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Systematic Credit Trading

The European corporate bond market

Postgraduate Diploma Thesis in
Quantitative Finance

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Abstract

The thesis analyses the European *corporate bond* market, highlighting its competitive landscape, regulatory framework, and future prospects. The core of the analysis is the development, in *Python* code, of a decision tree for the automatic response to *Request For Quote (RFQ)* on European corporate bonds, illustrating its functioning, results, critical issues, and *hedging* solutions.

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Introduction

Financial markets, originally conceived as physical venues where commercial agreements and securities transactions were negotiated and concluded, have undergone a radical transformation in recent decades. The image of the traditional *trading* floor, characterised by frenetic exchanges and loud open outcry, the so-called "*grida*", now belongs to the past. The premises of historic exchanges retain mostly symbolic value, while the vast majority of transactions take place electronically. Automation and the increasing use of algorithms have reshaped the role of the *trader*, who can no longer rely solely on financial expertise but must integrate statistical and computational skills.

In this context, this thesis analyses the changes affecting the European *corporate bond* market, namely debt securities issued by companies based in Europe, which have become an increasingly relevant source of funding as an alternative to bank financing.

The first chapter describes the structure of the market, presenting the main characteristics of the *asset class* and distinguishing between the primary and secondary markets.

The second chapter reconstructs the historical evolution of trading in European *corporate bonds*, focusing on operating practices, regulatory developments, and future challenges.

The third chapter is devoted to the role of algorithmic *trading*, analysing its advantages and risks, the main types employed, and the role of *Systematic Credit Trading*, which integrates algorithms, *Portfolio Trading*, and *ETFs*.

Finally, the fourth chapter presents a practical case study: the construction, in *Python*, of an algorithm based on a decision-tree model designed to provide quotations on the securities analysed, illustrating its functioning, results, *hedging* strategies, and critical issues.

1. European Corporate Bonds

1.1. Introduction

In this chapter, the European *corporate bond* market is analysed, namely the debt securities issued by companies to raise financial resources.

"*Bonds are debt instruments that represent the cash flows paid over a specific period of time*"[1]. They have a nominal value and generate a return, paid to the holder either as periodic coupons or as a single payment at maturity (*Zero Coupon Bond*[2]).

The main features of *bonds* include:

- *Type of issuer*: Government, Corporate, Supranational entities
- *Maturity*: the date on which the repayment will occur
- *Type of coupon*: fixed, floating, zero-coupon
- *Issue price*: equal to the redemption price (or "*at par*") or lower than the redemption price (or "*below par*")
- *Credit rating*: a measure of creditworthiness, determined by specialised agencies
- *Possible covenants*

Beyond the elements previously listed, *corporate bonds* are also characterised by their degree of *seniority*, which reflects their hierarchical position within the issuer's debt structure, determining the order of repayment in the event of default and, consequently, the associated level of risk[3].

Corporate bonds are classified into three main categories[4]:

- *Investment Grade Bonds*: debt securities issued by companies with high credit quality; therefore, they offer lower yields in exchange for a reduced default risk.
- *High–Yield Bonds* (or "*Junk Bonds*"): debt securities issued by companies with a credit rating below *BBB-*; therefore, they offer higher yields in exchange for a greater default risk.
- *Distressed Debt*: debt securities issued by companies in severe financial distress, if not already in a state of insolvency. The yields offered are substantial, as is the risk that these instruments may not be able to return the invested capital.

[1] "Fixed-Income Securities and Derivatives Handbook" – Moorad Choudhry, p.3

[2] A bond issued at a price below its redemption value; assuming it is held to maturity, the difference between the two amounts represents the interest paid to the holder.

[3] Ref. "https://economictimes.indiatimes.com/definition/seniority?from=mdr"

[4] "Fixed-Income Securities and Derivatives Handbook" – Moorad Choudhry, Ref. p.144

With regard to the risks inherent in investing in *corporate bonds*, it is possible to distinguish:

- *Credit Risk*: the risk that the issuer may fail to pay interest or repay the principal within the agreed time frame. The issuer's *credit risk*, monitored by *rating* agencies, refers both to delayed payments and to actual failure to repay.
- *Interest Rate Risk*: the risk that fluctuations in interest rates may negatively affect the value of the *bond*. This risk is negligible when the intention is to hold the bond to maturity, but must be carefully considered in case of liquidity needs, where selling the bond could generate a loss.
- *Liquidity Risk*: the risk that, in the event of a liquidity requirement, one may not be able to find a counterparty in the market to whom the bond can be sold.

There are also more specific and less common risks, such as the risk that a clause associated with that particular bond may be exercised, resulting, for example, in early redemption. Generally, *corporate bonds* are considered riskier than government securities, which is why they offer a higher yield.

1.2. Market

"*Except for certain cases, fixed-income securities are traded in Over The Counter (OTC) dealer-oriented markets, which differ significantly from equity markets*"[5]. Unlike the equity market, which is characterised by a strong presence of regulated exchanges, the bond market – and in particular the *corporate bond* segment – is characterised by a large volume of *Over The Counter* (*OTC*) trading between institutional participants. Due to this market structure, a lower level of transparency is observed compared to the equity market; specifically, liquidity is uneven, price formation is less efficient, and publicly available information is more limited.

[5] "*A Survey of the Microstructure of Fixed-Income Markets*" – Hendrik Bessembinder, Chester Spat & Kumar Venkataraman, p. 1

The size of the main components of the European bond market over the period 2015–2024, expressed in billions of euros, is shown in *Figure 1.1*:

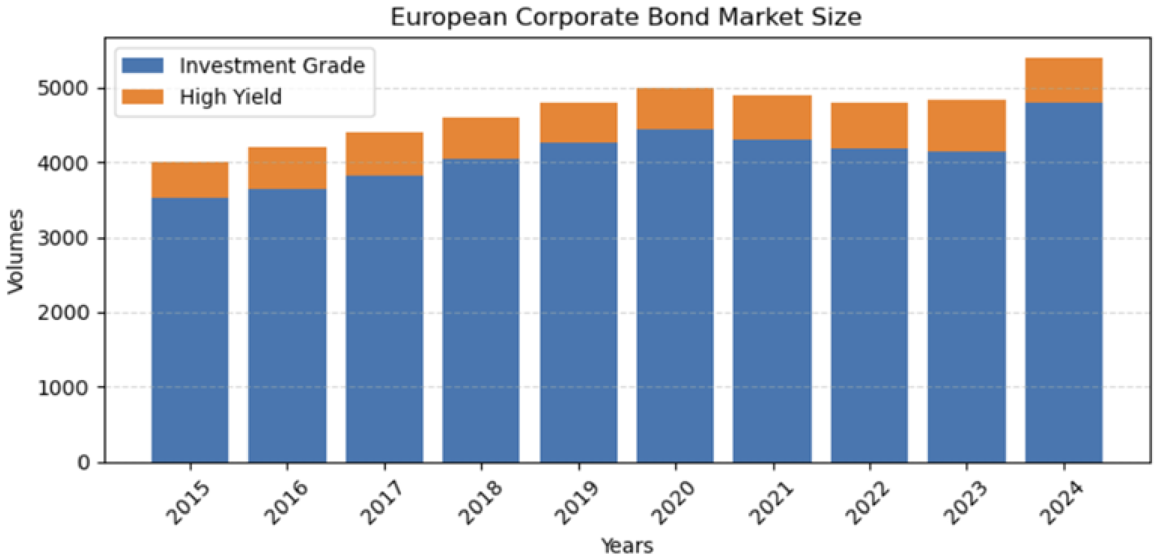

Figure 1.1

It can be observed that *Investment Grade* corporate bonds hold the largest market share, displaying an overall upward trend except for the period 2020–2023. At the end of the period, trading volume reaches *4,803.33* billion euros, with a total growth of *36%*. *High Yield* corporate bonds, instead, show smaller volumes, reaching *593.67* billion euros, with total growth of *24%*. In 2024, the overall volume of European corporate bonds stands at *5,397.00* billion euros, marking a *35%* increase over the analysed period.

Primary market

The primary market is the set of processes through which companies issue new bonds in order to raise financial resources from investors. Unlike equity issuance, which takes place through *IPOs* on regulated markets, *corporate bonds* are issued mainly on *Over The Counter* markets through transactions typically managed by an *Underwriting Syndicate*, namely a "*syndicate of banks, investment firms or brokerage companies whose purpose is to allocate securities on behalf of the issuing company*"[6].

Such issuance may occur through a public process, managed by a pool of *lead managers* and accompanied by the publication of a regulated prospectus, or through a private placement aimed at institutional investors that subscribe the entire issuance — a method generally more time-efficient.

In the case of a private placement, the *Underwriting Syndicate* acts as a subscriber (or

[6]https://www.bancobpm.it/magazine/glossario/consorzio-di-collocamento/

underwriter), purchasing the issuer's entire bond amount at a predetermined price (*offering price*) and reselling it to investors at a higher price (*reoffering price*). In this case, the Underwriting Syndicate responsible for the subscription and subsequent placement of the bonds assumes the risk related to potential difficulties in the placement process, compensated by the spread between the two prices[7].

The new-issuance process of *corporate bonds* through an *Underwriting Syndicate* does not exhibit the same level of transparency typical of *European Government Bond* auctions, and is instead characterised by a high degree of discretion on the part of the Syndicate itself.

Secondary market

"*In the secondary market for fixed-income securities, trading is dominated by institutional investors such as pension funds, mutual funds, hedge funds, insurance companies and sovereign wealth funds*[8]".

Secondary-market trading of *corporate bonds* typically takes place through *Request For Quote (RFQ)* mechanisms, meaning requests submitted by investors (*Buy side*) to one or more *dealers* (*Sell Side*) in order to obtain a quotation for one or more securities, either for purchase or sale[9]. Once the quotation is received, the end-client may accept the proposed price, often providing feedback on the aggressiveness of the offer based on its own assessment; if the price is accepted, the *dealer* proceeds with the execution of the order.

These trades are characterised by reduced liquidity and fragmentation, as each bond issuance possesses unique features. Pre-trade transparency is also limited, since the *screens* on which dealers publish their quotes are accessible only to professional operators and may be adjusted until the moment the transaction is finalised.

In the European context, regulation has introduced, in recent years, several obligations and measures aimed at increasing transparency. This is fostering a progressive electronification of *corporate bond* markets and, starting from early 2026, transparency will be further strengthened with the introduction of the *Consolidated Tape*, similar to the U.S. *TRACE* platform.

Despite these developments, informational asymmetries persist, penalising smaller operators[10].

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[7] Ref. "*A Survey of the Microstructure of Fixed-Income Markets*" – Hendrik Bessembinder, Chester Spat & Kumar Venkataraman, p.28

[8] "A Survey of the Microstructure of Fixed-Income Markets" – Hendrik Bessembinder, Chester Spat & Kumar Venkataraman, p.7

[9] "BondVision US Dealing Rules" – EURONEXT, p. 5

[10] "*A Survey of the Microstructure of Fixed-Income Markets*" – Hendrik Bessembinder, Chester Spat & Kumar Venkataraman, pp. 29–30

1.3. Functionality

Economic–financial system

The financial system of a country can be classified into one of the following two models[11]:

- *Bank-Oriented System*: a financial system in which the main source of corporate financing lies in bank lending. Generally, European countries and Japan fall into this category.
- *Market-Oriented System*: a financial system in which the main source of corporate financing lies in the capital markets, through the issuance of equity and debt securities. Typically, Anglo-Saxon countries belong to this category. "Bonds are the basic ingredient of the U.S. capital market, which is the backbone of the U.S. economy"[12].

Through the issuance of debt securities, companies can access a source of financing without the risk of altering their ownership structure, as would be the case with the issuance of new shares.

Role in asset allocation

Corporate bonds play a primary role in the portfolio choices of both institutional and retail investors. Compared to equity securities, they exhibit lower volatility and more predictable coupon payments, unlike dividends, which are uncertain in both frequency and amount. Their inclusion in a portfolio allows access to instruments with different risk levels, generally lower than those of equities, thus contributing to an improvement in the overall risk/return profile[13].

In recent years, marked by strong interest-rate instability, corporate bonds have shown lower volatility compared to government securities, which are considered risk-free[14]. This outcome is made possible by the combination of shorter duration—particularly in high-yield securities—and generally lower volatility of credit spreads[15] compared to the risk-free component.

From an asset-allocation perspective, these characteristics make corporate bonds effective instruments both for increasing diversification and for meeting long-term capital-preservation objectives, in line with the needs of specialized institutional investors such as insurance companies and pension funds[16].

[11] *"BANK-BASED OR MARKET-BASED FINANCIAL SYSTEMS: WHICH IS BETTER?"* – Ross Levine, pp. 1–5

[12] *"Fixed-Income Securities and Derivatives Handbook"* – Moorad Choudhry, p. 1

[13] See *"Strategic Asset Allocation; The Role of Corporate Bond Indices?"* – Antonios Sangvinatsos

[14] Refers to economically solid countries

[15] Difference between the yield of a corporate bond and that of a government bond of equal maturity and currency.

[16] *"Fixed Income Strategy: A Practitioner's Guide to Riding the Curve"* – Tamara Mast Henderson, p. 151

2. Evolution of the sector

2.1. Origins and functioning: OTC and bilateral trading

The history of the European corporate bond market differs significantly from that of the United States. Due to divergences between bank-oriented and market-oriented systems, while in the United States the first corporate bond was issued in the first half of the nineteenth century, in Europe it was necessary to wait until 1963 to observe the first issuance. In that year, the Italian company *Autostrade Concessioni e Costruzioni S.p.A.* placed a U.S.-dollar-denominated bond on the London market, later listed on the Luxembourg Stock Exchange[1].

This issuance marked, *de facto*, the birth of the European corporate bond market, which initially developed in the absence of specific regulation and was characterized by an entirely *OTC* trading structure, reserved for institutional investors. Transactions took place through the intermediation of dealers, who facilitated the matching of supply and demand through bilateral and relationship-based interactions. Within this context, an operational method emerged which, although not yet formalized, anticipated what is now known as the *Request For Quote (RFQ)* mechanism: the institutional investor contacted multiple dealers by telephone to obtain quotations, with the aim of selecting the most favourable proposal[2].

The first self-regulatory intervention came in 1969 with the foundation, in Zurich, of the *Association of International Bond Dealers (AIBD)*, which introduced a set of rules and recommendations designed to govern practices in the emerging European bond market[3]. In 1989, the same association launched *TRAX*, the first European electronic system for matching and confirming transactions in the *OTC* corporate bond market. During these years, the RFQ model was integrated in electronic form[4].

Until the late 1990s, the development of the European corporate bond market remained limited. At the end of 1999, corporate bonds represented approximately *3%* of the total liabilities of European firms, compared with values around *10%* recorded in the United States and Japan. However, by the end of 2001, this share had more than doubled, reaching *6.9%*[5].

[1] `https://web.archive.org/web/20090615051803/http://www.autostrade.it/en/chi-siamo/storia_index.html?initPos=1`

[2] See *"Drivers of Corporate Bond Market Liquidity in the European Union"* – European Commission, p. 83

[3] https://www.icmagroup.org/About-ICMA/history/

[4] See *"Remaking the corporate bond market"* – ICMA, p. 28

[5] See *"Euro Area Corporate Debt Securities Market: first empirical evidence"* – Gabe de Bondt, p. 15

As shown in *Figure 2.1*, the evolution of the total stock of bonds issued by European non-financial corporations (*NFCs*) over the period 31/03/1999–31/03/2025 is reported[6]:

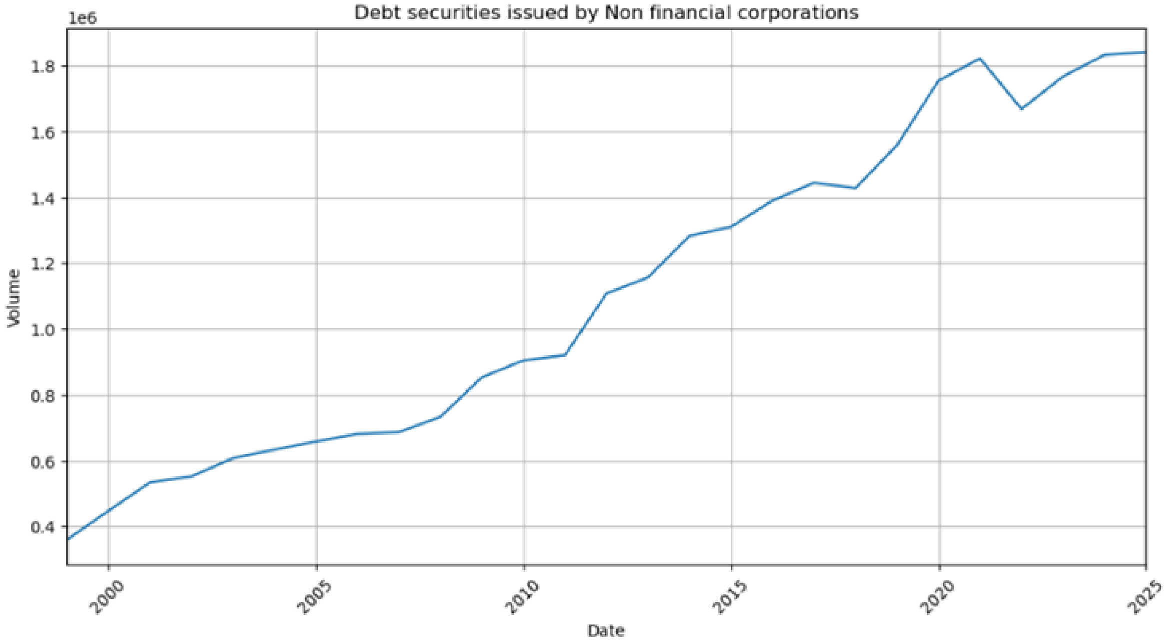


Figure 2.1

Until 2008, the growth of the outstanding bond stock was modest yet steady, whereas beginning in the year following the financial crisis, a marked increase can be observed. A sharp decrease is also evident in the fourth quarter of 2021, followed by a recovery in the third quarter of 2022.

As highlighted in *Figure 2.2*, firms have gradually identified bond issuance as a valid alternative source to bank financing, reducing their exposures toward the traditional credit channel, while still relying on it to a significant extent.

[6] `https://data.ecb.europa.eu/data/datasets/QSA/QSA.Q.N.I9.W0.S11.S1.N.L.LE.F3.T._Z.XDC._T.S.V.N._T`

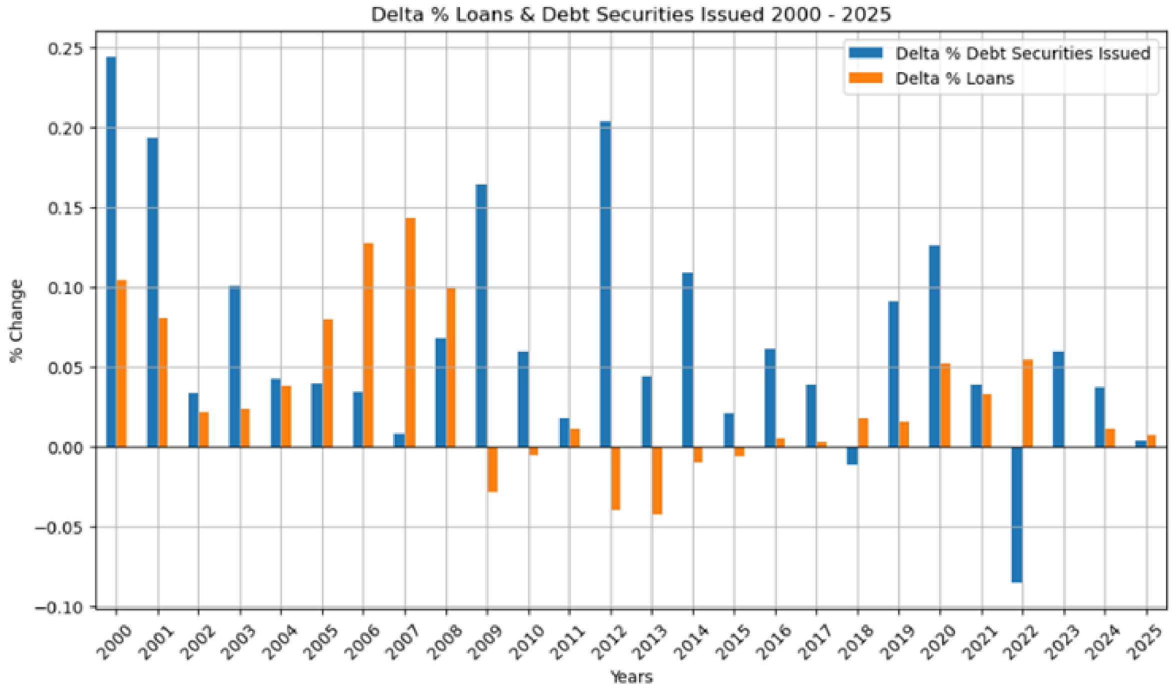


Figure 2.2: Personal reworking based on ECB data[7].

2.2. New regulation and technologies

Before the 2008 financial crisis, the *corporate bond* market had a profoundly different structure: dealers were not limited to acting as intermediaries, but took proprietary positions with the aim of stimulating liquidity and increasing profit margins.

"Since the financial crisis, the role of dealers in the bond market has changed, with dealers reducing their exposure and acting more frequently as mere intermediaries"[8].

The rules introduced after the crisis significantly restricted the operations of financial intermediaries, subjecting them to stricter capital and liquidity requirements, with the objective of strengthening the overall stability of the system.

One of the most significant regulatory interventions of the post-2008 period is represented by the *Basel III* framework and the *CRD IV* directive. The reform introduced tighter capital requirements, including several capital *buffers*, significantly increasing the cost of operations involving risky financial instruments. The regulatory evolution particularly affected *market making* activities, reducing intermediaries' ability to hold securities on their balance sheets and contributing to a contraction in liquidity in market segments that are less deep in terms of trading volume.

In 2018, the regulatory package composed of *MiFID II* and *MiFIR* came into force, introducing a series of *pre-* and *post-trade* transparency obligations for corporate bonds, requiring the publication of quoted prices and details of completed trans-

[7]Source: `https://data.ecb.europa.eu/data/datasets/BSI/BSI.M.U2.N.A.A20.A.1.U2.2240.Z01.E`

[8]See *"Analysis of European Corporate Bond Markets"* – European Commission, p. 45

actions, including those executed *OTC*. These rules increased the transparency of operations but also raised compliance costs, further limiting dealers' ability to take direct positions.

With the entry into force of *MiFID II*, the supervisory authority introduced a formal classification of execution venues, categorising them into four operational types[9]: *regulated markets (RM)*, *multilateral trading facilities (MTF)*, i.e., private platforms that allow the trading of financial instruments without listing or disclosure obligations[10], *organised trading facilities (OTF)*, reserved for non-equity instruments and lacking an automatic order-matching mechanism[11], and *systematic internalisers (SI)*, intermediaries that regularly execute client orders outside regulated markets[12].

In line with this regulatory environment, there has been progressive development of electronic trading platforms, initially based on *single-dealer* models and later evolving into *multi-dealer* systems. Today, according to estimates, platforms such as *Bloomberg*, *MarketAxess* and *Tradeweb* account for over *40%* of total trading in European *Investment Grade* corporate bonds[13].

This gradual electronification of the market has developed around two main operational models: the *RFQ* mechanism, used in the *dealer-to-client* segment, and the *Central Limit Order Book (CLOB)*, which resembles a traditional exchange-based structure. The adoption of these models has fostered the introduction of automated *market making* mechanisms, particularly in more liquid markets, enabling the automatic generation of responses to quote requests. The benefits include faster execution, reduced transaction costs, improved informational transparency, and easier compliance with regulatory obligations[14].

[9] See *"Analysis of European Corporate Bond Markets"* – European Commission, p. 77

[10] See `https://www.borsaitaliana.it/borsa/glossario/multilateral-trading-facilities.html`

[11] See *"Mercati degli strumenti finanziari"* – Government Act No. 413, p. 2

[12] See `https://www.borsaitaliana.it/borsa/glossario/internalizzatore-sistematico.html`

[13] See *"Drivers of Corporate Bond Market Liquidity in the EU"* – European Commission, p. 77

[14] See *"Beyond the Inflection Point: The Future of Credit Trading"* – Flow Traders, p. 6

2.3. Financial crises and the COVID-19 pandemic

Due to the COVID-19 pandemic, European markets experienced a severe downturn. In particular, *Figure 2.3* shows a vertical decline in the index of European *Investment Grade* corporate bonds:

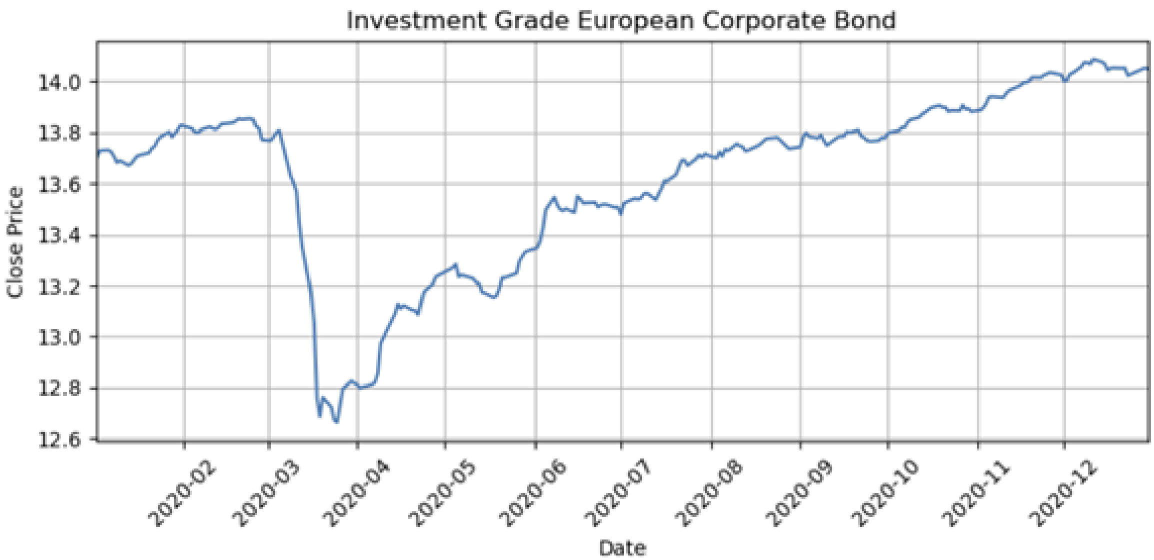


Figure 2.3: Performance of the European *Investment Grade* index[15].

One of the main drivers of this sharp downturn was the rapid deterioration in the liquidity of the secondary market for European corporate bonds. Under normal conditions, dealers are able to absorb selling pressure. However, in March 2020 this did not occur due to constraints imposed by the supervisory authority[16]. The ECB reported that *"the investment fund sector was hit by large investor redemptions and therefore had to cope with forced liquidations of its positions"*.

In response to these issues, on 18 March 2020 the ECB launched the *Pandemic Emergency Purchase Programme (PEPP)*, aimed at restoring liquidity in European bond markets[17]. The programme included secondary-market purchases of European *Investment Grade* corporate bonds to improve price formation and re-establish adequate liquidity levels in the most affected segments. As shown in the previous chart, the intervention proved successful, reversing the downward trend within weeks of the announcement.

The consequences of the COVID-19 crisis provided a real-world stress test for electronic *market making*. As highlighted in ICMA's May 2020 report, during the peak of the crisis most European electronic trading systems were switched off, with a return

[15] Source:https://www.investing.com/funds/blackrock-euro-investment-grade-coi-chart.

[16] See "https://www.ecb.europa.eu/press/research-publications/resbull/2021/html/ecb.rb211124~d9e3f578d2.en.html"

[17] See "https://www.ecb.europa.eu/press/economic-bulletin/articles/2020/html/ecb.ebart202007_02~b27e8089c5.en.html"

to traditional trading methods. This decision did not stem from technological limitations, but from the extreme volatility and illiquidity of the market, which made it too risky for dealers to provide electronic quotes.

2.4. Current scenario

In recent years, electronic trading of European corporate bonds has increased dramatically, with around *45%* of total volumes executed through automated workflows. A survey conducted by *Flow Traders* shows that, following the COVID-19 pandemic, this trend has further accelerated: *64%* of respondents reported having increased their use of electronic *RFQ*[18]. *Figure 2.4* shows the degree of electronification across major financial markets:

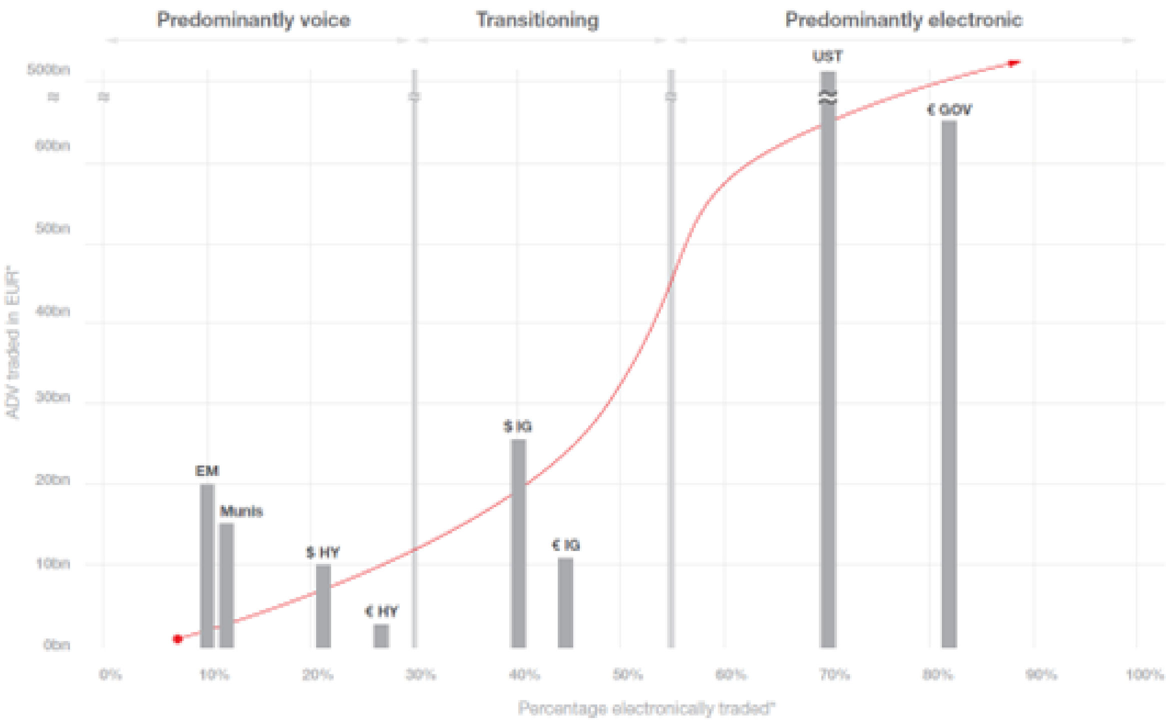


Figure 2.4[19]

It can be observed that the European market for *Investment Grade corporate bonds* is undergoing a full transition, confirming the shift away from the traditional model based on bilateral and telephone-based relationships, in favour of automated workflows. Technological progress and the increasing demands of investors have supported the entry of specialised operators in electronic trading. Among the main players are *Jane Street*, *Flow Traders*, *Tradeweb* and *MarketAxess*, platforms that offer electronic / algorithmic trading solutions oriented towards *Best Execution*, defined as the best possible execution of client orders, taking into account: price, total costs,

[18]See *"Beyond the Inflection Point: The Future of Credit Trading"* – Flow Traders, p. 3

[19]Source: *"Beyond the Inflection Point: The Future of Credit Trading"* – Flow Traders, p. 8.

speed, likelihood of execution and settlement, size, and nature of the order[20]. Investor attention, therefore, does not focus solely on obtaining the best price, but extends to a broader set of factors related to overall execution quality. Ineffective execution may result in significant consequences for the intermediary, such as *slippage*[21], partial or failed executions, settlement issues and potential reputational effects.

Since the effectiveness of *execution* strategies depends on the availability of reliable data, it is appropriate to mention the role played by *EDIPHY*, a global provider of technological solutions that has recently been selected by *ESMA* as the first *Consolidated Tape Provider* for bonds[22], namely an entity tasked with collecting, consolidating and distributing in real time the *post-trade* data from all trading venues. This contributes to the creation of a centralised European system aimed at ensuring transaction transparency, including for bond markets, similar to the U.S. *TRACE* system.

In an environment that is constantly evolving, characterised by increasingly complex *RFQs* and rising competitiveness, the effectiveness of electronic trading alone is continually being challenged. It therefore becomes necessary to implement a system of algorithms capable of addressing such demands. In this context, the concept of *Systematic Credit Trading* is introduced, which is articulated into three pillars:

- *Algotrading*
- *Portfolio trading*
- *ETF*

The automatic order-execution activity that characterises *algotrading* makes it possible to manage *RFQs* relating to large bond portfolios with greater speed and efficiency. The market risk arising from such operations is managed through the trading of bond *baskets*, represented by ETFs.

[20]See *"ORDER EXECUTION AND TRANSMISSION STRATEGY"*, Mediobanca, p.3

[21]Negative difference between the *pre-trade* estimated price and the executed price

[22]https://www.esma.europa.eu/press-news/esma-news/esma-selects-ediphy-fairct-become-first-consolidated-tape-provider-bonds

The reasons that justify the importance of adopting increasingly efficient operating methods emerge from the analysis of *Figure 2.5*, which shows the evolution of *portfolio trading* volumes between the first quarter of 2020 and the first quarter of 2025:

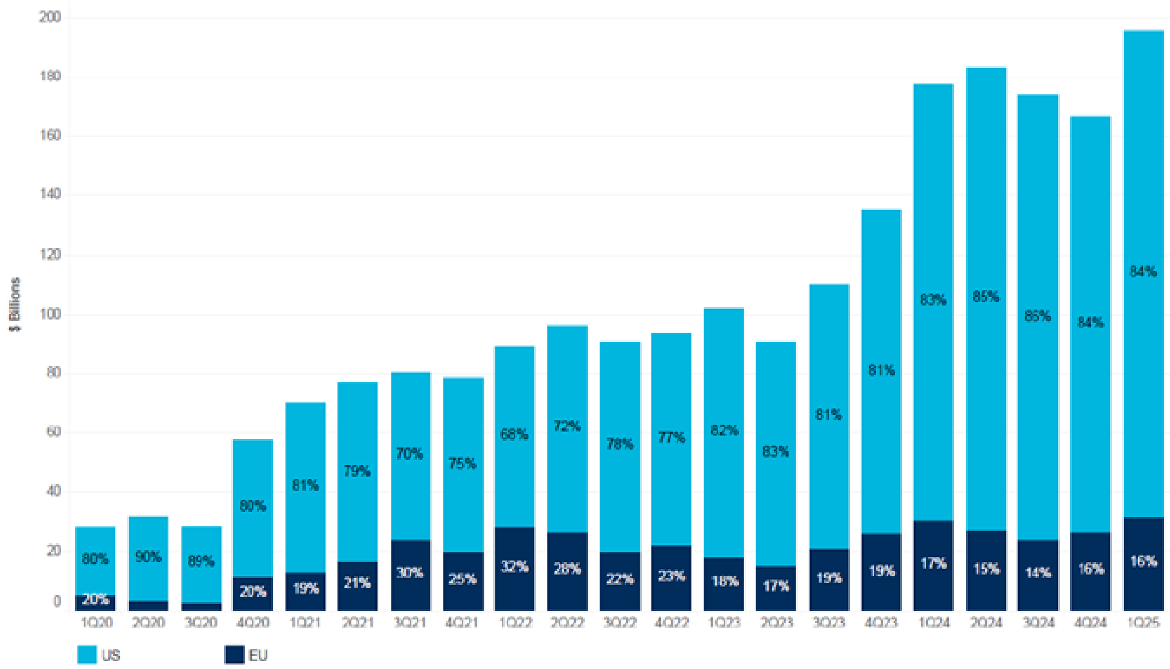


Figure 2.5: Corporate bond trading volumes [23].

As can be seen from the chart, European market volumes show slow but steady growth, in contrast with the more pronounced evolution of the U.S. market.

With *Systematic Credit Trading*, a new business model has emerged, making it necessary to adopt increasingly advanced technological infrastructures and specialised expertise, particularly in trading and *hedging* practices, in order to preserve competitiveness relative to the main global operators.

[23]Source: see *"European Portfolio Update"* – Tradeweb, p. 2.

3. The role of algorithmic trading

After analysing the microstructure of the European *corporate bond* market (*Chapter 1*) and describing its evolution and regulatory framework (*Chapter 2*), this chapter explores the role of algorithmic trading within this market.

In particular, the reasons behind its adoption, the main operational challenges, and the different algorithmic structures employed will be examined.

3.1. Reasons for adoption

Financial markets are undergoing profound transformation. In particular, the European *corporate bond* sector is gradually shifting from predominantly phone-based/discretionary activity to systematic activity. The motivations for this shift—which can be described as historical—lie in the various advantages offered by this type of operation[1]:

- *Speed*

  With the evolution of the credit market, particularly the European one, increasingly significant difficulties have emerged in manually providing a price for every *RFQ* received. Each request not satisfied translates into a missed profit opportunity for the *dealer* and a potential deterioration of the client relationship. The adoption of a systematic operational model makes it possible to mitigate these issues: once the operational parameters are defined, the system is able to automatically process requests, ensuring prompt responses to *RFQs*, even in the presence of high volumes.

- *Efficiency*

  The use of algorithmic structures has a significant impact on reducing human error, while simultaneously improving the precision and overall efficiency of operations. Moreover, automation allows resources to be optimised, both economically and in terms of time, thanks to the simplification of *front*, *middle*, and *back-office* activities. From an economic perspective, the most significant effects are reflected in the generation of higher *revenues* and a reduction in staffing needs (unless redeployed), as well as in the lowering of commissions charged to clients, promoting a more competitive operating model.

[1] Ref.https://fastercapital.com/topics/the-advantages-of-electronic-trading-for-market-maker-spreads.html

- *Transparency*

  Platforms enabling the systematic execution of transactions facilitate compliance with an increasingly complex regulatory framework. Furthermore, such tools support the orderly collection of data and ensure greater informational transparency, in line with the provisions introduced by the recent *Consolidated Tape*.

3.2. Operational challenges

At the regulatory level, the main European references in the field of algorithmic trading are represented by the *MiFIR* Regulation and *Article 17* of the *MiFID II* Directive. The former concerns the Markets in Financial Instruments Regulation (MiFIR), whose objective is to make European financial markets more transparent, efficient, and secure[2].

The Regulation governs several operational areas:

- *Transparency*

  Trading venues are required to publish pre- and post-trade quotation prices and volumes; moreover, the collected data must be made available to the public free of charge after 15 minutes from publication.

- *Rules on transactions*

  Investment firms must report completed transactions to supervisory authorities within precise deadlines, keeping the data for a period of five years (*Post Trade Transparency*). Likewise, trading venues must retain, for the same time period, "*the data of the financial instruments advertised through their systems*". Derivative instruments must be traded on regulated markets to ensure market stability, and the related transactions must be cleared promptly through central counterparties operating in a "*transparent and non-discriminatory*" manner.

The *MiFIR* Regulation assigns *ESMA* the task of preparing technical standards—particularly for derivative instruments and central counterparties—as well as monitoring activities related to financial instruments circulating within the European Union.

[2]Ref. "`https://eur-lex.europa.eu/IT/legal-content/summary/markets-in-financial-instruments-regulation-mifir.html`"

Article 17 of *MiFID II* regulates, in six points, the algorithmic trading activity of firms that use this operational model, summarised as follows[3]:

1. Systems must be resilient and capable of preventing malfunctions, ensuring that their operation does not compromise market stability.
2. Firms providing *market making* activity through algorithms must ensure transparency and, upon request, provide competent authorities with details of their operations.
3. The use of algorithms for *market making* entails the obligation to supply liquidity on a regular and stable basis during a significant portion of trading hours. These obligations, including any exemptions, are specified through a written agreement with the trading venue, and compliance must be ensured by an adequate system of internal controls.
4. Algorithmic *market making* activity is defined as "*the simultaneous publication of competitive bid and ask prices, with comparable sizes, on one or more financial instruments, with the objective of providing liquidity to the market on a regular and frequent basis*".
5. Firms offering Direct Electronic Access (*DEA*), allowing clients to send orders to the market through their infrastructure, must regulate this activity through a written agreement with clients. Such firms retain full legal responsibility for the transactions carried out and must keep records of operations, making them available, upon request, to competent authorities.
6. A firm acting as a *general clearing member* must ensure that entities to which it provides clearing services are suitable, regulating such relationships through a written agreement defining the rights and obligations of the parties.

One of Europe's main challenges is the creation of a unified capital market. As highlighted in the *Capital Markets Union 2020 Action Plan (CMU)*, the objective is to support the post-pandemic economic recovery, finance the digital and ecological transition, and contribute to building a more resilient, autonomous, and competitive society[4].

Among the initiatives included in the *CMU* is the *Consolidated Tape*, the electronic system providing the latest data on the price and trading volume of listed financial instruments[5], in this case *corporate bonds*. To comply with the European regulatory framework, the *Consolidated Tape Provider* selected by *ESMA*, namely *EDIPHY*, is

[3] https://www.esma.europa.eu/publications-and-data/interactive-single-rulebook/mifid-ii/article-17-algorithmic-trading

[4] https://finance.ec.europa.eu/capital-markets-union-and-financial-markets/capital-markets-union/capital-markets-union-2020-action-plan_en

[5] https://www.investor.gov/introduction-investing/investing-basics/glossary/consolidated-tape

required to meet the standards set out by the *MiFIR* Regulation and the *MiFID II* Directive.

3.3. Types of algorithms

In financial markets, operators can be divided into two main categories: *buy side* and *sell side*. *Buy side* operators (*asset managers*, funds, insurance companies) aim to execute trading operations in order to generate profit, whereas *sell side* operators (*dealers*, *market makers*) have the primary objective of providing liquidity to the market and offering consistent quotations on financial instruments.

This dissertation focuses on the main algorithmic strategies implemented by *sell side* operators in the market of *European corporate bonds*[6]:

- *D2C Market Making (quoting)*

  The *dealer*, through an automated system, provides continuous quotations on electronic platforms, reducing latency, improving efficiency, and ensuring constant liquidity to the reference market.

- *D2C Auto-response (pricing / trading)*

  Upon receiving the client's *RFQ*, the algorithm instantly evaluates the order size and calculates the price by taking market conditions into account. This operational framework increases response speed, reduces manual workload, and enhances the execution rate of *RFQs*, improving the overall quality of service offered to institutional clients.

- *Auto-hedging*

  Once the transaction is executed, the algorithm automatically calculates the risk associated with the new exposure on the portfolio and performs the appropriate hedging through suitable instruments.

The combination of the previous operational modes is achieved through the *D2C Algo Trading ("No-touch")* strategy, in which the entire process of managing *RFQs* takes place in a fully automated manner. The operator's role is limited to monitoring the correct functioning of the algorithm, ensuring efficiency in the execution of operations.

[6] Ref. *"Update on Algorithmic Trading"* – ECB Bond Market Contact Group, Citi, p.6

3.4. Systematic Credit Trading

As anticipated in the previous chapter, the combination of *Algo-trading*, *Portfolio Trading* and *ETF* gives rise to *Systematic Credit Trading*. Each of these three components is essential to maintain an adequate level of competitiveness and to ensure the efficiency of the services offered.

In the case of *Portfolio Trading*, when a client submits an *RFQ*, several *dealers*, usually up to six, are put into competition, with the obligation to provide a price for a given bond or bond portfolio within a time window typically of about 30 minutes. However, when dealing with large baskets, manual activity is often too slow or, in some cases, insufficient to provide a price within the required timeframe. The growing adoption of algorithms by *dealers* to manage operations has inevitably increased execution speed and the amount of liquidity available in the market, even during periods of low activity, helping to reduce seasonality[7].

Portfolio Trading is the operational mode that allows one to "*price a basket of bonds as if they were a single security*"[8]. In this way, it becomes possible to price bond baskets containing even hundreds of *ISINs* in a single transaction. An additional strength of *Portfolio Trading* lies in its resilience during crisis periods, when trading single securities may become difficult[9]. It is therefore clear that there is a strong synergy between *Algotrading* and *Portfolio Trading*: the former provides the speed and precision needed to enable effective use of the latter.

When a *dealer* wins an *RFQ* on a bond *basket*, meaning it provides the best price, it inevitably becomes exposed to directional risk. Since such exposure is not aligned with the *dealer*'s objectives, it becomes necessary to enter into an opposite position of equal size in order to hedge against market risk.

One possible solution would be to construct a basket of *corporate bonds* by purchasing them individually; however, individual securities are not always liquid and, in any case, this approach entails high transaction costs, proving economically inefficient. Alternatively, having already neutralised the idiosyncratic risk of the specific position thanks to the subscription of a broad bond *basket*, the *dealer* may opt for hedging through a *corporate bond ETF*, which provides an economically efficient solution to manage market risk.

As highlighted in the article "*ETFs are eating the bond market*" by the *Financial Times*, the integration of *Algotrading*, *Portfolio Trading* and *ETF* is described as a "*golden triangle*"[10], a clear reference to the operational model of *Systematic Credit Trading*. This configuration is contributing to making the *corporate bond* market more effi-

[7] Ref. *"Stress tests are less stressful"* – Barclays, p. 8-9-10.

[8] Ref. *"Portfolio Trading in Corporate Bond Markets"* – Meli, Todorova, p.1

[9] Ref. *"Stress tests are less stressful"* – Barclays, p. 2

[10] Ref. *"ETFs are eating the bond market"* – Robin Wigglesworth and Will Schmitt

cient, faster, more liquid and more transparent, driving a significant evolution in the credit market.

Under the previous operational framework, the market showed indifference to the *size* of *RFQs*: operators preferred to submit fewer large requests rather than many small ones. For instance, a single *RFQ* for *40* million euros was preferred over *40* requests of *1* million each.

From the *dealers'* point of view, this approach involved a significant strategic decision, having to balance the goal of winning the transaction with the need to offer a conservative price, given the main risk of being unable to liquidate the security quickly and thus being exposed to unfavourable price movements. The current operational model reflects the opposite logic: clients believe that splitting orders allows them to receive a better price, despite the increase in risks, commissions and execution time. This improvement is made possible by involving a greater number of *dealers*, especially operators specialised in small volumes that are willing to offer competitive quotations.

Among the main operators, *Jane Street* stands out, a U.S. firm specialised in systematic *market making* which, thanks to advanced technological infrastructures and a deep understanding of the structure and functioning of financial markets, has emerged in recent years as one of the most active *players* in the European credit market[11].

Following the adoption of systematic operational models, the sector has recorded a marked increase in trading volumes. According to *MarketAxess* reports, in line with the other major trading platforms such as *Bloomberg* and *TradeWeb*, summarising *European Credit Products*, between the third quarter of 2022 and the second quarter of 2025 average trading volumes rose from around 80 to 148 billion dollars. This expansion has been accompanied by a significant reduction in average execution times, now generally within a few seconds. Such progress is made possible by the implementation of algorithmic infrastructures capable of efficiently processing large flows of orders. To date, large-size *RFQs* are mainly handled outside electronic platforms through voice channels, duly recorded and tracked, such as *Bloomberg Chat*.

Figures 3.1 and *3.2* present the ranking of the main participants active in electronic trading of European corporate and financial bonds, broken down by the size of traded volumes and the total number of executed transactions during the period considered.

[11] Ref. *"How the buy-side is innovating in a volatile and uncertain market environment"* – Jane Street, WBR Insights

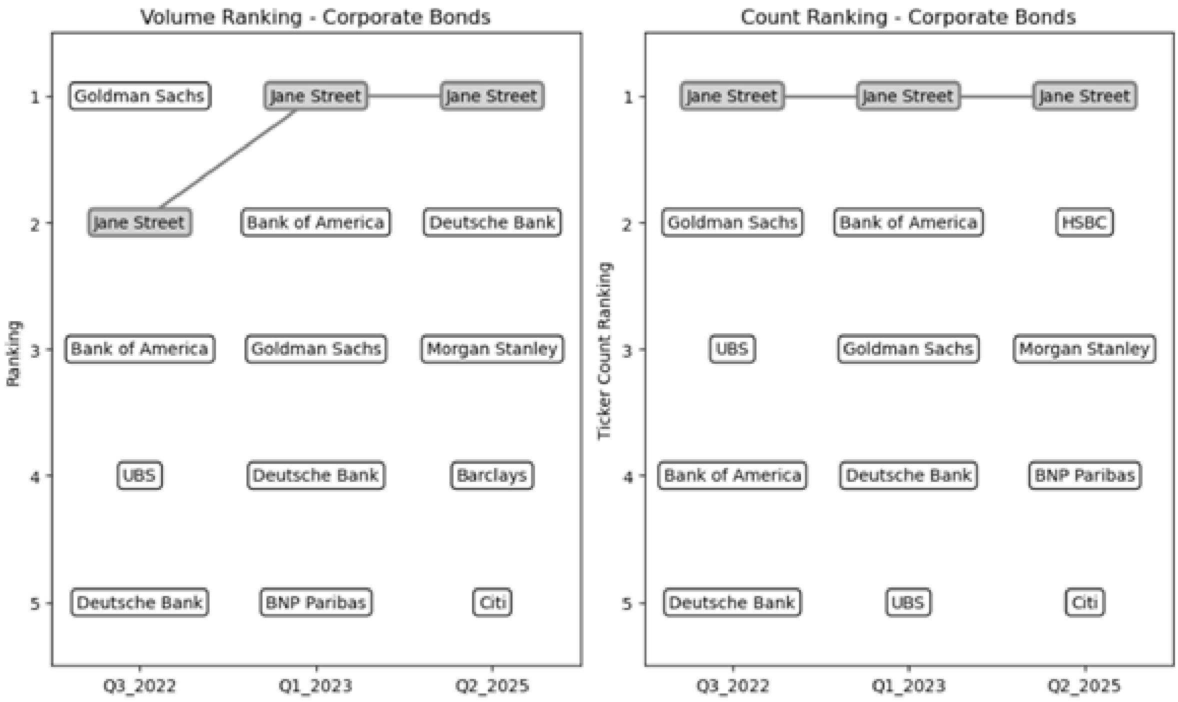


Figure 3.1

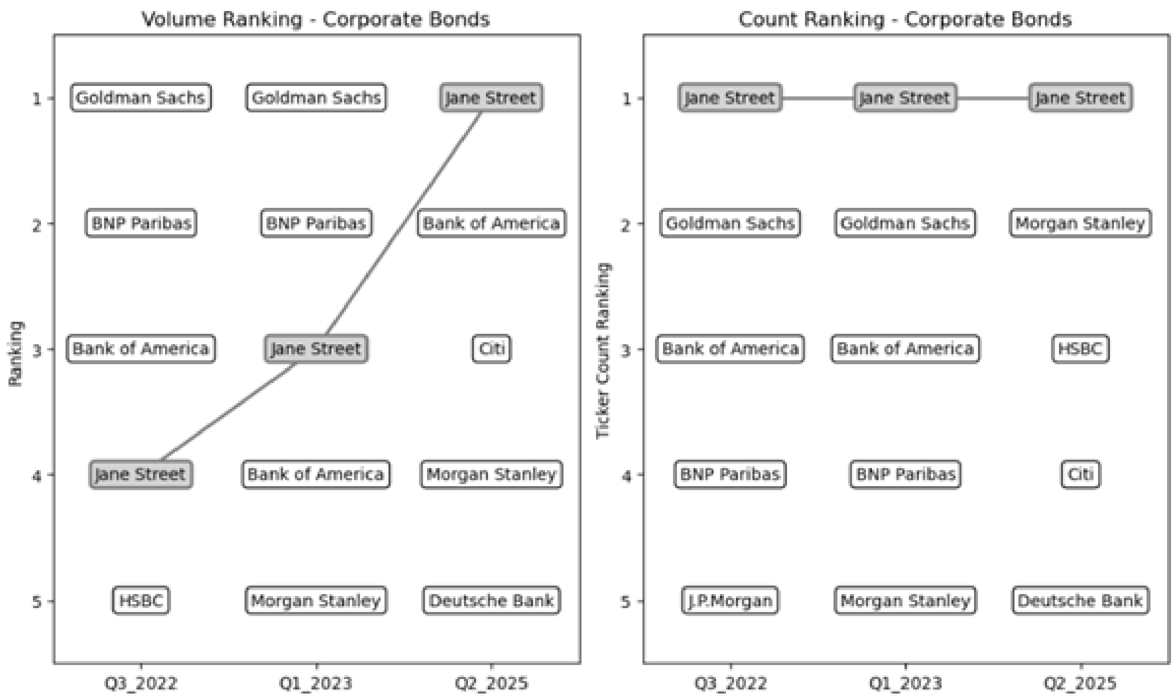


Figure 3.2

It can be observed that *Jane Street* ranks first in almost all the categories analysed. This result is attributable to the systematic approach with which the firm operates in the markets, supported by an advanced algorithmic infrastructure.

The firm has distinguished itself through its ability to execute a high number of small-sized transactions, consistently placing at the top of the ranking in terms of number of trades. In recent years, however, the progressive enhancement of its systems has enabled *Jane Street* to handle increasingly large orders, reaching first place also in the ranking related to total traded volumes.

This result has been made possible not only by an increasingly performant algorithmic infrastructure, but also by the adoption of advanced *hedging* strategies capable of assessing more accurately the risks inherent in each transaction and providing appropriate coverage.

Figure 3.3 shows the quarterly net revenues from *Jane Street*'s trading activity, expressed in billions of dollars:

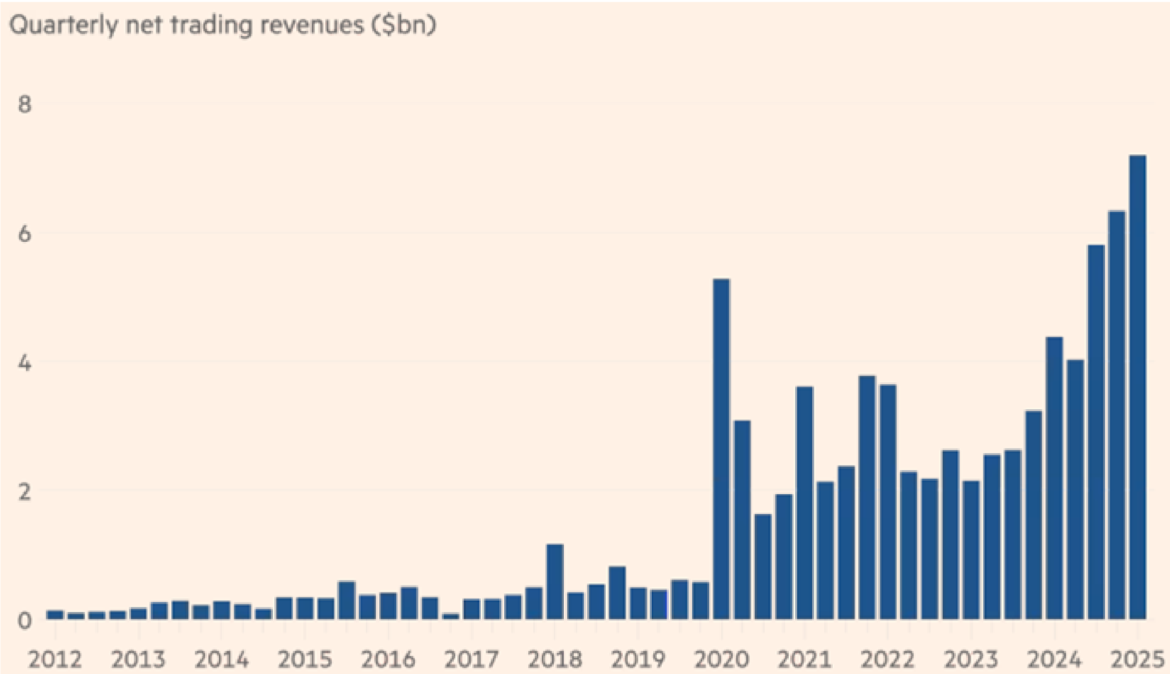


Figure 3.3

The evolution of the operating model adopted by *Jane Street* reflects a structural transformation of the market which, in certain *asset classes* and for specific *sizes*, is progressively abandoning the discretionary approach in favour of a systematic one, as confirmed by the steady increase in revenues starting from the first quarter of 2020.

[11]Source: Ref. *"Jane Street trading revenues nearly doubled in 2024 to more than $20bn"* – Financial Times

In 2024, *Jane Street* even managed to reach the revenues generated by *Morgan Stanley*'s *trading* activity, surpassing *Citi* and *Bank of America*:

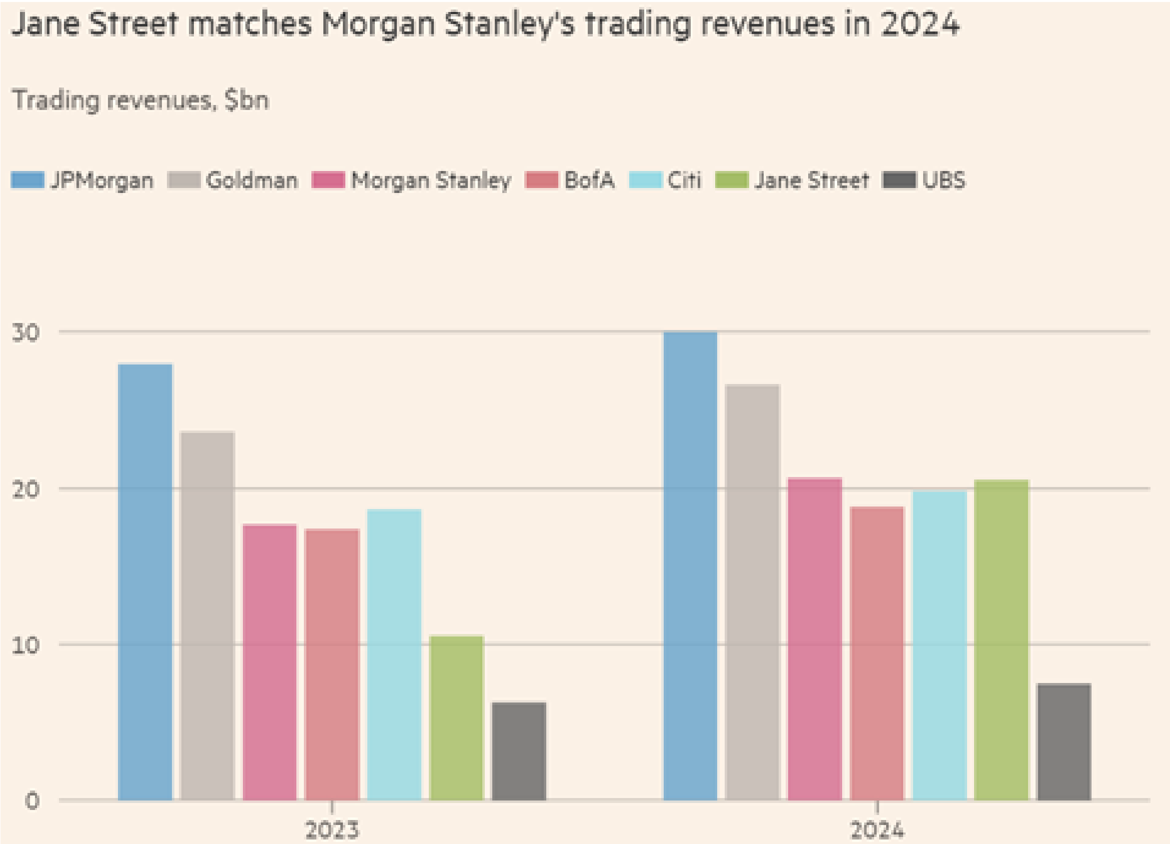


Figure 3.4

In light of these dynamics, it becomes evident that market participants must equip themselves with specialised skills and adequate infrastructures in order to address, effectively, the increasingly complex and competitive challenges imposed by the current market environment.

[11] Source: Ref. *"Jane Street trading revenues nearly doubled in 2024 to more than $20bn"* – Financial Times

4. Flow Credit Algo

After illustrating the European *corporate bond* market and analysing how the use of algorithms is taking on an increasingly central role in transactions, this chapter aims to show the operating logic of an algorithm developed to respond to *RFQs* of limited size.

4.1. Description of the operational context

As emerged in the previous chapters, one of the main issues of the European *corporate bond* market is the scarcity and fragmentation of data. Unlike the United States, where the *TRACE* system allows real-time publication of bond transactions, in Europe *post-trade* data are available with a minimum delay of 15 minutes, as required by the *MiFID II* regulation. Even relying on *Data Providers*, such as *MarketAxess* or *Tradeweb*, is not exempt from issues, since it entails a cost and brings a delay in data reception, albeit shorter. The main solution identified is the *Consolidated Tape*, awarded to *EDIPHY*, a project that will lead to the creation of a platform similar to the US one.

Greater transparency increases system efficiency: the information gap between *dealers* narrows, enhancing competition and forcing operators to quote tighter *spreads*, inevitably reducing profit margins. This scenario leads human operators to favour large-sized *RFQs*, negotiated via *voice* trading, while neglecting smaller ones. In 2016, the US bank *Morgan Stanley* realised that its *corporate bond traders* were not responding to about *80%* of the requests they received on the *MarketAxess* platform, most of which were for sizes below *100,000 dollars*[1].

Small-sized *RFQs*, which individually may seem insignificant, represent, in aggregate, a substantial portion of the market. For this reason, banks and investment firms, as discussed in the previous chapter, are investing significant resources in developing algorithms capable of automatically handling these requests, which are typically ignored by human operators.

In this context, we present the analysis of an algorithm capable of rapidly providing answers to the *RFQs* continuously received by the *market maker*.

[1] *"Humans and machines join forces in Morgan Stanley's Credit Trading revolution"* – International Financing Review, p.2

4.2. Algorithm and strategy

The algorithm discussed in this section responds to an *RFQ* through a decision-tree structure, as shown in *Figure 4.1*:

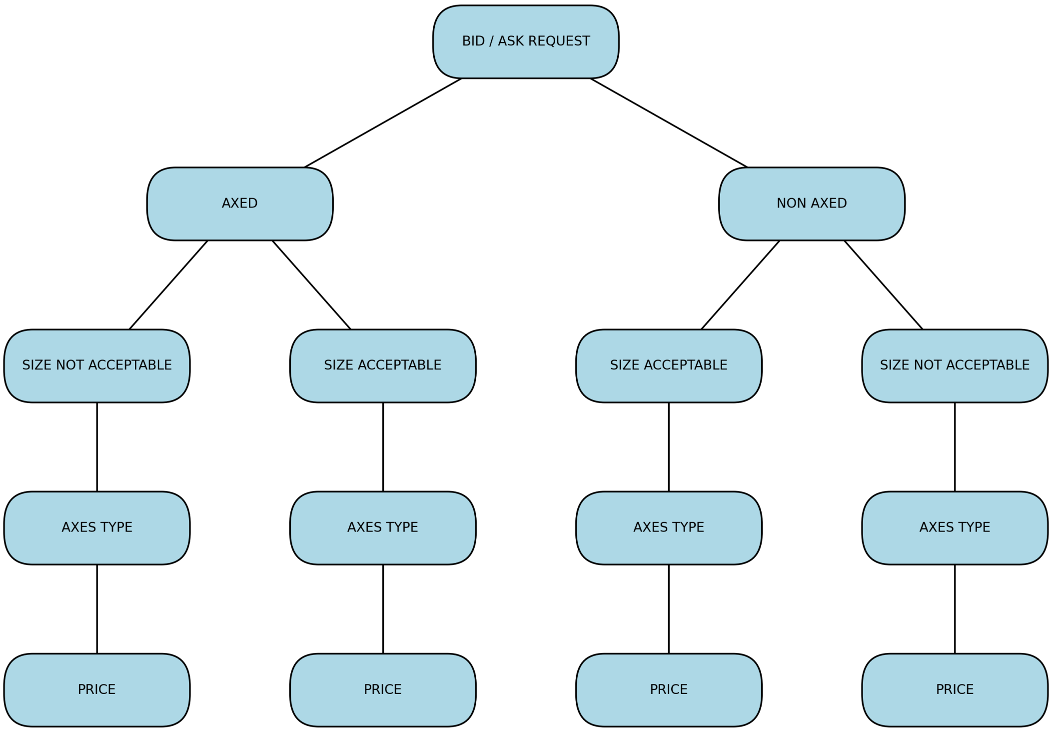


Figure 4.1: AlgoCredit decision tree

Starting from the highest level, a buy/sell request is received from the client; consequently, the *dealer* will be required to sell/buy securities, in this case European *corporate bonds*.

Once the algorithm classifies this request, it proceeds with the analysis of the *Axes status*, an indicator representing the market balance between supply and demand for a specific *corporate bond*[2]. An *Axe* signal shows a strong interest in buying or selling that security, which will therefore receive more competitive quotes.

After identifying the *Axes status*, the next step is the classification of the *Size*, meaning the assessment of the consistency between the potential new exposure and the dealer's target position.

[2]Ref. *"Industry guide to definitions and best practice for bond pricing distribution"* – ICMA, p.3

The calculation of the *Residual*, namely the remaining distance between the final position and the desired position[3], is essential to classify the *Size* as *Acceptable* or *Not acceptable*, since it must be less than or equal to the defined tolerance threshold or lower than the *Initial Distance* between the *Current Position* and the *Desired Position* on the security:

$$\text{Residual} = \begin{cases} \big|(\text{Current Position} + \text{Nominal}) - \text{Desired Position}\big| & \text{if Side = Buy} \\ \big|(\text{Current Position} - \text{Nominal}) - \text{Desired Position}\big| & \text{if Side = Sell} \end{cases}$$

$$\text{Initial\_Distance} = \big|\text{Current Position} - \text{Desired Position}\big|$$

$$\text{Size} = \begin{cases} \text{Acceptable} & \text{if Residual} \leq \text{Size}_{\text{threshold}} \text{ or Residual} < \text{Initial\_Distance} \\ \text{Not acceptable} & \text{otherwise} \end{cases}$$

The third identification concerns the slope of the *Axes*, distinguishing whether it is tilted toward the supply side, the demand side, or whether no inclination is present.

$$\text{Axes Type} = \frac{\textit{AXES Ask}}{\textit{AXES Bid} + \textit{AXES Ask}}$$

$$\text{Axes Category} = \begin{cases} \textit{Axe Bid only} & \text{if Axes Type} < 0.25 \\ \textit{Axed} & \text{if } 0.25 \leq \text{Axes Type} \leq 0.75 \\ \textit{Axe Ask only} & \text{if Axes Type} > 0.75 \end{cases}$$

The necessary condition is that at least one of the two sides of the *Axes status* is present.

Once the previous elements have been verified and the algorithm reaches the pricing stage, two values are introduced:

- *Composite Bloomberg Bond Trader (CBBT)*, which provides a real-time composite price, both on the *Bid* and *Ask* sides, based on the latest executable contributions[4]. In other words, it is an average of the quotations provided by the main *dealers* on the given security, used as a reference for price calculation[5].
- *Spread w*, which provides information on the level of liquidity, uncertainty, and market depth.

[3]Differentiating in the case of *Buy* or *Sell* orders

[4]*https://www.bloomberg.com/professional/insights/press-announcement/bloomberg-study-finds-automated-fixed-income-trading-boosts-performance/*

[5]For completeness, it should be noted that the *IBVL* data is also currently included in price formation, i.e., a *Bloomberg* metric that incorporates both *Axes* and traded volumes on the platform

Combinations between the average value of the *Composite Bloomberg Bond Trader (CBBT)* and the *Spread w*—defined as the difference between the two sides of the *CBBT*—are primarily used:

$$CBBT^*_{mid} = \frac{CBBT_{Bid} + CBBT_{Ask}}{2}$$

$$\text{Spread}_w = CBBT_{Ask} - CBBT_{Bid}$$

The average value of the *CBBT** may vary depending on three different situations:

- If an *Axed* condition is present, the value does not change.
- If an *Axed* condition is present but one entire side is missing, the *CBBT* is replaced with the corresponding *Prime Price*, namely the best price available on the market at that moment. For example, if the *Axes bid* is missing, the *CBBT bid* will be replaced with the *Prime Bid*.
- If a *Non Axed* condition is present, all *CBBT prices* are fully replaced with the *Prime prices*.

In this analysis, due to the limited availability of data, only the *CBBT* mid* will be considered. The decision tree described above has been converted into a function written in *Python*, which is available in the *Appendix* for consultation. In this chapter, *Figure 4.2* shows the final structure of the tree, which allows a price to be assigned to each individual security:

```
DataFrame["RFQ Price"] = np.select([Cond_Price_1, Cond_Price_2, Cond_Price_3, Cond_Price_4,
                                    Cond_Price_5, Cond_Price_6, Cond_Price_7, Cond_Price_8,
                                    Cond_Price_9, Cond_Price_10, Cond_Price_11, Cond_Price_12],

                                   [Price_1, Price_2, Price_3, Price_4,
                                    Price_5, Price_6, Price_7, Price_8,
                                    Price_9, Price_10, Price_11, Price_12],
                                   default = np.nan)
```

Figure 4.2

At each condition, that is, at each branch of the tree, a specific price is assigned[6] through the *select* function of the *numpy* library.

This dissertation presents an algorithm capable of reproducing the *pricing* logic of European *corporate bonds*, albeit in a simplified version compared to a professional system connected to a specialised platform capable of providing real-time quotations.

[6]For smoother reading, the individual *pricing* formulas are reported in the code in the *Appendix*

As an illustrative example, *Figure 4.3* reports a *Bloomberg* screen relating to a bond issued by *Mizuho*, with a coupon of *3.49%* and maturity on 05/09/2027:

MIZUHO 3.49 09/05/27 € 102.263 -.010 102.178 / 102.348 2.411 / 2.329
At 10:29 --x-- Source BGN
MIZUHO 3.49 09/05/2027 REGS Co Request Access Settings All Quotes
15:31:52 ALLX Overlay Axe Size Split Bid/Offer Bridge AXE Switch Buy Sell
Spreads vs DBR 0 ½ 08/15/2027 REGS @CBBT 97.207 / 97.233 1.908 / 1.895 15:31
Edit Filters Venue BTFE Legend

PCS	Firm Name	Bid Px / Ask Px	Bid Spd / Ask Spd	BSz(M) x ASz(M)	Time
	Total Axe Size	/	/	46,462 x 8,509	
IBVL	IBVAL Front Office	102.286 / 102.357	45.0 / 41.6	x	15:31
CBBT	FIT COMPOSITE	102.181 / 102.361	50.8 / 42.0	x	15:31
QMGR	Last QMGR Quote	102.180 / 102.340	51.0 / 43.0	x	15:30
UBSX	UBS Investment BK.	102.189 / 102.395	49.5 / 40.8	2,000 x 2,000	15:29
BXDL	Barclays Algo	102.209 / 102.499	47.1 / 35.5	1,000 x 1,000	15:31
BSCR	Santander Credit	102.219 / 102.363	48.3 / 42.6	1,000 x 1,000	15:31
MSFI	MORGAN STANLEY LDN	102.206 / 102.329	48.6 / 43.8	10,000 x 1,000	15:31
CGC	Citigroup Credit	102.203 / 102.336	49.0 / 43.9	1,000 x 1,000	15:31
EUBS	UBS Algo Europe	101.949 / 102.338	49.5 / 44.7	1,000 x 1,000	15:31
DZBB	DZ BANK AG	102.181 / 102.361	49.7 / 42.2	1,000 x 3,275	15:31
BXEC	Barclays	102.180 / 102.361	49.7 / 42.6	5,000 x 1,000	15:31
GSA	GS Algo Credit	102.212 / 102.369	49.8 / 42.4	1,000 x 1,000	15:31
TDCT	TD SECURITIES	102.186 / 102.317	49.9 / 44.9	1,000 x 1,000	15:31
INXS	ING BANK Singapore	102.185 / 102.315	50.0 / 45.0	1,000 x 1,000	15:31
DABC	Deutsche Bank-Credit	102.177 / 102.352	50.3 / 43.1	1,000 x 1,000	15:31
HSCT	HSBC	102.171 / 102.431	50.6 / 39.3	1,000 x 1,000	15:31
SGCR	Societe Generale	102.167 / 102.373	50.8 / 42.0	1,000 x 1,000	15:31
ABNX	ABN AMRO Markets	102.163 / 102.361	50.8 / 42.6	1,000 x 1,000	15:31
RBSM	NatWest Markets	102.162 / 102.398	51.0 / 40.9	1,000 x 1,000	15:31
NOLB	NORD LB	102.148 / 102.395	51.7 / 40.9	1,000 x 1,000	15:31
RBCL	RBC CM	101.971 / 102.259	60.3 / 47.6	1,000 x 1,000	15:31
MZLN	MIZUHO EMEA	102.239 / 102.383	48.0 / 41.0	1,000 x 1,000	15:30
FLWT	FLOW TRADERS	102.082 / 102.338	57.4 / 45.0	1,000 x 1,000	15:28
DBAL	Deutsche Bank-ALGO	102.166 / 102.379	51.6 / 42.5	1,000 x 1,000	15:26
DEKA	DEKABANK	102.166 / 102.372	50.8 / 42.0	500 x 1,000	15:31
SGAL	Soc Gen ALGO	102.106 / 102.436	53.6 / 38.8	1,000 x 400	15:31
BMRK	BBG REALTIME EVAL	102.129 / 102.396	53.3 / 40.4	2,000 x Indic Sz	15:31
CBBA	CBBT TCA Adjusted	102.228 / 102.332	47.7 / 43.8	1,000 x 1,000	15:31
MSG1	MSG Quotes	102.180 / 102.340	51.0 / 43.0	x	15:30
BVAL	BVAL (Score: 10)	102.236 / 102.341	47.9 / 44.7	x	13:00

Figure 4.3

From the screen, the following elements can be observed:

- *Firm Name*: the names of the dealers who have provided quotations
- *Bid/Ask price* provided by each of them
- *Bid/Ask spread* relative to a *benchmark*, in this case the German Bund
- *Axes status (BSz(M) x ASz(M))*
- *Time*, the timestamp of the most recent quote update

Except for the names of the *competitors* and the timestamp of the last quote, the remaining elements represent essential data for the correct functioning of the algorithm. Since real-time data are not available, historical data contained in an *Excel* file are used and subsequently uploaded into *Python*.

Regarding the price formation process, in addition to describing how the code works, it is important to highlight the underlying logic.

If a *market maker* receives a *Sell* request, the client intends to buy the bond; therefore, the *dealer* will be required to quote an *Ask* price. In this context, competition among different *dealers* becomes relevant: if the *market maker* were to quote the *CBBT Bid*, i.e. the lowest price available on the market, they would win the competition but obtain no profit margin, as they would sell at the same price at which other *dealers* are willing to buy.

The *dealer*'s ability therefore lies in offering a price that is as competitive as possible relative to the market, but still sufficiently distant from the *Bid* to ensure a positive spread. As the number of competitors increases, the price must be made more aggressive, thereby reducing the *spread*. Conversely, in the absence of *Axes Ask*, the *market maker* may afford to quote a less competitive price, increasing profitability.

In the opposite case, when receiving a *Buy* RFQ, the client intends to sell; therefore, the *dealer* will be required to buy, quoting a *Bid* price. Here as well, the central element is the *trade-off* between competitiveness and profitability: quoting a higher price increases the likelihood of winning the *RFQ*, but reduces the profit margin.

4.3. Analysis of the results

A flow of *35 European corporate bonds*, organised in a *pandas DataFrame*, is considered and the corresponding results analysed. Starting from the available data, *Figure 4.4* reports the first *10* instruments:

	ISIN	Description	Side	Notional	CBBT Bid	CBBT Ask	AXES Bid	AXES Ask	Current position
1	XS2582860909	ABESM 4.125 08/29	Buy	500000	103.838	104.105	0.000	5,000,000.000	750000
2	XS2577127967	ANZ 3/2/2033 5.101	Buy	500000	104.154	104.384	3,000,000.000	5,000,000.000	0
3	XS2294372169	ANZ 5/5/2031 0.669	Buy	500000	98.617	98.685	2,000,000.000	2,000,000.000	1700000
4	XS2267889991	ATOSTR 2.000 12/28	Sell	500000	97.362	97.556	7,000,000.000	14,000,000.000	-50000
5	IT0005549479	BAMIIM 6.000 06/28	Buy	500000	105.481	105.706	1,000,000.000	8,000,000.000	350000
6	XS2835902243	BBVASM 3.625 06/30	Buy	2000000	102.971	103.234	8,000,000.000	0.000	1600000
7	XS2340236327	BKIR 1.375 08/31	Sell	2000000	98.885	98.975	6,000,000.000	10,000,000.000	-350000
8	XS2310118976	CABKSM 1.250 06/31	Sell	2000000	98.950	99.160	5,000,000.000	9,000,000.000	-1900000
9	XS2385398206	CMCSA 14/9/2029 0.250	Sell	2000000	90.140	90.388	1,000,000.000	0.000	1550000
10	DE000CZ439B6	CMZB 5.250 03/29	Buy	2000000	105.921	106.161	1,000,000.000	8,000,000.000	-800000

Figure 4.4

From left to right, excluding the *ISIN* code and the bond description:

- *Side*: the client's buy/sell request
- *Notional*
- *CBBT Bid/Ask*
- *Axes Bid/Ask*
- *Current position*, the dealer's current exposure on the bond

For the implementation of the algorithm, instead of using traditional procedural programming based on elementary conditional structures (*if / else*), the matrix functions of the *pandas* and *numpy* libraries were preferred, thus achieving a faster and more computationally efficient solution. An *Axes Threshold* of *5,000,000*, a *Size Threshold* of *1,000,000*, and a *Desired Position* of *0* are set, and the *pricing function* is applied. The final *pandas DataFrame* is shown in *Figure 4.5*:

	ISIN	Description	Side	Notional	CBBT Bid	CBBT Ask	AXES Bid	AXES Ask	Current position	w spread	CBBT Mid	Axes	Final position	Residual	Size	Axes type	RFQ Price
1	XS2582860909	ABESM 4.125 08/29	Buy	500000	103.838	104.105	0.000	5,000,000.000	750000	0.267	103.971	Not Axed	1250000	1250000	Not acceptable	Axe Ask only	103.838
2	XS2577127967	ANZ 3/2/2033 5.101	Buy	500000	104.154	104.384	3,000,000.000	5,000,000.000	0	0.231	104.269	Not Axed	500000	500000	Acceptable	Axed	104.211
3	XS2294372169	ANZ 5/5/2031 0.669	Buy	500000	98.617	98.685	2,000,000.000	2,000,000.000	1700000	0.068	98.651	Not Axed	2200000	2200000	Not acceptable	Axed	98.634
4	XS2267889991	ATOSTR 2.000 12/28	Sell	500000	97.362	97.556	7,000,000.000	14,000,000.000	-50000	0.195	97.459	Axed	-550000	550000	Acceptable	Axed	97.508
5	IT0005549479	BAMIIM 6.000 06/28	Buy	500000	105.481	105.706	1,000,000.000	8,000,000.000	350000	0.225	105.593	Not Axed	850000	850000	Acceptable	Axe Ask only	105.509
6	XS2835902243	BBVASM 3.625 06/30	Buy	2000000	102.971	103.234	8,000,000.000	0.000	1600000	0.263	103.103	Axed	3600000	3600000	Not acceptable	Axe Bid only	103.103
7	XS2340236327	BKIR 1.375 08/31	Sell	2000000	98.885	98.975	6,000,000.000	10,000,000.000	-350000	0.090	98.930	Axed	-2350000	2350000	Not acceptable	Axed	98.953
8	XS2310118976	CABKSM 1.250 06/31	Sell	2000000	98.950	99.160	5,000,000.000	9,000,000.000	-1900000	0.210	99.055	Axed	-3900000	3900000	Not acceptable	Axed	99.107
9	XS2385398206	CMCSA 14/9/2029 0.250	Sell	2000000	90.140	90.388	1,000,000.000	0.000	1550000	0.248	90.264	Not Axed	-450000	450000	Acceptable	Axe Bid only	90.357
10	DE000CZ439B6	CMZB 5.250 03/29	Buy	2000000	105.921	106.161	1,000,000.000	8,000,000.000	-800000	0.240	106.041	Not Axed	1200000	1200000	Not acceptable	Axe Ask only	105.921

Figure 4.5

Leaving aside the simple calculations of the *CBBT mid* and the *Spread w*, it can be observed that the algorithm, by recognising the different conditions, is able to classify the *Axes status*, the *Size*, and the *Axes Type*, thereby determining the price of the *RFQ* for the individual European *corporate bond* on a *100* scale.

The first *10* prices are shown in Figure *4.6*:

	ISIN	RFQ Price
1	XS2582860909	103.838
2	XS2577127967	104.211
3	XS2294372169	98.634
4	XS2267889991	97.508
5	IT0005549479	105.509
6	XS2835902243	103.103
7	XS2340236327	98.953
8	XS2310118976	99.107
9	XS2385398206	90.357
10	DE000CZ439B6	105.921

Figure 4.6

Through the *datetime* library, it is possible to calculate the execution time of the algorithm, shown in *Figure 4.7*:

```
-----------------------------------------------------------
       * * *        Time Statistics         * * *
-----------------------------------------------------------

Start Time:                                 13:34:469080876
End Time:                                   13:34:469191925
                                              -------------
Execution Time:                                    11.05 ms
```

Figure 4.7

It can be observed that, for a flow of *35* securities, the algorithm was able to provide a price within an interval of *11.05* milliseconds, a result that cannot be replicated manually by a human operator.

To verify the functioning of the algorithm under extreme market conditions, three simulations are proposed, comparing their results (*Figure 4.8*):

- Scenario with *Axes Ask only (Axes Bid = 0)*
- Scenario with *Axes Bid only (Axes Ask = 0)*
- Scenario with no *Axes (Axes Bid = 0, Axes Ask = 0)*

	ISIN	Description	Side	Notional	CBBT Bid	CBBT Ask	CBBT Mid	AXES Bid	AXES Ask	Base Scenario	Ask Only	Bid Only	No Axes
1	XS2582860909	ABESM 4.125 08/29	Buy	500000	103.838	104.105	103.971	0.000	5,000,000.000	103.838	103.838	103.905	103.905
2	XS2577127967	ANZ 3/2/2033 5.101	Buy	500000	104.154	104.384	104.269	3,000,000.000	5,000,000.000	104.211	104.182	104.240	104.211
3	XS2294372169	ANZ 5/5/2031 0.669	Buy	500000	98.617	98.685	98.651	2,000,000.000	2,000,000.000	98.634	98.617	98.617	98.634
4	XS2267889991	ATOSTR 2.000 12/28	Sell	500000	97.362	97.556	97.459	7,000,000.000	14,000,000.000	97.508	97.435	97.532	97.508
5	IT0005549479	BAMIIM 6.000 06/28	Buy	500000	105.481	105.706	105.593	1,000,000.000	8,000,000.000	105.509	105.509	105.565	105.537
6	XS2835902243	BBVASM 3.625 06/30	Buy	2000000	102.971	103.234	103.103	8,000,000.000	0.000	103.103	103.037	103.103	103.037
7	XS2340236327	BKIR 1.375 08/31	Sell	2000000	98.885	98.975	98.930	6,000,000.000	10,000,000.000	98.953	98.975	98.975	98.953
8	XS2310118976	CABKSM 1.250 06/31	Sell	2000000	98.950	99.160	99.055	5,000,000.000	9,000,000.000	99.107	99.160	99.160	99.107
9	XS2385398206	CMCSA 14/9/2029 0.250	Sell	2000000	90.140	90.388	90.264	1,000,000.000	0.000	90.357	90.326	90.357	90.326
10	DE000CZ439B6	CMZB 5.250 03/29	Buy	2000000	105.921	106.161	106.041	1,000,000.000	8,000,000.000	105.921	105.921	105.921	105.981

Figure 4.8

Taking as an example the first security, with *ISIN XS2582860909*, it can be observed that, in the case of an *RFQ Buy*, since the *Axes Bid* is missing, the scenario with only *Axes Ask* is equivalent to the base scenario, while the scenario with only *Axes Bid* is equivalent to the scenario without *Axes*.

In the base scenario (and in the scenario with only *Axes Ask*), since there are no competing sellers, the *market maker* will quote the lowest price available on the market, namely the *CBBT Bid* (*103.838*).

Taking as an example the seventh security, with *ISIN XS2340236327*, it can be observed that, in the case of an *RFQ Sell*, since both *Axes* are present, the base scenario will result in a competitive price (*98.953*), positioned between the *CBBT Ask* (*98.975*) and the *CBBT mid* (*98.930*).

In the scenario with only *Axes Ask*, the price will be positioned at the *CBBT mid*, whereas in the scenario with only *Axes Bid*, the price will be positioned at the *CBBT Ask*; in this latter case, since no *dealer* is willing to satisfy the client's request, the *market maker* has no incentive to offer a competitive price.

By adopting an algorithmic approach, it is also possible to implement various *performance* metrics, customizing one's operational strategy.

A particularly important indicator is the distance between the price quoted by the *dealer* who wins the *RFQ* and the second-best price, commonly referred to as "*Epsilon*":

$$\varepsilon = \begin{cases} P_{\text{Cover}} - P_{\text{RFQ}} & \text{if Side = Buy} \\ P_{\text{RFQ}} - P_{\text{Cover}} & \text{if Side = Sell} \end{cases}$$

A smaller value of *Epsilon* indicates a better management of the *RFQ* by the *dealer*.

The difference between the two formulas depends on the client's request:

- If the client wishes to buy (*Buy*), the *dealer* will be required to sell; therefore, the second-best price will be higher than the winning price.
- If the client wishes to sell (*Sell*), the *dealer* will be required to buy; therefore, the second-best price will be lower than the winning price.

In this way, the indicator is always non-negative.

Another important value to consider is the *Cost of Funding*, namely the financing cost of the operation. It represents the difference between the yield offered by the security and the rate at which the *dealer* obtains liquidity from the market. By incorporating this value into the quotation, one avoids the possibility that an *RFQ*, although won at a competitive price, generates a loss.

4.4. Hedging Strategies

The dealer's profit objective derives from capturing the *bid/ask spread*; therefore, at the end of the trading day, they hedge their positions against directional risks.

Assuming that the number of securities held in the portfolio is sufficient to eliminate idiosyncratic risk, two *ETFs* are considered to hedge systemic risk:

- *iShares High Yield Corp Bond UCITS ETF*
- *IEAC LN iShares Core € Corp Bond UCITS ETF*

Considering the dealer's *Final Position* on each security, the portfolio weights are computed as follows:

$$PositionValue_i = FinalPosition_i \times RFQPrice_i$$

$$Weight_i = \frac{PositionValue_i}{\sum_j PositionValue_j}$$

The resulting *DataFrame*, shown in *Figure 4.9*, reports the first ten components of the portfolio:

ISIN	Description	Final position	RFQ Price	Type	Weight
XS2582860909	ABESM 4.125 08/29	1250000	103.838	IG	0.024
XS2577127967	ANZ 3/2/2033 5.101	500000	104.211	IG	0.010
XS2294372169	ANZ 5/5/2031 0.669	2200000	98.634	IG	0.040
XS2267889991	ATOSTR 2.000 12/28	-550000	97.508	IG	0.010
IT0005549479	BAMIIM 6.000 06/28	850000	105.509	HY	0.016
XS2835902243	BBVASM 3.625 06/30	3600000	103.103	IG	0.068
XS2340236327	BKIR 1.375 08/31	-2350000	98.953	HY	0.042
XS2310118976	CABKSM 1.250 06/31	-3900000	99.107	IG	0.071
XS2385398206	CMCSA 14/9/2029 0.250	-450000	90.357	IG	0.007
DE000CZ439B6	CMZB 5.250 03/29	1200000	105.921	IG	0.023

Figure 4.9

At this point, three different scenarios are computed:

a) *Hedging* with the *iShares High Yield Corp Bond UCITS ETF*[7]

b) *Hedging* with the *IEAC LN iShares Core € Corp Bond UCITS ETF*[8]

c) *Hedging* with both *ETFs*

In the first two scenarios, to determine the number of *ETF* units to purchase, the *Hedge Ratio* β[9] is computed as the product of the correlation ρ between the portfolio's *log returns* and those of the selected *ETF*, and the ratio between their respective standard deviations σ:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \qquad \sigma_r = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(r_t - \bar{r})^2} \qquad \rho_{XY} = \frac{\mathrm{Cov}(r_{X,t}, r_{Y,t})}{\sigma_{r_X}\sigma_{r_Y}}$$

$$\beta = \rho \times \frac{\sigma_{\text{Portfolio}}}{\sigma_{\text{ETF}}}$$

For the third scenario, a multiple linear *OLS* regression is applied, with the aim of estimating the relationship between the portfolio's *log returns* and those of the *ETFs* considered:

$$r_{P,t} = \alpha + \beta_{IEAC}\, r_{IEAC,t} + \beta_{HY}\, r_{HY,t} + \varepsilon_t$$

The estimated coefficients β from the regression represent the *Hedge Ratios*, that is, the sensitivities of the portfolio to changes in the respective *ETFs*. Once the *Hedge Ratios* β for the three scenarios have been obtained, the number of units to purchase is computed using the following formula:

$$N_{\text{shares}} = \beta \times \frac{\text{Portfolio Value}}{\text{ETF Value}}$$

The total value of the portfolio is determined as the sum of the values of the individual positions held.

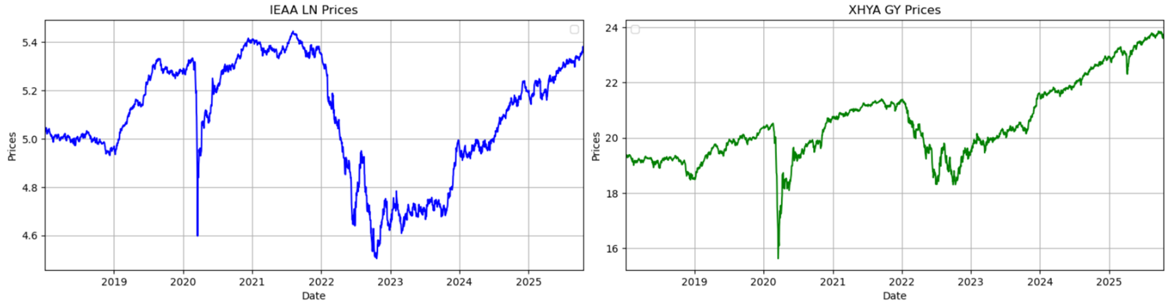
Continuing with the analysis of the results, it can be observed that the total portfolio value amounts to *€ – 1,328,140.73*, indicating a *short* position that needs to be hedged.

[7]Ticker *XHYA GY*

[8]Ticker *IEAA LN*

[9]See *"Options, Futures and Other Derivatives"* – John C. Hull, pp. 60–64

In *Figure 4.10*, the results of the first two hedging scenarios are reported:



	Hedging ETF Investment Grade (IEAA LN)	Hedging ETF High Yield (XHYA GY)
Correlation:	0,835	0,357
Hedge Ratio (B):	0,293	0,086
ETF Price:	5,376 €	23,706 €
ETF Shares to Buy:	72.408,099	4.843,982

Figure 4.10

In the case of the *IEAA LN ETF*, a high correlation with the portfolio can be observed, equal to *0.835*. Applying the formulas previously described and considering a unit price of € *5.376*, it follows that, in order to be fully hedged against market risk, it is necessary to purchase *72,408.099* shares.

In the case of the *XHYA GY ETF*, however, a low correlation is observed, equal to *0.357*. One possible reason is the limited number of *High Yield* securities in the portfolio, which amount to *8* out of *35*. By performing the appropriate calculations and considering a unit price of € *23.706*, it is obtained that, in order to hedge market risk, *4,843.982* shares would need to be purchased.

With regard to the third scenario, the *Augmented Dickey–Fuller (ADF)* test confirms that the time series of the portfolio and ETF *log returns* are stationary, whereas the *Breusch–Pagan* test highlights the presence of heteroscedasticity in the regression residuals (*p-value = 0.03278* < 0.05), indicating a non-constant error variance (*Figure 4.11*):

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              Portfolio   R-squared:                       0.700
Model:                            OLS   Adj. R-squared:                  0.697
Method:                 Least Squares   F-statistic:                     292.5
Date:                Sun, 16 Nov 2025   Prob (F-statistic):           2.67e-66
Time:                        18:32:47   Log-Likelihood:                 1532.5
No. Observations:                 254   AIC:                            -3059.
Df Residuals:                     251   BIC:                            -3048.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -9.438e-06   3.68e-05     -0.256      0.798   -8.19e-05    6.31e-05
IEAA LN        0.4705      0.022     21.871      0.000       0.428       0.513
XHYA GY        0.0200      0.017      1.202      0.230      -0.013       0.053
==============================================================================
Omnibus:                       29.179   Durbin-Watson:                   2.355
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               82.456
Skew:                          -0.467   Prob(JB):                     1.24e-18
Kurtosis:                       5.630   Cond. No.                         632.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

```
          -----------------------------------------
                ADF - Augmented Dickey-Fuller
          -----------------------------------------

Portfolio: p-value = 0.0000 --> Portfolio has a Stationary series!

IEAA LN: p-value = 0.0000 --> IEAA LN has a Stationary series!

XHYA GY: p-value = 0.0000 --> XHYA GY has a Stationary series!


               ------------------------------
                     Breusch-Pagan test
               ------------------------------

p-value BP: 0.03278 --> Presence of Heteroskedasticity!
```

Figure 4.11

This issue is addressed by employing robust standard errors, which assume that each observation may exhibit its own variance, rather than a constant variance across all observations.

Figure 4.12 reports the results of the *OLS* regression:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              Portfolio   R-squared:                       0.700
Model:                            OLS   Adj. R-squared:                  0.697
Method:                 Least Squares   F-statistic:                     156.1
Date:                Sun, 16 Nov 2025   Prob (F-statistic):           8.88e-45
Time:                        18:32:48   Log-Likelihood:                 1532.5
No. Observations:                 254   AIC:                            -3059.
Df Residuals:                     251   BIC:                            -3048.
Df Model:                           2
Covariance Type:                  HC0
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -9.438e-06   3.55e-05     -0.266      0.791   -7.94e-05    6.05e-05
IEAA LN        0.4705      0.033     14.087      0.000       0.405       0.536
XHYA GY        0.0200      0.028      0.704      0.482      -0.036       0.076
==============================================================================
Omnibus:                       29.179   Durbin-Watson:                   2.355
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               82.456
Skew:                          -0.467   Prob(JB):                     1.24e-18
Kurtosis:                       5.630   Cond. No.                         632.
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC0)
```

Figure 4.12

It can be observed that the variance of the *log returns* of the ETFs considered explains approximately *70%* of the variance of the portfolio's *log returns* (R^2 = *0.70*). However, while the *IEAA LN* ETF is highly significant in explaining the variance (*p-value* = *0*), the *XHYA GY* ETF is not (*p-value* = *0.482*).

Figure 4.13 reports the results of the third hedging scenario:

```
                    ----------------------------------------------------------
                                          OLS Hedging
                    ----------------------------------------------------------

IEAA LN:

   Hedge Ratio (B):                            0,471

   ETF Price:                                  5,376 €

   ETF Shares to Buy:                    116.244,574

XHYA GY not significant!
```

Figure 4.13

The coefficient β, estimated through the *OLS* regression, is directly used to compute the number of ETF shares to be purchased, amounting to *116,360.544*.

To conclude the analysis, *Figure 4.14* reports the comparison between the effects of the different *hedging* strategies, obtained by applying the formula[10]:

$$\ln\left(r_{Portfolio,t}^{\text{hedged}}\right) = \ln\left(r_{Portfolio,t}\right) - \beta\, \ln\left(r_{ETF,t}\right)$$

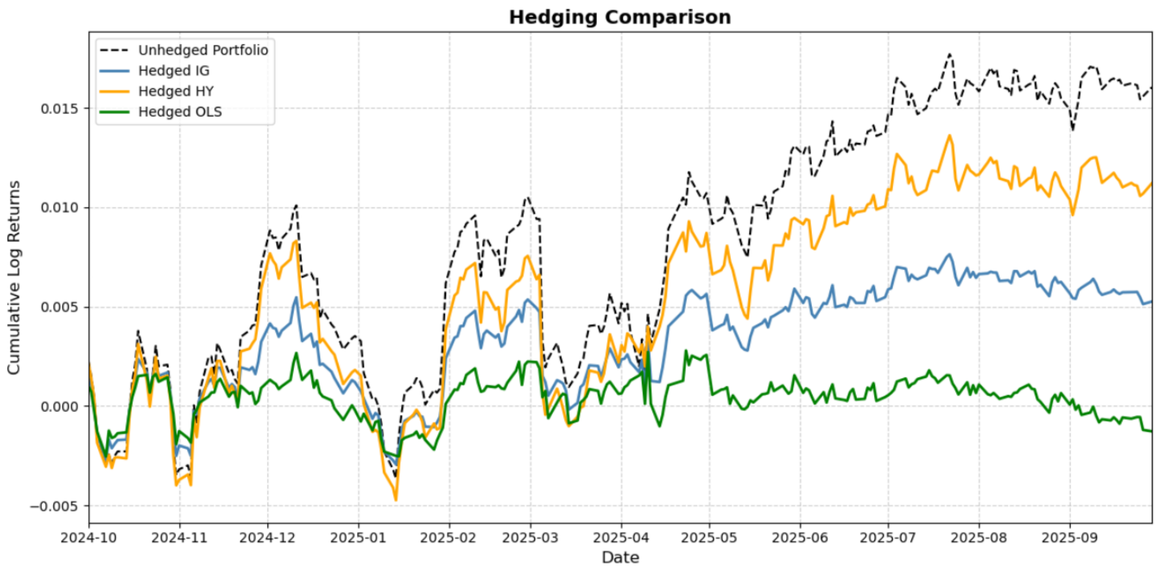


Figure 4.14

[10] https://medium.com/@deepml1818/hedging-with-python-creating-and-backtesting-hedging-strategies-for-portfolios-23af0ec28d94

The use of the two *ETFs* allows for the hedging of both credit risk and interest rate risk.

To isolate credit risk, it is possible to replicate the previous analyses by employing financial instruments that track the *Itraxx* indices, specifically:

- *Itraxx Main Index (ITRXEBE)*, related to *Investment Grade corporate bonds*
- *Itraxx Crossover Index (ITRXEXE)*, related to *High Yield corporate bonds*

The results of this analysis are reported in *Figure 4.15*:

```
Correlation ITRXEXE:      -0.158       Correlation ITRXEBE:      -0.143

                            OLS Regression Results
==============================================================================
Dep. Variable:              Portfolio   R-squared:                       0.027
Model:                            OLS   Adj. R-squared:                  0.019
Method:                 Least Squares   F-statistic:                     3.322
Date:                Sun, 16 Nov 2025   Prob (F-statistic):             0.0377
Time:                        18:32:49   Log-Likelihood:                 1365.6
No. Observations:                 251   AIC:                            -2725.
Df Residuals:                     248   BIC:                            -2715.
Df Model:                           2
Covariance Type:                  HC0
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       5.446e-05   6.77e-05      0.805      0.422   -7.88e-05      0.000
ITRXEBE        0.0088      0.012      0.765      0.445      -0.014      0.032
ITRXEXE       -0.0181      0.013     -1.363      0.174      -0.044      0.008
==============================================================================
Omnibus:                       47.183   Durbin-Watson:                   1.748
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              229.229
Skew:                          -0.617   Prob(JB):                     1.67e-50
Kurtosis:                       7.516   Cond. No.                         278.
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC0)
```

Figure 4.15

The series are stationary; however, the presence of heteroskedasticity, detected through the *Breusch–Pagan test*, required the use of robust standard errors.

The results show a weak correlation between the portfolio and the indices, of approximately *-0.15*, with an R^2 coefficient of *2.7%*, confirming the limited explanatory power of the model.

It is therefore concluded that the portfolio does not exhibit a statistically significant relationship with the *iTraxx Main (ITRXEBE)* and *iTraxx Crossover (ITRXEXE)* indices, as the portfolio's movements are likely influenced by other factors, such as sensitivity to interest rate variations, which credit spread indices are not able to capture.

4.5. Critical Issues

Despite the rapid quotes provided by the algorithm, several operational issues emerge that may limit its effectiveness.

The first concerns volatility, particularly when it stems from macroeconomic shocks or unexpected news (*headline risk*).

Since the algorithm is calibrated primarily on historical data, a sudden increase in volatility may compromise the accuracy of the quotes provided in the time window immediately following the event.

Another critical issue concerns informational asymmetries.

Not all market participants have access to the same quality or timeliness of data. Larger *dealers* may access more detailed information compared to smaller *competitors*, gaining tangible advantages.

Finally, and no less important, not all *RFQs* are handled through algorithms.

When the request involves a significant *Size*, or comes from a strategic client, the transaction is redirected (*rerouting*) to the trading desk and managed manually. In particular, relationship trades are predominantly executed through the *voice* channel, in order to preserve the client relationship.

An adequate IT infrastructure and a sufficiently large operational scale can help mitigate the issues just described, increasing the efficiency of the algorithm.

Conclusions

The European corporate bond market is undergoing a phase of profound transformation, driven by the technological development of trading activities.

Throughout this work, it has been shown how the pursuit of greater efficiency—initially linked to improving client service—has progressively reduced RFQ response times, allowing new players such as *Jane Street* to reach top positions thanks to substantial investments in technological infrastructure and research.

A simplified model for the pricing of European corporate bonds was then implemented and presented, developed in *Python* code and based on a limited dataset.

Although too simple to be used as an operational tool, this model aims to contribute to the understanding of the logic underlying RFQ pricing and to highlight the strategic relevance of systematic solutions. Several hedging strategies were also analysed, showing how the use of ETFs helps reduce the portfolio's directional exposure.

In the near future, it is plausible that further acceleration of algorithmic components will progressively become dominant. Regulatory developments—particularly the introduction of the *Consolidated Tape*—will reduce informational fragmentation, while increasingly sophisticated models will allow for timely management of volatility shocks. In this environment, *voice* trading will likely become concentrated on strategic clients, while most transactions will be handled systematically.

In a context of rapidly and profoundly evolving financial markets, the ability to adapt to changes in trading practices and to continuously update one's strategies represents, for any financial institution, an essential requirement to compete globally in the market making of corporate bonds.

Appendix

RFQ pricing function

```
import pandas as pd
import numpy as np
import datetime as dt
from IPython.display import display, HTML

import warnings
warnings.filterwarnings("ignore")

################################################

def RFQ_Ticker_Price(df, Axes_threshold, Size_threshold, Target_Position, Print_DF = True):
    """
    Function that prices RFQs for single European Corporate Bonds.
                          *** Input ***
    - DataFrame with Columns:
       - Side
       - Notional
       - Bid / Ask Price
       - CBBT Bid / Ask
       - Axes Bid
    - Axes_threshold = Threshold for Axed condition
    - Size_threshold = Threshold for Size condition
    """
    Start = dt.datetime.now()

    pd.options.display.float_format = "{:,.3f}".format  # Round everything to the 3rd decimal place


    DataFrame = df.copy()

    DataFrame["w spread"] = (DataFrame["CBBT Ask"] - DataFrame["CBBT Bid"])
    DataFrame["CBBT Mid"] = (DataFrame["CBBT Bid"] + DataFrame["CBBT Ask"]) / 2

    if np.isnan(DataFrame["CBBT Mid"]).any():
        print("WARNING! Some CBBT*mid do not have a valid value!")

    #############################
    # Side

    Ask_Side = DataFrame["Side"].eq("Sell")
    Bid_Side = DataFrame["Side"].eq("Buy")

    #############################
    # Axes Condition

    DataFrame["Axes"] = np.where(Ask_Side, np.where(DataFrame["AXES Ask"] > Axes_threshold, "Axed", "Not Axed"),
                                            np.where(DataFrame["AXES Bid"] > Axes_threshold, "Axed", "Not Axed"))

    Cond_Axed_Buy = (Ask_Side) & (DataFrame["Axes"].eq("Axed"))
    Cond_Not_Axed_Buy = (Ask_Side) & (DataFrame["Axes"].eq("Not Axed"))

    Cond_Axed_Sell = (Bid_Side) & (DataFrame["Axes"].eq("Axed"))
    Cond_Not_Axed_Sell = (Bid_Side) & (DataFrame["Axes"].eq("Not Axed"))

```

```
    ############################
    # Size Condition

    Distanza_iniziale = (DataFrame["Current position"] - Target_Position).abs()

    DataFrame["Final position"] = np.where(Ask_Side, DataFrame["Current position"] - DataFrame["Notional"],
                                           DataFrame["Current position"] + DataFrame["Notional"])

    DataFrame["Residual"] = np.abs(DataFrame["Final position"] - Target_Position).astype(int)

    DataFrame["Size"] = np.where((DataFrame["Residual"] <= Size_threshold) | (DataFrame["Residual"] < Distanza_iniziale),
                                 "Acceptable", "Not acceptable")

    Cond_Size_Acc_Buy = (Ask_Side) & (DataFrame["Size"] == "Acceptable")
    Cond_Size_Not_Acc_Buy = (Ask_Side) & (DataFrame["Size"] == "Not acceptable")

    Cond_Size_Acc_Sell = (Bid_Side) & (DataFrame["Size"] == "Acceptable")
    Cond_Size_Not_Acc_Sell = (Bid_Side) & (DataFrame["Size"] == "Not acceptable")

    ############################
    # Axes type

    condizione = (DataFrame["AXES Bid"]  + DataFrame["AXES Ask"]) != 0
    Axes_type = np.where(condizione, DataFrame["AXES Ask"] / (DataFrame["AXES Bid"] + DataFrame["AXES Ask"]), 0.5)

    Cond_w_spread_1 = (Axes_type < 0.25)
    Cond_w_spread_2 = (Axes_type >= 0.25) & (Axes_type <= 0.75)
    Cond_w_spread_3 = (Axes_type > 0.75)
    DataFrame["Axes type"] = np.select([Cond_w_spread_1, Cond_w_spread_2, Cond_w_spread_3],
                                       ["Axe Bid only", "Axed", "Axe Ask only"],
                                       default="Not Axed")

    #############################
    ######### CBBT* mid #########
    #############################

    # CBBT Bid/ask

    Cond_onlyBid = (DataFrame["AXES Bid"] >= Axes_threshold) & (DataFrame["AXES Ask"] == 0)
    Cond_onlyAsk = (DataFrame["AXES Bid"] == 0) & (DataFrame["AXES Ask"] >= Axes_threshold)
    Cond_NoAxes = (DataFrame["AXES Bid"] == 0) & (DataFrame["AXES Ask"] == 0)

    ##############
    #   PRICES   #
    ##############

    ### Axed ###

    # Not Acceptable Size
    Price_1 = np.where(Ask_Side, DataFrame["CBBT Mid"] + 0.5 * DataFrame["w spread"],   # Buy
                                 DataFrame["CBBT Mid"])      # Sell

```

```
    Price_2 = np.where(Ask_Side, DataFrame["CBBT Ask"] - 0.25 * DataFrame["w spread"],  # Buy
                                 DataFrame["CBBT Bid"] + 0.25 * DataFrame["w spread"])  # Sell

    Price_3 = np.where(Ask_Side, DataFrame["CBBT Ask"],                                 # Buy
                                 DataFrame["CBBT Bid"] - 0.5 * DataFrame["w spread"])   # Sell

    # Acceptable Size
    Price_4 = np.where(Ask_Side, DataFrame["CBBT Mid"] + 0.25 * DataFrame["w spread"],   # Buy
                                 DataFrame["CBBT Mid"] + 0.125 * DataFrame["w spread"])  # Sell

    Price_5 = np.where(Ask_Side, DataFrame["CBBT Ask"] - 0.25 * DataFrame["w spread"],   # Buy
                                 DataFrame["CBBT Bid"] + 0.25 * DataFrame["w spread"])    # Sell

    Price_6 = np.where(Ask_Side, DataFrame["CBBT Mid"] - 0.125 * DataFrame["w spread"],   # Buy
                                 DataFrame["CBBT Mid"] - 0.25 * DataFrame["w spread"])     # Sell


    ### Not Axed ###

    # Not Acceptable Size
    Price_7 = np.where(Ask_Side, DataFrame["CBBT Mid"] + 0.5 * DataFrame["w spread"],   # Buy
                                 DataFrame["CBBT Mid"] - 0.5 * DataFrame["w spread"])   # Sell

    Price_8 = np.where(Ask_Side, DataFrame["CBBT Mid"] + 0.25 * DataFrame["w spread"],   # Buy
                                 DataFrame["CBBT Mid"] - 0.25 * DataFrame["w spread"])    # Sell

    Price_9 = np.where(Ask_Side, DataFrame["CBBT Ask"] + 0.5 * DataFrame["w spread"],   # Buy
                                 DataFrame["CBBT Mid"] - 0.5 * DataFrame["w spread"])   # Sell

    # Acceptable Size
    Price_10 = np.where(Ask_Side, DataFrame["CBBT Mid"] + 0.375 * DataFrame["w spread"],  # Buy
                                  DataFrame["CBBT Mid"] - 0.125 * DataFrame["w spread"])  # Sell

    Price_11 = np.where(Ask_Side, DataFrame["CBBT Mid"] + 0.25 * DataFrame["w spread"],    # Buy
                                  DataFrame["CBBT Mid"] - 0.25 * DataFrame["w spread"])    # Sell

    Price_12 = np.where(Ask_Side, DataFrame["CBBT Mid"] + 0.125 * DataFrame["w spread"],   # Buy
                                  DataFrame["CBBT Mid"] - 0.375 * DataFrame["w spread"])   # Sell

```

```
    ##################
    #   CONDITIONS   #
    ##################

    ### Axed ###

    # Not Acceptable Size
    Cond_Price_1 = (Cond_Axed_Buy & Cond_Size_Not_Acc_Buy & Cond_w_spread_1) | (Cond_Axed_Sell & Cond_Size_Not_Acc_Sell & Cond_w_spread_1)

    Cond_Price_2 = (Cond_Axed_Buy & Cond_Size_Not_Acc_Buy & Cond_w_spread_2) | (Cond_Axed_Sell & Cond_Size_Not_Acc_Sell & Cond_w_spread_2)

    Cond_Price_3 = (Cond_Axed_Buy & Cond_Size_Not_Acc_Buy & Cond_w_spread_3) | (Cond_Axed_Sell & Cond_Size_Not_Acc_Sell & Cond_w_spread_3)

    # Acceptable Size
    Cond_Price_4 = (Cond_Axed_Buy & Cond_Size_Acc_Buy & Cond_w_spread_1) | (Cond_Axed_Sell & Cond_Size_Acc_Sell & Cond_w_spread_1)

    Cond_Price_5 = (Cond_Axed_Buy & Cond_Size_Acc_Buy & Cond_w_spread_2) | (Cond_Axed_Sell & Cond_Size_Acc_Sell & Cond_w_spread_2)

    Cond_Price_6 = (Cond_Axed_Buy & Cond_Size_Acc_Buy & Cond_w_spread_3) | (Cond_Axed_Sell & Cond_Size_Acc_Sell & Cond_w_spread_3)


    ### Not Axed ###

    # Not Acceptable Size
    Cond_Price_7 = ((Cond_Not_Axed_Buy | Cond_NoAxes) & Cond_Size_Not_Acc_Buy & Cond_w_spread_1) | ((Cond_Not_Axed_Sell | Cond_NoAxes) & Cond_Size_Not_Acc_Sell & Cond_w_spread_1)

    Cond_Price_8 = ((Cond_Not_Axed_Buy | Cond_NoAxes) & Cond_Size_Not_Acc_Buy & Cond_w_spread_2) | ((Cond_Not_Axed_Sell | Cond_NoAxes) & Cond_Size_Not_Acc_Sell & Cond_w_spread_2)

    Cond_Price_9 = ((Cond_Not_Axed_Buy | Cond_NoAxes) & Cond_Size_Not_Acc_Buy & Cond_w_spread_3) | ((Cond_Not_Axed_Sell | Cond_NoAxes) & Cond_Size_Not_Acc_Sell & Cond_w_spread_3)

    # Acceptable Size
    Cond_Price_10 = ((Cond_Not_Axed_Buy | Cond_NoAxes) & Cond_Size_Acc_Buy & Cond_w_spread_1) | ((Cond_Not_Axed_Sell | Cond_NoAxes) & Cond_Size_Acc_Sell & Cond_w_spread_1)

    Cond_Price_11 = ((Cond_Not_Axed_Buy | Cond_NoAxes) & Cond_Size_Acc_Buy & Cond_w_spread_2) | ((Cond_Not_Axed_Sell | Cond_NoAxes) & Cond_Size_Acc_Sell & Cond_w_spread_2)

    Cond_Price_12 = ((Cond_Not_Axed_Buy | Cond_NoAxes) & Cond_Size_Acc_Buy & Cond_w_spread_3) | ((Cond_Not_Axed_Sell | Cond_NoAxes) & Cond_Size_Acc_Sell & Cond_w_spread_3)

    ###################

    DataFrame["RFQ Price"] = np.select([Cond_Price_1, Cond_Price_2, Cond_Price_3, Cond_Price_4,
                                        Cond_Price_5, Cond_Price_6, Cond_Price_7, Cond_Price_8,
```

```
                                        Cond_Price_9, Cond_Price_10, Cond_Price_11, Cond_Price_12],

                                       [Price_1, Price_2, Price_3, Price_4,
                                        Price_5, Price_6, Price_7, Price_8,
                                        Price_9, Price_10, Price_11, Price_12],
                                       default = np.nan)

    if DataFrame["RFQ Price"].isna().any():
        print("WARNING! Some RFQ Prices do not have a valid value!")

    ###########################
    ###### Final Price #######
    ###########################

    DataFrame["RFQ Price"] = DataFrame["RFQ Price"].astype("float")
    col = ["CBBT Bid","CBBT Ask","CBBT Mid","w spread"]
    DataFrame[col] = DataFrame[col].apply(pd.to_numeric, errors="coerce")

    ############################
    End = dt.datetime.now()
    TimeDelta = End - Start
    ms = TimeDelta.total_seconds() * 1000

    #pd.options.display.float_format = "{:,.2f}".format
    DataFrame.columns.name = None
    DataFrame.index = range(1, len(DataFrame) + 1)

    if Print_DF == True:
        print("Source: BBGBTS_CREDIT", "", "Counterparty: BPF SGR", "", "Status RFQ: Done")
        display(HTML("<style>.dataframe td, .dataframe th {font-size: 11px;}</style>"))
        display(DataFrame)

    ################################
    ###### Performance Report ######
    ################################
    print("------------------------------------------------------------")
    print("         * * *      Single RFQ Prices        * * *          ")
    print("------------------------------------------------------------")
    print("")
    display(DataFrame[["ISIN", "RFQ Price"]])
    print("")
    print("------------------------------------------------------------")
    print("        * * *         Time Statistics         * * *         ")
    print("------------------------------------------------------------")
    print("")
    print("Start Time:                                ", Start.strftime("%H:%M:%S%f"))
    print("End Time:                                  ", End.strftime("%H:%M:%S%f"))
    print("                                             ---------------")
    print(f"Execution time:                                   {ms:.2f} ms")

    return DataFrame
```

For the complete Jupyter Notebooks, visit: https://github.com/TommasoTom98

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I hope that this path may continue in the future with a PhD, possibly in collaboration with the company where I will have the opportunity to work.

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The best is yet to come.

Dr. Tommaso Tomellini