Margin Optimization AI

Sell-side trade automation and P&L optimization

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Overbond

A new bond market landscape

The structure of fixed income markets has changed dramatically over the past decade, making it more difficult for sell-side fixed income desks to remain profitable. The emergence of electronic all-to-all platforms and non-dealer liquidity providers has introduced new competition and the use of algorithmic and high-frequency trading has reduced the time dealers have to respond to inquiries.

After the 2008 financial crisis, regulators worldwide recognized the need to create a safer banking system. As a result, regulators increased capital requirements and reduced the risk banks are allowed to take, which increased costs for intermediaries. The unintended consequence of these new regulations has been a reduction in liquidity in the bond market. Dealers are less willing and able to hold inventories, so they are less willing to act as a principal in bond trading.

These structural changes have reduced the ability of the fixed income marketplace to operate efficiently. But with the increasing popularity and regulatory acceptance of cloud computing and ever-improving on-demand processing power, it has become plausible and cost-effective to produce real-time AI-driven analytics. As a result, credit workflows are increasingly being automated. For example, traders are improving their market-making efficiency and profitability by using precise automated request-for-quote (RFQ) services with automated margin optimization.

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The current sell-side trading desk process

Sell-side dealers and buy-side asset managers are rapidly embracing AI applications to price fixed income securities algorithmically in a live trading environment or for end-of-day reconciliation. Overbond analyzed the credit trading process at a typical large European bank and determined how it could be improved by integrating an AI bond pricing model. Under the legacy credit trading process, traders receive RFQs through one of two processes:

1. **Electronic RFQ through a Bloomberg, iQbonds, ION or similar terminal window**
    1) Electronic RFQ windows appear chronologically on top of each other, along with a timer to expiration (usually no more than two minutes).
    2) The trader may check a third-party pricing source to validate the pricing on the RFQ or use their judgment to adjust the price higher or lower.
    3) The trader confirms and submits the price based on the third-party pricing source and/or their judgement of the current market conditions (the trader may also allow the RFQ to expire if they are not interested in quoting)
    4) The client then accepts or rejects the updated price

2. **Manual RFQ through a phone call**
    1) The trader checks the price of the security or similar securities on the Bloomberg terminal (or other third-party pricing service) with the ISIN or Ticker.
    2) The trader also checks the quotes from other dealers on the terminal and possibly other inter-dealer pricing sources.
    3) The trader uses their judgment and knowledge to arrive at a price to be quoted.

** The phone call is prioritized, and RFQs received electronically are put on hold until a quote has been given.**

When the trader receives the RFQ, there are four main ways to price the bond:

- Prices from Bloomberg CBBT, iQbonds, ION or similar
- Fixed yield
- Price range
- A certain spread range

The trader must decide which of these methods should be used case-by-case. RFQs may trade away due to the manual and time-consuming nature of checking fixed yields/prices, certain spread ranges or comparing the bond to similar bonds.

The legacy challenge: low confidence in prices

Traders must price RFQs while meeting workflow objectives and facing constraints:

- The time window within which the trader is supposed to respond to an RFQ is three to five minutes, but one to two minutes is considered ideal
- The current cover (difference between accepted trade price and next best quote) is two to five cents
- The trader must deal with approximately 300 to 700 RFQs per day
- On average, around 30%- 40% of RFQs are responded to with a hit rate of 10%– 12%

The primary problem traders face is the low confidence in prices suggested by Bloomberg CBBT and other third-party applications.

1. **Bloomberg CBBT**
   The price suggested by Bloomberg CBBT is a composite price based on the most relevant executable quotations on Bloomberg's fixed income trading platform. The composite is based on current market activity for the bond, so if the bond is illiquid the CBBT price will not represent the true price. This is especially the case when dealing with high yield bonds or bonds with varying liquidity profiles.

2. **Current third-party pricing provider**
   The pricing methodology is based on a specific pre-defined method. The trader's confidence in this system is low as the pricing methodology is not dynamic, which may lead to the suggested pricing being incorrect. As perceived by the trader, there is a significant difference in cover (the difference between the accepted price and the next best available quote) when the deal is won (five -10 cents).

These factors lead to low confidence in the suggested prices, and traders must constantly spend a great deal of time and effort manually adjusting prices based on prior knowledge and intuition. The major trade-off is thus accuracy versus time, leading to missed deals and direct downward pressure on desk P&L.

The solution: AI-powered bond pricing

AI offers an advantage over traditional statistical methods

AI modeling techniques share many similarities with classic statistical modeling techniques. Statistics provides the building blocks upon which the machine learning that drives AI is built and both use large amounts of data. But statistics is purely mathematical and primarily descriptive with some ability for inference. AI adds additional programming, made possible with modern computing power, to move one step beyond statistics and become predictive.

The goals of the two methods are different. Statisticians start with a set of known assumptions that are given to the model and best explain the expected behavior of the financial outcome in consideration. With AI techniques, the underlying assumptions are unknown and the aim of the model is to determine itself the method that best predicts the outcome in consideration.

Overbond has harnessed the AI advantage for pricing bonds

Corporate and Government Bond Intelligence (COBI)-Pricing was created as part of Overbond's suite of AI algorithms for the fixed income capital markets. It algorithmically finds the optimal indicative new issue bond prices and secondary market bond prices for global investment grade (IG) and high yield (HY) bonds, using machine-learning (ML) algorithms. The ML algorithms analyze millions of data points related to factors such as historical pricing trends between similar bonds and similar issuers, intra-day pricing volatility, trading volume and counterparty composition, company fundamentals, investor sentiment and industry, rating or tenor cluster comparables. Data is aggregated from multiple types of data sources, including:

Transactions data	Transactions occurring in the secondary market and historical issuance spreads
Investment banking data	Fundamentals on corporations, their balance sheet indicators, proprietary data sets treasury groups of the corporations themselves had on file, such as dealer quotations and trade points
Proprietary data	Client book data and direct access to a large community of issuers and institutional investors via established feedback loops

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The solution: Overbond COBI-Pricing Live

Overbond's COBI-Pricing LIVE is a customizable AI pricing engine that assists traders in automating pricing and trading workflows for global investment-grade bonds. It generates prices and liquidity scores for more than 100,000 fixed income instruments and builds curves for more than 10,000 issuers in various real-time liquidity scenarios.

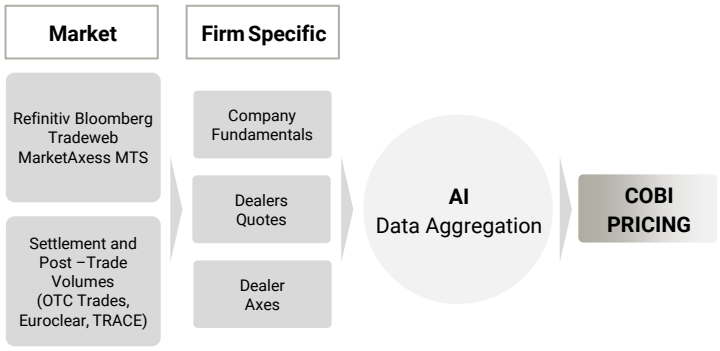
The full interoperability of COBI-Pricing LIVE allows its AI algorithms to ingest, aggregate and process data from live and historical vendor feeds, internal historical records, OTC settlement layer volume records, and now voice transactions. As a result, Overbond AI pricing, liquidity scoring, LIVE trading automation and routing algorithms can now capitalise on all primary and agency trading routes, voice or electronic, across all venues and counterparty types.

COBI-Pricing LIVE has a refresh rate of less than three seconds, enabling sell-side trading desks to fully automate 30% of their RFQs and execute an additional 20% with trader supervision. COBI-Pricing LIVE allows traders to automate trade flow, improve liquidity risk, improve price monitoring and reporting, respond to 80% to 120% more RFQs, maintain an optimal hit ratio and significantly increase desk P&L.

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The solution: the Overbond COBI-Pricing algorithm

Overbond Solution

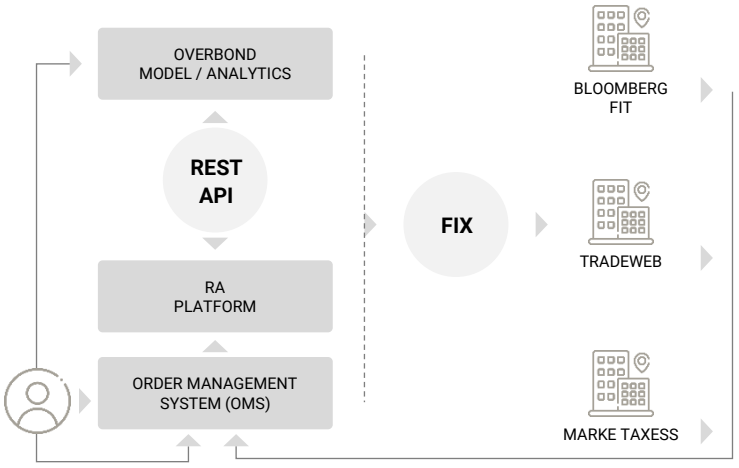


Data Aggregation

Overbond's AI algorithms can ingest, aggregate and process data from multiple data sources to generate prices and liquidity scores for more than 250,000 fixed income instruments and can build credit curves for more than 10,000 issuers.

Interoperable Automated Trading

Overbond is fully interoperable with other systems on the desk so traders can use a single interface for data, analysis, monitoring, execution and automate 50% of their trading.



Data Intake & Pre-processing

The Overbond platform sources fundamental live raw trading data, which are then structured and mapped to the appropriate issuer ID. The data is scrubbed for anomalies and null values, and a set of key input factors are generated based on the raw input. These include, but are not limited to, factors that measure secondary market spread movements, recent issuance pricing levels, nearest neighbor credit ratings and fundamental financial metrics.

These factors are then divided into sector and company-specific factors and are used as inputs to the machine learning models.

Model Training

After the data is processed, the machine learning algorithm trains and applies several models to calculate the output pricing levels. An ensemble learning strategy is used in three phases, meaning multiple models are combined to elevate the overall robustness at each training stage. These models are each trained using subsets of past data that range from one day to a maximum of ten years. Advanced sampling techniques are used to account for illiquid issuers' data gaps to construct yield curves for all tenors and all issuers in the coverage universe.

The solution: COBI-Pricing data intake

Successful data pre-processing is the key stage and a prerequisite for the operation of the COBI-Pricing algorithm. The precision of the algorithm output is critically dependent on the accuracy, timeliness, and relevance of the pre-processed input data. Overbond sources raw data from major data suppliers in the financial sector, including Refinitiv, Ice, The Six Group, EDI, MarketAxess, Tradeweb, Euroclear, Clearstream, DTCC, CDS, S&P Global Market Intelligence, major credit rating agencies, as well as other sources. The data used by the COBI-Pricing algorithms includes the following:

Pre-processed Data	Source	Update Frequency	Relevance
Secondary market transactions data	Refinitiv, Ice, The Six Group, EDI, MarketAxess, Tradeweb	Intraday	Live prices and yields of companies' bonds are used to measure spread movements in the coverage universe.
Settlement layer data per ISIN liquidity profile	Euroclear, Clearstream, DTCC, CDS	Intraday, end-of-day and historical	Settlement layer data, when adjusted and merged with the correct trading time stamp, can augment the view into the true liquidity of the particular ISIN as it contains settled trades by counterparties that were executed over-the-counter (OTC) and otherwise do not appear in other consolidated data feeds.
Nearest neighbour credit per rating and industry sector	Refinitiv, Ice, The Six Group, EDI, MarketAxess, Tradeweb, DBRS, Moody's, Fitch, S&P	Weekly updates, quarterly filing cadence	The issuer's industry sector cluster, past bond issuance and ratings, as well as the issuer rating indicate the company's risk level and benchmarking category. They are used to train the models and to back-test the accuracy of COBI- Pricing output.
Fundamental financial metrics	S&P Global Market Intelligence	Weekly updates, quarterly filing cadence	The company's fundamental financial data is an indicator of its creditworthiness and, by extension, its cost of borrowing across tenors reflected in the bond pricing. Fundamental metrics also indicate the liquidity need of the company, its short-term need to raise financing and its leverage ratios. The financial profile of a company aids with the clustering analysis of companies with similar characteristics.

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The P&L enhancement: margin optimization AI model

The case for margin optimization

With restricted liquidity, a reduced ability to take risk, and increased speed, fixed income market participants are looking for advantages beyond electronification and automation. Over the past couple of years, we have witnessed increased adoption of quantitative investing, AI-driven liquidity risk monitoring techniques, transaction cost optimization and margin optimization.

Margin optimization AI modeling measures the distance to cover on all prior executed transactions and RFQs and minimizes it with respect to trade information at the point of execution. As a result, sell-side market-making desks can double or triple the volume of RFQs they can respond to without incurring negative margin on those trades and increase profitability in an environment where it is becoming increasingly difficult.

The Overbond approach to margin optimization AI model

The Overbond margin optimization model incorporates a variety of factors as inputs to the AI ensemble to arrive at a distance to cover price for each transaction. The model aims to capture and convert various margin optimization measures to one unified, optimized distance to cover price. These factors include but are not limited to the following:

Distance-To-Cover Metric	Relevance
Bid / Ask Spread	Capture the transaction cost of a secondary trade
Tenor	Assess the time remaining before the bond's expiration date
Number of Dealer Competitors	Assess the competitiveness of the market situation Indirect measure of market depth that captures the availability of market making for that bond
Trade Size / Quantity	Assess the volume generated by each trade

The P&L enhancement: margin optimization AI model

Margin is dynamic: training for **bond availability** and risk

The Overbond margin optimization model adjusts to the desk's approach by adapting margin based on the availability of a bond in the market and a market risk tolerance.

Total market capacity

Total market capacity (TMC) is reached when there's not enough of a bond readily available in the market to fill a trade. It's the portion of the outstanding amount of a bond not tied up by buy-and-hold accounts unwilling to trade. Traders are likely to alter their margin for trade sizes approaching TMC.

To train for TMC, learning and prediction are applied to six or more months of historical data to bridge data delays and discern trade size and volume patterns. For instance, by tracking what's added daily, the algorithm uses TRACE data to determine how much inventory dealers add incrementally over several months.

Market risk

To train the margin model to adapt to market risk conditions at the time of the trade, it’s necessary to separate the impact of market conditions on historical margin levels, which entails isolating the effects of individual risk categories reflected in the price of a bond at the time of the historical trades.

The P&L enhancement: margin optimization AI model

CMAC: A breakthrough in bond trading risk analysis

The model uses case-mix adjusted cluster (CMAC) analysis to separate country, sector, issuer and issue-specific risks in bond prices and isolate market conditions through time.

CMAC is used to group similar observations into a group or cluster. So, for instance, all bonds whose prices rise when oil prices fall might be lumped together irrespective of their other characteristics.

But there are hundreds of dimensions that affect bonds. For instance, bonds sensitive to oil prices could include bonds from airlines, manufacturing or trucking, have multiple maturities and be rated differently —the number of clusters of like attributes can quickly become staggering.

Overbond borrowed CMAC from medical research, and it has provided the modeling breakthrough needed to handle the many dimensions of characteristics and risk affecting bonds.

CMAC analysis adjusts for differences in populations and population size before clustering results according to certain common variables. This might mean adjusting for call features or bond tenor before clustering results according to spread movements.

The automated trading AI algorithm uses CMAC analysis to remove pricing movements related to risks at the issuer level and isolate the security-specific risk demonstrated in the pricing movement. The main success of applying CMAC analysis is the ability to isolate those attributable pricing movements versus the broader market purely algorithmically.

When training the model, CMAC is applied to a historical series of post-trade data from the desk to determine if trades occurred in a normal, heightened, or low-risk environment. This allows the model to discern the margin patterns attributable to these markets and adjust according to current market conditions. Margin in the automated trading system becomes dynamic and adapts to current market conditions as the trader would.

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The implementation: project structure

Overbond structured a project implemented for a large European bank into two phases. Overbond first deployed and tested end-of-day data on a smaller universe of ISINs to which ML algorithms were applied to find the best executable secondary market bond price for each bond.

Intra-day pricing was approached as a Phase 2 deliverable of the project because Overbond ML algorithms analyze millions of data points aggregated from multiple data sources and the models are computationally intensive.

a) Phase 1 deliverables (Duration: 1 month)

1) Test web access to Overbond's COBI pricing platform for a predefined list of 100 corporate issuers
2) Delivery of EOD mid-spreads as per the COBI engine output for agreed ISIN universe in the form of a table in a flat csv file
3) Delivery of calculated bond prices based on the COBI output indicative of the mid price
4) Error/difference analysis (COBI Price, BBG I-Spreads, quoted prices, traded prices, covered)

b) Phase 2 deliverables (Duration: 3 months)

1) AI model pricing

Front-end interface developed to incorporate side by side visualization of the output of the fine-tuned and calibrated intra-day COBI pricing model

- Intermediate results delivered with all ISINs/securities considered for intra-day pricing, confidence level of the modeled price and liquidity score for each ISIN
- Input variables, such as aggregated transaction levels, fundamental data, rating and other

2) AI model for margin optimization

- Bond buyer matching module output to serve as an input for the margin optimization
- Modelling trained on a two-year record of the bank's trading book
- Results of AI model for margin optimization minimize the distance-to-cover for every RFQ on top of the best executable price determined by COBI-Pricing model

The implementation: back-testing simulation

A back-test was conducted for a sell-side trading desk that trades in Euro and USD. The trading performance of the Overbond model was compared with the record of the trading desk without AI assistance.

REQUEST_STATUS	ASK	Ratio_ASK(%)	BID	Ratio_BID(%)
ACCEPTED	7,550	2.73%	4,956	2.23%
ACCEPTED_TIED	1	0.00%	2	0.00%
COVERED	7,163	2.59%	4,335	1.95%
COVERED_TIED	27	0.01%	21	0.01%
CANCELLED	69	0.02%	91	0.04%
EXPIRED_CUSTOMER	7,051	2.55%	5,468	2.46%
EXPIRED_DEALER	4,780	1.73%	1,994	0.90%
INPUT_ERROR	2	0.00%	3	0.00%
NO_INTEREST	2	0.00%	1	0.00%
PASSED	25,971	9.38%	15,365	6.90%
PASSED_UNKNOWN	665	0.24%	174	0.08%
REJECTED	178,325	64.38%	155,936	70.06%
TIED_TRADED_AWAY	40	0.01%	32	0.01%
TRADED_AWAY	45,329	16.37%	34,209	15.37%
TOTAL	276,975	100.00	222,587	100.00

	ASK	BID	Total
Accepted & Covered	14,741	9,314	24,055
Non-USD & Non-EUR	(2,556)	(1,611)	(4,167)
Non Senior Unsecured	(974)	(778)	(1,752)
Non-Corporate Bonds	(2,027)	(1,216)	(3,243)
No quotes over last 24 hours	(1,725)	(929)	(2,654)
Price to mid spread > 4× bid/ask to mid spread	(2,232)	(303)	(2,535)
Total Exclusion	(9,514)	(4,837)	(14,351)
Total Accepted & Covered	5,227	4,477	9,704
Accepted Trades	2,657	2,426	5,083
Model Accepted Trades	1,769	1,249	3,018
Model Accepted / Accepted	66.6%	51.5%	59.4%

All RFQ volumes traded in Q2 and Q3 in 2022 were compared, which included 7,551 accepted (and accepted but tied) RFQs and 7,190 covered (and covered but tied) RFQs on both the bid and ask sides. The trades were filtered to include only 9,704 trades that involved senior unsecured corporate bonds, of which the trading desk accepted 5,083 and the model accepted 3,018.

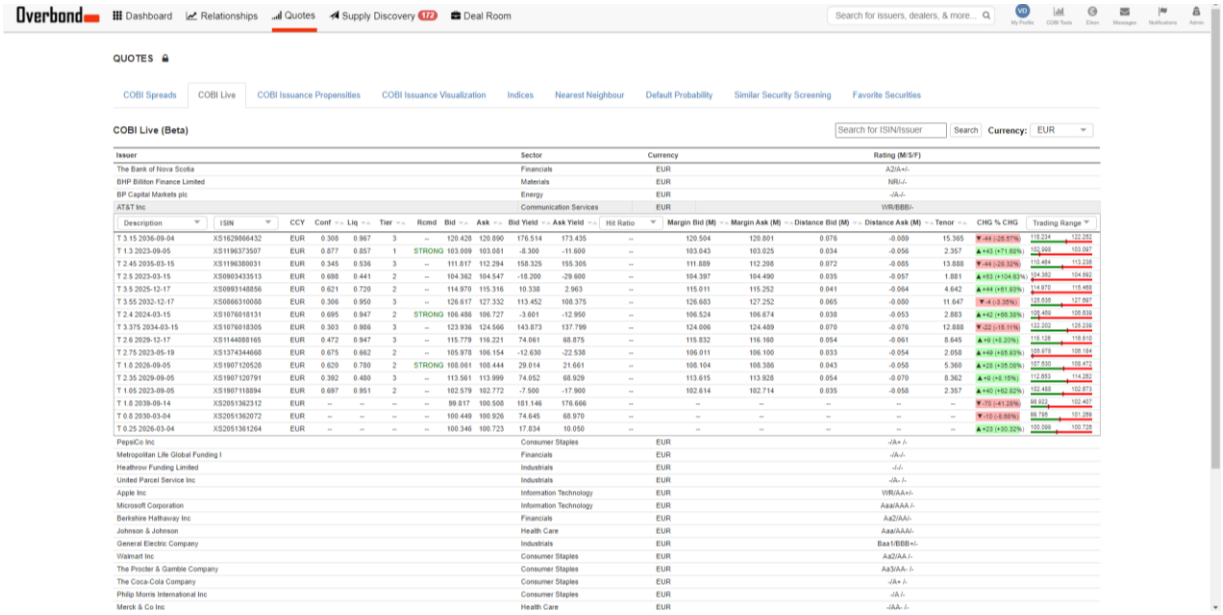
Tier 1 / Hit Ratio	10%	20%	30%	40%	50%	60%	70%
25%	235,854	483,091	732,188	983,767	1,238,473	1,492,263	1,742,753
50%	255,477	511,996	767,866	1,020,737	1,277,461	1,535,950	1,790,523
75%	274,112	540,097	801,712	1,058,572	1,319,876	1,578,892	1,838,231
Q2 - Q3 Average	255,858	512,208	767,091	1,022,055	1,278,889	1,535,989	1,791,703

The margin optimization model was optimized for maximum profit capture or minimum distance-to-cover, so the prices produced by the model would be expected to be closer to cover than those quoted by the trader. The cost of margin for each trade was measured as the distance to cover (in cents) multiplied by the size of the trade (in Euros).

The model additionally looks at the rejected RFQ's and based on the proportion falling into the Tier 1 category (the most liquid bonds) then performs a scenario analysis to determine the potential opportunistic P&L capture. The above table shows the scenario analysis for actual Q2 - Q3 2022 data, along with 3 additional scenarios to highlight the potential variance for portfolios with differing numbers of Tier 1 categorized bonds. Assuming a mid-range 40% increase in hit rate for the book in question, the trader would expect to see an opportunistic annualized P&L gain of over EUR 2 million.

The implementation: the user interface

Overbond normally outputs by API but results can also be displayed on the Overbond user interface. The figure below shows how the results would appear to a trader using the Overbond UI front-end platform.



The columns “Margin Bid (M)” and “Margin Ask (M)” are composed of the “distance to Bid (M)” and “distance to Ask (M)” respectively, on top of the COBI priced “Bid” and “Ask” quotes for each bond.

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The business impact

Overbond has created positive business impact for clients around the globe, including sell-side institutions with significant trading volumes (200-500 RFQs+ a day per trader). We work with clients' innovation groups to actively explore the application of new technologies that can serve as the catalyst for trading automation and improved risk management, trade flow, pre-trade and post-trade analytics. These technologies have direct business benefits.

AI Application	Business Objectives	Key Benefits of Overbond's AI Analytics Suite
Intelligent automation and enhanced decision-making	• Automate trade flow and margin optimization • Preserve optimal hit • ratio • Significantly increase desk P&L	Trading desks can create a desk-specific proprietary consolidated data tape by aggregating historical and live data from multiple sources, Trading desks can fully automate 30% of their RFQs and execute an additional 20% with trader supervision. Trading desks can respond to 80% to 120% more RFQs. Bond trading execution desk revenue can be grown significantly. COBI-Pricing enables the creation of various curve visualizations and front-end trade analytics tools that are natively integrated with trader's desktop. Dealers can boost their RFQ hit ratio with Overbond's margin optimization model add-on. COBI-Pricing liquidity modeling allows desks to determine the liquidity of little-traded bonds, construct liquidity profiles for holdings and monitor liquidity. Traders can predict investor behaviour with buy/sell indicators. Traders can predict bond issuance probabilities.

Implementation considerations

Institutions considering implementing AI predictive analytics and big-data transformation projects can accelerate the process using externally calibrated models and market signals. Below are several key considerations and questions for executives in charge of their firm's AI roadmap:

- What is the current state of our fixed income in-house data?
- What are our data science and engineering capabilities?
- Are we building AI capabilities to grow revenue or cut cost?
- How can we redefine the boundaries of our data universe or identify alternative data sources necessary to feed the AI engine?
- Given that the AI learning curve is steep, where do we begin?
- How do we rapidly create and execute AI proof of concept use cases?
- What are the key success factors for our AI roadmap?

Custom AI Services

Overbond works with clients to identify and recommend practical AI analytics use cases that are aligned with the strategic goals of the financial institution.

We assess your current AI capabilities and design a roadmap to help you realize value from AI applications. We manage cross-channel data flows across multiple systems and enable custom front-end visualizations.

Proven Methodology

With our targeted approach and implementation methodology, we quickly demonstrate the value of AI analytics to test use cases. This enables clients to plan and implement change management and facilitates stakeholder buy-in.

Operational Acceleration

We help clients build and deploy custom AI solutions to deliver proprietary analytics to achieve tangible business outcomes. Our experience combines calibrated models, design patterns, engineering and data science best practices to accelerate value realization and reduce implementation risk.

AI Analytics-as-a-Service

Overbond helps customers design and oversee mechanisms to harness AI to optimize and improve existing fixed income credit valuation, issuance and pricing prediction and pre-trade opportunity monitoring. Our team of world-class data scientists and engineers manage an iterative implementation approach from current state assessment to operational handover.

About Overbond

Overbond is a developer of process-redefining, AI-driven data and analytics and trade automation solutions for the global fixed income markets. Overbond performs market surveillance, data aggregation and normalization, and deep AI quantitative observation on more than 250,000 corporate bonds and fixed income ETFs. Applying proprietary artificial intelligence to pricing, curve visualization, market liquidity, issuance propensity, new issuance spreads, default risk and automated reporting, Overbond enables trade automation and enhances trade performance and portfolio returns. Clients of Toronto-based Overbond include global investment banks, broker-dealers, institutional investors, corporations and governments across the Americas, Europe and Asia. For more information, please visit www.overbond.com.

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