A Quantamental Boost to Semi-Systematic Credit Trading

A preliminary proposal

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# Executive Summary

* Proposal for a Quantamental Boost to Semi-Systematic Credit Trading.
* Advocates for the development of fundamentally driven forward-looking analytics.
* Aims to aggregate various elements, including financial ratios, analyst estimates, and events.
* Focus on deriving an issuer-level fundamental score for insights into credit quality.
* Combines exploratory data analysis and forward-looking modeling for significance assessment.
* Significance analysis involves statistical machine learning and econometrics methods.
* Modeling components include analyst estimates, earnings impact, and events modeling.
* Proposes a more robust bias-adjusted aggregation of analyst forecasts.
* Explores the short, mid, and long-term impact of earnings announcements.
* Categorizes and models various events such as new issues, deleveraging, and M&A scenarios.
* Anticipates the likelihood of events occurring in the short, mid, and long-term future.
* Introduces a comprehensive aggregate score based on analyst consensus, earnings impact, and events analysis.
* Outlines applications for systematic and discretionary usage of derived fundamental scores.
* Identifies data requirements from fundamental, analyst estimates, and transaction sources.
* Specifies resource requirements for computational, development, and modeling needs.
* References relevant literature supporting the proposed methodologies.
* Appendix provides a detailed breakdown of financial ratios according to CFA curriculum classification.

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# Background

The (semi) systematic strategies heavily lean on technical analysis and cross-sectional/longitudinal modeling, excluding consideration of the fundamental landscape. This note aims to advocate for the development of several fundamentally driven forward-looking analytics. These analytics can then be aggregated to form an issuer-level fundamental score, providing an estimate of the fundamental quality of the issuers' credit.

To elaborate further, we specifically confine the fundamental information to two categories:

1. Ratio-based:
   1. Financial ratios derived from income statements, balance sheets, and cash flow statements.
   2. Analysts' estimates and recommendations.
   3. Earnings announcements.
2. Event-based:
   1. Capital structure events, encompassing new issuances (debt/equity), equity buybacks, and deleveraging.
   2. Mergers and acquisitions events, distinguishing between leveraged buyouts (LBO) and non-LBO scenarios.
   3. Hedge funds' activism.

# Approach

We suggest initiating an exploratory data analysis as a preliminary step to assess the significance of various elements such as financial ratios, analyst estimates, corresponding surprises, and events. This evaluation aims to determine their relevance in providing insights into future credit (excess) returns. Subsequently, upon confirming the hypothesis regarding the importance of ratios and events, we transition to forward-looking modeling.

## Significance analysis

The analysis of significance involves examining numerous ratios and events to determine their correlation with future total and excess returns on corporate bonds. Statistical machine learning methods, particularly those related to feature significance and selection [3,4,5,6], can be applied to assess the importance of financial ratios. Additionally, for evaluating the impact of events, techniques from the econometrics literature, specifically event-based analysis [2], can be employed.

## Modeling

Having gained insight into the significance of ratios and events in gauging future credit performance, our attention can now shift towards modeling. This includes:

* Incorporating financial ratios within the context of analyst estimates,
* Examining the impact of earnings announcements, with a particular emphasis on post-earnings announcement drift (PEAD) modeling,
* Assessing the likelihood and impact of various events.

The primary aim of these models is to refine ratios and events, extracting signals that forecast forward-looking credit (excess) returns.

### Analyst Estimates modeling

The conventional approach to aggregating Analyst estimates typically employs the median. While widely adopted, the consensus median overlooks the effectiveness of individual analysts, influenced by behavioral, incentive-based, discriminatory biases, and systematic errors.

We propose a more robust bias-adjusted aggregation of analyst forecasts for key financial ratios, crucial indicators of corporate bond performance, drawing inspiration from related work [1, 9, 10]. Given that these estimates are only accessible for publicly traded companies, the question arises: does it make sense to extrapolate them for private firms, particularly in the High Yield market?

The aggregated forecasts can be further calibrated to forward bond (excess) return.

This approach can also be extended to a curated dataset encompassing fundamental analysts' estimates and recommendations for individual credits, inclusive of Jefferies' own credit analysts.

### Earnings Impact modeling

The objective is to model the short, mid, and long-term impact of earnings announcements by establishing a relationship between a bond's T+N (where N can be 1, 5, 10, 20 days) excess performance and its underlying fundamentals. This entails examining how the fundamentals of an issuer influence its bonds’ performance in the specified time frames following an earnings announcement. The modeling approach aims to capture the nuanced dynamics between fundamental factors and its surprise versus analyst estimates and the subsequent market reactions, providing insights into the varying impacts over different temporal horizons.

### Events modeling

The events of interest are:

* New issues
  + Debt
  + Equity follow-ons
* Deleveraging
* Equity Buybacks
* M&A:
  + LBO (typically negative event for bond spreads since it is a leveraging event)
  + Non-LBO (typically positive event for bond spreads)
  + Does hedge fund activism affect debt spreads ?

#### Event impact modeling

The goal is to predict the influence of each specific event on the future credit (excess) return over varying time horizons (T+N, where N can be 1, 5, 10, 20 days), with the possibility of aggregating the impacts at the issuer level. An initial approach involves creating a baseline classifier to assess the probability of the event resulting in a positive or negative effect on credit performance.

The existing literature comprises numerous endeavors to model the impact of M&A events [11,12,13,14] on credit, which we will examine. Additionally, we will conduct a literature review for other types of events.

#### Event likelihood modeling

Apart from modeling the impact of events, we also endeavor to anticipate the likelihood of these events occurring, or in other words, estimate their probability in the short, mid, and long-term future. Recognizing an event with high confidence can be advantageous for strategic repositioning and risk management given its impact on credit performance.

From a modeling standpoint, we can forecast whether an event will occur within a fixed forward window (e.g., the next quarter) or predict the time until the next event. In terms of features and signals, we can utilize pure fundamentals and momentum features[8, 14,17], or enhance them by incorporating unstructured data from sources such as news articles or SEC filings [15,16].

The probabilities of various events can be calibrated or projected to predict future credit (excess) returns. Alternatively, these event likelihoods can be integrated with their respective impacts to offer insights into the anticipated performance of credit in the forward trajectory.

### Fundamental one score

The final aggregate score will have four components:

* Analyst Consensus implied score
* Earnings-impact implied score
* Events-likelihood implied score
* Events-impact implied score

## Applications/Use cases

### Systematic usage

Use the combined or components scores as features in other models:

* Demand prediction
* Inquiry prediction
* Imputed performance attribution
* Inquiry edge modeling

### Discretionary usage

The data can be visualized through a dashboard that facilitates the detailed examination of individual credits. This includes the presentation of realized or actual fundamental information, events, analyst aggregate estimates, impacts of earnings announcements, events likelihood, and associated credit performance implied scores. Furthermore, the dashboard provides functionality for ranking various credits based on actual or estimated analytics and displays their dynamic evolution over time through time series representations. Additionally, cohort aggregation features are available for a comprehensive view of credit performance across different groups.

# 

Since we have existing work on style factors, for instance , two versions of a value score, it makes sense to to tackle value modeling as a first phase.

The first version of the existing value modeling consists of estimating bond value exposues using linear modeling, while the second version leverages a non-linear machine elarning approach. The first version covers both HY and IG, while the non-linear model is only available for HY.

We propose exploring combining/ensembling both models and expanding the exercise to IG.

With the availability of bond exposures to several style factors, one can optimize daily/weekly factor specific target portfolios.

These optimized factors can be used to estimate bodn elvel contribution to risk (CTR)[] of every bond to every factor.

Our initial investigation suggests tghat a market portfolio based CTR change is indicative of foreward residual/excess spread change in IG.

The hypostehsis is that factor based (instead of market based) CTR metrics would constitute a significant set of signals/features for down stream predictions …

Considering our existing work on style factors, such as two versions of a value score, it's logical to address value modeling as an initial phase. The first version of our current value modeling involves estimating bond value exposures through linear modeling, while the second version utilizes a non-linear machine learning approach. The first version encompasses both High Yield (HY) and Investment Grade (IG) bonds, whereas the non-linear model is exclusively available for HY bonds. Our proposal involves exploring the combination or ensembling of both models and extending the analysis to IG bonds.

Given the availability of bond exposures to various style factors, we can optimize factor-specific target portfolios on a daily or weekly basis. These optimized factors can then be utilized to assess the bond-level contribution to risk (CTR) for each factor. Our preliminary investigation suggests that changes in CTR based on a market portfolio are indicative of forward residual or excess spread changes in IG bonds.

We hypothesize that factor-based CTR metrics, rather than market-based ones, would serve as a significant set of signals or features for downstream predictions.

# Data requirements

## Fundamentals

Vendors:

1. Bloomberg
2. Refinitiv
3. CapIQ

## Analyst estimates

Vendors:

1. Refinitiv: I/B/E/S data base
2. CapIQ

## Transactions

Vendor:

* CapIQ Transactions package
* Dealogic

# Resources Requirements

# Resource Requirements:

Computational: Utilization of dedicated on-premises or cloud-based machines.

Development: Establishment of dedicated management and maintenance protocols for databases.

Modeling: Involvement of 1-2 quantitative researchers.

# References

[1] Bew, David and Harvey, Campbell R. and Ledford, Anthony and Radnor, Sam and Sinclair, Andrew, 2018, [Modeling Analysts’ Recommendations via Bayesian Machine Learning](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3269284)

[2] John Y. Campbell, Andrew W. Lo, and A. Craig Mackinlay, 1996, “[The Econometrics of Financial Markets](https://www.amazon.com/Econometrics-Financial-Markets-John-Campbell/dp/0691043019)”, Princeton University Press

[3] Kevin Murphy, 2022, [Probabilistic Machine Learning, An Introduction](https://probml.github.io/pml-book/book1.html), The MIT Press

[4] Marcos Lopez de Prado, 2020, [Machine learning for asset managers](https://www.amazon.com/Machine-Learning-Managers-Elements-Quantitative/dp/1108792898), Cambridge University Press

[5] John Lee et al, 2007, [Non-linear dimensionality reduction](https://www.amazon.com/Nonlinear-Dimensionality-Reduction-Information-Statistics/dp/0387393501/ref=sr_1_2?crid=1UVSPLO3936MY&keywords=nonlinear+dimensionality+reduction&qid=1693230472&s=books&sprefix=non+linear+dimensionality+reduction%2Cstripbooks%2C108&sr=1-2&ufe=app_do%3Aamzn1.fos.f5122f16-c3e8-4386-bf32-63e904010ad0), Springer

[6] Isabelle Guyon et al, 2006, [Feature extraction, foundations and applications](https://www.amazon.com/Feature-Extraction-Foundations-Applications-Fuzziness/dp/3540354875/ref=sr_1_1?crid=3JZW2BBFRN59L&keywords=Feature+extraction%2C+foundations+and+applications&qid=1693230501&s=books&sprefix=feature+extraction%2C+foundations+and+applications%2Cstripbooks%2C175&sr=1-1), Springer

[7] Arik Ben Dor, Albert Desclee, Lev Dynkin, Jay Hyman, Simon Polbennikov, 2020 “[Systematic investing in credit](https://www.amazon.com/Systematic-Investing-Credit-Frank-Fabozzi/dp/1119751284)”, Wiley

[8] Joshua Rosenbaum, Joshua Pearl, Joshua Harris, Joseph R. Perella, 2013 “[Investment Banking: Valuation, Leveraged Buyouts, and Mergers and Acquisitions](https://www.amazon.com/Investment-Banking-Valuation-Leveraged-Acquisitions/dp/1118656210)”, Wiley

[9] Chirag Nagpal et al, “[Latent Bayesian Inference for Robust Earnings Estimates](https://www.jpmorgan.com/content/dam/jpm/cib/complex/content/technology/ai-research-publications/pdf-6.pdf)”, NIPS 2019 (JPMorgan)

[10] Kenton K, Yee , “[A Bayesian Framework for combining valuation estimates](https://arxiv.org/pdf/0707.3482.pdf)”, 2008

[11] Luc Renneboog, Peter G. Szilagyi , 2007, “[Bond Performance in Mergers and Acquisitions: The impact and Spillover of Governance and Legal Standards](https://www.ecgi.global/sites/default/files/working_papers/documents/SSRN-id907141.pdf)”

[12] Qi Chang, 2015, “[The impact of Mergers and Acquisitions on Corporate Bond Ratings](https://spectrum.library.concordia.ca/id/eprint/979844/4/Chang_MSc_S2015.pdf)”

[13] Rainer Jankowitsch, Florian Pauer, 2021, “[The Effect of Credit, Liquidity and Rollover Risk on Bondholder Wealth in Mergers and Acquisitions](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3859921)”

[14] Casper Dahlberg and Max Lundberg, 2022, “[The impact of Mergers and Acquisitions on Credit and Investment risk.](https://www.diva-portal.org/smash/get/diva2:1669775/FULLTEXT01.pdf)”

[15] Bryan R. Routledge , Stefano Sacchetto, and Noah A. Smith, “[Predicting Merger Targets and Acquirers from Text.](http://sulawesi.tepper.cmu.edu/pdf/ma_ste_latest.pdf)

[16] Ryan Moriarty, Howard Ly, Ellie Lan, Suzanne K . McIntosh , 2019, [Deal or No Deal: Predicting Mergers and Acquisitions at Scale.](https://ieeexplore.ieee.org/document/9006015?denied=)

[17] Hendrik G. Froese, 2013, “[Predicting Takeover Targets](https://www.professionsfinancieres.com/sites/default/files/docsupload/u213/M%20Hendrik%20FROESE.pdf)”

# Appendix

## Financial Ratios

Following the Chartered Financial Analyst (CFA) curriculum classification, financial ratios can be classified into the following families:

* Activity : activity ratios measure how efficiently a company performs day- to-day tasks, such as the collection of receivables and management of inventory.
* Liquidity : Liquidity ratios measure the company’s ability to meet its short- term obligations
* Solvency : Solvency ratios measure a company’s ability to meet long-term obligations. Subsets of these ratios are also known as ”leverage” and ”long-term debt” ratios
* Profitability : Profitability ratios measure the company’s ability to generate profits from resources (assets)
* Valuation : Valuation ratios measure the quantity of an asset or flow (e.g., earnings) associated with ownership of a specified claim (e.g., a share or ownership of the enterprise )
* Credit : credit ratios measures the credit risk of the company.

### Activity Ratios

A table with text on it

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### Liquidity Ratios

A table of currency

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### Solvency Ratios

#### Debt ratios

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#### Coverage ratios

A close-up of a receipt

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### Profitability ratios

#### Return on sales

A screenshot of a computer

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#### Return on investment

A table with text on it

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### Valuation ratios

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### Credit Ratios

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