slightly above, the market in terms of bond sizes, the *top-10%* and *top-1%* portfolios are dominated by bonds with significantly larger market values. This is consistent with the underlying factor construction, which is weighted by market value.

Finally, in terms of yield, all three portfolios exhibit higher yields than the overall market. There is a clear pattern where greater portfolio concentration corresponds to higher yields. Although elevated, the yield distributions of the portfolios still remain relatively close to that of the broader market.

The two concentrated portfolios consist of the top 10% and top 1% of bonds by weight within the *long-only* portfolio, respectively. On average, the *long-only* portfolio holds approximately 1,500 bonds, while the *top-10%* and *top-1%* portfolios contain roughly 150 and 15 bonds, respectively.

Table 6.2 shows how much of the total portfolio weight in the *long-only* portfolio is captured by these concentrated subsets. For the *top-10%* portfolio, the median share of total weight is 42%, while the *top-1%* portfolio accounts for around 10% of the weight at the median. However, these proportions can vary substantially across months.

TABLE 6.2: Concentration of portfolio weights in the long-only portfolio. At each time point, I identify the top 10% and top 1% of bonds within the long-only portfolio based on their net portfolio weights. The figure shows the distribution of the weight share these concentrated sub-portfolios represent relative to the entire long-only portfolio. Although the *top-10%* and *top-1%* sub-portfolios consist of a small fraction of bonds, they may account for a disproportionately large share of the portfolio's total weight due to the unequal weighting scheme. The figure reports the distribution (minimum, first quartile, median, third quartile, maximum) of these weight shares over time.

Portfolio	Minimum	25th	Median	75th	Maximum
Top-10%	0.30	0.40	0.42	0.47	0.61
Top-1%	0.05	0.09	0.10	0.12	0.19

6.3 Performance

In Table 6.3 and Figure 6.1, I assess the performance of the different long-only strategies. As expected, the more concentrated portfolios exhibit higher returns and higher volatility. In terms of maximum drawdown and Value-at-Risk, we also observe consistent patterns. As the portfolios become less diversified, their risk increases.

TABLE 6.3: Performance metrics of the long-only portfolios. The table reports annualized return, annualized volatility, worst drawdown, Sharpe ratio, and 5% Value-at-Risk (VaR) for the long-only, top-10%, top-1%, and market portfolios.

	Long-Only	Top-10%	Top-1%	Market
Ann. Return	10.07	12.69	13.56	5.73
Ann. Volatility	8.16	9.37	13.29	5.64
Worst Drawdown	19.52	20.02	25.81	13.07
Sharpe Ratio	1.23	1.35	1.02	1.02
VaR (95%)	-3.04	-3.41	-5.17	-2.19

More interestingly, when looking at Sharpe ratios, which reflect risk-adjusted returns, we see that the *long-only* and *top-10%* portfolios show notable improvements compared to the market portfolio, with Sharpe ratio increases of 0.21 and 0.33, respectively. These results indicate that both strategies enhance risk-adjusted performance considerably. Interestingly, the even more concentrated *top-1%* portfolio does not show a further improvement in the Sharpe ratio.

This suggests that the *long-only* strategy, based on multi-factor timing, effectively improves risk-adjusted performance relative to the *market* portfolio. Furthermore, the *top-10%* portfolio appears to select bonds with the strongest timing signals, thereby further enhancing performance. However, at some point, the benefits of concentrating on bonds with strong signals are outweighed by the drawbacks of reduced diversification. In the case of the *top-1%* portfolio, the concentration becomes too high, and the portfolio begins to suffer from idiosyncratic risk that cannot be diversified away.

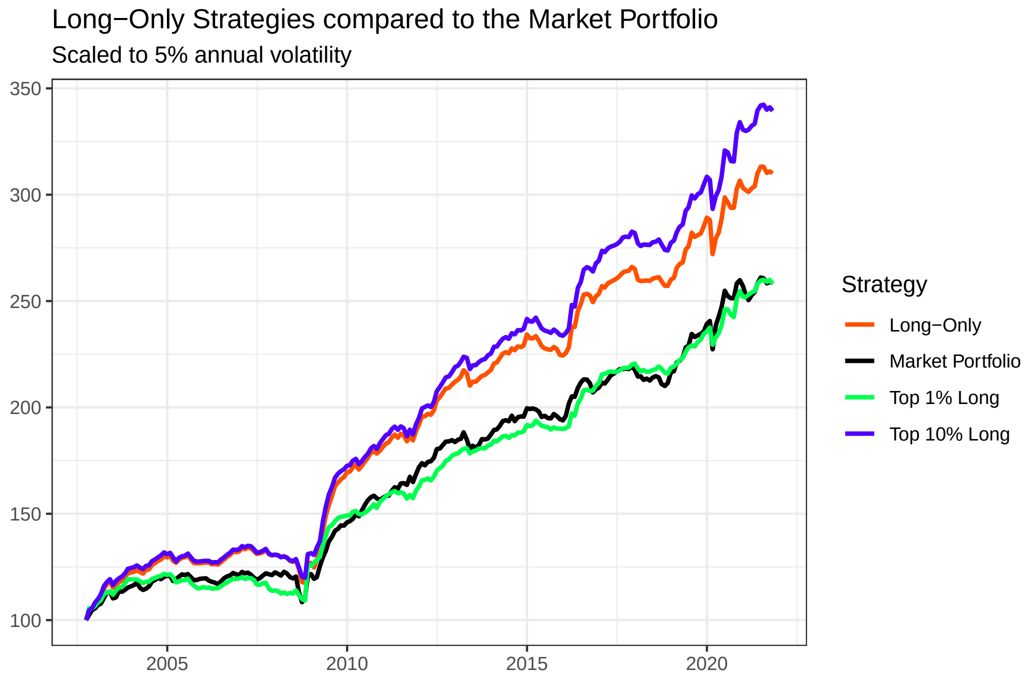

FIGURE 6.1: This figure shows the cumulative return paths of the long-only, top-10%, top-1%, and market portfolios, with all portfolios starting at a normalized value of 100. Returns are volatility-scaled such that each portfolio exhibits an annualized volatility of 5%. The plot illustrates the relative performance differences over time after adjusting for risk.

To statistically test the significance of the improvement in risk-adjusted returns, I apply the test proposed by Ledoit and Wolf, 2008. The results of this test are reported in Table 6.4. They confirm the earlier observations. The *long-only* portfolio significantly improves the monthly Sharpe ratio by 0.06 at the 10% level, with a p-value of 0.09. Furthermore, the *top-10%* portfolio shows a statistically significant improvement of 0.09 at the 5% level, with a p-value of 0.03. In contrast, the *top-1%* portfolio does not show a significant improvement in risk-adjusted returns.

TABLE 6.4: Sharpe ratio comparison of long-only portfolios relative to the market. This table compares the monthly Sharpe ratios of the long-only, top-10%, and top-1% portfolios to the market portfolio. For each strategy, the table reports the number of observations, the portfolio's Sharpe ratio, the market Sharpe ratio, and the difference between them. Statistical significance is assessed using the robust test by Ledoit and Wolf, 2008, with the resulting test statistics and p-values reported in the final columns.

	Strategy	Obs.	Strategy SR	Market SR	Difference	T-Stat	P-Value
1	Long Only	229	0.35	0.29	0.06	1.71	0.09
2	Top-10%	229	0.38	0.29	0.09	2.15	0.03
3	Top-1%	229	0.29	0.29	0.00	0.01	0.99

6.4 Performance in Different Regimes

As shown in Table 6.1, the constructed long-only portfolios and the market portfolio exhibit distinct characteristics. For example, the long-only portfolio has a higher median duration (6.24 compared to 5.36). This raises the question of how these portfolios behave under different macroeconomic regimes.

For bonds, the two most influential macroeconomic variables are the Federal Funds Rate (risk-free rate) and inflation, typically measured by the Consumer Price Index (CPI). In Table 6.5, I analyze the performance of the *long-only* and *market* portfolios across varying macroeconomic environments.

Focusing first on the top section of the table, which examines interest rate regimes, we observe that the *market* portfolio behaves as expected. When interest rates are cut, bond prices generally increase, resulting in the highest forward-looking returns. Conversely, an interest rate hike leads to the lowest returns. Interestingly, the *long-only* portfolio does not follow this conventional pattern. While returns are indeed higher during rate cuts compared to rate hikes, the highest returns occur in periods when interest rates remain unchanged. I attribute this phenomenon to the timing mechanism of the *long-only* strategy, which is more effective at capturing alternative risk premia in stable environments. As a result, its performance becomes less correlated with the fundamental duration risk premium that typically drives bond returns.

In contrast, when analyzing performance across different inflation regimes, both portfolios exhibit a similar response pattern. Although the *long-only* portfolio consistently achieves higher returns across all inflation environments, the distribution of returns mirrors that of the market portfolio. This suggests that the *long-only* portfolio maintains a similar sensitivity to changes in inflation as the broader market.

TABLE 6.5: Portfolio performance conditional on Federal Funds Rate and inflation regimes. This table reports the average one-month-ahead returns of the long-only and market portfolios after sorting observations into macroeconomic regimes. The upper section splits returns based on Federal Funds Rate changes (cut, no change, hike), while the lower section groups returns by inflation regimes (falling, stable, increasing CPI). The table highlights how portfolio performance varies across different macroeconomic environments.

Federal Funds Rate

Regime	Long-Only	Market
Cut	0.40	0.98
No Change	0.97	0.50
Hike	0.03	0.12

Inflation (CPI)

Regime	Long-Only	Market
Falling	1.06	0.71
No Change	0.89	0.44
Increasing	0.56	0.32

6.5 Regression against the Market portfolio

To further assess the statistical significance of the performance differences between the long-only strategies and the market, I estimate the following regression model:

$$\text{Long-Only}_t = \alpha + \beta \cdot \text{Market}_t + \epsilon_t$$

The results of this regression are reported in Table 6.6. For all three portfolios, the estimated beta coefficients are highly significant at conventional significance levels. The beta estimates are greater than one in all cases, indicating that the long-only strategies exhibit substantial exposure to overall market risk. Moreover, the beta estimates increase with portfolio concentration.

Turning to the intercepts (α), we find that all three portfolios display statistically significant positive alphas, suggesting the presence of positive risk premia beyond market exposure. This implies that the long-only strategies generate additional outperformance after accounting for corporate bond market risk. Consistent with earlier findings, the *top-10%* portfolio shows the strongest performance, with an additional monthly risk premium of 0.38%.

These results indicate that, even after controlling for market risk, all three long-only strategies produce statistically significant positive returns. This supports the conclusion that factor timing is effective not only in a long-short theoretical framework, but also in a realistic long-only setting.

TABLE 6.6: Regression of long-only portfolio returns on the market portfolio. This table reports the results from regressing the returns of the long-only, top-10%, and top-1% portfolios on the market portfolio using the specification $\text{Long-Only}_t = \alpha + \beta \cdot \text{Market}_t + \epsilon_t$. Standard errors are corrected for heteroscedasticity and autocorrelation using the Newey–West procedure with a lag length of five months. The intercept α measures the risk-adjusted excess return unexplained by market exposure.

	Dependent variable:		
	Long-Only	Top-10%	Top-1%
Market	1.253^{***}	1.373^{***}	1.710^{***}
	(0.067)	(0.081)	(0.290)
Constant	0.231^{***}	0.379^{***}	0.313^{**}
	(0.081)	(0.109)	(0.160)
Observations	229	229	229
R^2	0.749	0.681	0.526
Adjusted R^2	0.748	0.680	0.523
Residual Std. Error (df = 227)	1.184	1.531	2.649
F Statistic (df = 1; 227)	676.398^{***}	485.538^{***}	251.407^{***}

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

6.6 Regression against the ICE BofA US Corporate Index

To further validate my results, I test the three long-only portfolios not only against the self-constructed market portfolio but also against the ICE BofA US Corporate Index. This serves to ensure that the observed performance is not merely a result of specific benchmark construction choices. The index is a widely recognized benchmark that tracks the performance of U.S. dollar-denominated, investment-grade corporate debt publicly issued in the U.S. domestic market.

Table 6.7 presents the results of this regression. Overall, the findings are highly consistent with those in Table 6.6. All three long-only strategies exhibit statistically significant exposures to the index, with beta estimates above one. In addition, we find strong evidence of statistically significant positive alphas, indicating that the long-only portfolios capture excess returns beyond those explained by the benchmark. Once again, the *top-10%* portfolio shows the highest α, with a monthly risk premium of 0.51% after adjusting for market exposure.

The consistency of the results across both benchmarks strengthens the conclusion that the long-only strategies effectively capture additional risk premia beyond general market risk.

TABLE 6.7: Regression of long-only portfolio returns on the ICE BofA Corporate Bond Market index. This table reports the results from regressing the returns of the long-only, top-10%, and top-1% portfolios on the ICE BofA Corporate Bond Market index using the specification $\text{Long-Only}_t = \alpha + \beta \cdot \text{Index}_t + \epsilon_t$. Standard errors are corrected for heteroscedasticity and autocorrelation using the Newey–West procedure with a lag length of five months. The intercept α captures the risk-adjusted excess return unexplained by exposure to the market index.

	Dependent variable:		
	Long-Only	Top-10%	Top-1%
ICE BofA	1.128***	1.176***	1.309***
	(0.095)	(0.114)	(0.209)
Constant	0.318***	0.505***	0.541***
	(0.111)	(0.148)	(0.204)
Observations	226	226	226
R^2	0.626	0.516	0.318
Adjusted R^2	0.624	0.514	0.315
Residual Std. Error (df = 224)	1.453	1.896	3.193
F Statistic (df = 1; 224)	374.845***	239.136***	104.494***
Note:	*p<0.1; **p<0.05; ***p<0.01		

6.7 Transaction Costs

Finally, an important consideration in constructing a realistic portfolio for investors is transaction costs. This is particularly relevant in corporate bond markets, where transaction costs can significantly impact the profitability of a strategy. Since the long-only strategies involve monthly bond trading, the question arises as to whether their outperformance persists after accounting for such costs.

One way to approach this issue is by analyzing portfolio turnover, that is, the proportion of the portfolio that must be reallocated each month. Table 6.8 reports the turnover statistics for each long-only portfolio.

We observe that the *long-only* portfolio has the highest turnover among the three strategies. This is likely due to the inclusion of bonds with very weak positive signals, which receive minimal weights and frequently enter and exit the portfolio. As a result, the portfolio requires continual reweighting. For the *long-only* portfolio, the median monthly turnover is 31.48%, meaning that nearly one-third of the portfolio must be sold and reinvested each month. This level of trading activity could lead to substantial transaction costs. In the worst case, up to 50.99% of the portfolio would need to be reallocated in a single month.

The other two strategies show more favorable results. The *top-10%* and *top-1%* portfolios exhibit median turnover rates of 23.63% and 23.50%, respectively. While still relatively high, these levels represent a meaningful reduction compared to the *long-only* portfolio. Reallocating less than one-quarter of the portfolio each month may be operationally feasible for an investor. However, turnover can spike, and in some months, up to half of the portfolio may still need to be reallocated, which could pose challenges during periods of low market liquidity, such as financial crises.

	Portfolio	Minimum	25th	Median	75th	Maximum
1	Long-Only	9.18	27.92	31.48	35.13	50.99
2	Top-10%	6.82	19.71	23.63	28.08	41.55
3	Top-1%	8.85	18.07	23.50	30.04	50.00

TABLE 6.8: Monthly turnover distribution of the long-only portfolios. This table reports the distribution of monthly turnover for each portfolio, showing the minimum, first quartile, median, third quartile, and maximum values. Turnover is defined as the percentage of the portfolio's holdings that are sold and reinvested each month, illustrating how portfolio rebalancing varies over time.

Precisely estimating transaction costs for corporate bond portfolios is challenging due to limited data quality. A common approach is to use proxies to approximate the cost of trading individual bonds. One recent example is Ivashchenko and Kosowski, 2024, who adapt the trading cost functions from the MMI of Kyle and Obizhaeva, 2016 to corporate bonds. By estimating transaction costs at the individual bond level, the authors construct several long-only factor portfolios and evaluate their performance after costs. They find that portfolios with high turnover (above 70%) lose their pre-cost alpha. In contrast, low-turnover portfolios, as well as their constructed multi-factor portfolio, retain a positive but smaller risk premium after accounting for transaction costs. Furthermore, the authors explore cost-reduction techniques such as partial rebalancing or investing in only a subset of the portfolio, the latter being conceptually similar to my *top-10%* and *top-1%* portfolios. These measures further lower transaction costs and improve post-cost performance. Overall, Ivashchenko and Kosowski, 2024 show that systematic factor portfolios can maintain positive risk premia after transaction costs, provided turnover is reduced.

To estimate transaction costs for my long-only timed multi-factor portfolio, I attempted to build on the results of Ivashchenko and Kosowski, 2024. However, their approach is rooted in market microstructure research, and replicating it would require daily transaction-level data with prices and volumes. The dataset I use, originating from Dick-Nielsen et al., 2023, contains only monthly bond returns, making such replication infeasible. I therefore adopt a different approach. In their paper, Ivashchenko and Kosowski, 2024 report, for each constructed factor portfolio, the monthly return before and after transaction costs along with the corresponding turnover. I use this information to estimate the relationship between the difference in monthly returns with and without transaction costs (Δr_t) and turnover via the regression

$$\Delta r_t = \alpha + \beta \cdot \text{turnover}_t + \epsilon_t$$

This specification allows me to approximate the cost impact on the monthly returns of all long-only portfolios, as turnover is available for each month. For the market, I assume a flat turnover of 1.53%, consistent with the turnover of the authors' market portfolio. Admittedly, this approach is imperfect as it amounts to using a proxy for a proxy. Nonetheless, given the data limitations and the fact that the regression achieves an R^2 of 98.4%, I believe it provides a reasonable approximation of realistic transaction costs.

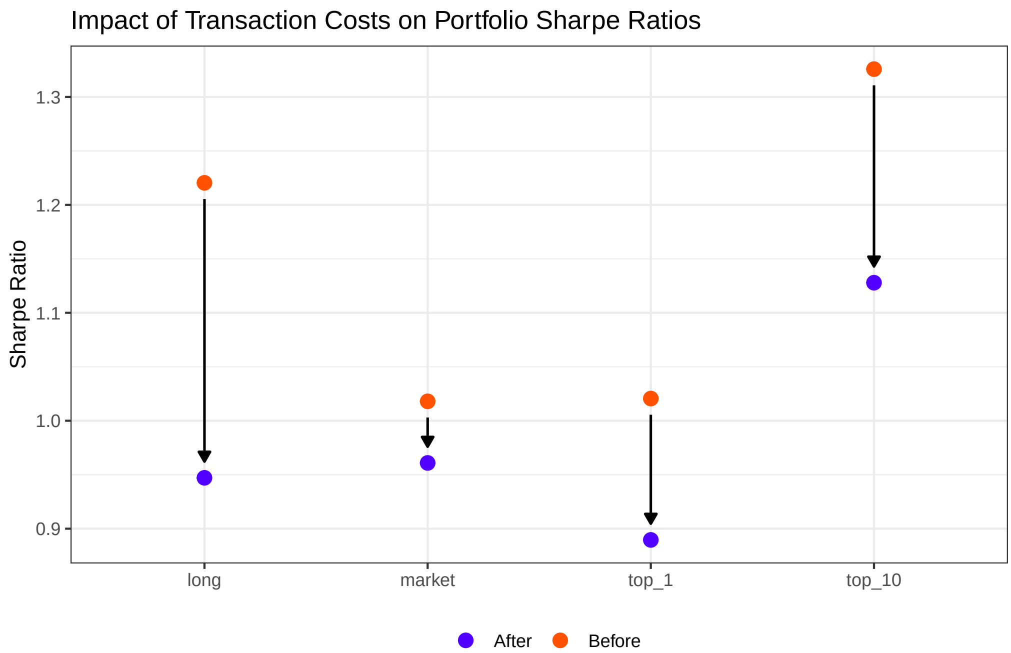

FIGURE 6.2: Impact of transaction costs on annualized Sharpe ratios. This figure compares the annualized Sharpe ratios of all long-only portfolios and the market portfolio before and after accounting for transaction costs. Orange dots represent Sharpe ratios before transaction costs, and purple dots represent Sharpe ratios after transaction costs, highlighting the performance reduction attributable to trading frictions.

To assess the impact of transaction costs on portfolio performance, I compare the Sharpe ratio before and after costs. Figure 6.2 reports the Sharpe ratios of all long-only portfolios and the market portfolio in both cases. The market portfolio is affected the least, reflecting its low turnover. The long-only portfolio's Sharpe ratio declines from a high value of 1.22 to 0.95, which is below that of the market portfolio (0.96). This indicates that, without any turnover-reduction technique, the long-only timed multi-factor portfolio does not deliver risk-adjusted outperformance relative to the market.

Restricting investments to a subset of bonds, as in the *top-10%* portfolio, reduces turnover without compromising performance, resulting in a post-cost Sharpe ratio of 1.13. By contrast, the *top-1%* portfolio is overly exposed to idiosyncratic risk, and after transaction costs it records the lowest Sharpe ratio of 0.89.

Overall, Figure 6.2 illustrates that transaction costs materially affect performance. The long-only timed multi-factor portfolio, which exhibited notable outperformance before costs, delivers returns comparable to the market after costs. However, applying turnover-reduction techniques, as in the *top-10%* portfolio, preserves persistent outperformance.

To statistically test the outperformance of the long-only portfolios after transaction costs, I apply the same methodology as before. For each long-only portfolio, I regress the monthly cost-adjusted returns on the cost-adjusted market returns. The results are reported in Table 6.9.

TABLE 6.9: Regression of transaction cost–adjusted portfolio returns on the market portfolio. This table reports the results from regressing the transaction cost–adjusted excess returns of the long-only, top-10%, and top-1% portfolios on the market portfolio using the specification $\text{Long-Only}_t = \alpha + \beta \cdot \text{Market}_t + \epsilon_t$. Standard errors are corrected for heteroscedasticity and autocorrelation using the Newey–West procedure with a lag length of five months. The intercept α measures the risk-adjusted excess return, net of transaction costs, unexplained by market exposure.

	Dependent variable:		
	Long Only	Top-10	Top-1
	(1)	(2)	(3)
Market	1.253^{***}	1.377^{***}	1.710^{***}
	(0.067)	(0.082)	(0.289)
Constant	0.078	0.258^{**}	0.214
	(0.081)	(0.106)	(0.159)
Observations	228	228	228
R^2	0.750	0.688	0.526
Adjusted R^2	0.749	0.687	0.524
Residual Std. Error (df = 226)	1.181	1.514	2.651
F Statistic (df = 1; 226)	679.026^{***}	498.405^{***}	250.744^{***}
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

As before, the estimated βs increase as portfolios become less concentrated. This is expected, as these portfolios are more volatile and take on more market risk. Also in line with expectations, the βs are almost identical to those from the regression without transaction costs in Table 6.6. This shows that including transaction costs does not alter the portfolios' exposure to market risk, as it should not.

Turning to the more interesting results, the α represents the monthly risk-adjusted excess return net of transaction costs. Here, we find statistical confirmation of the patterns observed in the Sharpe ratios. The α of the *long-only* portfolio effectively disappears and is statistically insignificant, indicating that, after accounting for transaction costs, this portfolio does not generate excess returns beyond those of the market.

In contrast, the concentrated *Top-10* portfolio retains its outperformance, consistent with the Sharpe ratio results. For this portfolio, we estimate a monthly risk-adjusted premium of 0.258% after transaction costs. This demonstrates that applying a turnover-reduction technique can preserve much of the return generated by the timed multi-factor approach. Although the monthly risk premium declines from 0.379% before transaction costs to 0.258%, the *Top-10* portfolio still appears to outperform.

Meanwhile, the α of the *Top-1* portfolio, similar to that of the *long-only* portfolio, effectively vanishes. Although the point estimate of the monthly risk premium is relatively high at 0.214%, it is not statistically significant due to the portfolio's high volatility.

6.8 Conclusion

In this chapter, I analyzed whether the promising timed multi-factor (TMF) portfolio can be translated into a realistically investable strategy for practitioners. To do so, I computed the net weight of each bond in the TMF portfolio and constructed a portfolio consisting of all bonds with a positive net weight (*long-only*). To explore even more practical implementations, I also constructed two additional portfolios that invest only in the top 10% and top 1% of bonds by net weight.

Analyzing the performance of these portfolios, I found that the *long-only* and *top-10%* portfolios improve the annualized Sharpe ratio of a simple market portfolio by 0.21 and 0.33, respectively. These improvements are both economically meaningful and statistically significant. In contrast, the *top-1%* portfolio does not exhibit an improvement in Sharpe ratio.

To assess the presence of additional risk premia, I regressed the long-only portfolios against the market portfolio. All three strategies exhibited statistically significant positive alphas. The *top-10%* portfolio performed best, offering an additional monthly return of 0.38% after controlling for market exposure. Importantly, this result remained robust when replacing the self-constructed market portfolio with an exogenous benchmark, the ICE BofA US Corporate Index.

Finally, I examined portfolio turnover to assess the potential impact of transaction costs. The *long-only* portfolio exhibits relatively high turnover, which leads to substantial transaction costs. As a result, its Sharpe ratio and additional risk premia vanish when compared to an efficient market portfolio. In contrast, the more concentrated *top-10* portfolio, with its lower turnover, retains both statistically and economically significant outperformance after transaction costs.

Overall, the results suggest that the risk premia identified in earlier chapters persist in long-only implementations. This implies that timing corporate bond risk premia may have meaningful implications for practitioners.

Chapter 7

Conclusion

This thesis asks whether cross-sectional risk premia in corporate bonds that fail to replicate in prior work can be recovered through timing. To address this question, I first reproduced established factor constructions, then evaluated whether estimated premia vary over time, next applied a broad set of timing methods to those factors, and finally assessed whether any timed gains survive when translated into realistic portfolio implementations. The central motivation was to move beyond unconditional factor portfolios and to test whether predictable episodes of elevated premia can be identified and harvested in practice.

The methodology built mainly on two prior contributions. For factor replication methodology and the data foundation, I relied on Dick-Nielsen et al., 2023, which provides the dataset underpinning the entire analysis. For the timing methodology, I adapted the signal construction and evaluation framework of Neuhierl et al., 2024 to the corporate bond setting. The sample covered July 2002 through November 2021, and the timing analysis applied 31 signals to 21 factors, yielding a comprehensive assessment of the ability to forecast factor returns in corporate bonds.

The replication confirmed that many previously reported unconditional factor premia are difficult to reproduce, yet several characteristics exhibited notable outperformance, with monthly risk premia of 0.27% for low-term risk, 0.35% for high credit risk, 0.38% for value, and 0.48% for short-term reversal. The timing analysis showed that short-horizon momentum variants, such as the one-month momentum signal (mom1), improved Sharpe ratios by an average of 0.11, while certain macro signals, such as the Federal Funds Rate (fed), yielded an average improvement of 0.09. Most improvement came from aggregation signals, in particular the simple aggregated signal *all*, implemented as the naïve average of available timing signals, which increased Sharpe ratios by 0.13 on average. We have seen that this signal made it possible to time multiple factors simultaneously, leading to outperformance of 0.39% in monthly risk premia relative to a benchmark portfolio. In summary, we have seen that timing factors, whether singular or multiple, statistically and economically enhanced returns and helped capture risk premia.

A key part of the thesis was the examination of implementability. The timed multifactor portfolio in its unconstrained long–short form is impractical for many investors due to shorting limits and very high turnover. I therefore constructed alternative implementations: a long-only portfolio, a concentrated top-10 percent portfolio, and a highly concentrated top-1 percent portfolio. Before trading frictions, these portfolios delivered monthly alphas of 0.23% for the long-only version, 0.38% for the top-10 percent, and 0.31% for the top-1 percent when regressed against the market portfolio, indicating that they successfully harvested risk premia. After applying transaction cost estimates, the long-only implementation's alpha declined to 0.08% and lost statistical significance, whereas the concentrated top-10 percent portfolio retained a monthly alpha of 0.26%, which remained both economically and statistically relevant. Thus, we have seen that the timing success observed earlier is not only theoretical but also yields a concrete investable portfolio that captures risk premia even after accounting for transaction costs.

The analysis has limitations. The sample ended in 2021, and extending it would improve external validity. Relying on externally cleaned TRACE data constrained the ability to estimate bond-level transaction costs, as detailed daily price and volume series are required for transaction cost estimates. Finally, although the timing framework followed a principled template, some choices in signal variants and parameter settings were somewhat ad hoc and could be standardized.

There are three natural directions for follow-up. First, precisely estimate bond-level transaction costs and re-test whether timed multi-factor returns survive under more sophisticated cost estimates. Second, investigate the economic and behavioral mechanisms behind the time variation to understand why particular factors are timable by specific signals. Third, explore more systematic aggregation methods and machine learning approaches to combine signals and to construct timed multi-factor portfolios in a way that improves upon the naïve aggregation *all* used in this thesis.

In conclusion, the findings of this thesis suggest that corporate bond risk premia persist in a time-varying form. When timed with suitable signals and implemented realistically, they can be harvested by investors beyond simple market exposures.

Appendix A

Supplementary Information

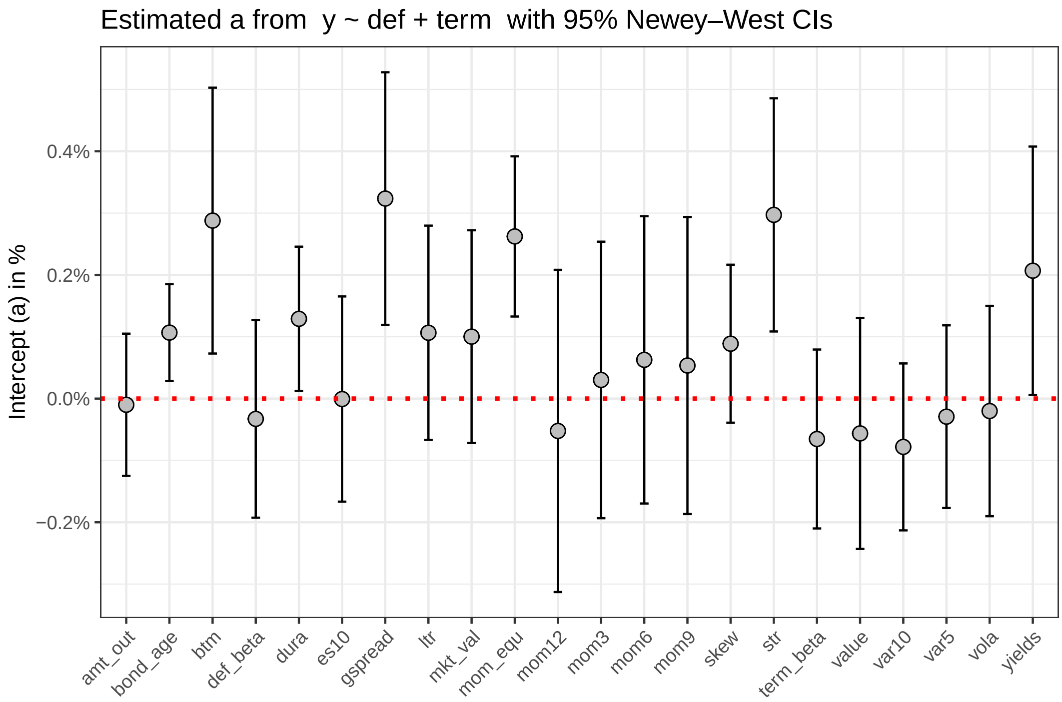

FIGURE A.1: Estimated α and CIs (95% Newey-West adjusted) using the factor returns by Dick-Nielsen et al., 2023

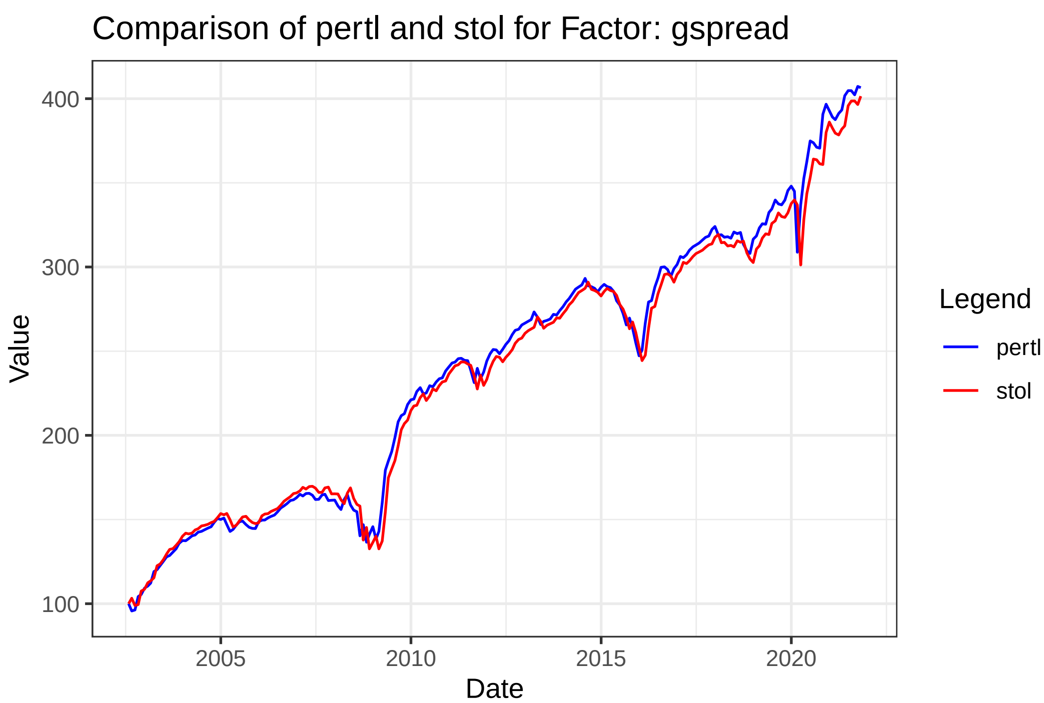

FIGURE A.2: Comparison of my Credit Spread factor against the factor constructed by Dick-Nielsen et al., 2023. (Legend: *pertl* being mine)

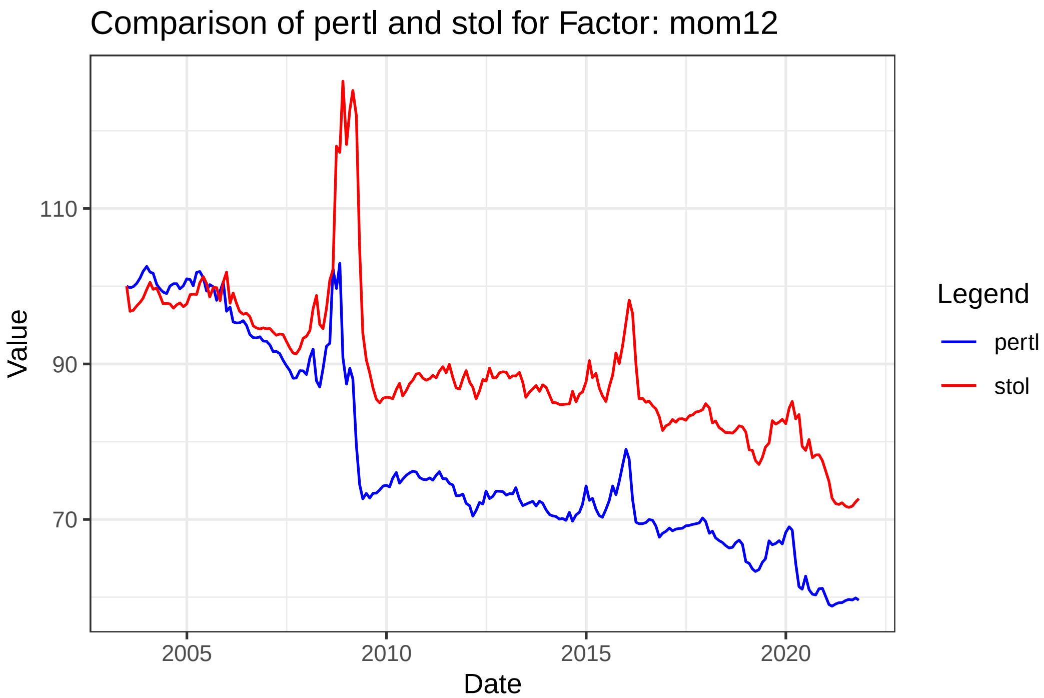

FIGURE A.3: Comparison of my Momentum 12 factor against the factor constructed by Dick-Nielsen et al., 2023. (Legend: *pertl* being mine)

TABLE A.1: Overview of constructed Factors in Corporate Bonds

Name	Abbreviation	Description	Cite	Dir.
12m. Momentum	mom12	12-month momentum	Jostova et al. (2013)	1
3m. Momentum	mom3	3-month momentum	Jostova et al. (2013)	1
6m. Momentum	mom6	6-month momentum	Jostova et al. (2013)	1
9m. Momentum	mom9	9-month momentum	Jostova et al. (2013)	1
Amount Outstanding*	amt_out	Bond notional * number of bonds outstanding	Houweling et al. (2005)	-1
Bond Age	bond_age	Fraction of bond life expired	Houweling et al. (2005) & Van Mencxel (2022)	1
Book-to-price	btm	Bond book value / market price	Bartram et al. (2019)	1
Credit Rating	rating	Numerical credit rating from 1–21	Bai et al. (2019)	1
Credit Spread	gspread	Yield to maturity minus the yield on a cash-flow matched portfolio of treasuries	Israel et al. (2018)	1
Duration*	dura	Modified Macaulay duration	Israel et al. (2018)	-1
ES(10%)	es10	-1 * mean of 4 lowest obs. in 36-month rolling window	Bai et al. (2019)	1
Kurtosis	kurt	36-month kurt	Bai et al. (2019)	1
Liquidity	spread	Observed Ask - Bid		1
Long Term Reversal	ltr	Loser minus winners from t-48 to t-13	Bali et al. (2021)	1
Market Value*	mkt_val	Price * Amount Outstanding	Houweling and Zundert (2018)	-1
Short Term Reversal	str	Return from t-1 to t, sign flipped	Bai et al. (2019)	1
Skewness*	skew	36-month skew	Bai et al. (2019)	-1
VaR(10%)	var10	-1 * 4th lowest observation in a 36-month rolling window	Bai et al. (2019)	1
VaR(5%)	var5	-1 * 2nd lowest observation in a 36-month rolling window	Bai et al. (2019)	1
Volatility	vola	36-month vol	Bai et al. (2019)	1
Yield to maturity	yields	Promised yield to maturity	Gebhardt et al. (2005a)	1

TABLE A.2: Overview of Constructed Signals

Name	**Abbreviation**	**Description**	**Cite**	**Dir.**
Momentum 1M	mom1	Sign of cumulative return over months $t-1$ to t	Ehsani, Linnainmaa (2019)	
Scaled Momentum 1M	smom1	mom1 scaled by 3Y past return volatility and annualized	Gupta and Kelly (2019)	
Momentum 3M	mom3	Sign of cumulative return over months $t-3$ to t	Ehsani, Linnainmaa (2019)	
Scaled Momentum 3M	smom3	mom3 scaled by 3Y past return volatility and annualized	Gupta and Kelly (2019)	
Momentum 6M	mom6	Sign of cumulative return over months $t-6$ to t	Ehsani, Linnainmaa (2019)	
Scaled Momentum 6M	smom6	mom6 scaled by 3Y past return volatility and annualized	Gupta and Kelly (2019)	
Momentum 12M	mom12	Sign of cumulative return over months $t-12$ to t	Ehsani, Linnainmaa (2019)	
Scaled Momentum 12M	smom12	mom12 scaled by 3Y past return volatility	Gupta and Kelly (2019)	
Volatility 1	vol1	Inverse rolling 12-month vola, scaled by 12-month average	Moreira and Muir (2017)	
Volatility 2	vol2	Inverse rolling 12-month vola, scaled by 6-month average	Moreira and Muir (2017)	
Volatility 3	vol3	Inverse rolling 12-month vola, scaled by 3-month average	Moreira and Muir (2017)	
Reversal 3M	rev1	1 minus annualized avg return over $t-3$ to t	Moskowitz, Ooi, Pedersen (2012)	
Reversal 6M	rev2	1 minus annualized avg return over $t-6$ to t	Moskowitz, Ooi, Pedersen (2012)	
Reversal 12M	rev3	1 minus annualized avg return over $t-12$ to t	Moskowitz, Ooi, Pedersen (2012)	
Characteristic Spread 12M	char1	12-month z-score of the factor signal	Huang, Liu, Ma, Osiol (2011)	
Characteristic Spread 6M	char2	6-month z-score of the factor signal	Huang, Liu, Ma, Osiol (2011)	
Characteristic Spread 3M	char3	3-month z-score of the factor signal	Huang, Liu, Ma, Osiol (2011)	
Federal Funds Rate	fed	Rolling Beta of look-ahead return against signal, times current signal value. Scaled by 10 with baselevel 0.5	Pertl (2025)	
Real GDP Growth	gdp	Rolling Beta of look-ahead return against signal, times current signal value. Scaled by 10 with baselevel 0.5	Pertl (2025)	
CPI YOY Inflation	cpi	Rolling Beta of look-ahead return against signal, times current signal value. Scaled by 10 with baselevel 0.5	Pertl (2025)	
Yield Slope	slope	Rolling Beta of look-ahead return against signal, times current signal value. Scaled by 10 with baselevel 0.5	Pertl (2025)	
Treasury VIX	tvix	Rolling Beta of look-ahead return against signal, times current signal value. Scaled by 10 with baselevel 0.5	Pertl (2025)	
CBOE VIX	vix	Rolling Beta of look-ahead return against signal, times current signal value. Scaled by 10 with baselevel 0.5	Pertl (2025)	
Overall Momentum	mom	Simple Mean of all momentum signals	Pertl (2025)	

Name	Abbreviation	Description	Cite	Dir.
Overall Volatility	vol	Simple Mean of all volatility signals	Pertl (2025)	
Overall Reversal	rev	Simple Mean of all reversal signals	Pertl (2025)	
Overall Characteristic Spread	char	Simple Mean of all characteristic spread signals	Pertl (2025)	
Overall Macro	macro	Simple Mean of all macro signals	Pertl (2025)	
All Signals	all	Simple mean of all aggregated signals	Pertl (2025)	
PLS Aggregation Sign	pls1	Sign of 12-month rolling PLS prediction	Pertl (2025)	
PLS Aggregation Scaled	pls2	12-month rolling PLS prediction. Scaled by 10 with baselevel 0.5	Pertl (2025)	

Bibliography

Bai, Jennie, Turan G. Bali, and Quan Wen (Mar. 2019). "RETRACTED: Common risk factors in the cross-section of corporate bond returns". In: *Journal of Financial Economics* 131.3, pp. 619–642. ISSN: 0304-405X. DOI: 10.1016/j.jfineco.2018.08.002. URL: https://www.sciencedirect.com/science/article/pii/S0304405X18302095 (visited on 01/03/2025).

Benjamini, Yoav and Yosef Hochberg (1995). "Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing". In: *Journal of the Royal Statistical Society. Series B (Methodological)* 57.1. Publisher: [Royal Statistical Society, Oxford University Press], pp. 289–300. ISSN: 0035-9246. URL: https://www.jstor.org/stable/2346101 (visited on 01/03/2025).

Chang, Eric C. and Roger D. Huang (1990). "Time-Varying Return and Risk in the Corporate Bond Market". In: *The Journal of Financial and Quantitative Analysis* 25.3. Publisher: [Cambridge University Press, University of Washington School of Business Administration], pp. 323–340. ISSN: 0022-1090. DOI: 10.2307/2330699. URL: https://www.jstor.org/stable/2330699 (visited on 06/16/2025).

Cochrane, John H. (2011). "Presidential Address: Discount Rates". en. In: *The Journal of Finance* 66.4. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2011.01671.x, pp. 1047–1108. ISSN: 1540-6261. DOI: 10.1111/j.1540-6261.2011.01671.x. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2011.01671.x (visited on 01/03/2025).

Dick-Nielsen, Jens (Sept. 2009). "Liquidity Biases in TRACE". en. In: *The Journal of Fixed Income* 19.2. Company: Institutional Investor Journals Distributor: Institutional Investor Journals Institution: Institutional Investor Journals Label: Institutional Investor Journals Publisher: Portfolio Management Research Section: Asset Classes, pp. 43–55. ISSN: 1059-8596, 2168-8648. DOI: 10.3905/jfi.2009.19.2.043. URL: https://www.pm-research.com/content/iijfixinc/19/2/43 (visited on 06/10/2025).

– (Dec. 2014). *How to Clean Enhanced TRACE Data*. en. SSRN Scholarly Paper. Rochester, NY. DOI: 10.2139/ssrn.2337908. URL: https://papers.ssrn.com/abstract=2337908 (visited on 06/10/2025).

Dick-Nielsen, Jens et al. (Sept. 2023). *Corporate Bond Factors: Replication Failures and a New Framework*. en. SSRN Scholarly Paper. Rochester, NY. DOI: 10.2139/ssrn.4586652. URL: https://papers.ssrn.com/abstract=4586652 (visited on 01/03/2025).

Dickerson, Alexander, Philippe Mueller, and Cesare Robotti (Nov. 2023). "Priced risk in corporate bonds". In: *Journal of Financial Economics* 150.2, p. 103707. ISSN: 0304-405X. DOI: 10.1016/j.jfineco.2023.103707. URL: https://www.sciencedirect.com/science/article/pii/S0304405X23001393 (visited on 02/19/2025).

Dickerson, Alexander, Cesare Robotti, and Yoshio Nozawa (Dec. 2024). *Factor Investing with Delays*. en. SSRN Scholarly Paper. Rochester, NY. DOI: 10.2139/ssrn.5074221. URL: https://papers.ssrn.com/abstract=5074221 (visited on 03/10/2025).

Ehsani, Sina and Juhani T. Linnainmaa (2022). "Factor Momentum and the Momentum Factor". en. In: *The Journal of Finance* 77.3. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111 pp. 1877–1919. ISSN: 1540-6261. DOI: 10.1111/jofi.13131. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.13131 (visited on 01/03/2025).

Fama, Eugene F. and Kenneth R. French (Nov. 1989). “Business conditions and expected returns on stocks and bonds”. In: *Journal of Financial Economics* 25.1, pp. 23–49. ISSN: 0304-405X. DOI: 10.1016/0304-405X(89)90095-0. URL: https://www.sciencedirect.com/science/article/pii/0304405X89900950 (visited on 06/16/2025).

– (1992). “The Cross-Section of Expected Stock Returns”. en. In: *The Journal of Finance* 47.2. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1992.tb04398.x, pp. 427–465. ISSN: 1540-6261. DOI: 10.1111/j.1540-6261.1992.tb04398.x. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1992.tb04398.x (visited on 01/13/2025).

– (Feb. 1993). “Common risk factors in the returns on stocks and bonds”. In: *Journal of Financial Economics* 33.1, pp. 3–56. ISSN: 0304-405X. DOI: 10.1016/0304-405X(93)90023-5. URL: https://www.sciencedirect.com/science/article/pii/0304405X93900235 (visited on 01/03/2025).

Financial Industry Regulatory Authority (2024). *TRACE Fact Book*.

Gupta, Tarun and Bryan Kelly (Feb. 2019). “Factor Momentum Everywhere”. en. In: *The Journal of Portfolio Management* 45.3, pp. 13–36. ISSN: 0095-4918, 2168-8656. DOI: 10.3905/jpm.2019.45.3.013. URL: http://pm-research.com/lookup/doi/10.3905/jpm.2019.45.3.013 (visited on 01/03/2025).

Harvey, Campbell R., Yan Liu, and Heqing Zhu (2016). “... and the Cross-Section of Expected Returns”. In: *The Review of Financial Studies* 29.1. Publisher: [Oxford University Press, The Society for Financial Studies], pp. 5–68. ISSN: 0893-9454. URL: https://www.jstor.org/stable/43866011 (visited on 01/03/2025).

Houweling, Patrick, Albert Mentink, and Ton Vorst (June 2005). “Comparing possible proxies of corporate bond liquidity”. In: *Journal of Banking & Finance* 29.6, pp. 1331–1358. ISSN: 0378-4266. DOI: 10.1016/j.jbankfin.2004.04.007. URL: https://www.sciencedirect.com/science/article/pii/S0378426604000998 (visited on 03/15/2025).

Houweling, Patrick and Jeroen van Zundert (Apr. 2017). “Factor Investing in the Corporate Bond Market”. In: *Financial Analysts Journal* 73.2. Publisher: Routledge _eprint: https://doi.org/10.2469/faj.v73.n2.1, pp. 100–115. ISSN: 0015-198X. DOI: 10.2469/faj.v73.n2.1. URL: https://doi.org/10.2469/faj.v73.n2.1 (visited on 01/03/2025).

Huang, Jing-Zhi and Zhan Shi (Nov. 2021). “What Do We Know About Corporate Bond Returns?” en. In: *Annual Review of Financial Economics* 13.Volume 13, 2021. Publisher: Annual Reviews, pp. 363–399. ISSN: 1941-1367, 1941-1375. DOI: 10.1146/annurev-financial-110118-123129. URL: https://www.annualreviews.org/content/journals/10.1146/annurev-financial-110118-123129 (visited on 01/03/2025).

Israel, Ronen, Diogo Palhares, and Scott A. Richardson (Apr. 2018). “Common factors in corporate bond returns”. en. In: *Journal of Investment Management* 16.2, pp. 17–46. DOI: 10.2139/ssrn.2576784. URL: https://papers.ssrn.com/abstract=2576784 (visited on 01/03/2025).

Ivashchenko, Alexey and Robert Kosowski (Oct. 2024). “Transaction Costs and Capacity of Systematic Corporate Bond Strategies”. In: *Financial Analysts Journal* 80.4. Publisher: Routledge _eprint: https://doi.org/10.1080/0015198X.2024.2360390, pp. 53–80. ISSN: 0015-198X. DOI: 10.1080/0015198X.2024.2360390. URL: https://doi.org/10.1080/0015198X.2024.2360390 (visited on 08/10/2025).

Jobson, J. D. and Bob M. Korkie (1981). "Performance Hypothesis Testing with the Sharpe and Treynor Measures". In: *The Journal of Finance* 36.4. Publisher: [American Finance Association, Wiley], pp. 889–908. ISSN: 0022-1082. DOI: 10.2307/2327554. URL: https://www.jstor.org/stable/2327554 (visited on 01/13/2025).

Jostova, Gergana et al. (July 2013). "Momentum in Corporate Bond Returns". In: *The Review of Financial Studies* 26.7, pp. 1649–1693. ISSN: 0893-9454. DOI: 10.1093/rfs/hht022. URL: https://doi.org/10.1093/rfs/hht022 (visited on 01/03/2025).

Kelly, Bryan and Seth Pruitt (2013). "Market Expectations in the Cross-Section of Present Values". In: *The Journal of Finance* 68.5. Publisher: Wiley, pp. 1721–1756. ISSN: 0022-1082. URL: https://www.jstor.org/stable/42002595 (visited on 01/03/2025).

Kyle, Albert S. and Anna A. Obizhaeva (2016). "Market Microstructure Invariance: Empirical Hypotheses". en. In: *Econometrica* 84.4. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.39 pp. 1345–1404. ISSN: 1468-0262. DOI: 10.3982/ECTA10486. URL: https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA10486 (visited on 08/10/2025).

Ledoit, Oliver and Michael Wolf (Dec. 2008). "Robust performance hypothesis testing with the Sharpe ratio". In: *Journal of Empirical Finance* 15.5, pp. 850–859. ISSN: 0927-5398. DOI: 10.1016/j.jempfin.2008.03.002. URL: https://www.sciencedirect.com/science/article/pii/S0927539808000182 (visited on 06/10/2025).

Lin, Hai, Junbo Wang, and Chunchi Wu (Mar. 2011). "Liquidity risk and expected corporate bond returns". In: *Journal of Financial Economics* 99.3, pp. 628–650. ISSN: 0304-405X. DOI: 10.1016/j.jfineco.2010.10.004. URL: https://www.sciencedirect.com/science/article/pii/S0304405X10002400 (visited on 01/03/2025).

Lin, Hai, Chunchi Wu, and Guofu Zhou (June 2016). *Forecasting Corporate Bond Returns: An Iterated Combination Approach*. en. SSRN Scholarly Paper. Rochester, NY. DOI: 10.2139/ssrn.2346299. URL: https://papers.ssrn.com/abstract=2346299 (visited on 06/16/2025).

Moreira, Alan and Tyler Muir (2017). "Volatility-Managed Portfolios". en. In: *The Journal of Finance* 72.4. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12513, pp. 1611–1644. ISSN: 1540-6261. DOI: 10.1111/jofi.12513. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12513 (visited on 01/03/2025).

Moskowitz, Tobias J., Yao Hua Ooi, and Lasse Heje Pedersen (May 2012). "Time series momentum". In: *Journal of Financial Economics*. Special Issue on Investor Sentiment 104.2, pp. 228–250. ISSN: 0304-405X. DOI: 10.1016/j.jfineco.2011.11.003. URL: https://www.sciencedirect.com/science/article/pii/S0304405X11002613 (visited on 06/14/2025).

Neuhierl, Andreas et al. (July 2024). *Timing the Factor Zoo*. en. SSRN Scholarly Paper. Rochester, NY. DOI: 10.2139/ssrn.4376898. URL: https://papers.ssrn.com/abstract=4376898 (visited on 01/03/2025).

R Core Team (2022). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. Vienna, Austria. URL: https://www.R-project.org/.

Sharpe, William F. (1964). "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk". en. In: *The Journal of Finance* 19.3. _eprint: https://onlinelibrary.wiley.com/doi/p 6261.1964.tb02865.x, pp. 425–442. ISSN: 1540-6261. DOI: 10.1111/j.1540-6261.1964.tb02865.x. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1964.tb02865.x (visited on 08/08/2025).