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The US Treasury Market: Bridging Theoretical Framework and Empirical Findings

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Abstract

The US Treasury market stands as one of the largest and most liquid financial markets globally, serving as the backbone of the international financial system. Given this crucial role, a deep understanding of its functioning and the fundamental drivers governing its dynamics is essential. The study opens with an extensive theoretical exploration, mapping the ecosystem of US fixed income instruments, the hierarchy of market participants, and the transmission mechanisms of monetary policy. Building upon this framework, the second section conducts an empirical analysis focused on forecasting volatility using a dataset spanning from 2018 to 2025. The dataset comprises daily Treasury futures data, enriched with key cross-asset drivers and an economic calendar. Additionally, intraday data (15-minute and 1-minute intervals) are included for 2025 to capture microstructure dynamics. Through the application of OLS regression and machine learning classifiers, the research tests the extent to which theoretical drivers translate into predictive power over the daily range (utilized as a proxy for volatility). The results confirm that, while point forecasting and linear models proved ineffective, classification algorithms (*LDA and GBDT*) demonstrated superior performance. However, the analysis reveals that predictability is not uniform across the curve: both the short end and intermediate maturities exhibited better statistical performance compared to the long end, which showed lower predictive power. The thesis concludes that effective modeling in efficient markets suggests a methodological shift: prioritizing regime classification over the pursuit of precise point forecasting.

Abstract (ita)

Il mercato statunitense dei Treasury rappresenta uno dei mercati finanziari più vasti e liquidi a livello globale, fungendo da asse portante dell'intero sistema finanziario internazionale. Alla luce di tale ruolo, è essenziale comprenderne a fondo il funzionamento e le variabili fondamentali che ne governano le dinamiche. Lo studio si apre con un'ampia esplorazione teorica volta a mappare l'ecosistema dei Treasury statunitensi, i suoi partecipanti e i meccanismi di trasmissione della politica monetaria. A partire da questo quadro di riferimento, la seconda parte consiste in un'analisi empirica focalizzata sulla previsione della volatilità in questo mercato. Il dataset utilizzato copre l'arco temporale 2018–2025 e comprende le serie storiche giornaliere dei futures sui Treasury, insieme a quelle di altri principali asset come indici azionari, commodities e valute, e un calendario economico. Per l'anno 2025 sono stati inoltre integrati dati intraday (a intervalli di 15 minuti e 1 minuto) al fine di catturare le dinamiche di microstruttura del mercato. Attraverso l'applicazione di regressioni OLS e modelli di classificazione, la ricerca prova a verificare in che misura i driver teorici si traducano in un effettivo potere predittivo sul range giornaliero (utilizzato come variabile proxy per la volatilità). I risultati dimostrano che, mentre il tentativo di previsione puntuale della volatilità attraverso i modelli di regressione lineare si è rivelato inefficace, gli algoritmi di classificazione (*LDA* e *GBDT*) hanno invece mostrato performance superiori. Tuttavia, si è potuto notare come la prevedibilità non risulti uniforme lungo la curva: infatti le scadenze brevi e quelle intermedie hanno evidenziato performance statistiche migliori rispetto alla parte a lunga scadenza, caratterizzata da una capacità predittiva sensibilmente inferiore. Quindi, in presenza di mercati efficienti, lo studio suggerisce una svolta metodologica: privilegiare la classificazione dei regimi di volatilità rispetto alla ricerca di una previsione puntuale.

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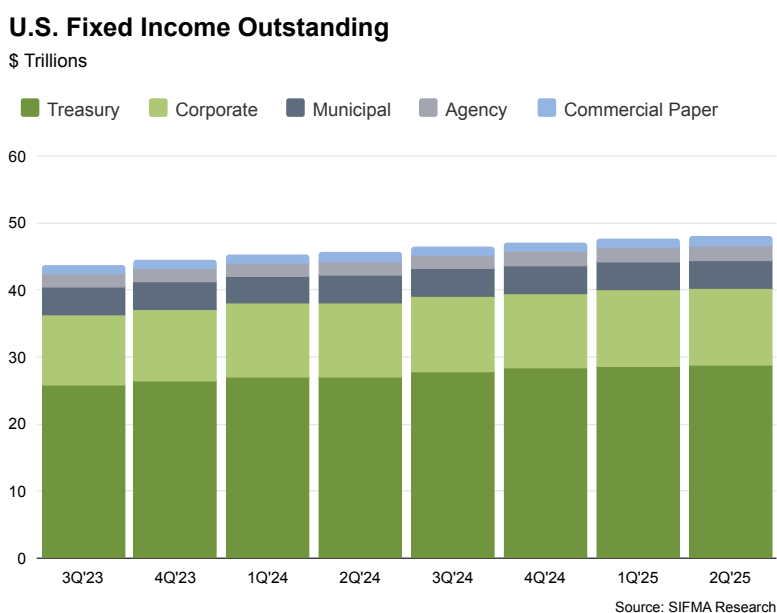
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Introduction

1.1 Motivation and Research Setting

The US Treasury market is considered to be the cornerstone of the global financial system. With outstanding securities exceeding \$28 trillion and daily trading volumes averaging more than \$900 billion, it represents the second largest and most liquid government bond market worldwide [1]. At the core of this market lie Treasury securities, which are nothing more than debt instruments issued by the US government to finance its budget deficit [2]. Beyond financing government operations, US Treasuries serve also as the benchmark for global interest rates and risk-free assets, function as safe haven assets during episodes of market turmoil, and provide essential collateral for derivatives and funding markets thanks to their unparalleled creditworthiness and exceptional liquidity [3] [4]. As such, their significance extends across virtually all areas of global finance.



The above graph shows that Treasury securities constitute more than half of the

total US fixed income outstanding, highlighting their central role in shaping US, and also global, market dynamics.

Furthermore, to put the magnitude of this market into perspective, every day over a trillion dollars worth of Treasury securities are traded, which corresponds to three times of US equities daily volume [2]. The following graph compares the size of the US Treasury market with that of other major sovereign bond markets, as well as with the world’s largest equity market, the New York Stock Exchange, showing its scale relative to other major financial markets.

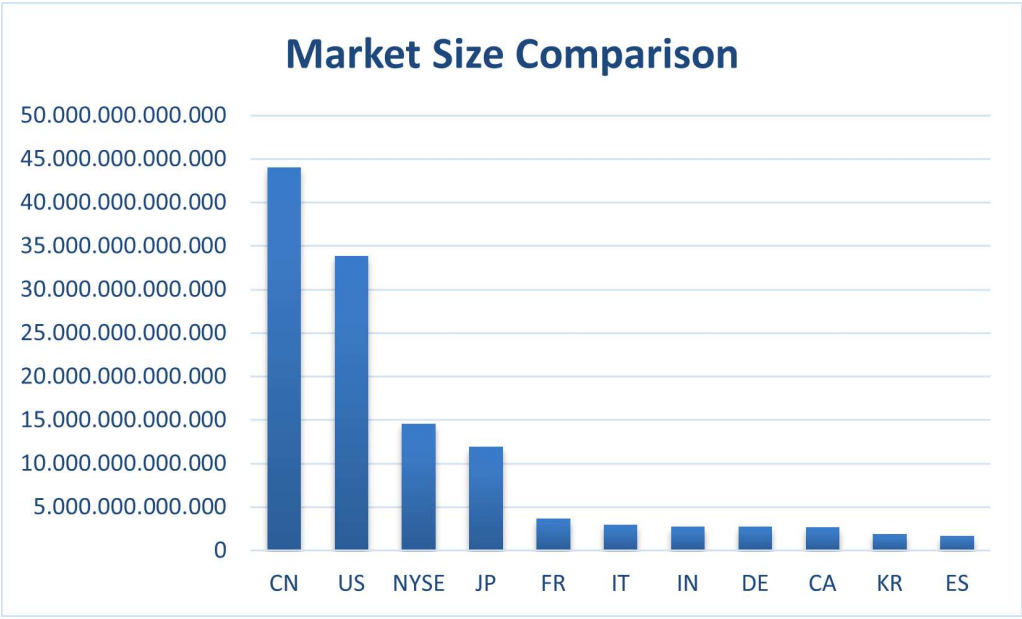


Figure 1.1: Markets Capitalization (Total Outstanding \$) [5] [6]

Given this, a thorough understanding of US Treasuries market, which is second in total outstanding only to the Chinese market, is essential not only for analyzing domestic financial conditions but also for interpreting broader trends in global capital markets.

While the global relevance of Treasuries underscores their strategic importance, the practical reality of analyzing them is far from straightforward. The Treasury market and its derivatives segment is characterized by substantial complexity. Price formation and volatility are influenced not only by macroeconomic releases and monetary policy expectations but also by the interaction of different market par-

ticipants, shifts in liquidity and cross-asset correlations. For traders and analysts, especially those operating on short time horizons, this complexity makes it difficult to interpret the prevailing market context and anticipate intraday dynamics. This thesis aims to bridge this gap by combining academic analysis with practical insights, providing a structured approach to understanding and navigating Treasury futures markets.

1.2 Research Objectives

The goal of this thesis is to provide a comprehensive structural analysis of the US Treasury market, and to assess the predictability of daily volatility across the yield curve, bridging the gap between economic theory and market practice. By deploying statistical and machine learning models, the study seeks to test whether established theoretical assumptions regarding market drivers can be translated into accurate volatility forecasts, thereby clarifying where theory aligns with market reality.

In order to achieve this objective, the thesis has to answer several key questions:

- Which macroeconomic releases, monetary policy signals, and market-based indicators are most influential in shaping treasury futures dynamics?
- How do these effects differ across maturities, from short term instruments to the long end of the curve?
- To what extent can daily volatility be anticipated based on available information?
- Can empirical findings be translated into a systematic framework that traders and analysts can apply in real time?

For the study to fulfill its purpose and address the research questions outlined above, it is structured around the following four objectives:

- Provide a comprehensive overview of the US Treasury market, including its instruments, structure, derivatives and key participants.

- Identify the primary macroeconomic, monetary policy, and market-based variables that influence Treasury market.
- Empirically test the significance of these variables in shaping market volatility, with particular attention to differences across the yield curve.
- Synthesize the empirical findings to provide an interpretive lens for the daily trading environment.

1.3 Thesis Structure

The thesis is organized into two main parts, designed to bridge the gap between theoretical understanding and empirical validation, followed by a concluding discussion.

The **first part** is dedicated to the **Theoretical Foundations** of the US Treasury market and establishes the framework necessary to understand this complex ecosystem. It begins by defining the fundamental nature of fixed income securities and the institutional purpose of the US Treasury, before delineating the full spectrum of available instruments. The analysis then proceeds to dissect the specific structure of the primary and secondary markets, as well as the hierarchy of key participants. Furthermore, the chapter examines the fundamental drivers of price formation, ranging from Federal Reserve monetary policy and critical macroeconomic indicators, to market factors like cross-assets correlation and the role of expectations.

The **second part** shifts the focus to the **Empirical Analysis**. It starts with the data collection and dataset composition methodology, which details the construction of the time series used for the study. It then proceeds with an Exploratory Data Analysis (EDA) designed to characterize the statistical properties of the variables and identify underlying patterns, and it concludes with the model specification phase where the predictive power of the theoretical drivers is tested.

The work concludes with **Chapter 4**, which synthesizes the findings by comparing the empirical results with the theoretical expectations established in the first part.

This final chapter discusses the confirmations and contradictions that emerged regarding the drivers of the yield curve, outlines the limitations of the study, and proposes a roadmap for future research directions.

Theoretical Foundations of the US Treasury Market

2.1 Overview of Treasury Instruments

Having established the importance of the US Treasury market within both domestic and global finance, it is essential to explicit the specific instruments that constitute it. Treasury securities are not a single homogeneous asset but rather a set of distinct instruments designed to meet a range of maturity, risk, and investment needs. Understanding the features of these securities is crucial, as differences in maturity, coupon structure, and issuance frequency directly shape their market behavior and investor appeal. The following section begins with an overview of bond characteristics and then introduces the various types of marketable Treasury securities, which together form the foundation of the broader Treasury market.

2.1.1 Fundamentals of Fixed-Income Securities

Before turning to the specific instruments that compose the US Treasury market, it is useful to outline the fundamental characteristics and mechanics common to all bonds. Concepts such as yield, duration, and convexity provide the analytical foundation for understanding how treasury securities are priced and how they react to changes in interest rates.

Starting from the basics, when dealing with a fixed-income security it is important to clarify some fundamental characteristics:

- the **issuer** which defines the source of the obligation; in the case of US Treasuries, this is always the United States Department of the Treasury [7]
- the **par value** (also referred to as principal), namely the nominal amount that

will be returned to the bondholder at maturity [7]

- the **maturity date**, which specifies the date when the issuers is obligated to redeem the bond by paying the outstanding principal amount [7]
- the **coupon rate**, which represents the interest rate that the issuer agrees to pay each year until the maturity date ; depending on the instrument, this rate may be fixed, floating, or indexed to inflation [7]
- lastly the **currency denomination**, which for US Treasuries is always US dollars [7]

Having covered these fundamental aspects, we can now turn to additional characteristics that are essential for understanding the behavior of fixed-income securities.

The **yield** of a bond can be defined as the discount rate that equates the present value of all future cash flows to the bond's current market price. In other words, it is the rate $\hat{r}_t^B$ such that, for a coupon bond with current price B_t and payments $Y_1, \dots, Y_n$ occurring at times $T_1, \dots, T_n$, the following condition holds under annual compounding [8]:

$$B_t = \sum_{T_i > t} Y_i (1 + \hat{r}_t^B)^{-(T_i - t)}$$

It is also well established that bond prices and yields share an inverse relationship: when bond prices rise, their yields correspondingly decline, and vice versa. This occurs because the bond's fixed interest payments, or coupons rates, remain constant, while their value changes based on the bond's current price [9].

Another important metric is **duration** (typically expressed in days or years) which represents, at a given point in the life of a fixed-income security, the weighted average time required for the bond to repay the initially invested principal through its coupon payments. An increase in either the frequency of coupon payments or their yield reduces a bond's duration. Conversely, a rise in interest rates set by the central bank leads to a decline in bond prices, negatively impacting investment performance and effectively increasing the duration [10]. The most commonly

used measure of duration is the one introduced by Frederick Macaulay in 1938, known as the Macaulay duration, which represents the weighted average time until cash flows are received. It is formally expressed as follows:

$$D_{(t,x)} = \frac{\sum_{k=1}^m (t - t_k) x_k (1 + j)^{t-t_k}}{\sum_{k=1}^m x_k (1 + j)^{t-t_k}}$$

Here, t represents the time of a given cash flow, t_m denotes the bond's maturity, and consequently the difference $t_m - t$ corresponds to the time remaining until maturity (time to maturity) [10].

It is also important to introduce **modified duration**, which measures the percentage change in a bond's price in response to a given change in interest rates. Modified duration is an adjusted form of Macaulay duration that provides a more accurate estimate of a bond's price sensitivity to interest rate fluctuations [11]. In summary, duration and modified duration are used as approximate measures of a bond's price volatility. A higher duration generally indicates greater sensitivity to interest rate changes, implying higher risk but potentially higher returns, whereas a lower duration suggests reduced interest rate risk and correspondingly lower expected returns [10].

Closely related to duration is **convexity** which is a measure that shows the relationship between bond price and yield. As we told before, the bond price and the yield are inversely related, however, this relation is not a straight line but is a convex curve. Convexity measures the curvature in this relationship, i.e., how the duration changes with a change in yield of the bond [11].

2.1.2 The Spectrum of US Treasury Securities

Having outlined the fundamental characteristics of fixed-income securities, we now turn to the specific instruments that make up the US Treasury market. US Treasury securities are divided into marketable and non-marketable categories. **Marketable securities** are those that can be transferred among investors and traded in secondary markets before maturity. Non-marketable securities, such as certain government 'account series' or savings bonds, are typically held until redemption

and cannot be freely sold. Marketable securities therefore form the backbone of liquidity and price discovery in the Treasury market and they constitute the primary object of interest in this thesis [12].

The US Treasury issues five primary types of marketable securities:

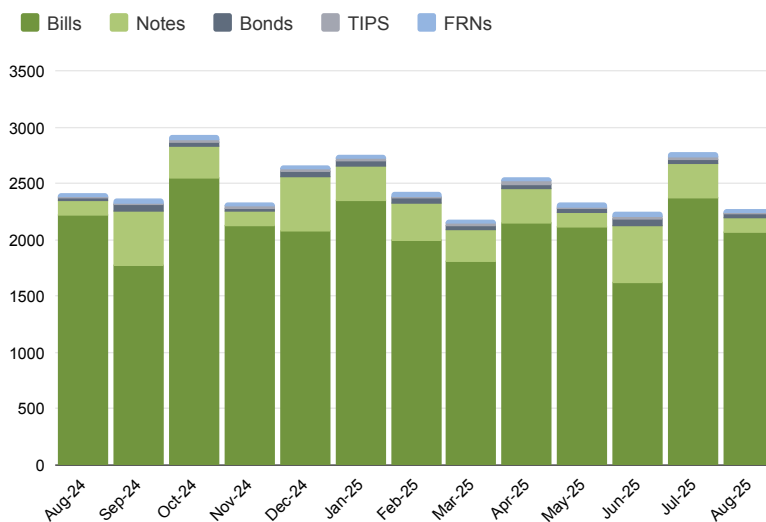
- **Treasury Bills:** short-term debt instruments with maturities from one month to one year (4, 6, 8, 13, 17, 26, and 52 weeks); they are sold at a discount or at par (face value) and pay no coupon, therefore the return is represented by the difference between the purchase price and the redemption amount [13].
- **Treasury Notes:** medium-term securities (mature in 2, 3, 5, 7, or 10 years); they pay a fixed interest rate every six months until they mature [14].
- **Treasury Bonds:** long-term securities (mature in 20 or 30 years); they pay a fixed rate of interest every six months until they mature like T-Notes [15].
- **Floating Rate Notes (FRNs):** they mature in 2 years; the interest rate is the sum of two components: a spread and an index rate based on a benchmark (currently the 13-week T-Bill rate) which reset every week; this floating interest rate is paid four times each year [16].
- **Treasury Inflation-Protected Securities (TIPS):** medium- and long-term floating rate securities (mature in 5, 10 or 30 years); as the name suggests the principal of a TIPS varies with inflation; they pay a fixed real coupon on the inflation-adjusted principal every six months until they mature [17].

Considering the issuance pattern of US Treasury securities, Treasury bills account for the largest share, as illustrated in the graph below [18].

This predominance reflects not only their short maturities and high liquidity but also their crucial role in providing flexibility for short-term Treasury financing. Indeed T-bills are auctioned on a weekly basis for 4, 6, 8, 13, 17, and 26-week maturities and on a monthly basis for 1-year maturity [13]. In contrast, the issuance

U.S. Treasury Securities Issuance

\$ Billions



Source: SIFMA Research

of Treasury Notes, Bonds, FRNs and TIPS occurs far less frequently, reflecting their longer-term nature and the structural financing role they serve [14, 15, 16, 17].

The graph also indicates that, at least during the past year, the issuance of Treasury securities has remained relatively steady, reflecting the consistency of government financing operations and the regularity of scheduled auctions [18]. The details of the auction process will be discussed more thoroughly in the following sections, when we will examine the broader market structure and the mechanisms through which Treasury securities are issued and traded.

2.2 Market Structure and its Main Participants

Having introduced the main instruments that compose the Treasury market, it is now essential to examine the environment in which these securities are issued and traded. Understanding the mechanics of the primary and secondary markets is crucial, as the process of issuance and the subsequent trading activity directly influence price formation, liquidity, and the allocation of risk across participants. In turn, this framework naturally leads to the analysis of the key institutions and

investors whose trading behavior and strategic positioning critically affect market dynamics.

2.2.1 The Primary Market

The functioning of the Treasury market begins with the **primary market**, in which new securities are allocated through scheduled auctions, where the government raises funds directly from investors. The frequency of these auctions varies according to the type of security and is summarized in the table below.

Security	Original issue	Reopenings
Bills	Weekly	/
1-year Bills	Monthly	/
Notes	Monthly	/
10-year Notes	Feb., May, Aug., Nov.	8 per year
Bonds	4 per year	8 per year
FRNs	Jan., April, July, Oct.	All other months
5-year TIPS	April, Oct.	June, Dec.
10-year TIPS	Jan., July	March, May, Sept., Nov.
30-year TIPS	Feb.	Aug.

Table 2.1: Treasury Securities Auctions frequency [13, 14, 15, 16, 17]

The table distinguishes between the original issue, in which a security is sold to the public for the first time, and reopenings, in which the US Treasury issues additional amounts of an existing security. In a reopening, the security retains the same maturity date and coupon (or spread) as the original issuance, but features a new issue date and typically a different purchase price [19]. Reopenings are conducted to increase the size of an outstanding issue, thereby enhancing its liquidity and making it more attractive to investors. This strategy helps to create a large, liquid offering of debt instruments, facilitating more efficient trading and better pricing in the secondary market [20].

Formally treasury **auctions** are open to all investors; however, a specific group of participants known as **primary dealers** play a central role in the process. Primary dealers are financial institutions with an established trading relationship with the

Federal Reserve Bank of New York. In particular, primary dealers act as trading counterparties of the New York Fed in its implementation of monetary policy. Beyond this role, they are also expected to provide market-making services for the New York Fed on behalf of its official accountholders when required, as well as to participate in all Treasury auctions by submitting pro-rata bids at reasonably competitive prices, thereby helping to ensure that the full issuance is placed at fair market conditions [3] [21]. Some of them operate as subsidiaries of large bank holding companies, while others are independent securities broker-dealers [3]. The current roster of primary dealers includes 25 institutions, and to provide a clearer sense of who these primary dealers are, we can cite some globally recognized firms such as J.P. Morgan, Goldman Sachs, Morgan Stanley and Deutsche Bank which operates alongside a range of other major banking and securities institutions [22].

Alongside them, other investor, including asset managers, pension funds, and foreign monetary authorities, also participate in the auctions, either directly or indirectly through primary dealers acting as intermediaries [3]. In 2024, the average daily turnover (the volume traded) of US Treasury securities by primary dealers ranged from \$545 billion to \$944 billion per week, underscoring their crucial role in efficiently intermediating the market and ensuring liquidity [23]. Due to their status and to ensure both transparency and effective oversight, primary dealers are required to provide accurate data on their market activity on a weekly basis, and are also surveyed on their expectations on economy, monetary policy, and financial market developments [22].

In conclusion, the following diagram provides a synthetic representation of the primary market:

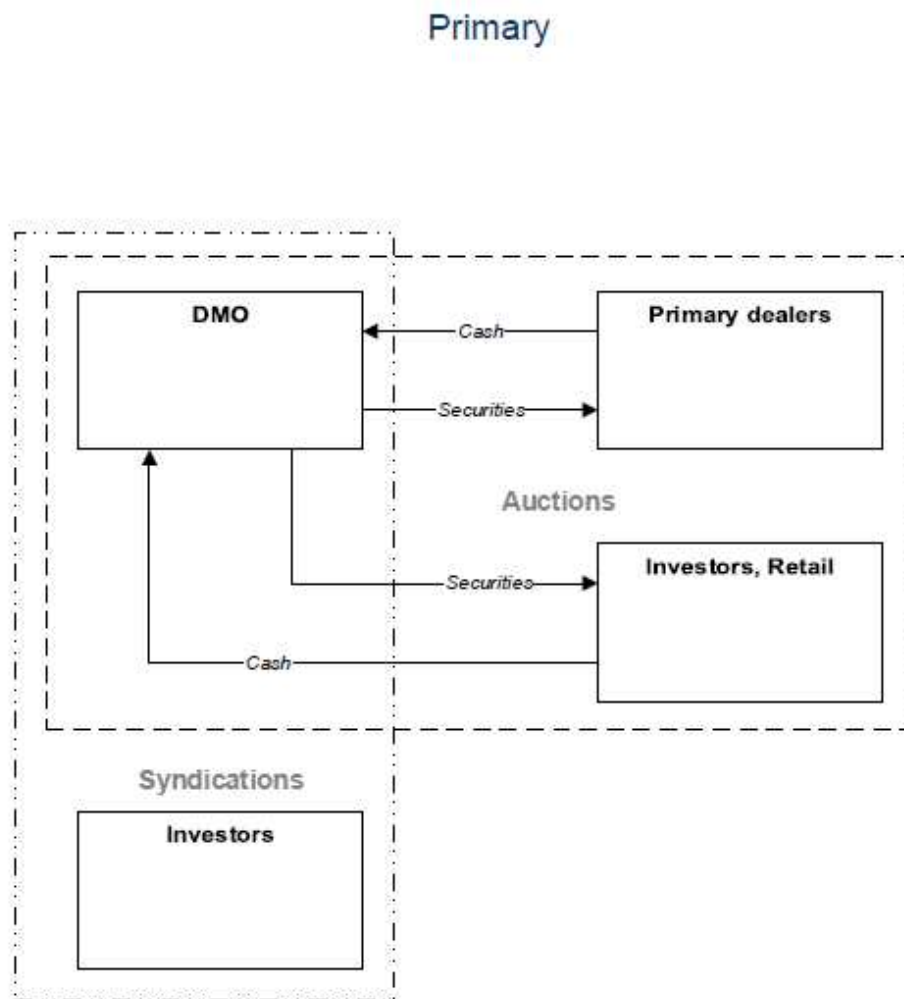


Figure 2.1: Primary Market Structure [24]

2.2.2 The Secondary Market

Once securities have been issued in the primary market, their economic significance truly unfolds in the **secondary market**, where treasuries are continuously exchanged among investors. This market ensures liquidity, enables price discovery, and allows participants to rebalance portfolios, making it the backbone of the Treasury's role as a global benchmark asset.

The secondary market for Treasury securities operates predominantly in the over-the-counter (OTC) space. An **OTC market** (as opposed to an exchange market) is

a decentralized market where geographically dispersed dealers, connected through telecommunication networks and electronic platforms, trade securities not listed on a stock or derivatives exchange [25]. This structure is particularly suited to debt securities for several reasons. First, there is a very large population of debt securities compared with equities and this make centralized trading impractical: while a few thousand equities are listed on major exchanges, there are hundreds of thousands of bonds in circulation globally. Second, the average size of bond transactions is often in the range of millions of dollars, significantly larger than equities. Third, unlike equities, almost all bonds trade very infrequently, so there is rarely a constant supply of buyers and sellers able to sustain a sufficient central pool of liquidity [26]. Therefore, in this market, liquidity is provided mainly by **dealers** who operate in two ways:

- They commit their own capital by, for example, purchasing securities from investors even in the absence of an immediate counterparty. In doing so, they assume the risk of holding these positions until a buyer can be found, with the expectation of eventually reselling the securities at a profit [26].
- Alternatively, dealers may act as intermediaries by executing client orders. In such cases, they take an order from a client who wants, for instance, to buy a quantity of a particular bond and then they search the market to locate a counterparty willing to take the opposite side of the trade. Once both buyer and seller are identified, the dealer negotiates prices that satisfy each party, capturing a profit from the spread between the purchase and sale prices [26].

In this context, it is important to recognize that at any given time, multiple securities of the same maturity coexist. For example, 2-year notes, issued monthly, can have more than 20 separate issues outstanding simultaneously. To properly analyze trading activity and pricing behavior in the secondary market, it becomes essential to distinguish between **”on-the-run”** security, which corresponds to the most current issue, and **”off-the-run”** securities which comprise all earlier outstanding issues of the same maturity [27]. Usually, the on-the-run security ex-

hibits a higher turnover, defined as the average daily trading volume relative to the amount outstanding. As a result, it is considered the benchmark for its maturity segment, serving as the primary reference point for pricing and valuation. By contrast, off-the-run securities are traded less actively and therefore tend to be less liquid. As a consequence, investors typically demand a liquidity premium to hold them, which translates into slightly higher yields compared to their more recently issued counterparts (liquidity premium) [27, 28].

Another important aspect to highlight is that, although the Treasury market operates as an OTC market, in order to fully grasp its functioning, it is essential to recognize that trading activity is not homogeneous but distributed across several interconnected segments. Each of these segments plays a distinct role in the provision of liquidity and the transmission of market information. The following image provides a simplified representation of this structure, highlighting the three principal areas of activity: the Dealer-to-Client (DTC) market, the Dealer-to-Dealer (DTD) market, and the Interdealer Broker (IDB) market.

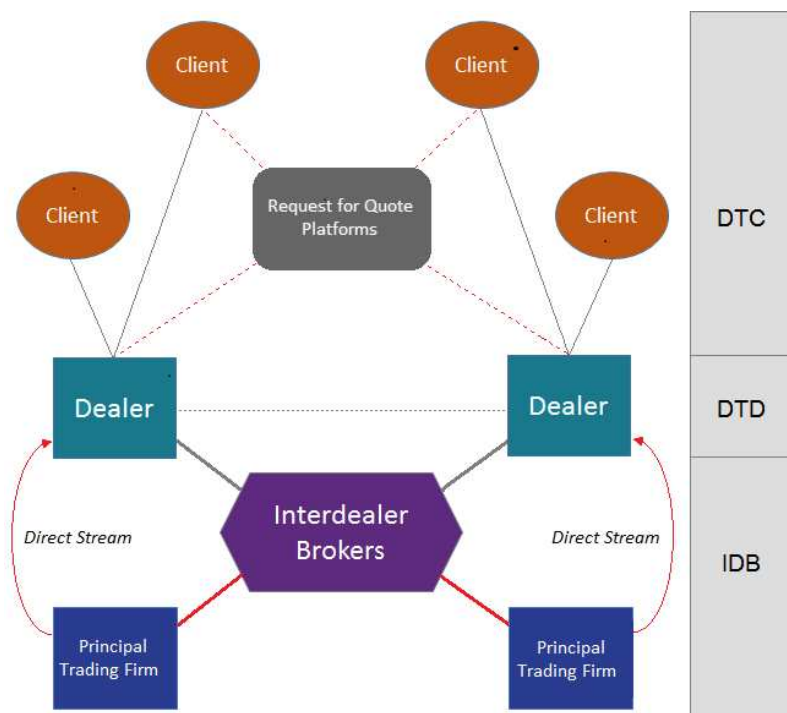


Figure 2.2: Treasury Market Structure [29]

At the top of the diagram lies the **Dealer-to-Client (DTC) segment**, where investors such as asset managers, hedge funds, and other institutional clients interact with dealers. In this segment transactions occur either bilaterally, through direct dealer–client relationships, or via electronic request-for-quote (RFQ) platforms. In the middle, the **Dealer-to-Dealer (DTD) segment** illustrates how dealers trade directly with each other. This layer is essential for maintaining liquidity across the market, as it allows dealers to offload risk, manage inventory, and quote tighter spreads to their clients. Moving to the bottom half of the diagram, we have the **Interdealer Broker (IDB) segment**, where both dealers and principal trading firms trade with each other via Interdealer brokers as well as through direct stream platforms [30].

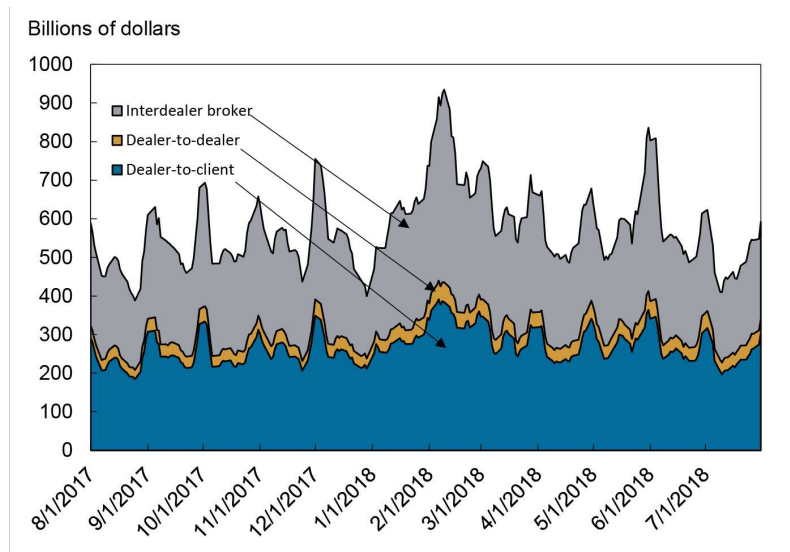


Figure 2.3: Trading Volume by Segment [29]

5-day moving averages of daily trading volumes by market segment from August 1 2017 to July 31 2018

Furthermore, as shown in Figure 2.3, the **Dealer-to-Dealer (DTD) segment** accounts for the smallest share of activity, while the majority of trading volume is approximately evenly split between the **Interdealer-Broker (IDB)** and **Dealer-to-Client (DTC)** segments [29].

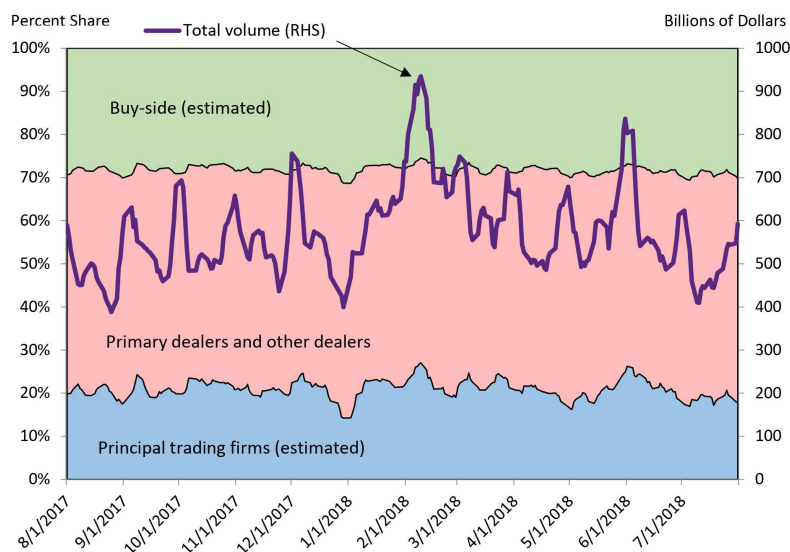


Figure 2.4: Trading Volume Shares by Participant Type [29]

5-day moving averages of daily trading volume shares by participant type and total daily trading volumes from August 1 2017 to July 31 2018

Figure 2.4 provides an additional layer of insight into the composition of the Treasury market. It can be observed that **dealers dominate trading activity**, accounting for roughly 51 percent of overall market volume. Also principal trading firms (PTFs) contribute an estimated 21 percent, while buy-side institutions such as asset managers and pension funds represent about 28 percent. This distribution underscores the central role of dealers as liquidity providers, complemented by the growing presence of PTFs and the stable participation of the buy-side [29].

To complete the discussion, Figure 2.5 summarizes the structure of the secondary market:

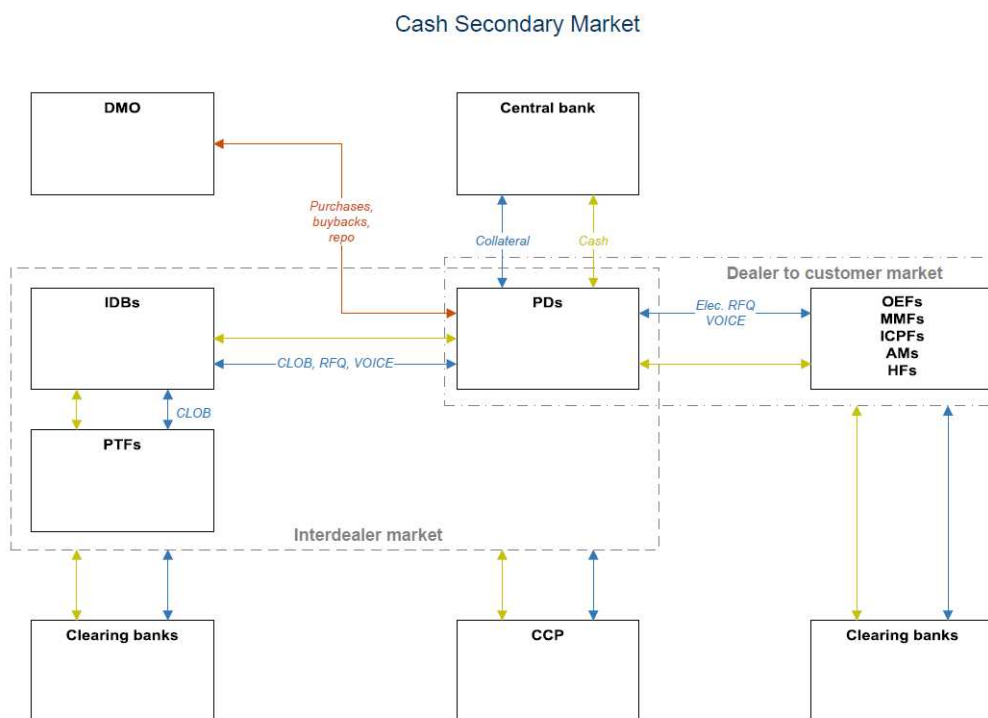


Figure 2.5: Secondary Market Structure [24]

In addition to the cash market discussed thus far, a fundamental component of the Treasury ecosystem is the **repo market** (repurchase agreement market). In a repurchase agreement (**repo**), one party sells an asset (typically a fixed-income security) to another party at an initial price, while simultaneously committing to repurchase the same asset at a later date (US repo market is mainly overnight [31]). In this operation the counterparty providing cash is typically described as engaging in a *reverse repo* (ie buying, then selling) [32]. The repo market plays a pivotal role in the functioning of modern financial markets by providing both secured short-term funding and safe investment opportunities. For cash lenders (repo buyers), repos offer a **low-risk investment** because the transferred collateral can be liquidated in the event of counterparty default, and at the same time the counterparty can benefit of **cheap and abundant funding** [33]. Given these essential characteristics, the repo market supports multiple critical functions across financial markets. It facilitates efficient collateral management, enhances liquidity in both cash and securities markets, and enables investors to hedge positions or take leveraged exposures. Re-

pos also help central bank operations, support primary and secondary debt markets, foster price discovery, and improve settlement efficiency. By providing a flexible and secure mechanism for the transfer of cash and securities, the repo market also contributes to the resilience and stability of the broader financial system [34]. Finally, Figure 2.6 presents a synthetic overview of the repo market, summarizing its structural features and the key relationships among participants:

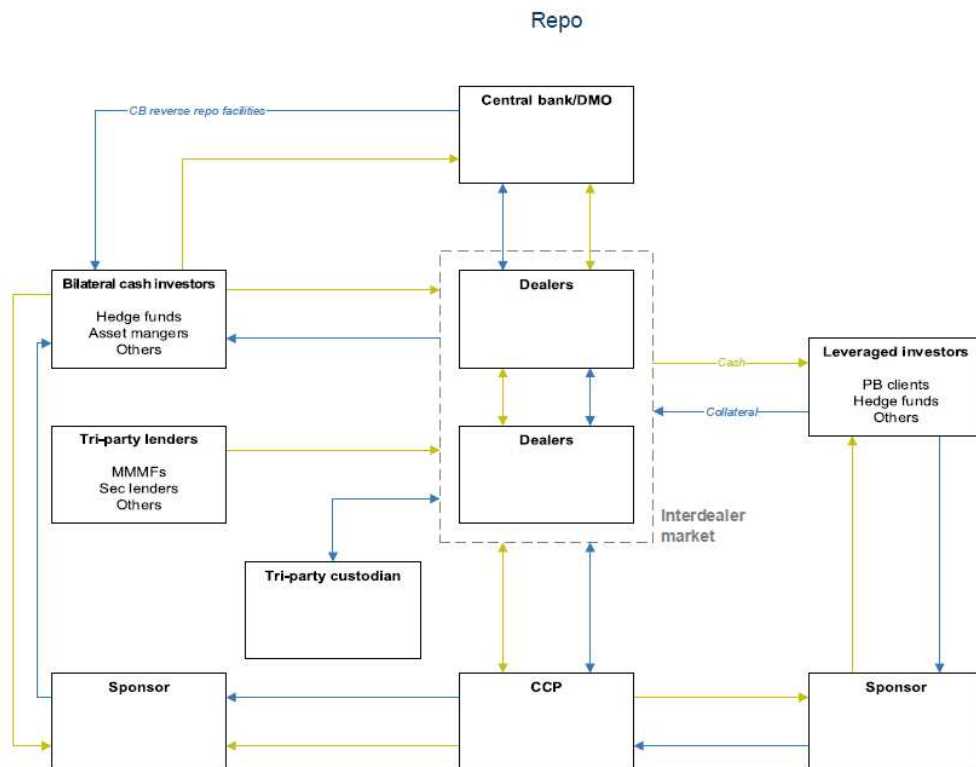


Figure 2.6: Repo Market Structure [24]

2.2.3 The Treasury Futures Market

Beyond the cash and repo markets, the **Treasury futures market** constitutes the third major pillar of the US government securities ecosystem. To begin, it is necessary to clarify the nature of a futures contract. A **futures contract** represents a legally binding agreement between two parties to buy or sell a *standardized asset* on a specific date or during a specific month. Furthermore, this transaction is facilitated through a *futures exchange*. The standardized nature of futures contracts implies that their specifications are identical for all market participants. This

uniformity allows buyer or seller to easily transfer contract ownership to another party by way of a trade. The exchange plays a fundamental role in the functioning of futures markets. It is responsible for standardizing the specifications of each contract and for guaranteeing that the contract will be honored, eliminating counterparty risk. This is possible because every exchange-traded futures contract is centrally cleared, meaning that once a trade is executed, the exchange (through its clearinghouse) becomes the buyer to every seller and the seller to every buyer. This mechanism effectively eliminates counterparty risk, ensuring that the default of a single participant does not compromise the integrity of the market. In contrast to OTC markets, exchange trading brings together a broad base of confident buyers and sellers on a unified electronic platform and promotes deep liquidity and efficient price discovery [35].

In the case of US Treasury futures, trading takes place on the **CBOT** exchange, which is part of the CME Group, the world's largest derivatives marketplace [36]. The CME Group also provides a centralized electronic platform, known as *CME Globex*, where participants can trade Treasury futures almost continuously across global time zones. Another fundamental feature is the CME Group clearinghouse, *CME Clearing*, which serves as the central counterparty for all transactions, eliminating bilateral credit exposure.

With the functioning of the exchange established, the next step is to examine the main Treasury futures contracts. The table 2.2 summarizes their specifications and key characteristics:

Table 2.2: CBOT US Treasury futures contract details

Contract	Face Amount	Deliverable Maturities	Min Tick	Min Tick Value
2-Year T-Note (ZT)	\$200,000	1 $\frac{3}{4}$ – 2 yrs	1/8 of 1/32	\$7.8125
3-Year T-Note (Z3N)	\$200,000	2 $\frac{9}{12}$ – 3 yrs	1/8 of 1/32	\$7.8125
5-Year T-Note (ZF)	\$100,000	4 $\frac{1}{6}$ – 5 $\frac{1}{4}$ yrs	1/4 of 1/32	\$7.8125
10-Year T-Note (ZN)	\$100,000	6 $\frac{1}{2}$ – 8 yrs	1/2 of 1/32	\$15.625
Ultra 10-Year T-Note (TN)	\$100,000	9 $\frac{5}{12}$ – 10 yrs	1/2 of 1/32	\$15.625
T-Bond (ZB)	\$100,000	15 – 25 yrs	1/32	\$31.25
20-Year T-Bond (TWE)	\$100,000	19 $\frac{2}{12}$ – 19 $\frac{11}{12}$ yrs	1/32	\$31.25
Ultra T-Bond (UB)	\$100,000	25 – 30 yrs	1/32	\$31.25

Source: CME Group, *The basics of US Treasury futures*[37].

From the table, it is evident that most US Treasury futures contracts have a face

value at maturity of \$100,000, with the exception of the 2-Year and 3-Year contracts, which have a face value of \$200,000. Prices are quoted in points per \$2,000 for the 2-Year and 3-Year contracts, and per \$1,000 for all other contracts, with fractional points expressed in 1/32nds, in line with the convention in US government bond market. The minimum tick size varies by contract: 1/32nd of a point (\$31.25) for the 30-Year, 20-Year, and Ultra T-Bond; 1/2 of 1/32nd (\$15.625) for the 10-Year and Ultra 10-Year; 1/4 of 1/32nd (\$7.8125) for the 5-Year; and 1/8 of 1/32 (\$7.8125) for the 2-Year and 3-Year contracts [37].

Before diving into the delivery process of treasuries futures contracts, it is important to emphasize that all these products share the same (electronic) trading hours: from 5:00 p.m. to 4:00 p.m., Sunday - Friday (Central Time); and the same expiration contract calendar: March quarterly cycle [37].

Furthermore, it should be noted that the 3-Year T-Note (Z3N) and 20-Year T-Bond (TWE) contracts have been introduced only recently and currently exhibit limited trading volume and open interest. The same applies to micro contracts, which represent one-tenth the size of the standard contracts and similarly lack sufficient liquidity. For these reasons, these products will not be included in our analysis. Figure 2.7 shows volume and open interest of futures treasuries products, and we can notice that ZN and ZF represent the most liquid part of the curve.

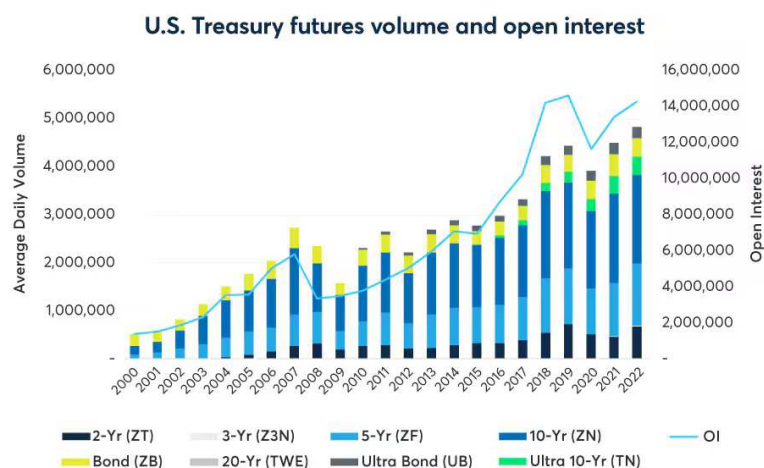


Figure 2.7: US Treasury futures volume and open interest [37]

Now, in order to fully understand the connection between the futures and the cash Treasury markets, it is essential to examine the **delivery process** underlying Treasury futures contracts. Futures contracts may generally be settled in two ways: through physical delivery of the underlying asset or through cash settlement. In the case of US Treasury futures, settlement occurs via *physical delivery* of an eligible Treasury security at contract expiration.

In table 2.3 it is explained what the characteristics of an eligible Treasury security are for each future contract. These criteria primarily concern the *remaining term to maturity* at the time of delivery and, in some cases, the *original term to maturity* at issuance.

Table 2.3: Deliverable grades for Treasury note and bond futures [38].

Futures Product	Deliverable Grade
ULTRA U.S. TREASURY BOND FUTURES (UB)	Treasury bonds. Remaining term to maturity: at least 25 years
U.S. TREASURY BOND FUTURES (ZB)	Treasury bonds. Remaining term to maturity: at least 15 years and less than 25 years
20-YEAR U.S. TREASURY BOND (TWE)	Treasury bonds. Remaining term to maturity: at least 19 years 2 months and not more than 19 years 11 months
ULTRA 10-YEAR U.S. TREASURY NOTE (TN)	Treasury notes. Remaining term to maturity: at least 9 years 5 months and not more than 10 years
10-YEAR T-NOTE FUTURES (ZN)	Treasury notes. Remaining term to maturity: at least 6 years but less than 8 years
5-YEAR T-NOTE FUTURES (ZF)	Treasury notes. Remaining term to maturity: at least 4 years 2 months. Original term to maturity: not more than 5 years 3 months.
3-YEAR T-NOTE FUTURES (Z3N)	Treasury notes. Remaining term to maturity: not less than 2 years 9 months and not more than 3 years. Original term to maturity: not more than 7 years.
2-YEAR T-NOTE FUTURES (ZT)	Treasury notes. Remaining term to maturity: at least 1 year 9 months and not more than 2 years. Original term to maturity: not more than 5 years 3 months

It can be observed from table 2.3 that often the nominal maturity of a Treasury futures contract does not coincide with the effective maturity of the underlying deliverable securities. For instance, the 10-Year T-Note futures contract (ZN), despite its name, allows delivery of Treasury notes with a remaining maturity ranging between six and eight years.

We now proceed to examine in detail the mechanics of the **delivery process** which

takes place over, or near, the quarterly contract delivery months (March (H), June (M), September (U), and December (Z)) and spans a fixed three-day period. These three days are known respectively as *Intention Day*, *Notice Day*, and *Delivery Day* [39].

- On *Intention Day*, which occurs two business days prior to the first business day of the expiration month, the short position notifies CME Clearing of its intention to make delivery, causing the process to begin. Then, on this day, the final contract price is determined and CME Clearing assigns the delivery to the oldest outstanding long position [39].
- On *Notice Day* the short position declares which US Treasury security they will deliver versus cash payment to the long position. The selected security must satisfy the eligibility criteria illustrated in table 2.3 and each eligible security is associated with a unique conversion factor, determined by its coupon rate, maturity date and the expiration date of the futures contract. This conversion factor is used along with the final futures price and accrued interest to determine the final invoice amount of the delivery. By the end of Notice Day, both counterparties are aware of the final price, the specific security to be delivered, its conversion factor, and the corresponding accrued interest. At this point CME Clearing verifies these details for each matched short and long position and assures the respective parties have exchange bank wire instructions [39].
- On the third and final day, the *delivery day*, after all details and settlement instructions have been verified, all security versus cash transactions are completed by 1 p.m., officially concluding the delivery procedure [39].

It is important to note that, in this process, the long (buyer) position remains passive until delivery is assigned by the clearing house. Conversely, the short (seller) position may deliver security for contract on any business day of the expiring quarterly contract month. In this case, futures on US Treasuries behave like an American-style option, in the sense that the short can exercise its option before the last trading

day of the contract [39].

As is typical for most futures contracts, only a very small proportion of US Treasury futures positions proceed to physical delivery at expiration. Table 2.4 illustrates this phenomenon clearly, showing that the number of contracts reaching delivery remains consistently low relative to total open interest throughout the 1990–2022 period.

Table 2.4: Treasury futures delivery activity (Dec 1990 – Dec 2022)[38].

Futures product	Physical deliveries as % of mature open interest
Ultra U.S. Treasury Bond Futures (UB)	1.5 %
U.S. Treasury Bond Futures (ZB)	1.9 %
Ultra 10-Year U.S. Treasury Note Futures (TN)	1.4 %
10-Year T-Note Futures (ZN)	2.8 %
5-Year T-Note Futures (ZF)	3.4 %
2-Year T-Note Futures (ZT)	6.3 %
Total	2.8 %

Note: The measure of activity shown is physical deliveries in proportion to mature open interest. For a futures contract for a given delivery month, “physical deliveries” is the number of contracts that go to delivery, and “mature open interest” is the median daily level of open interest during the 42 exchange business days ending on and including the contract’s First Position Day. For UB futures the data set comprises 52 delivery months, and for TN futures 28 delivery months. For each other futures product the corresponding data set comprises 129 delivery months. Data for 3-Year and 20-Year futures are included in the Total but product-specific results are not shown due to relatively small sample size. *Source: CME Group (2023).*

This pattern reflects the behavior of large open interest holders, such as institutional investors and dealers, who generally prefer to avoid assuming the responsibility of delivery. Then, in order to avoid it, they chose to “roll” their positions into the next quarterly contract prior to intention day. By rolling their positions forward, market participants effectively transfer liquidity from the expiring (front) quarterly contract to the next active one. This process causes the roll, or calendar spread between the front and next quarterly contract. Such behavior is distinctive of physically settled futures contracts and contrasts with cash-settled instruments, where no delivery obligation exists and liquidity remains more evenly distributed across maturities [39].

Having established the criteria that determine which securities are eligible for delivery, the next question concerns how the short position decides which specific security to deliver and in order to do that we’ve to introduce the concept of the **Cheapest-to-Deliver (CTD)** security. As we told before each US Treasury futures contract has a designated basket of eligible securities available for delivery, but,

among these, typically one, or occasionally two, securities prove to be the most efficient for the short position to deliver to the long position. A security is defined the most efficient because, as the name suggest, it is considered cheaper or cheapest to deliver versus the other alternative securities [40].

There are two main methods commonly employed to determine the cheapest-to-deliver (CTD) security:

- the **net basis method** which consists in identifying the security exhibiting the lowest net basis. This approach begins by finding the *basis* for each deliverable security, which is defined as:

$$\text{Basis} = \text{Cash Price} - (\text{Futures Price} \times \text{Conversion Factor})$$

The next step is to adjust it for *carry*, which represents the net cost (or benefit) of holding the bond until delivery and is calculated as:

$$\text{Carry} = \text{Coupon Income} - \text{Financing Cost}$$

Carry can be either positive or negative depending on the level of interest rates and the slope of the yield curve. The resulting *net basis* is given by:

$$\text{Net Basis} = \text{Basis} - \text{Carry}$$

As we told in the beginning, the security exhibiting the *lowest net basis* is generally identified as the CTD, as it represents the most cost-efficient option for delivery [40].

- the **implied repo rate (IRR) method** which name comes from the theoretical yield obtained by executing a cash-and-carry arbitrage. In particular the IRR is the rate produced by buying the cash security, selling the futures contract, lending the cash security in the repo market and finally, delivering the security into the futures contract on last delivery day. The issue with the *highest IRR* is generally considered the CTD, since it offers the most attractive implied financing return for the short position [40].

Knowing which security is the CTD is very important since the futures contract's price tends to mirror the behavior of its CTD security. Moreover, the CTD security plays a crucial role in the computation of hedge ratios because the futures contract's theoretical basis point value is derived directly from it [40].

To summarize, and to address the question of why market participants may prefer Treasury futures over cash instruments, it is important to underline the main advantages that futures market brings:

- First, *deep and centralized liquidity* which permits efficient price discovery and immediate execution even for large orders.
- The *ease of going short* by selling contracts, unlike the cash market where shorting requires borrowing securities from the repo market.
- *Market transparency and counterparty credit risk mitigation* thanks to the centralized clearing mechanism.
- *Contract standardization*, which simplifies participation and comparison across maturities.
- And finally, *superior capital efficiency*, achieved through the use of margining systems, and *lower transaction costs* enable participants to manage large exposures and rebalance positions more efficiently through leverage.

Together, these attributes make Treasury futures an indispensable instrument in the broader treasury market [41].

To conclude this section, the following diagram provides a schematic summary of the structure of the US Treasury futures market:

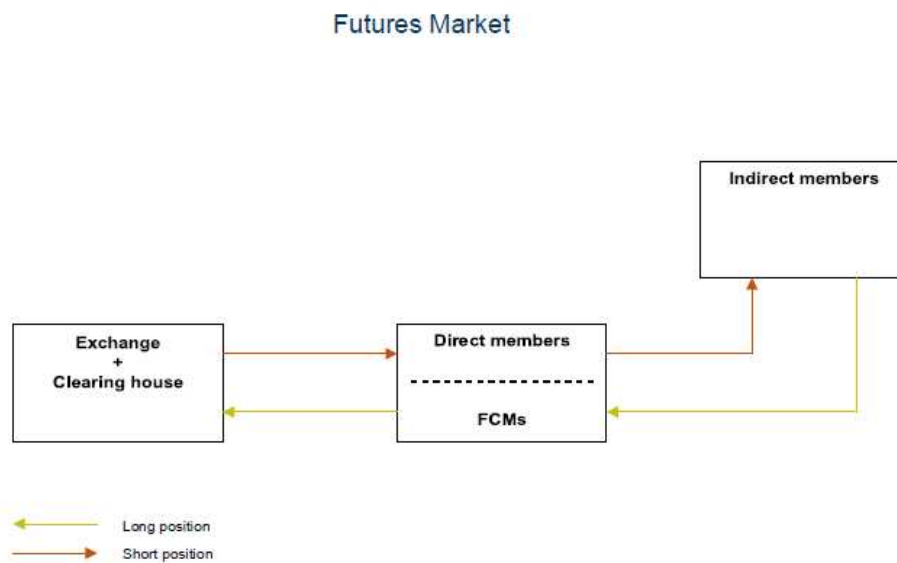


Figure 2.8: Futures Market Structure [24]

2.2.4 The Main Actors in Treasury Trading

Having outlined the structural segments of the Treasury market, it is now crucial to identify the key participants whose trading activity sustains liquidity, shapes price discovery, and ultimately determines the efficiency of this market. These actors range from traditional dealers to modern algorithmic traders, institutional investors, foreign central banks, and the Federal Reserve itself.

It is first essential to distinguish between two categories of market participants (though they often overlap in practice): those who are long-term holders of US treasuries, and those who actively trade them on a daily basis, thereby providing the liquidity in the market.

Focusing on the latter category, those who sustain the daily functioning of the market providing liquidity, it is possible to identify three main groups of participants whose relative importance was outlined in the previous subsection (2.2.2).

Summarizing briefly we have:

- **Primary dealers and other registered dealers**, which account for roughly half of the daily market volume in US treasury market and whose role has been previously analyzed and mainly consists in market-making services ensuring

liquidity and facilitating the efficient functioning of the market.

- **Principal Trading Firms (PTFs)** which are non-bank proprietary trading entities that specialize in electronic, high-frequency, and algorithmic strategies. These firms typically generate large volumes of orders, maintain positions for extremely short periods (often less than one second) and usually end each trading day flat. For these reasons PTFs are active in most futures markets and, to a lesser extent, in some cash markets (especially in the US treasury cash market where their participation is estimated to account for roughly 20% of total daily trading volume). Conversely, their presence in the repo market remains limited, as their trading strategies generally do not require overnight financing. Instead, they rely primarily on intraday liquidity provided by prime brokers and clearing banks to support their high-frequency operations. Furthermore, in contrast to traditional dealers, PTFs do not engage in client intermediation or external capital raising; their participation is purely proprietary [24] [29].
- **Buy-side institutions** which include asset managers, pension funds, insurance companies, together with other institutional investors and account for roughly 30% of daily market volume in US treasury market [29].

While the day-to-day functioning of US treasury market depends on a relative small group of active participants who provide liquidity and facilitate trading, the ownership of US Treasury securities is widely distributed across a diverse set of investors. Figure 2.9 illustrates the composition of US treasuries holders:

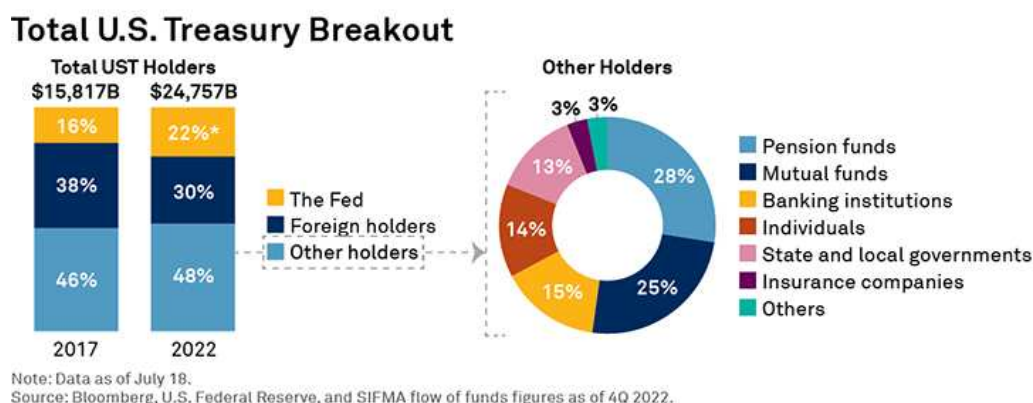


Figure 2.9: Total US Treasury Breakout [42]

We can notice that foreign governments and monetary authorities, including the Federal Reserve, collectively hold approximately 60% of outstanding Treasury securities, with private investors, both institutional and retail, accounting for about a third. While this distribution has evolved over time in response to shifts in interest rates and global economic conditions, US government debt continues to be bought as it is recognized worldwide as a safe and reliable store of value [42].

From the point of view of the Federal Reserve and others foreign monetary authorities, the accumulation of US treasuries reflects distinct but complementary macro-financial objectives.

The **Federal Reserve** holds treasuries primarily as part of its monetary policy implementation, using them as the main instrument for conducting open market operations and managing the supply of reserves in the banking system [43], a mechanism that will be analyzed in greater detail in the following sections.

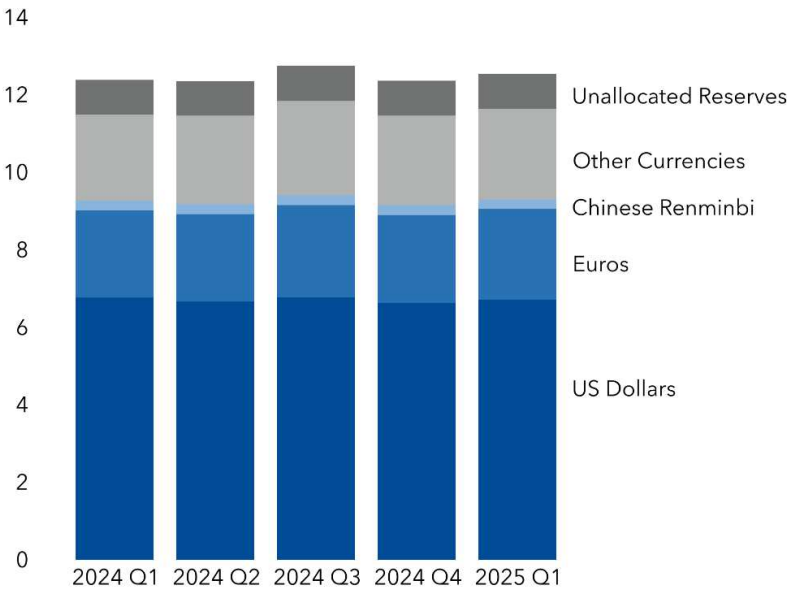
On the other hand **foreign governments and central banks** hold US treasuries mainly for reserve management and exchange rate stabilization. As the US dollar remains the dominant reserve currency and vehicle for international trade and finance, foreign monetary authorities accumulate treasuries as safe, liquid, dollar-denominated assets to back their foreign exchange reserves. These reserves provide a buffer against external shocks, help manage capital flows, and allow interventions in currency markets to maintain exchange rate stability. In addition, treasuries deep liquidity and minimal credit risk make them the preferred instrument

for preserving the value and accessibility of official reserves. These same characteristics (safety, liquidity, and reliability) also explain why pension funds, mutual funds, banks, insurance companies, and even individual investors often allocate a significant share of their portfolios to US treasuries.

As shown in the following graph, the US dollar constitutes the predominant currency in which foreign reserves are held, thereby supporting the argument presented above.

World Official Foreign Currency Reserves Increased in the First Quarter of 2025

Trillions of US Dollars



Source: IMF COFER Dataset.

IMF

Figure 2.10: IMF Currency Composition of Official Foreign Exchange Reserves, World Aggregates, First Quarter of 2025 [44]

However, foreign holders are not limited to governments and central banks. As of December 2024, foreigners detained 30% of the publicly held debt, but official institutions accounted for only 44.2% of this (approximately \$3.8 trillion), while the remaining 55.8% (around \$4.8 trillion) was held by private investors.

Including both private and institutional investors, the top three estimated foreign holders of US federal debt by country are Japan (\$1.15 trillion), the United Kingdom (\$0.89 trillion) and China (\$0.73 trillion). According to estimates as of July

2025, Japan holds approximately 12.6% of all foreign investment in US publicly held federal debt, while the United Kingdom approximately 9.8% and China roughly 8.0% [45].

This graph summarizes the composition of foreign participation in the US Treasury market by country:



Figure 2.11: Major Foreign Holders of Treasury Securities (Billions of dollars) (July 2025) [46])

2.3 Fundamental Drivers of US Treasury Pricing

Having examined the main participants in the US treasury market and their respective roles, the next step is to analyze the underlying factors that govern their actions and ultimately determine the dynamics of price formation. The valuation of US Treasuries is essentially influenced by a combination of monetary policy expectations, macroeconomic developments, and market-specific conditions. Understanding these drivers is crucial for interpreting both the short-term dynamics and long-term equilibrium of Treasury yields.

2.3.1 Monetary Policy and the Role of the Federal Reserve

Among all the factors influencing the pricing of US Treasuries, monetary policy expectations play the most fundamental role, because through its policy decisions, the Fed directly affects the short end of the yield curve and indirectly shapes expectations across all maturities. In this context, treasury yields can be interpreted as the market's collective assessment of the current and expected stance of monetary policy. For this reason it is essential to understand the dynamics that shape Federal Reserve's actions.

In its *Statement on Longer-Run Goals and Monetary Policy Strategy* [47], the Federal Reserve defines the two pillars of its **dual mandate**: *maximum employment* and *price stability*.

With regard to employment, the Federal Open Market Committee (FOMC)¹ acknowledges that the **maximum level of employment** is not directly measurable because it depends largely to non-monetary factors that affect the structure and dynamics of the labor market and they define it as the highest level of employment that can be achieved on a sustained basis in a context of price stability. Consequently, the Committee refrains from specifying a fixed numerical target for employment; instead they recognize that policy decision must be informed by assessments of the maximum level of employment, assessments that are necessarily uncertain and subject to revision [47].

By contrast, the objective of **price stability** is expressed more precisely: the FOMC affirms that an inflation rate of 2 percent, as measured by the annual change in the price index for personal consumption expenditures (PCE), is most consistent with its statutory mandate over the longer run. It is possible for them to define a precise number because the inflation rate (over the longer run) is primarily determined by monetary policy, and not by structural and non-monetary factors like employment. The Committee emphasizes that well anchored long-term inflation expectations around 2 percent support price stability and foster moderate long-term interest

¹The Federal Open Market Committee (FOMC) consists of twelve members—the seven members of the Board of Governors of the Federal Reserve System; the president of the Federal Reserve Bank of New York; and four of the remaining eleven Reserve Bank presidents, who serve one-year terms on a rotating basis [48].

rates, enhancing its ability to sustain maximum employment even during significant economic disturbances [47].

The Federal Reserve acknowledges that its employment and inflation objectives are generally complementary. However, in circumstances where these objectives are perceived to be in conflict, the FOMC adopts a balanced approach in pursuing them. This approach takes into account both the magnitude of the deviations from the respective goals and the potentially different time horizons over which employment and inflation are expected to return to levels consistent with the dual mandate. Moreover, the Committee recognizes that employment may, at times, exceed real-time assessments of maximum employment without necessarily posing risks to price stability [47].

In practice, the pursuit of the dual mandate is conducted through the management of the **federal funds rate (FFR)** target range, which is the interest rate charged by banks to borrow from each other overnight [49].

Movements in this key policy rate propagate through a well-defined transmission mechanism, shown in the figure below, affecting short-term funding markets, broader financial conditions, and, in turn, the real economy.

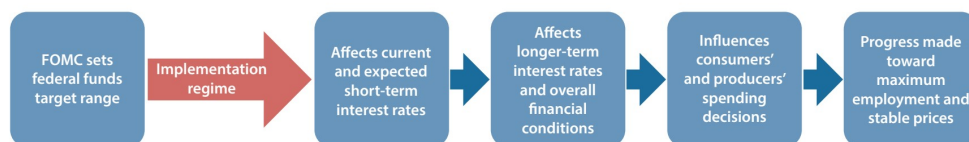


Figure 2.12: Transmission of Monetary Policy [50]

The FOMC's policy stance is transmitted through financial markets to affect consumers' and producers' spending decisions, which ultimately moves the economy toward the Fed's objectives—maximum employment and stable prices. This monetary policy implementation framework ensures that when the FOMC changes its policy stance (raises or lowers the federal funds [FFR] target range), financial markets move in the desired direction. [50]

One of the first market rates to incorporate changes in monetary policy is the **Secured Overnight Financing Rate (SOFR)**, which represents a broad and transaction-based measure of the cost of overnight borrowing collateralized by US treasury securities. It is computed as a volume-weighted median across several underlying data sources: tri-party treasury repo transactions collected from the Bank of New

York Mellon, General Collateral Finance (GCF) repo transactions cleared through the Fixed Income Clearing Corporation (FICC), and bilateral treasury repo transactions cleared via FICC's Delivery-versus-Payment (DVP) service [51].

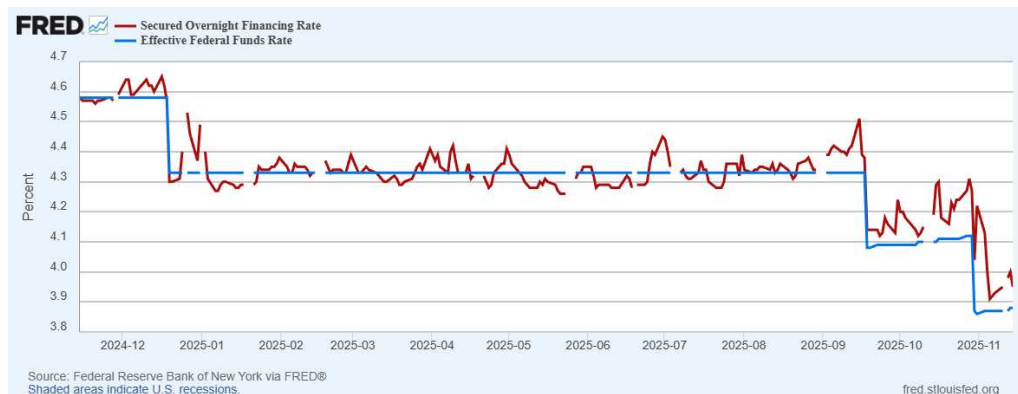


Figure 2.13: Transmission of Monetary Policy [52]

Figure 2.13 illustrates the behaviour of the SOFR and the EFFR over the past year, highlighting how the SOFR exhibits higher volatility compared with the second one [52]. This outcome is consistent with the structural characteristics of the markets from which the two rates are derived since the EFFR reflects a narrow set of unsecured overnight lending transactions between depository institutions, a market whose volumes have declined over time and whose pricing tends to be anchored by Federal Reserve facilities, while the SOFR is calculated from a vast and diverse set of secured overnight repo transactions [53].

Figure 2.12 has showed the general transmission mechanism but, specifically, the Federal Reserve can implement either an *expansionary* or a *contractionary* policy stance, depending on the prevailing economic conditions and deviations from its dual mandate.

When the economy weakens and employment falls short of the maximum employment objective, while inflation shows signs of declining below the 2 percent target, the FOMC may adopt an **expansionary monetary policy** to stimulate economic activity, which translates into lowering the FFR target range. A reduction in policy rates decreases the cost of borrowing money, thereby encouraging consumers to increase consumption and firms to expand investment. The increase in consump-

tion and investment spending increases the overall demand for goods and services in the economy. Also, with increased production, firms are likely to hire additional employees and spend more on other resources. As these increases in spending ripple through the economy, unemployment decreases, moving the economy toward maximum employment [54].

Conversely, if inflation has exceeded the 2 percent target for a sustained period and inflation expectations begin to drift upward, the FOMC may pursue a **contractionary monetary policy** to restore price stability. This is generally achieved by raising the target range for the FFR. Higher interest rates increase the cost of borrowing money, discouraging consumer spending and corporate investment. The decrease in consumption and investment spending decreases the overall demand for goods and services in the economy, which causes the firms to slow production and hiring. As these decreases in spending ripple through the economy, inflationary pressures would diminish and the inflation rate would fall back toward 2 percent. In the case of contractionary policy it is important to underline that the objective is to decrease the rate of demand for goods and services, not to stop it [54].

Having established that the Federal Reserve implements its policy stance setting a target range within which the FFR is expected to fluctuate, it is time to explore which are the operational tools that ensure that the effective federal funds rate (EFFR) (which is market-determined) remains within its target corridor.

Firstly we have the **interest on reserve balances (IORB)** which represents the interest paid by the Federal Reserve on reserve balances that banks hold at the Fed. Since IORB makes cash deposited at the Fed a risk-free investment option, banks are unlikely to lend reserves in the federal funds market for less than the IORB rate. Therefore, the IORB acts as a *benchmark floor* for interbank lending. This rate act as a floor because if the FFR were to fall below the IORB rate, banks would be likely to borrow in the federal funds market and deposit those reserves at the Fed, earning a riskless profit on the difference (this is known as an arbitrage) [50].

However, not all important institutions in financial markets are allowed to have an account at the Fed and this leaves the possibility that important short-term rates

(including the FFR) might drop below the IORB rate. For this reason, in 2014, the FOMC announced that it intended to use a complementary mechanism to help control the FFR: the **Overnight Reverse Repurchase Agreement Facility (ON RRP)**. This is a form of open market operation between the Fed and a non-bank financial institution where the first sells a security overnight and agrees to repurchase it the following day while the second essentially deposits reserves at the Fed overnight, receiving a security as collateral. Then the rate paid on ON RRP transactions, which is set below the IORB rate, acts like a *floor* for the FFR, as institutions are unlikely to lend funds at rates below what they can earn from the Fed via the ON RRP facility [50]. Here figure 2.14 summarizes how an ON RRP transaction works:

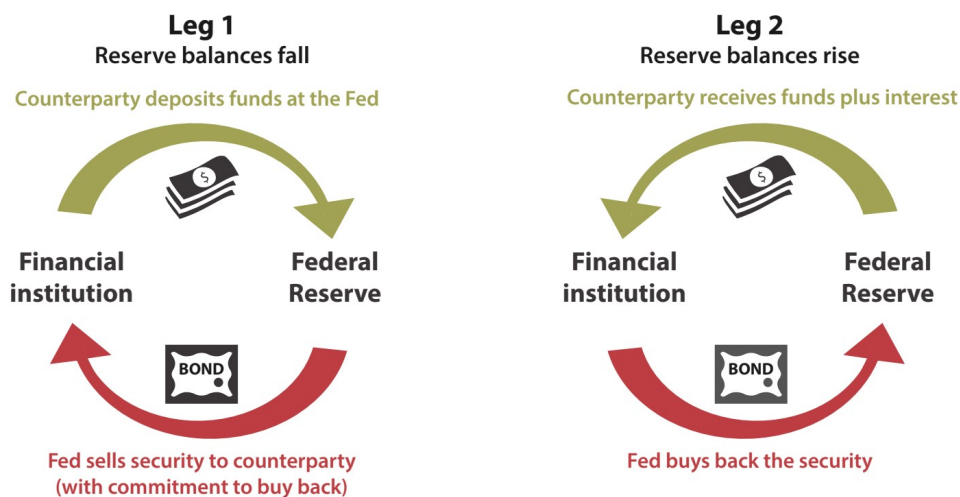


Figure 2.14: Illustration of an ON RRP Transaction [50]

When using the Fed's ON RRP facility, the counterparty interacts with the Fed in two steps. First, today (Leg 1) the counterparty deposits funds at the Fed. Second, because this is an ON (overnight) RRP, tomorrow (Leg 2) the counterparty gets its cash back with a bit of interest. [50]

Having described the instruments that establish the effective floor for the federal funds rate, it is natural to consider what mechanism sets the upper bound of the rate corridor. This role is fulfilled by the **discount window**, a facility established by the Fed through which depository institutions, US branches and agencies of foreign banks can borrow funds directly from the Federal Reserve, provided the necessary legal agreements and eligible collateral. The discount rate, the interest rate applied

to these loans, functions as a *ceiling* for FFR transactions since institutions are generally unwilling to borrow at a higher rate than what they would pay to borrow from the Fed at the discount window. However, the perceived stigma of borrowing from the Fed generally dampens the rate's effectiveness as a ceiling [50] [55].

In addition to the three main tools explained above, which are generally referred as *administered rates*, the Federal Reserve relies on two further instruments to implement monetary policy: *open market operations* and *reserve requirements*.

Open market operations are basically the buying and selling of government securities by the Federal Reserve. In particular, when the Fed purchases a security, it pays for it by crediting the reserve account of the selling bank at the Federal Reserve, thereby increasing the total level of reserves in the banking system. Conversely, when it sells securities, reserves are withdrawn. While these operations historically served as the primary mechanism for adjusting liquidity and influencing the federal funds rate, in the current regime, characterized by ample reserves, they are used mainly to ensure that reserve levels remain sufficient for the effective implementation of monetary policy through the administered rates [56] [50].

On the other hand **reserve requirements** are regulatory constraints that determine the fraction of deposits banks must hold as cash in their vaults or as reserves at the Federal Reserve. In the present monetary policy framework, where banks maintain large quantities of excess reserves, reserve requirements play a minimal operational role. Indeed, since March 26 2020, reserve requirements have been set to zero percent, formally retaining their place among the policy tools but no longer influencing day-to-day monetary policy implementation [50].

Together, the instruments presented above, are referred as the *conventional* monetary policy tools and the table 2.5 provides a summary of them:

Table 2.5: Conventional Monetary Policy Tools

Tool	Definition	In Practice
IORB	Interest paid on reserve balances that banks hold in their accounts at a Federal Reserve Bank.	The IORB rate is an administered rate set by the Fed. Banks are unlikely to lend their reserves in the federal funds market for less than they get paid by the Fed. As such, IORB is an effective tool for guiding the FFR. In fact, interest on reserves is the principal tool for moving the FFR within the target range.
ON RRP	An overnight transaction in which the Federal Reserve sells a security to an eligible counterparty and simultaneously agrees to buy the security back the next day.	The ON RRP rate is an administered rate set by the Fed. More types of financial institutions can participate in the ON RRP facility than can earn IORB. Because these institutions are unlikely to lend funds for lower than the ON RRP rate, and institutions can arbitrage the difference between short-term rates, the FFR is unlikely to fall below the ON RRP rate. As such, the ON RRP rate is a supplementary tool that acts like a floor for the FFR. NOTE: The ON RRP facility is a form of open market operations.
Discount Rate	The interest rate charged by the Federal Reserve to banks for loans obtained through the Fed's discount window.	The discount rate is an administered rate set by the Fed. It is set above the FFR target range with the intention of it serving as a ceiling for FFR transactions because banks are unlikely to borrow at a higher rate than they can borrow from the Fed at the discount window. The perceived stigma of borrowing from the Fed, however, generally dampens the rate's effectiveness as a ceiling. The spread between the discount rate and the FFR target tends to be constant: The Fed typically adjusts the discount rate at the same time the FOMC moves the FFR target range.
Open market operations	The buying and selling of government securities by the Federal Reserve.	While daily purchases and sales are no longer used to adjust the supply of reserves and influence the FFR, open market operations are an important tool for ensuring that reserves remain ample.
Reserve requirements	Funds that banks must hold in cash, either in their vaults or on deposit at a Federal Reserve Bank.	With reserves ample, and many banks holding excess reserves, reserve requirements remain a stated tool but are not a factor in policy implementation. In fact, as of March 26, 2020, reserve requirements have been set to zero.

Source: Federal Reserve Bank of St. Louis, "The Fed's New Monetary Policy Tools" [50]

Beyond the conventional instruments, the Federal Reserve also employs a range of *unconventional* policy measures to influence market conditions and expectations. These measures have proven particularly valuable during periods when the federal funds rate approached the zero lower bound because, in such circumstances, the Fed could no longer rely solely on its administered rates to implement monetary policy. The most notably alternative mechanism that the Fed employed are *large-scale asset purchases (quantitative easing)* and *forward policy guidance* [57].

As far as concern large-scale asset purchases (LSAPs), commonly referred to as **quantitative easing (QE)**, they represent a key mechanism for providing additional monetary accommodation, especially when short-term policy rates approach the zero lower bound. Indeed, the primary objective of QE is consistent with that of conventional monetary policy: to lower longer-term interest rates and thereby stimulate aggregate demand and economic activity. What happens in practice is

that the Federal Reserve purchases substantial quantities of longer-term Treasury securities or agency mortgage-backed securities (MBS), causing the available supply of these assets in private markets to decline, pushing their prices upward and yields downward. These effects also spill over to other fixed-income instruments, such as corporate bonds and mortgages, as investors rebalance their portfolios toward substitutes with similar risk and duration characteristics. The overall outcome is a broad compression of longer-term yields across asset classes, which reduces borrowing costs for households and firms, encouraging spending and investment [57]. If quantitative easing essentially refers to policies that substantially expand the size of the Fed's balance sheet, on the other hand we can define **quantitative tightening (QT)** as the policies that reduce the size of the Fed's balance sheet. In a QT process the Fed, rather than selling securities directly into the market, allows its holdings of Treasury and agency securities to mature without reinvestment, thereby allowing the balance sheet to shrink passively over time. To ensure a gradual decline in the balance sheet the Federal Reserve introduced monthly redemption caps: the monthly amounts of securities that were allowed to mature and not be replaced were capped, and amounts above the cap would be reinvested and left on the balance sheet [58].

Figure 2.15 shows the EFFR along with the QE and QT policies.

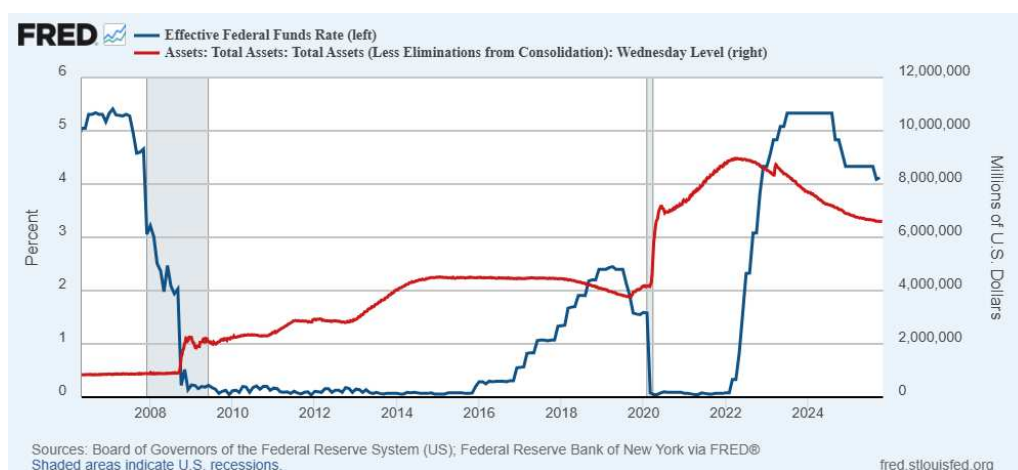


Figure 2.15: Federal Reserve's Balance Sheet and EFFR [59]

We can notice that the first large-scale asset purchase program (QE) started in 2008,

in the midst of the Global Financial Crisis, as the EFFR approached the zero lower bound and conventional policy tools had become constrained. The asset purchase program continued until 2014, when the Federal Reserve stopped net acquisitions of long-term securities, maintaining the size of its balance sheet at an elevated but stable level until 2018. In that year, the Federal Reserve started the first significant episode of quantitative tightening (QT), during which the EFFR was well above the zero lower bound. A new and substantially larger round of QE followed in response to the COVID-19 crisis in 2020, as the policy rate once again returned to near-zero levels. This purchasing process concluded in 2022, when the Federal Reserve initiated another QT cycle to prevent overheating of the economy, again coinciding with a period of rising short-term interest rates [59].

Although quantitative tightening is often described as the mirror image of quantitative easing, theoretical and empirical evidence suggest that their financial and macroeconomic effects may be asymmetric. According to the *baseline neutrality theory*, when the policy rate is well above the zero lower bound (when QT policy is applied), temporary changes in the size of the Federal Reserve's balance sheet have negligible effects, as administered rates remain the dominant tools for influencing financial conditions. By contrast, during periods when the policy rate is constrained near zero, balance sheet expansions, through large-scale asset purchases, can make a significant impact through the *signaling channel*, because they communicate the Fed's commitment to maintain a "*lower-for-longer*" policy stance. Consequently, balance sheet reduction under QT does not generate effects equal and opposite to those of QE, as it has relatively limited macro-financial consequences [60].

The other major unconventional monetary policy instrument employed by the Federal Reserve is **forward guidance**, which consists in the communication, by the central bank, of the likely future path of monetary policy. Thanks to forward guidance individuals and businesses can make solid expectations about the future behaviour of the Federal Reserve and use this information in making decisions about spending and investments. Then, by providing clear information about the future

stance of policy, the Fed can affect longer-term interest rates, asset prices, and borrowing costs, even when administered rates are constrained by the zero lower bound like during the Global Financial Crisis [61].

Indeed, similar to LSAPs, forward guidance proved particularly valuable during periods when conventional policy tools had reached their limits. Over time, the form of forward guidance employed by the FOMC evolved significantly. During the Global Financial Crisis, the FOMC initially adopted qualitative guidance, providing broad statements on how long prevailing economic conditions would justify maintaining the policy rate at exceptionally low levels, then followed by calendar-based guidance, and later transitioned to state-contingent guidance, linking policy adjustments explicitly to macroeconomic conditions, such as unemployment and inflation thresholds. During the COVID-19 pandemic, the FOMC reaffirmed its commitment to this state-contingent approach, indicating that the federal funds rate would remain in the 0 to 0.25 percent range until the economy had achieved maximum employment and inflation had risen to 2 percent and was on track to moderately exceed that level [62].

The effectiveness of forward guidance ultimately depends on the Federal Reserve's ability to communicate its policy intentions in a clear, credible, and transparent manner and to achieve this the Fed employs a structured set of communication channels designed to guide market expectations and reduce uncertainty regarding the future path of monetary policy. To this end, the Federal Open Market Committee (FOMC) serves not only as the primary decision-making body for monetary policy but also as the central channel for policy communication. The FOMC holds eight regularly scheduled meetings per year (every six weeks), during which it reviews economic and financial conditions, determines the appropriate stance of monetary policy, and assesses the risks to its long-run objectives of price stability and sustainable economic growth [48]; furthermore, four of these meetings feature also quarterly projections.

The FOMC communicates its forward guidance principally through four key channels:

- **Post-meeting policy statements**, released at the conclusion of each FOMC meeting at 2:00 p.m. ET and issued to provide a concise summary of the Committee’s assessment of economic conditions, its policy decision, and voting outcomes.
- Chair’s **press conference**, held after the statement (typically at 2:30 p.m. ET), gives the Chair an opportunity to elaborate on the Committee’s rationale given in the statement. During this conference the Chairman also answer the questions from the press, enhancing clarity on the near-term policy outlook.
- **FOMC minutes**, published approximately three weeks after each meeting, offer detailed insight into the deliberations and individual views of participants.
- **Summary of Economic Projections (SEP)**, released at every meetings that feature quarterly projections, include the “*dot plot*” chart and present each participant’s projections for the federal funds rate, inflation, unemployment, and GDP growth, serving as an explicit forward-looking signal of expected policy paths.

An example of the well-known *dot plot chart*, taken from the latest Summary of Economic Projections (SEP) released on September 17, 2025, is presented below (figure 2.16). Each dot represents an individual FOMC participant’s assessment of the appropriate level of the federal funds rate at the end of the current year, the subsequent few years, and over the longer run. Collectively, these projections provide valuable insight into the Committee’s policy outlook and help market participants gauge the expected trajectory of monetary policy.

Figure 2. FOMC participants' assessments of appropriate monetary policy: Midpoint of target range or target level for the federal funds rate

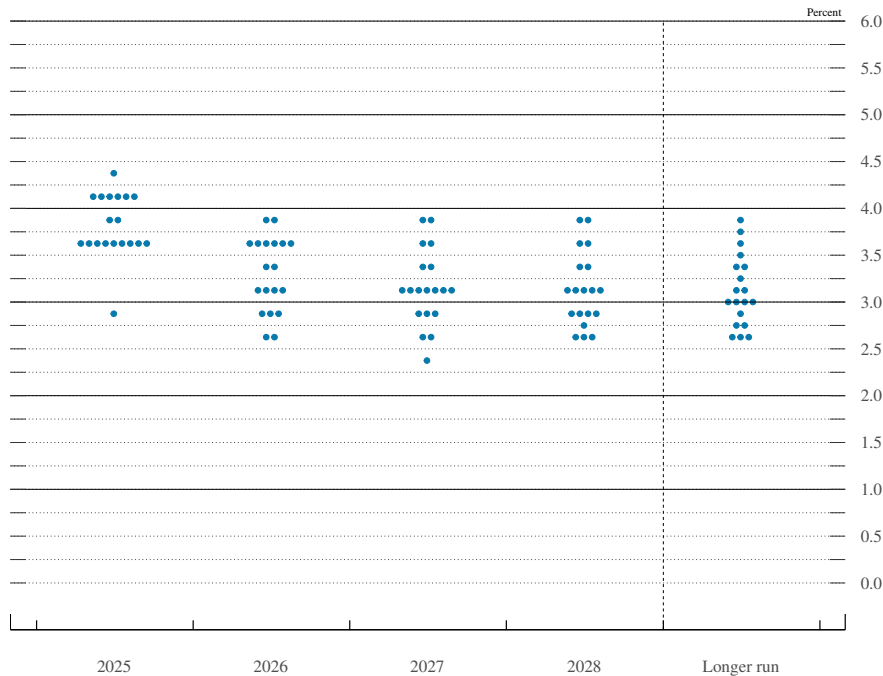


Figure 2.16: FOMC participants' "dot plot" [63]

NOTE: Each shaded circle indicates the value (rounded to the nearest 1/8 percentage point) of an individual participant's judgment of the midpoint of the appropriate target range for the federal funds rate or the appropriate target level for the federal funds rate at the end of the specified calendar year or over the longer run [63].

2.3.2 Macroeconomic Indicators: Inflation, Employment, and Growth

Having examined how the Federal Reserve formulates and implements monetary policy, it is important to underline again that these policy decisions are fundamentally guided by the ongoing assessment of macroeconomic conditions. In particular, indicators of *inflation*, *employment*, and *economic growth* play a central role in shaping the FOMC's judgment on the appropriate policy stance. These variables not only inform the calibration of policy tools, but also influence market expectations about the future path of interest rates, thereby linking macroeconomic performance with Treasury pricing dynamics.

As we saw before, **inflation**, which is the rate at which the price of goods and

services increases over time, represents one of the central variables guiding US monetary policy, directly relating to the Federal Reserve's price stability mandate [64]. From the perspective of financial markets, inflation is a key determinant of Treasury yields for two main reasons: firstly because it shapes expectations regarding the future path of short-term interest rates, in the second place because rising inflation make the bondholders demand higher yields (lower bond prices) as compensation for the expected loss of purchasing power [65]. For this reason, inflation-related data releases often generate immediate and significant movements in treasuries' yields, especially at the front end of the curve where monetary policy expectations exert the strongest influence.

The most widely recognized indicator of inflation in the United States is the **Consumer Price Index (CPI)**, published monthly by the Bureau of Labor Statistics (BLS). The CPI measures the average change over time in the prices paid by urban consumers for a representative "market basket" of goods and services. This basket is constructed to reflect typical patterns of household consumption and is periodically updated to account for evolving spending habits. The most commonly referenced measure is the *CPI All Items (CPIAUCSL)* which captures the overall change in the price level, however, beyond this aggregate measure, the CPI is available also for specific expenditure categories (food and beverages, housing, apparel, transportation, medical care, recreation, education and communications, and other goods and services) and also for items within each group. It is important to notice that, since the CPI All Items includes volatile food and oil prices, it may not always provide a reliable measure of inflationary and deflationary periods. For this reason, policymakers and analysts often focus on the *Core CPI (CPILFESL)* which excludes food and energy expenditures from the consumption basket [66] [67] [68] [69].

While the CPI remains the most widely referenced inflation measure in public discourse and financial media, it is not the Federal Reserve's primary inflation benchmark for monetary policy decisions. Instead, the Fed relies on the **Personal Consumption Expenditures (PCE) Price Index**, which is released monthly by

the Bureau of Economic Analysis (BEA) and, although it is similar to the CPI, it is constructed differently, resulting in different inflation rates. We can summarize the differences between the indexes into four categories. Firstly, the two indices are constructed using different aggregation *formulas*, with the consequence that the PCE index can more readily adjust to changes in consumer behavior. A second distinction concerns the underlying data used to assign expenditure *weights*: the CPI draws primarily on household surveys, whereas the PCE derives its weights from business expenditure data. Moreover, the *scope* of the two indices diverges: the CPI measures out-of-pocket spending by urban consumers, while the PCE captures the value of all goods and services consumed on behalf of households, including those financed by employers or government programs. This difference is particularly relevant in categories such as healthcare, where third-party payments are significant. Finally, additional *technical* differences, such as methods of seasonal adjustment and price sampling, also contribute to persistent gaps between measured inflation rates [70] [71] [72]. As with the CPI, the PCE price index is also published in a core version that excludes food and energy prices, thereby reducing the influence of highly volatile components and providing a clearer signal of underlying inflationary trends. The Federal Reserve places greater emphasis on the PCE index rather than the CPI mainly because the PCE is constructed to reflect shifts in consumer spending behavior more dynamically. As a result, the PCE is viewed as offering a more comprehensive and responsive measure of inflation for the purposes of monetary policy [73] [74].

Figure 2.17 illustrates the divergence between the CPI and PCE inflation measures, highlighting that PCE generally reports lower inflation than CPI.

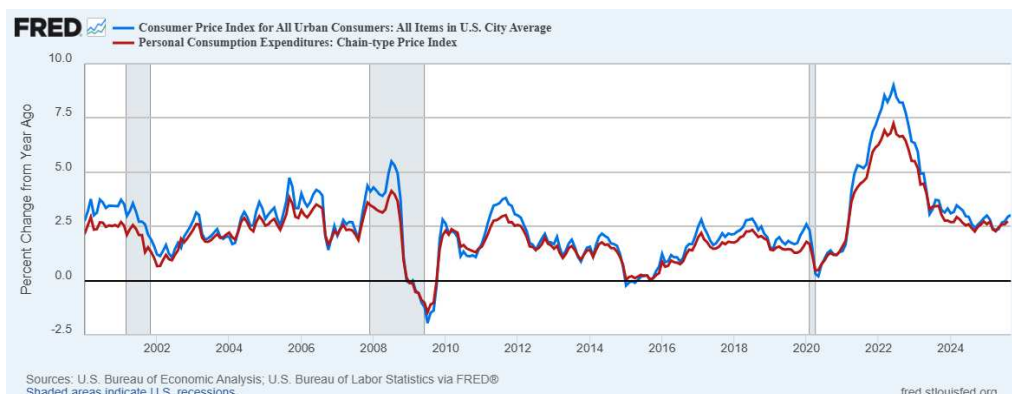


Figure 2.17: CPI and PCE Price Index [68] [71]

Whereas CPI and PCE provide measures of inflation from the consumer’s perspective, an additional dimension comes from examining price pressures earlier in the production chain. In particular, cost dynamics faced by producers can anticipate subsequent changes in consumer prices, as firms often pass input costs forward through supply chains. To capture these upstream inflationary pressures, analysts and policymakers frequently rely on the **Producer Price Index (PPI)**, which measures the average change over time in selling prices received by domestic producers of goods and services. The PPI program is based on a broad and detailed dataset collected from a large sample of US industries. Each month, approximately 64,000 price quotations are reported voluntarily by more than 16,000 establishments across mining, manufacturing, agriculture, energy, construction, and a wide share of the service sector. In total, the PPI covers nearly all market sectors involved in domestic production, making it one of the most comprehensive measures of producer-level price dynamics. The structure of the PPI is organized along three main classification frameworks. First, the *industry classification* which allows direct comparability of employment, production, productivity, and wage data. Second, the *commodity classification* which organizes goods and services based on similarities in physical composition or use, regardless of the industry producing them. Finally, the modern and most policy-relevant framework is the *Commodity-based Final Demand–Intermediate Demand (FD–ID) system*, which reorganizes price indices based on the stage of the supply chain and the intended

use of the product. The FD–ID system allows analysts and policymakers to differentiate price pressures affecting final demand (goods and services purchased for personal consumption, capital investment, export, or government use) from those affecting intermediate demand (products purchased for further processing or resale). This distinction makes the PPI especially valuable for assessing how cost pressures may propagate along production networks and eventually influence consumer inflation. In this way, the PPI functions as a leading indicator of potential inflation trends: persistent increases in producer prices often precede increases in CPI or PCE, especially in sectors with highly integrated supply chains. However, the transmission of producer price changes to consumer prices is not automatic and depends on factors such as firms’ pricing power, competitive conditions, and demand strength. For these reasons, the PPI provides context, rather than a direct prediction, for future consumer inflation dynamics [75].

In Figure 2.18, the comparison between CPI, PCE, and PPI reveals that the PPI series is significantly more volatile, which is consistent with the nature of producer pricing behavior, where changes in input costs are transmitted more promptly than in consumer price indices.

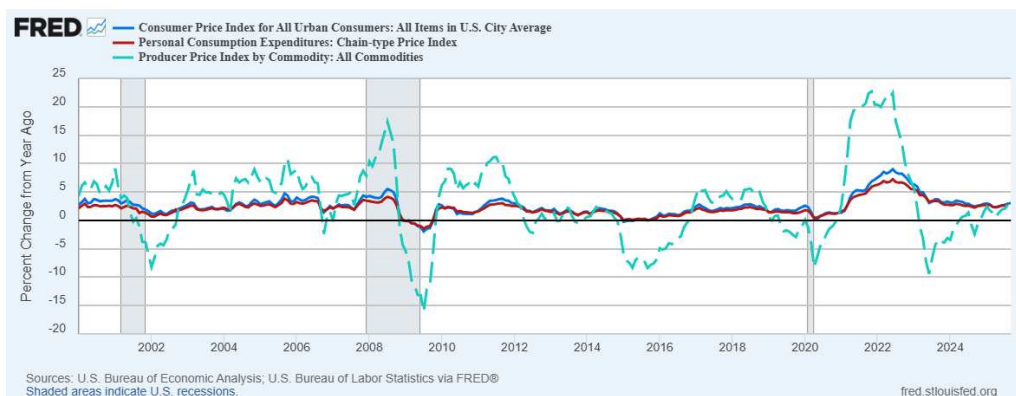


Figure 2.18: CPI, PCE Price Index and PPI [68] [71] [76]

Up to this point, the focus has been on realized inflation, as measured through consumer price indices (CPI and PCE) and producer-level pricing pressures (PPI), however it is also important to consider how financial markets expect inflation to evolve in the future. This information can be gathered thanks to market-based

measures derived from Treasury Inflation-Protected Securities (TIPS). In particular the **5-Year Breakeven Inflation Rate (T5YIE)**, calculated as the spread between nominal Treasury yields and Treasury Inflation-Protected Securities (TIPS) of the same maturity, reflects investors' expectations for average inflation over the next five years. To assess longer-term expectations, analysts turn to the **5-Year, 5-Year Forward Inflation Expectation Rate (T5YIFR)**, which measures expected inflation over the five-year period beginning five years from today. While the former is more sensitive to current economic conditions and near-term policy developments, the latter is viewed as a gauge of whether long-run inflation expectations remain anchored around the Federal Reserve's 2% target. Both measures provide valuable real time signals on how financial markets assess the future path of inflation but it is important to consider that they also carry a compensation premium for inflation risk and TIPS liquidity, and for this reason their interpretation must be always contextualized within prevailing market conditions [77] [78].

Figure 2.19 illustrates that market-based inflation expectations, as proxied by the 5-year, 5-year forward inflation expectation rate, frequently deviates substantially from realized inflation, indicating that financial markets systematically overreact to macroeconomic signals.

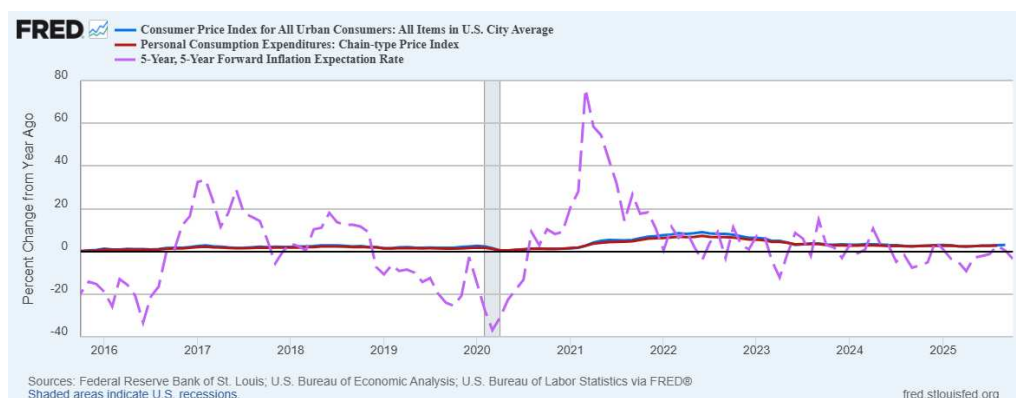


Figure 2.19: CPI, PCE Price Index and 5-Year, 5-Year Forward Inflation Expectation Rate [68] [71] [78]

The inflation metrics examined capture distinct layers of the price formation process, from consumer expenditures to producer cost structures to financial market

expectations on future inflation and, although additional indicators exist, their informational content is largely complementary to the core suite discussed here. We now move to the second fundamental component of the economic environment and of the Federal Reserve's mandate: the state of the labor market and the indicators used to evaluate **employment** conditions. As we've seen labor market conditions represent a key determinant of monetary policy decisions, influencing expectations about future interest rate paths and, consequently, treasury yields across maturities. Strong job creation and wage growth typically signal economic expansion and potential inflationary pressures, prompting tighter policy expectations and upward movements in yields, whereas labor market weakness tends to generate the opposite effect.

A central indicator for assessing the state of the US labor market is the **Nonfarm Payrolls (NFP)**, formally reported as *All Employees: Total Nonfarm* and released at 8:30 a.m. ET on the first Friday of each month by the Bureau of Labor Statistics (BLS) in the Employment Situation Report. The NFP series captures the number of paid workers on business and government payrolls, excluding farm workers, private household employees, proprietors, unpaid family workers, and self-employed. Covering roughly 80 percent of the workers who contribute to Gross Domestic Product (GDP), the NFP series provides a meaningful representation of overall employment dynamics in the economy. Monthly changes in payroll employment signal whether firms are expanding or contracting their workforce and therefore serve as an indicator of broader economic momentum. For instance, increases in NFP typically suggest that business are growing and, furthermore, that those who are newly employed have increased their personal incomes, thus fostering further economic expansion. Since employment levels are influenced by predictable seasonal patterns the BLS publishes both seasonally adjusted and not seasonally adjusted versions of the data, but the first is the one generally used for policy and macroeconomic analysis, as it allows underlying trends in employment to be observed more clearly [79]. Given the scale and complexity of data, the Non-Farm Payroll Report is often subject to large revisions of the previous month's head-

line, but the BLS also revises up to two months from the release (two month net revision) [80].

In light of the central role played by the NFP series in shaping market expectations and policy assessments, financial markets also pay close attention to a set of early indicators that provide signals on labor market conditions ahead of the official monthly release. One of the most notable among these is the **ADP Non-Farm Employment Change** which provides an independent measure of private sector employment derived directly from real time payroll processing records across firms of various sizes and industries. Importantly, the ADP report is not designed to forecast the BLS' NFP release, but, since is released two days prior to that, it often shapes market sentiment and expectations regarding the direction of job creation [81]. A second indicator closely monitored by analysts is **weekly unemployment claims**, which is released by the US Department of Labor and tracks the number of individuals filing for unemployment insurance benefits providing an early signal of layoffs and labor market stress. Its weekly frequency makes it particularly valuable for detecting turning points in labor demand, often ahead of both the ADP and the NFP releases [82] [83].

Beyond tracking hiring flows, it is equally important to examine *labor demand*: the extent to which firms are actively seeking workers. While indicators such as the NFP, ADP employment change, and weekly unemployment claims provide timely information on job creation and separations, they do not directly capture the underlying strength of employer demand for labor. To fill this gap, analysts rely on the **Job Openings and Labor Turnover Survey (JOLTS)**, published monthly by the Bureau of Labor Statistics. The JOLTS report provides data on job openings, hires, and separations (including quits and layoffs), offering a detailed picture of labor market tightness. In particular, the level of job openings is interpreted as an indicator of firms' willingness to expand employment, and the quits rate (the share of workers who voluntarily leave their jobs) is often viewed as a measure of workers' confidence in their ability to find new employment. Therefore, JOLTS serves as a key complementary indicator, helping to contextualize the hiring data

discussed above and offering insights into the underlying balance between labor supply and demand [84] [85].

However, the number of jobs added or lost each month tells only part of the story. To assess the degree of labor market slack or tightness, it is necessary to examine indicators that capture the share of individuals who are unemployed. The most commonly referenced measure is the **unemployment rate**, also known as **U-3**, which is published monthly as part of the BLS' Household Survey, and represents the number of unemployed as a percentage of the labor force² [86].

In Figure 2.20 we observe that peaks in the unemployment rate consistently coincide with the shaded areas, which correspond to periods of US recessions, reflecting the characteristic cyclical sensitivity of labor markets to macroeconomic downturns.



Figure 2.20: Unemployment Rate (UNRATE) [86]

Although U-3 is the standard headline unemployment rate used in public discourse, the BLS also publishes alternative measures of labor underutilization, labeled **U-1** through **U-6**, which progressively broaden the definition of labor market slack. At the narrowest end, U-1 captures only those individuals who have been unemployed for 15 weeks or longer, thereby emphasizing persistent, long-term joblessness. At the opposite extreme, U-6 provides the broadest assessment of labor underutilization by including not only the conventionally unemployed (U-3), but also marginally attached workers (individuals who are not currently searching for work

²Labor force data are restricted to people 16 years of age and older, who currently reside in 1 of the 50 states or the District of Columbia, who do not reside in institutions (e.g., penal and mental facilities, homes for the aged), and who are not on active duty in the Armed Forces[86].

but would accept a job if available) and those employed part-time for economic reasons, who would prefer full-time employment but are unable to obtain it. Since U-6 reflects both hidden unemployment and involuntary underemployment, it is often considered one of the most informative indicator about labor market's health [87].

Because unemployment indicators are calculated as a share of the labor force, their interpretation depends crucially on the size of the labor force itself. It is therefore necessary to complement these measures with the **Labor Force Participation Rate (LFPR)**, defined by the Current Population Survey (CPS) as the percentage of the civilian non-institutional population that is either employed or actively seeking employment. Changes in the LFPR can substantially influence unemployment readings, clarifying whether declines in unemployment reflect stronger labor demand or withdrawals from the labor market [88].

Finally, to complete the assessment of labor market conditions, it is necessary to examine not only how many people are working, searching, or leaving the labor force, but also how much they are being paid, since wage dynamics play a central role in the transmission from labor market tightness to inflation pressures. A widely used measure in this respect is the **Average Hourly Earnings of All Private Employees (AHE)**, published monthly by the BLS as part of the Current Employment Statistics Establishment Survey. This indicator measures the average hourly pay received by private sector employees on a gross basis, including overtime and shift differentials. Unlike contractual wage rates, AHE captures the actual earnings workers receive per hour worked, excluding benefits, irregular bonuses, retroactive pay, and employer-paid payroll taxes. As a result, AHE provides a timely and practical gauge of wage pressures emerging in the labor market. One of the main issues of this indicator is that, since it reflects the earnings of the entire pool of workers employed in a given month, changes can arise either from true wage increases or from composition effects. For example, during recessions lower-wage positions often disappear at a disproportionate rate, mechanically raising the average hourly earnings even in the absence of broad based pay increases. For

policymakers and macroeconomists, this distinction is crucial. Sustained increases in AHE, particularly when outpacing productivity growth, may indicate rising unit labor costs, which firms can pass through to consumer prices and, in this way, this indicator provides the bridge between the employment and inflation sides of economic analysis [89].

After discussing inflation and employment it is now essential to complement this analysis with indicators that describe the overall pace of economic growth. **Growth indicators** influence market expectations of the sustainability of expansion and the timing of future policy adjustments, thus playing a central role in shaping treasury yields. To obtain a comprehensive picture of economic momentum, analysts rely on a range of indicators, including *GDP growth*, *industrial production*, *retail sales*, and business cycle surveys such as the *ISM and PMI indexes*. Together, these measures provide valuable insights into the economy's cyclical position, the likely direction of monetary policy and consequently the bond market behavior.

Among these, **Gross Domestic Product (GDP)** stands as the most comprehensive indicator of the US overall economic activity. It is released by the Bureau of Economic Analysis' *National Income and Product Accounts* and it captures the market value of the final goods and services produced in the United States (without double counting the intermediate goods and services used up to produce them) [90]. In particular the pace at which GDP expands or contracts from one period to another, i.e. the **GDP growth rate** *year over year (YoY)* or *quarter over quarter (QoQ)*, is widely interpreted as a critical barometer for business cycles [91]. To account for changes in the general price level, the BEA also publishes **Real Gross Domestic Product (Real GDP)**, which expresses the inflation-adjusted value of output, allowing for meaningful comparisons of economic growth across time. Indeed, while *Nominal GDP* measures output at prevailing market prices, *Real GDP* isolates volume changes by removing the effects of inflation [92] [93]. Such as other financial metrics, GDP data are seasonally adjusted to remove the effects of yearly patterns (winter weather, holidays, factory production schedules, etc.) in order to better reflect genuine shifts in economic activity. It is also fundamental to under-

line that the BEA doesn't release an unique GDP measure, instead it releases GDP data on a quarterly basis through three successive monthly estimates: *advance*, *preliminary*, and *final*: each incorporating progressively more comprehensive and updated source data. Policymakers, including both the Federal Reserve but also the White House and the Congress, rely on GDP statistics to guide fiscal and monetary policy decisions, while private-sector analysts and firms use them to inform investment, hiring, and expansion strategies. Being more specific they often focus on the *advance estimate*, because, although subsequent revisions may meaningfully alter the reported pace of growth, it offers an early indication of economic momentum approximately one month after the quarter's end [94].

Following the aggregate view provided by GDP, a more detailed and higher frequency measure of real economic activity is offered by the **Industrial Production (IP) Index**, published monthly by the Board of Governors of the Federal Reserve System in the *G.17 Industrial Production and Capacity Utilization release*. The index measures the real output of the nation's manufacturing, mining, and electric and gas utilities sectors, industries that together account for the bulk of the cyclical variation in national output. Because these sectors are highly sensitive to shifts in demand, monetary policy, and external shocks, industrial production provides a timely indicator of turning points in the business cycle and often precedes changes in GDP growth [95] [96].

While industrial production offers a quantitative measure of real output, *Purchasing Managers' Indexes (PMIs)* provide a more immediate, survey-based assessment of business conditions and expectations. The **ISM Manufacturing PMI**, compiled monthly by the *Institute for Supply Management (ISM)*, summarizes responses from purchasing and supply executives across major manufacturing industries weighted by their contribution to GDP. It aggregates diffusion indexes of new orders, production, employment, supplier deliveries, and inventories into a single composite indicator where values above 50 indicate expansion and below 50 contraction. Historically, a reading above roughly 42 percent has been associated with overall GDP growth, making the PMI a leading indicator of industrial activity and

business cycles [97]. Complementing this, the **ISM Services PMI** (formerly Non-Manufacturing PMI) captures sentiment across a broad range of service industries (including finance, healthcare, real estate, and transportation) which together account for the majority of US GDP. Its composite index, derived from business activity, new orders, employment, and supplier deliveries, signals expansion above 50 and contraction below. Because services dominate the US economy, this measure is particularly influential in shaping expectations about aggregate growth and inflation trends [98]. Taken together, the manufacturing and services PMIs, available on the first and third business day of each month, offer forward looking insights into economic momentum, often reacting ahead of changes in industrial production or GDP and thus exerting a significant influence on treasury yields through their implications for monetary policy expectations [99].

Following the forward looking insights provided by the ISM Manufacturing and Services PMIs, which capture business sentiment and production intentions, the **Retail Sales Report** offers a timely snapshot of realized consumer demand, a critical driver of US economic growth. Released monthly by the US Census Bureau, the report measures total receipts from thirteen major categories of retailers, including motor vehicles and parts dealers (20.6%), food and beverage stores (12.80%), general merchandise (12.60%), food services (11.70%), and gas stations (8.2%). As household consumption represents roughly two thirds of US GDP, retail sales data serve as a key barometer of economic momentum and potential inflationary pressures. Analysts typically focus on the headline *Advance Retail Sales* figure, as well as the *core measure*, which excludes volatile components such as cars, gas, and building materials to better capture core consumer spending trends. While more volatile than aggregate output measures, fluctuations in retail sales are closely monitored by the Federal Reserve and market participants, as they offer early indications of shifts in consumption patterns that can influence expectations for growth, inflation, and, consequently, treasury yields [100].

Whereas retail sales highlight the strength of consumer activity **Durable Goods Orders** provide a complementary view of the economy's productive and invest-

ment side. Published monthly by the US Census Bureau, this report measures new orders placed with domestic manufacturers for factory hard goods, such as refrigerators and cars, but also business investment such as industrial machinery, electrical machinery and computers. Because these items represent significant financial commitments, fluctuations in durable goods orders provide valuable insight into business confidence and capital spending intentions: if companies commit to spending more on equipment and other capital, they are obviously experiencing sustainable growth in their business. From a financial market perspective, healthy economic growth is not necessarily a negative for the bond market, but bond investors are highly sensitive to inflationary pressures, for this reason stronger than expected readings can fuel expectations of faster economic growth and potential inflationary pressures, tending to push Treasury yields higher, whereas weaker data often lead to lower yields amid growth concerns [101].

As with inflation and employment, numerous other indicators can be used to assess US economic growth, including housing starts, building permits, and energy production data, but this analysis focuses on the most influential and policy relevant measures. Housing and oil related metrics, while significant in specific sectors, are omitted here to maintain analytical clarity and focus on indicators that exert the most direct and consistent influence on monetary policy expectations and treasury market dynamics.

2.3.3 Market Factors, the Yield Curve and the Role of Expectations

The Federal Reserve's dual mandate establishes the macroeconomic foundations of interest rate policy, yet treasury yields frequently move in anticipation of, rather than in response to, policy actions. Market participants continuously update expectations about future monetary policy, risk conditions, and liquidity, producing yield adjustments that cannot be fully explained by fundamental indicators alone. Indeed, beyond the macroeconomic environment defined by inflation, employment, and output growth, treasury yields are also the result of market-based mechanisms that transmit and amplify expectations. These include market's volatility condi-

tions, the configuration of the yield curve and cross-asset capital flows: together these elements play a decisive role in shaping yields even when fundamental data remain stable.

In order to analyze volatility conditions we study volatility indices, which quantify investors' expectations of future price variability across asset classes. The most famous one is the **Cboe Volatility Index (VIX)**, widely known as the “fear index” of financial markets, which measures the market implied 30-day volatility of the S&P 500 based on option prices. Elevated VIX levels typically coincide with episodes of heightened uncertainty, equity market sell offs, and capital flows toward safe haven assets such as gold or US treasuries (thereby exerting downward pressure on yields). Conversely, periods of low volatility often accompany higher risk appetite and upward movements in treasury yields [102] [103]. An analogous measure within the fixed income universe is the **ICE BofA MOVE Index**, sometimes referred to as the “VIX for bonds”. Compiled by the Intercontinental Exchange (ICE), the MOVE index reflects the implied volatility of US treasury yields derived from one month options on 2, 5, 10, and 30-year maturities. Spikes in the MOVE index generally indicate uncertainty about future interest rate paths or monetary policy surprises, both of which can provoke sharp adjustments along the yield curve [104]. Together, the VIX and MOVE indices encapsulate the role of volatility as a transmission channel between risk perception and yield dynamics: when fear dominates markets, investors seek duration and safety, when confidence returns, they rotate back into riskier assets, lifting yields.

These shifts in risk appetite and asset allocation are eventually mirrored in the **yield curve**, which translates short-term uncertainty into a structured view of how investors expect rates and economic conditions to evolve across maturities. The yield curve, also known as the term structure of interest rates, refers to the relationship between the remaining time to maturity of debt securities and the yield on those securities. There exist several yield curves which are closely watched by market participants and policymakers, let us cite the most frequently utilized: the *nominal yield curve*, based on the yields on coupon-bearing nominal govern-

ment securities, and the *TIPS yield curve*, based on yields on the US government's inflation-indexed debt [105]. By plotting yields on treasury securities across maturities, the curve provides a visual and quantitative measure of how the market prices borrowing costs over time enabling market participants to embed their expectations about the path of policy rates, growth and inflation into observable yield differentials and term premia [106].

One of the main feature of the yield curve consists in its *shape*, which provides essential insights into investor expectations. A **normal yield curve** slopes upward, with short-term yields lower than long-term yields. This configuration reflects investors' demand for a higher return to compensate for the greater uncertainty associated with holding longer-term bonds. A normal curve is typically observed during periods of economic expansion, when both growth and inflation are rising, and markets expect that the central bank will gradually increase policy rates to contain inflationary pressures [107]. The yield curve exhibited on January 1, 2018, serves as a prototypical example of the normal configuration described above. At this time, the global economy was experiencing a period of synchronized growth, and the Federal Reserve was in the midst of a transparent and gradual rate-hiking cycle. Consequently, the upward slope in Figure 2.21 reflects a market environment where investors demanded a higher premium for long-term duration.

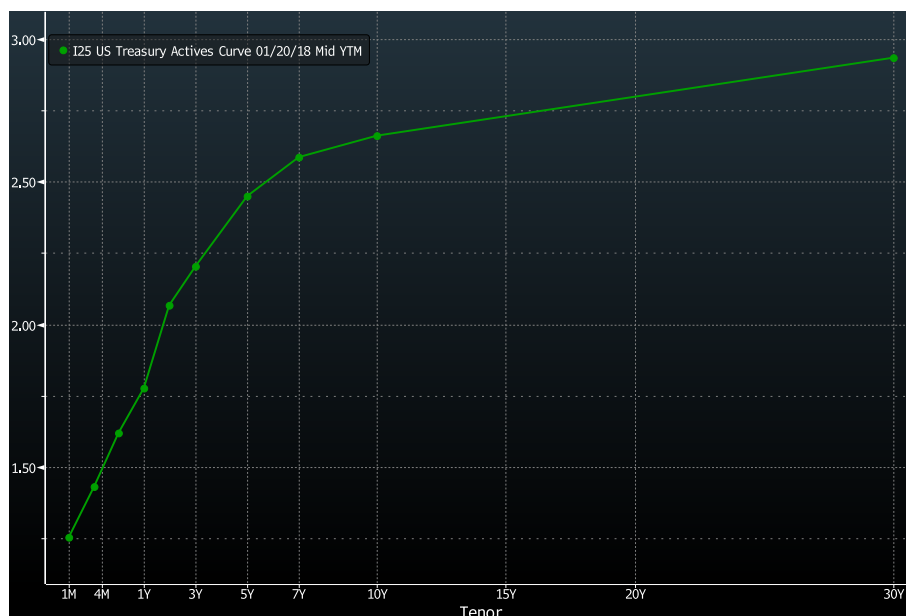


Figure 2.21: US Treasuries Yield Curve - Normal (20 January 2018) [108]

An **inverted yield curve**, by contrast, slopes downward, as short-term yields exceed long-term yields. This unusual configuration suggests that investors anticipate future rate cuts, typically in response to a slowing economy or declining inflation. Historically, in the United States, inversions of the yield curve, particularly between the 10-year and 2-year maturities, have preceded economic recessions, as markets price in expectations of monetary easing [107].

Finally a **flat yield curve** occurs when short-term and long-term yields are roughly equal. This shape often appears during transitions between normal and inverted phases, as investors reassess the outlook for growth and monetary policy. Flat curves can also emerge in environments of low overall interest rates or under unconventional monetary policy, when forward guidance and quantitative easing compress yields across maturities [107].

To provide the most informative and straightforward illustration of these dynamics, we utilize two classic historical examples from the 2006–2007 pre-crisis period. As shown in Figure 2.22, the US Treasury curve became notably flat by the end of the first quarter of 2006. At this juncture, the economy was operating at high capacity with soaring property prices. In response, the Fed began lifting short-term interest rates. While the short-end of the curve rose due to policy hikes, bond

investors, anticipating an eventual slowdown, began aggressively purchasing long-term bonds to lock in relatively high yields, resulting in the flat configuration seen below [109].

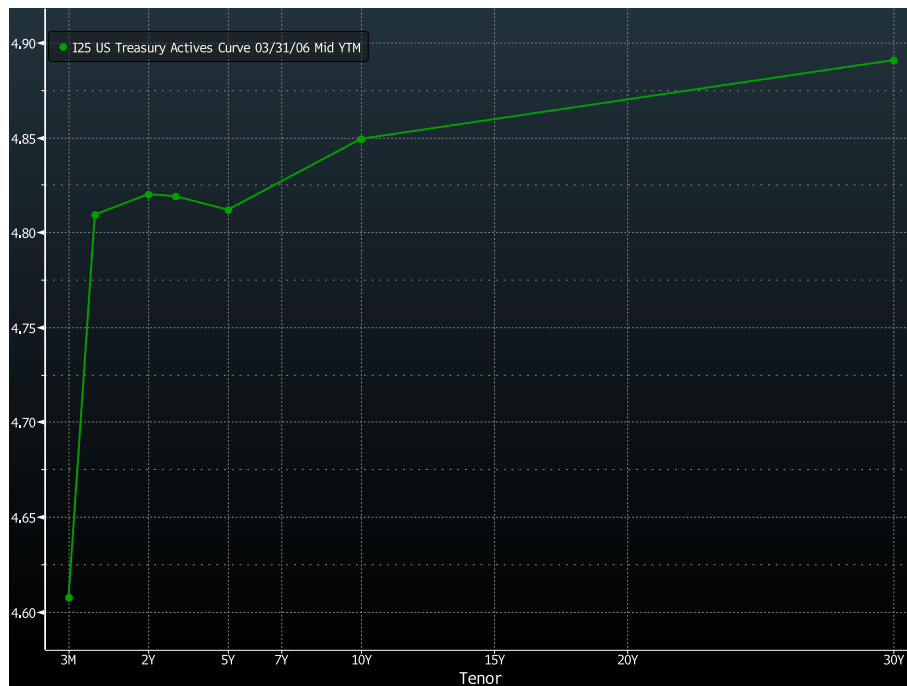


Figure 2.22: US Treasuries Yield Curve - Flat (31 March 2006) [108]

With fears of a downturn intensifying, investors began betting heavily on future rate cuts, driving long-term yields below the 5% level where the short end was effectively "trapped" by prevailing Fed policy and, for this reason, by the end of 2006, the curve moved into a clear inversion, as depicted in Figure 2.23 [109].

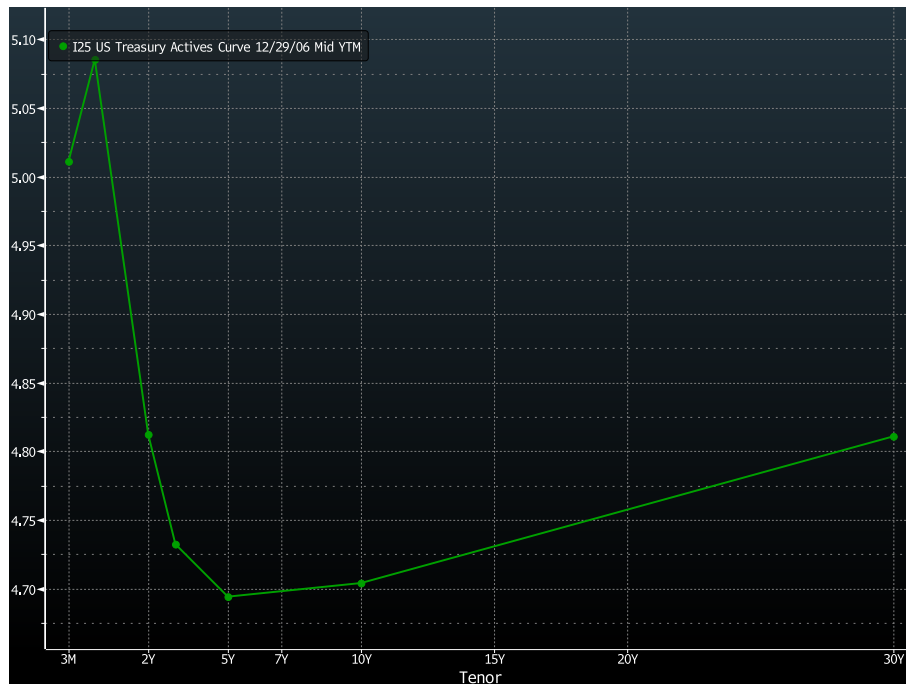


Figure 2.23: US Treasuries Yield Curve - Inverted (29 December 2006) [108]

Beyond its static shape, it is also fundamental to analyze the *movement* of the yield curve, which captures how different segments of the curve respond to shifts in rates and expectations. When yields are falling, the yield curve typically **steepens**, because short-term yields tend to decline more rapidly than long-term yields. This reflects market expectations that the central bank will cut policy rates to support economic activity, while longer-term yields remain anchored by stable inflation expectations. For example, if 5-year Treasury yields drop by 20 basis points³ while 10-year yields decline by only 10 basis points, the slope between them widens, resulting in a steeper curve [111]. In Figure 2.24, we can see an example of a steepening yield curve taken from February 2021.

³A basis point is a unit of measure used in finance to describe the percentage change in the value or rate of a financial instrument. One basis point is equivalent to 0.01% (1/100 of a percent) or 0.0001 in decimal form. If interest rates rose from 2.00% to 2.50%, it would be said that rates rose 50 basis points [110].

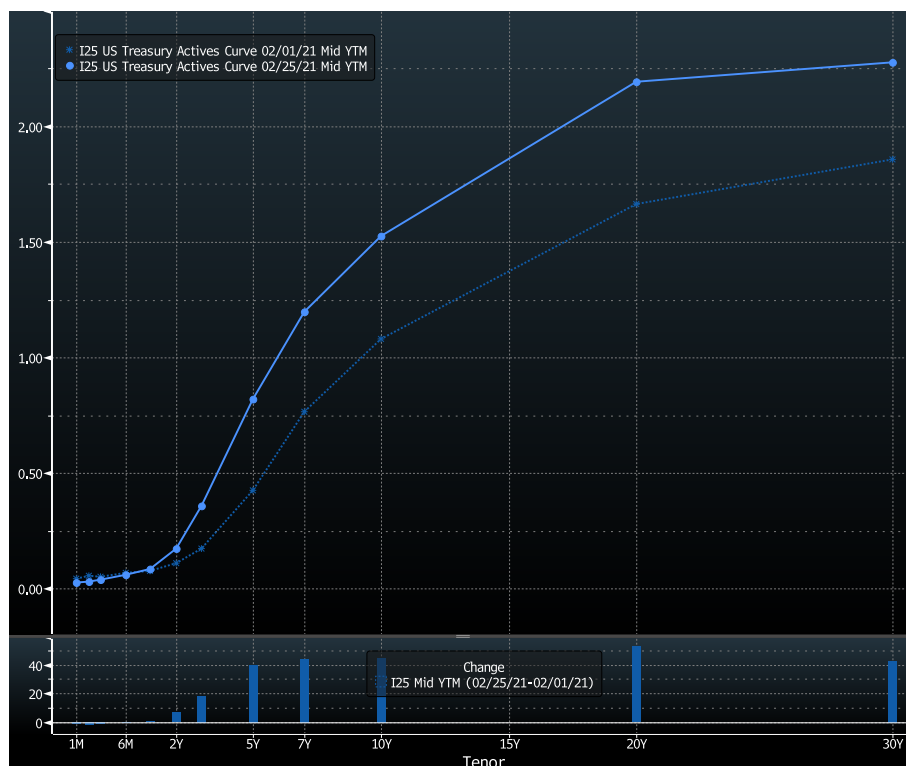


Figure 2.24: US Treasuries Yield Curve - Steepening (1 Feb 2021 - 25 Feb 2021)
[108]

Conversely, when yields are rising, the yield curve generally **flattens**, as shorter-term yields react more sensitively to expectations of policy tightening. In this scenario, the spread between long- and short-term yields narrows, signaling that the market expects restrictive monetary conditions to cool future growth and inflation. Using the same example, if the 5-year yield increases by 20 basis points and the 10-year yield rises by only 10 basis points, the slope compresses, flattening the curve [111]. In Figure 2.25, we can see an example of a flattening yield curve taken from January 2022.

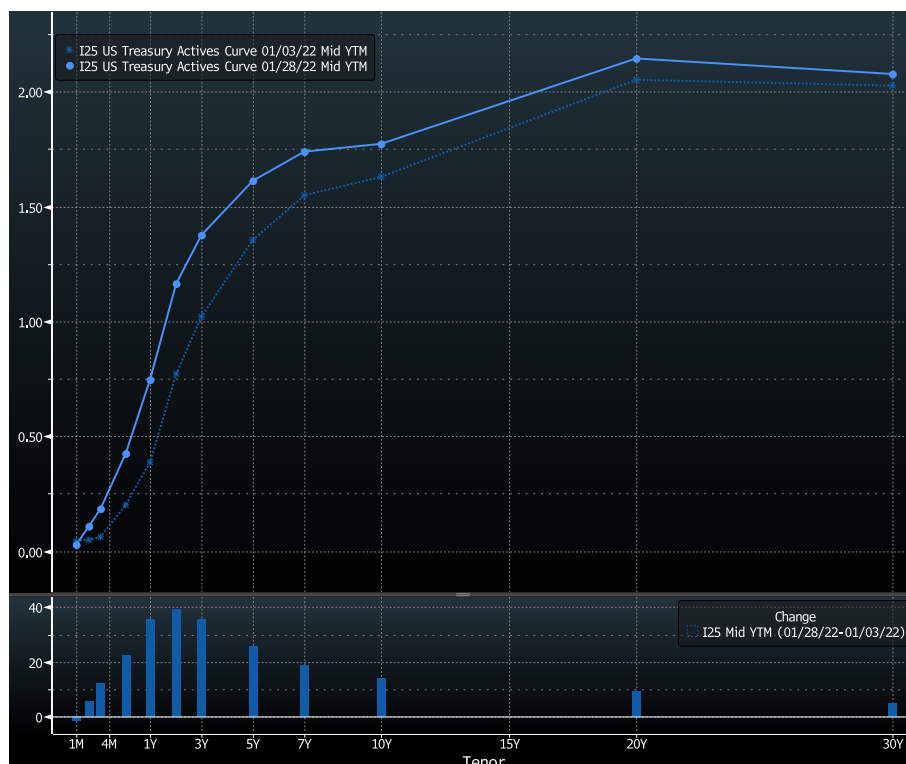


Figure 2.25: US Treasuries Yield Curve - Flattening (3 Jan 2022 - 28 Jan 2022) [108]

However, these general patterns can deviate under special circumstances. For instance, during a Fed tightening cycle, the curve would normally flatten; yet if markets perceive that rate hikes will not sufficiently control inflation, long-term yields may rise even faster than short-term ones, causing a bear steepening. Likewise, supply and demand imbalances in specific maturities, such as heavy treasury issuance in the 5-year sector, can distort the curve's shape independently of macroeconomic shifts. Recognizing these dynamics is essential for interpreting yield curve movements as both a reflection of and a signal for changing market expectations.

In analyzing the term structure of interest rates, it is useful to divide the yield curve into the *front-end* segment (which we loosely define as maturities from one month to one year), the *belly* segment (which corresponds to the middle of the curve and reflect rates from two years to about ten years) and the *back-end* segment (with maturities typically of ten years and beyond).

As we can expect the main difference between these segments is that the front-end of the curve is more reactive to immediate shifts in monetary policy and macroeconomic shocks (since shorter interest rates are influenced more directly by the Fed) rather than the belly and the back-end of the curve which reflect more structural and forward-looking changes, including long-term growth expectations, inflation forecasts, and term premia. This can be noticed in Figure 2.26 where we can see that the short-end of the curve has a completely different behaviour compared to the long-end.

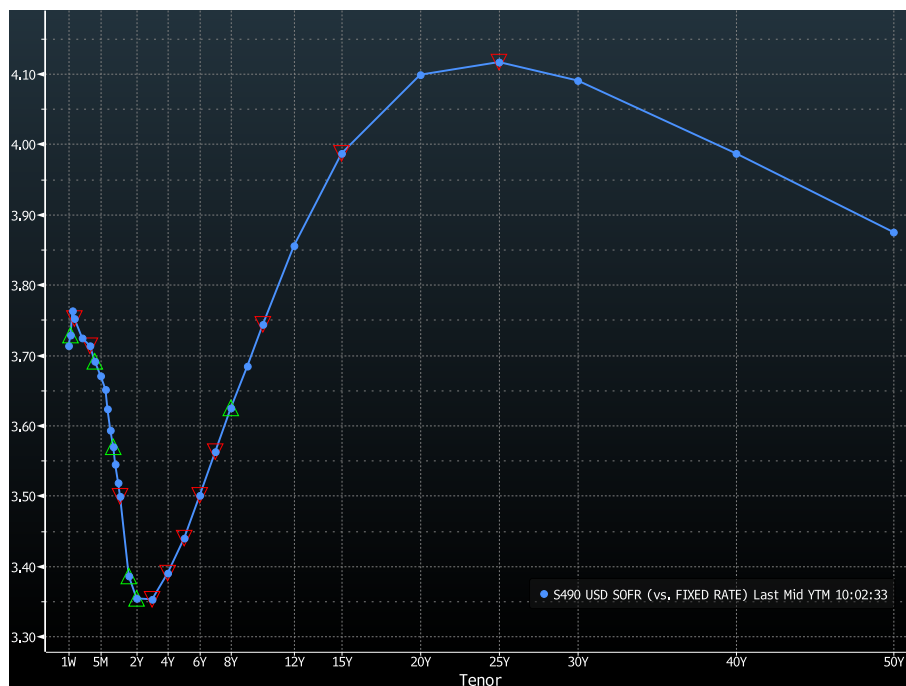


Figure 2.26: US Treasuries Yield Curve (11 December 2025) [108]

The term structure thus summarizes how markets price macroeconomic and monetary policy expectations across maturities. Yet, treasury yields rarely move in isolation. As global investors rebalance portfolios in response to shifting risk conditions, developments in equities, currencies, and commodities interact with the treasury market and can either amplify or offset yield-curve dynamics. Examining these **cross-asset relationships** is therefore crucial: they provide additional context for interpreting yield movements, reveal how shocks propagate through the financial system, and help explain why similar macroeconomic news can generate

different yield responses depending on the broader market environment. One of the most widely studied cross-asset interactions is the relationship between treasury yields and *equity markets*. Empirical research shows that the correlation between government bond returns and equity returns is not constant but regime-dependent. In particular, since inflation determines how markets expect monetary policy to respond to new information, it is strongly influenced by the inflation environment. When inflation is low and stable, investors place greater weight on growth-related news. For example, a negative growth surprise lowers expected corporate earnings and pushes equity prices down, while simultaneously increasing expectations of monetary easing. This anticipated policy response lowers discount rates, raising bond prices. Under these conditions, equities and bonds tend to move in opposite directions, producing negative correlation. By contrast, when inflation is high or volatile, monetary policy expectations are driven primarily by inflation developments. For instance, positive inflation surprise lowers bond prices by eroding the real value of nominal cash flows and increases expectations of policy tightening. Higher expected rates also reduce firms' future earnings, depressing equity prices. In this regime, both asset classes tend to move in the same direction, resulting in a positive correlation between equity and bond returns [112].

Furthermore, the interaction between US treasury yields and global currencies provides an additional layer of information about risk sentiment and capital flows. The forex market, indeed, embeds investor preferences for liquidity, safety, and interest rate differentials, making currency movements a powerful complement to yield curve analysis. Among global currencies, the US dollar, Japanese yen, and Swiss franc have historically exhibited safe haven characteristics, meaning they tend to appreciate during episodes of heightened uncertainty, accompanied by lower treasury yields. This pattern reflects a global "flight to safety" dynamic in which investors liquidate risky assets, purchase highly liquid government bonds, and demand the currencies of economies perceived as stable during risk-off episodes [113].

But safe-haven behavior is not limited to currencies: the *gold*, a non-yielding asset

with no credit risk, it is also regarded as a safe-haven asset due to its tangible nature, absence of default risk, and its universally recognized store of value across countries and cultures. Unlike classical financial assets, gold is not directly affected by corporate balance sheets or central-bank policy rates, and its supply is naturally constrained by limited reserves and costly extraction. These characteristics support its role as a hedge during episodes of extreme uncertainty. Compared with US treasuries, gold behaves as a crisis specific or “tail-risk” safe-haven: investors turn to gold primarily in periods of acute stress or geopolitical instability, when trust in financial institutions weakens. Treasuries, by contrast, serve as the primary liquidity safe haven and react strongly to shifts in monetary policy expectations, making them more sensitive to macroeconomic cycles [114].

Empirical analysis

The previous chapter has outlined the key theoretical mechanisms underlying the behaviour of US treasury securities and the yield curve, providing a useful map of the forces that shape this market. However, it is important to acknowledge the inherent limitations of any conceptual framework: in reality, interest rate dynamics, macroeconomic shocks, investor behaviour, and cross asset interactions operate in a highly interconnected and often non-linear manner and no single theoretical model can fully encompass this complexity. For this reason, the next step of the analysis turns to the data, since an empirical investigation is essential for quantifying the magnitude, stability, and statistical significance of the relationships described above. The following chapter adopts this approach, using treasury futures as the main empirical vehicle to analyse expectations, volatility transmission, and cross-asset interactions with a level of granularity that theory alone cannot provide.

3.1 Data Collection and Processing

The empirical analysis covers the period from January 1, 2018, to November 28, 2025. This observation window, comprising nearly eight years of daily trading data, is deliberately selected to ensure the statistical robustness of the proposed models while maintaining direct relevance to the current market structure. Indeed the choice of the 2018 start date balances two competing statistical needs: *sample size* and *structural homogeneity*.

First, by extending the sample back to 2018, the dataset captures a complete life-cycle of monetary policy, as shown in the chart below which displays the trajectory of the Effective Federal Funds Rate (EFFR) throughout this period.

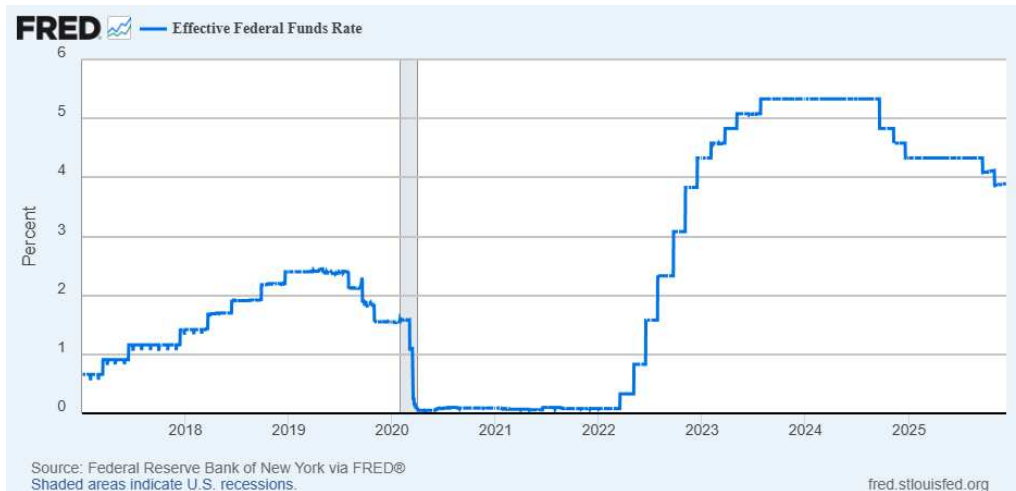


Figure 3.1: Effective Federal Funds Rate [115]

This allows us to test how volatility behaves across four distinct phases:

- The "Normalization" Attempt (2018–2019): the sample begins during the late cycle rate hikes of 2018 and the quantitative tightening (QT) phase, followed by the "insurance cuts" of 2019. It provides a baseline for how the yield curve reacts to standard, incremental policy adjustments.
- The Zero Lower Bound (ZLB) Shock (2020–2021): the onset of the COVID-19 pandemic triggered an emergency cut to the Zero Lower Bound (0-0.25%). For the model, this period is critical as it represents a regime where short-term rates are pinned (low volatility at the front end) while long-term yields fluctuate purely based on inflation expectations and QE supply dynamics.
- The Aggressive Tightening Cycle (2022–2023): this phase marks the most rapid repricing of risk in four decades. As the Fed combated structural inflation, the EFFR rose from near-zero to over 5.25%.
- The "Higher for Longer" and Pivot Phase (2024–2025): the final portion of the sample captures the plateauing of rates and the market's transition toward an easing cycle.

By encompassing this full monetary policy cycle, the dataset ensures the predictive framework is not overfitted to a single direction of interest rates.

Second, and crucially, the decision not to extend the dataset prior to 2018 is motivated by the risk of structural obsolescence. Financial markets undergo continuous evolution in terms of participant composition, regulation, and technology. Analyzing data from earlier decades (e.g., the pre-2008 era or early 2010s) increases the risk of training models on market dynamics that no longer exist. By restricting the analysis to the post-2018 period, we ensure that the model learns from a market structure that statistically resembles the current execution environment, while at the same time maintaining a sample size sufficiently large to ensure robust statistical inference.

3.1.1 Dataset Composition and Construction

The composition of the dataset can be broadly classified into two primary categories: *financial market instruments* and *macroeconomic indicators*. All data series utilized in this empirical analysis were retrieved from the Bloomberg Professional Service, ensuring a unified and high fidelity source for both price action and fundamental release data.

The central component of the dataset, fundamental for the analysis, focuses on the US Treasury yield curve, and in particular on the **US Treasury Futures complex**. The selection of this market over the underlying cash one is driven mainly by the advantages of the futures market explained in section 2.2.3: the centralization of liquidity on the exchange, the transparency of volume and open interest data, and the futures market’s established dominance in high-frequency price discovery.

To capture the dynamics of the entire term structure, the dataset includes seven specific futures contracts, selected to provide granular coverage from the immediate short end of the curve to the ultra-long duration sector. At the front end of the curve, we incorporate the 30-Day Federal Funds (*ZQ*) (*Bloomberg: FF1 Comdty*) and the 2-Year Treasury Note (*ZT*) (*TU1 Comdty*). These contracts are particularly significant for the analysis as they are the most sensitive to immediate shifts in monetary policy and Federal Reserve rate expectations. Moving to the belly part of the curve the dataset includes the 5-Year (*ZF*) (*FV1 Comdty*) and the benchmark

10-Year Treasury Note (*ZN*) (*TY1 Comdty*). Finally, to analyze the long end of the curve, which is driven primarily by inflation expectations and term premia, we include the Ultra 10-Year (*TN*) (*UXY1 Comdty*), the 30-Year Treasury Bond (*ZB*) (*US1 Comdty*), and the Ultra 30-Year Bond (*UB*) (*WNI Comdty*). This comprehensive selection allows the models to detect not only parallel shifts in volatility but also changes in the slope and curvature of the yield curve.

Recognizing that Treasury yield volatility is frequently driven by spillover effects from **competing asset classes**, the dataset is augmented with a selection of liquid instruments representing equities, commodities and currencies. These assets are also sourced via futures contracts rather than spot indices or ETFs in order to ensure structural homogeneity with the core Treasury complex.

To capture broad market risk sentiment and growth expectations (risk-on dynamics), we incorporate the E-mini S&P 500 (*ES*) (*ES1 Index*) and the E-mini NASDAQ 100 (*NQ*) (*NQ1 Index*). Conversely, to model risk-off periods, where capital often rotates simultaneously into bonds and other defensive assets, we included Gold (*GC*) (*GC1 Comdty*), as well as the Japanese Yen (*6J*) (*JY1 Curncy*) and the Swiss Franc (*6S*) (*SF1 Curncy*). Finally, the Euro (*6E*) (*EC1 Curncy*) is included to control for broader US Dollar strength, distinguishing between idiosyncratic Treasury moves and general currency debasement.

For each of the mentioned futures instruments, the primary data vector comprises daily Open, High, Low, and Close (*OHLC*) price sequences spanning the period from January 1, 2018, to November 28, 2025. However, price action alone offers an incomplete picture of market sentiment and, for this reason, the primary price vectors are supported by two complementary liquidity metrics: Trading Volume and Open Interest. While Volume is calculated as the aggregate count of contracts bought and sold during a specific trading session [116], Open Interest (OI) is defined as the total number of outstanding contracts held by market participants at the close of the trading day. Although these metrics are intrinsically linked, they capture distinct informations since Volume counts all contracts that have been traded, while OI represents the total of contracts that remain open in the market [117].

Having defined the fundamental components of the dataset, it is necessary to address the methodological approach used to construct the historical time series. A fundamental challenge in utilizing futures data for long horizon time series analysis is the finite expiration of individual contracts. Simply concatenating raw price series introduces artificial discontinuities on rollover dates, where price jumps reflect the premium or discount between the expiring contract and the new front month rather than genuine market volatility. To mitigate this *rollover issue*, the study employs continuous front-month contracts for all futures instruments, identified by the generic Bloomberg suffix "1" (e.g., TY1 Comdty). However, the standard Bloomberg setting, which typically effects the rollover on the *Last Trade Date* or a fixed number of days prior to expiration, was rejected. This decision has been made because such rigid calendar-based rules often fail to capture the actual liquidity transition, potentially forcing the analysis to rely on prices from an expiring contract that has already suffered a significant decline in volume. Instead, this thesis utilizes the *Active Future* rollover methodology which, unlike static calendar rules, is dynamic: it links contracts based on the *active ticker* designation, which shifts from the front month to the next month only when the prevailing market conditions dictate a roll. This transition is typically determined by the crossover in Open Interest and Volume, ensuring that the model is continuously fed data from the specific contract where institutional liquidity is concentrated [118].

The empirical impact of this selection is underscored by the comparison provided below: Figure 3.2 depicts the Volume (green) and OI (orange) generated by the default rollover configuration, whereas Figure 3.3 illustrates the corresponding liquidity dynamics obtained using the active future methodology.

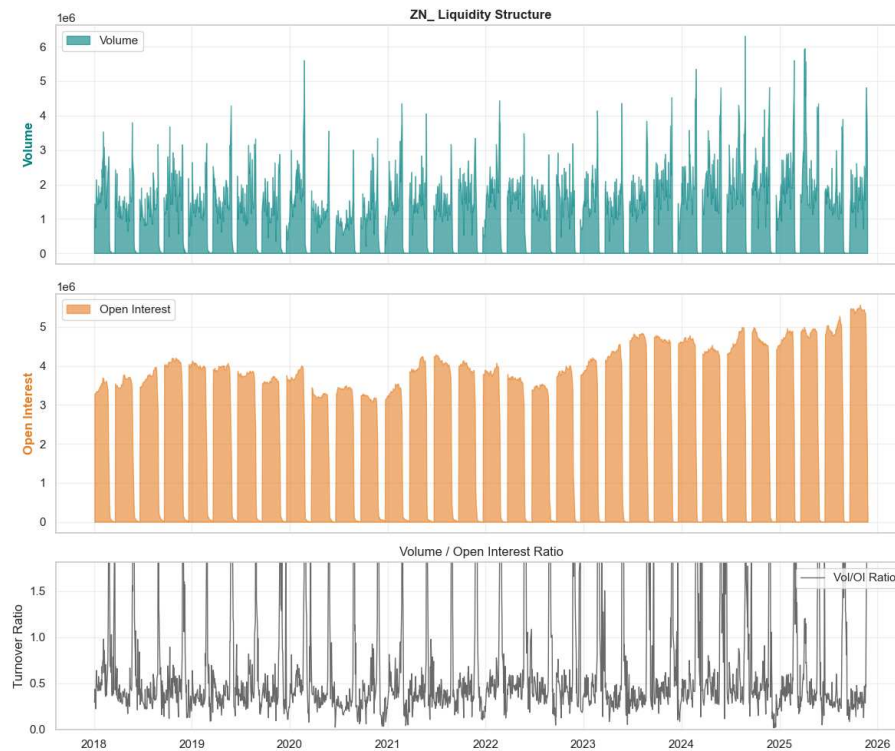


Figure 3.2: ZN Default Future Rollover Volume & OI

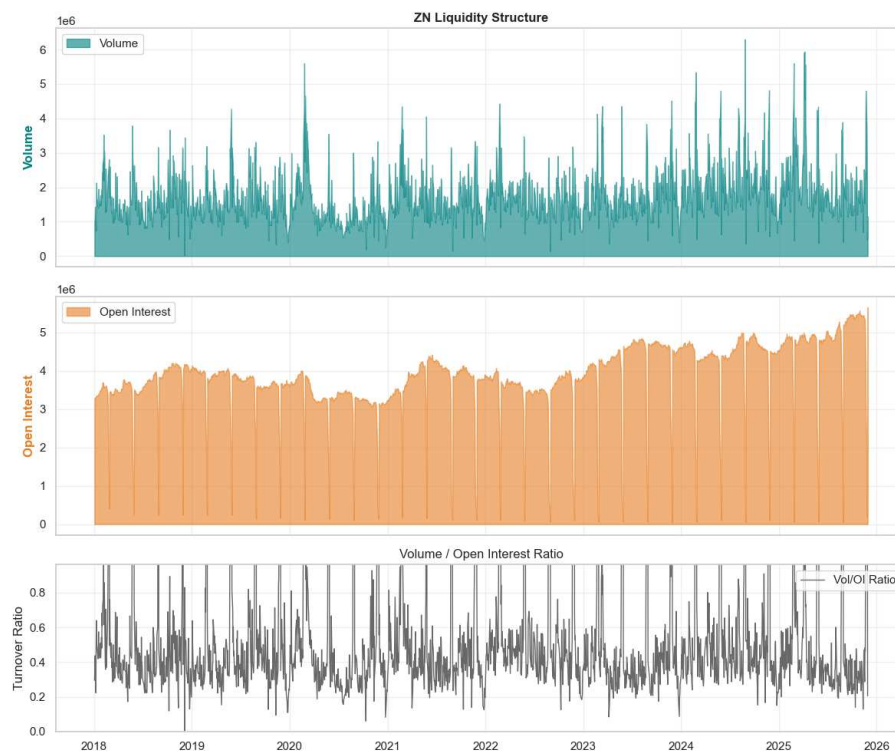


Figure 3.3: ZN Active Future Rollover Volume & OI

For the futures instruments mentioned above, the dataset, in order to complement daily data, also incorporates **intraday data**. This component is stratified into two distinct resolutions to maximize the available historical depth within the constraints of the data provider. Specifically, the analysis utilizes *1-minute interval* data covering the period from June 1, 2025, to December 12, 2025 comprising standard Open, High, Low, Close (OHLC) price vectors and Volume. For the broader *15-minute interval* dataset spanning from December 15, 2024, to December 14, 2025, the feature set is augmented to include also Tick Count¹ alongside prices and volume.

The decision to separate and define these specific windows was necessitated by the export limitations of the Bloomberg Professional Service, which restricts the retrieval of intraday data history. While the optimal research design aimed to reconstruct a five-year horizon of 1-minute data to parallel the daily analysis, the selected windows represent the maximum historical extent retrievable for these specific resolutions.

Consequently, it is acknowledged that the intraday portion of this study possesses a narrower statistical scope compared to the multi-year daily regression. However, despite this limitation, the sample remains sufficiently robust to fulfill its primary objective: to identify salient microstructural patterns and to characterize the immediate behavior of volatility during specific intraday liquidity regimes.

Finally, to ensure temporal consistency across these high-frequency time series, all timestamps were standardized to Eastern Standard Time (EST). This normalization mitigates the alignment errors typically introduced by Daylight Saving Time shifts, ensuring that critical intraday milestones, such as the 08:30 AM economic release window, are perfectly aligned across the entire sample regardless of the calendar date.

Beyond the tradable futures complex, the dataset is completed by a set of **non-tradable indices** used to gauge structural market stress and broad currency trends. For these instruments, daily Open, High, Low, and Close (OHLC) data was col-

¹The Tick Count represents the frequency of individual transactions within the bar interval, regardless of trade size

lected for the full sample period of January 1, 2018, to November 28, 2025. The selection includes the *CBOE Volatility Index (VIX)* and the *MOVE Index* which, as detailed extensively in Section 2.3.3, serve as empirical proxies for market sentiment and systemic risk aversion, quantifying the implied volatility premium embedded in equity and fixed income markets respectively. Secondly, the *US Dollar Index (DXY)* was integrated into the dataset to serve as a comprehensive measure of the aggregate strength of the US Dollar. Methodologically, the DXY is constructed as a geometrically-averaged calculation of six major global currencies weighted against the US dollar, as illustrated in the figure below [119].

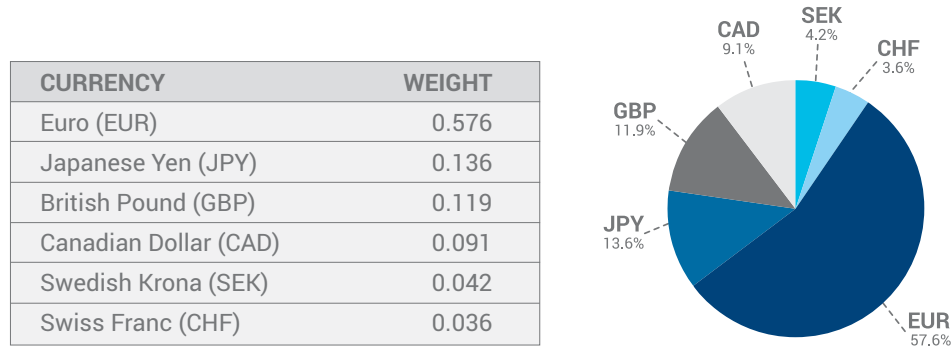


Figure 3.4: US Dollar Index Weights Composition [119]

With the financial instrument data now fully established, the focus shifts to the second data category: macroeconomic releases. This portion of the dataset was retrieved through the **Bloomberg Economic Calendar** for the entire sample period and, to maintain analytical focus on the primary drivers of the yield curve and avoid the dilutive effects of lower-impact data, the selection was filtered to include only those announcements classified by Bloomberg as having maximum market relevance. Within this subset every announcement is logged with its precise date and time, standardized to Eastern Standard Time (EST), as it allows for the volatility spikes observed in the 1-minute and 15-minute intraday futures data to be mapped exactly to the moment the economic news reached the market. Furthermore, we collected the *Actual* realized figure, the *Survey consensus*, and the resulting *Surprise Factor* for every individual release, which are essential to the

study since they allow for the quantification of the market’s information shock. By capturing these variables, the model can isolate how specific segments of the yield curve reprice in response to unpriced shocks in economic data, rather than just reacting to the scheduled arrival of the news. As presented in Table 3.1, the dataset comprises a broad inventory of economic indicators categorized by their absolute frequency and reporting periodicity (weekly, monthly, quarterly, or discretionary). From this comprehensive list, we will proceed to filter out and focus on only the most critical indicators. This selective approach is intended to maintain the simplicity and clarity of the analysis, ensuring that the empirical results focus on the primary catalysts of market volatility [120].

Table 3.1: Economic Events Inventory and Frequency Distribution (2018–2025) [120]

Economic Event	Freq. Code	Abs. Frequency
MBA Mortgage Applications	W	406
Initial Jobless Claims	W	406
S&P Global US Manufacturing PMI	M	191
U. of Mich. Sentiment	M	190
Durable Goods Orders	M	188
Wholesale Inventories MoM	M	184
ISM Manufacturing	M	96
Empire Manufacturing	M	95
MNI Chicago PMI	M	95
ISM Services Index	M	95
Conf. Board Consumer Confidence	M	95
Existing Home Sales	M	95
Factory Orders	M	94
CPI MoM	M	94
Trade Balance	M	94
Unemployment Rate	M	94
Retail Sales Advance MoM	M	94
PPI Final Demand MoM	M	94
Change in Nonfarm Payrolls	M	94
CPI YoY	M	94
Construction Spending MoM	M	94
ADP Employment Change	M	93
New Home Sales	M	93
Leading Index	M	93
Housing Starts	M	93
Industrial Production MoM	M	93
Personal Income	M	92
GDP Annualized QoQ	Q	92
Personal Spending	M	92
FOMC Rate Decision (Upper Bound)	D	64

3.2 Exploratory Data Analysis (EDA)

With the dataset now formally defined, this section shifts to the exploratory analysis of the data's statistical properties. The objective is to characterize the stylized facts of the Treasury futures and economic releases, ensuring that the subsequent econometric models are built upon a robust understanding of the underlying distributions and liquidity regimes.

3.2.1 Descriptive Statistics

Before delving into the statistical moments of returns distributions, it is essential to establish a visual baseline of the **raw price trajectories** over the sample period. This initial visual inspection allows for the identification of distinct market regimes, structural breaks, and the evolving correlations between asset classes during periods of systemic stress versus relative calm.

To facilitate a direct comparative analysis across instruments with vastly different notional values and pricing conventions, all series displayed in Figure 3.5 have been normalized to a base value of 100 as of the start of the sample period (January 2018). This normalization allows the relative performance and volatility magnitude of each instrument to be assessed on a common scale.

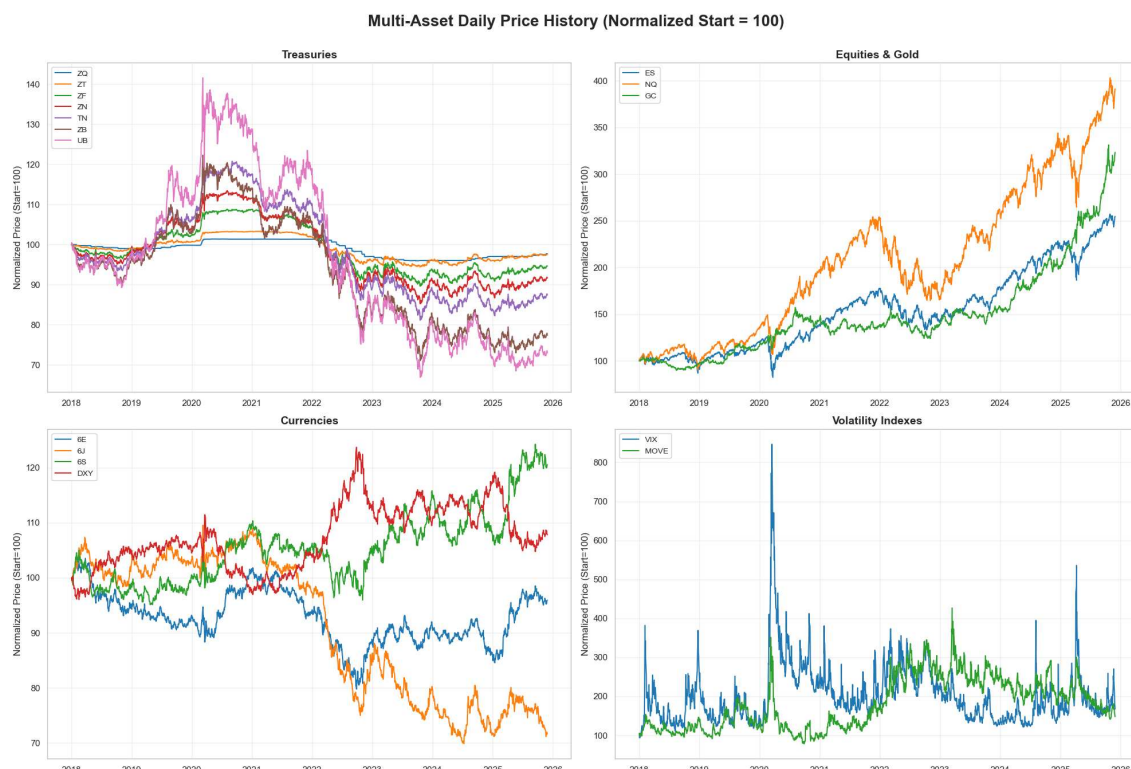


Figure 3.5: Daily Price History [121]

Figure 3.5 presents a view of financial assets price history across four distinct panels: *Treasuries*, *Equities & Gold*, *Currencies*, and *Volatility Indexes*.

The **Treasuries** panel (*top-left*) illustrates a highly synchronized co-movement across the entire maturity spectrum, reflecting the unified response of the fixed income complex to shifting discount rate expectations. As we can notice the magnitude of these price swings is exacerbated by the duration of the instrument. In a textbook demonstration of interest rate sensitivity, the volatility increases in perfect sequential order of maturity, from the 30-Day Federal Funds (ZQ) (*blue*) and 2-Year Note (ZT) (*orange*) to the 5-Year (ZF) (*green*), 10-Year (ZN) (*red*), and Ultra 10-Year (TN) (*purple*), culminating in the extreme price fluctuations of the 30-Year Bond (ZB) (*brown*) and Ultra Bond (UB) (*pink*). While the directional trend remains identical across all contracts, the amplitude of the moves expands as one moves further out the yield curve.

Looking at the *top-right* panel, the **Equities & Gold** one, we can see a high degree of correlation between the S&P 500 (ES) (*blue*) and the Nasdaq-100 (NQ)

(orange). While they track each other closely in direction, it can be observed that the NQ has significantly outperformed the broader market index, highlighting the exceptional growth and dominance of the technology sector within the last years. Simultaneously, also Gold (GC) (green) maintains a steady upward trend, reinforcing its role as a fundamental store of value with cumulative returns that remain remarkably comparable to those of the major equity indices over the full sample period.

Turning to the **Currencies** panel (*bottom-left*), the data highlights several interesting features of the foreign exchange market. Primarily, the US Dollar Index (DXY) (red) and the Euro (6E) (blue) exhibit a near perfect inverse relationship, a result of the Euro's dominant weighting within the DXY basket seen in Figure 3.4. Furthermore, a noteworthy divergence is observed among instruments traditionally classified as safe-haven assets: despite their shared reputation for defensive qualities, the Swiss Franc (6S) (green) and the Japanese Yen (6J) (orange) have followed surprisingly divergent trajectories over the sample period, with the first one largely outperformed the second.

Finally, the **Volatility Indexes** panel (*bottom-right*) allows to compare the fear and systemic stress levels within the equity and fixed income markets using the VIX (blue) and MOVE Index (green) as proxies. It can be observed that these indexes frequently move together, however, their correlation remains imperfect, suggesting that bond and equity market stress often diverge depending on the catalyst of the volatility.

Across all four panels, the exogenous shock of the COVID-19 pandemic in early 2020 is clearly visible as a transformative event. However, the outcomes across these instruments were very different. In the Treasury complex, the shock triggered a vertical rally as yields dropped down. In the equity sector, it caused a sharp but temporary collapse followed by a liquidity driven surge. Lastly Currencies and volatility indices recorded their most violent price actions of the decade during this window, marking a definitive shift in market regimes.

After reviewing the raw price trends, the analysis now shifts toward a statistical

breakdown of the data. One fundamental property in time series econometrics is *stationarity*, which describes a condition where the statistical features of a series (such as the mean, variance, and autocovariance) remain constant over time. This property is fundamental because it ensures the stability of the models and allows for reliable forecasting. For this reason, while raw prices provide a clear view of market history, they are not suitable for econometric modeling because they are considered non-stationary. To ensure that the results are statistically sound, these prices must be converted into logarithmic returns, which are theoretically expected to be stationary, making them suitable for rigorous econometric analysis [122].

Given that, daily logarithmic returns were calculated for all instruments in the dataset and, to assess the behavior of these returns, two primary visualizations were generated for each series: a time-series plot of the return history to identify patterns of volatility clustering, and a frequency histogram to evaluate the shape of the empirical data. For the sake of brevity and clarity, this section details the results for the 10-Year Treasury Note (ZN), which serves as the primary benchmark for the US Treasury market. The results of the plots for the remaining instruments, which exhibit similar structural characteristics, are summarized later in the final descriptive statistics table.

As shown in Figure 3.6, the time series of ZN daily log-returns clearly demonstrates the phenomenon of volatility clustering.

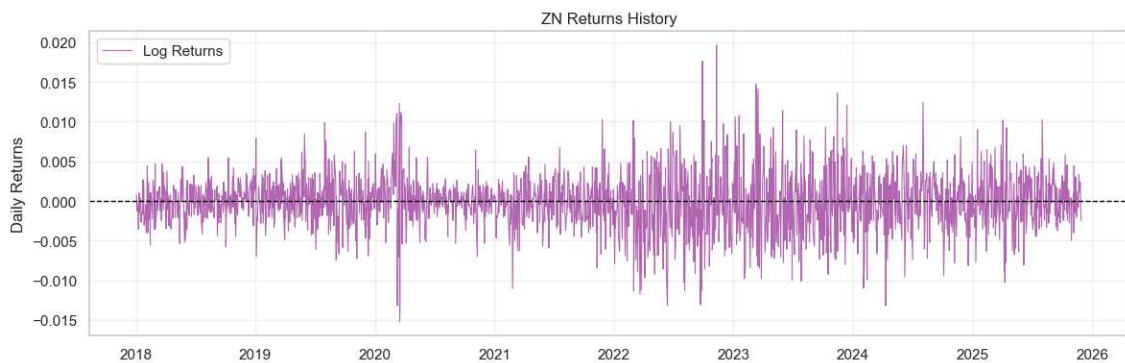


Figure 3.6: ZN Daily Returns & Volatility Clustering [121]

It can be noticed that the returns are centered around a mean of zero, confirming the removal of the price trends observed before, however, the variance is clearly

not constant over time. We can observe distinct periods where high returns (both positive and negative) are followed by further large moves like during the COVID-19 shock of early 2020 and again during the 2022–2023 inflationary cycle.

Furthermore, to evaluate the statistical profile of these returns, we compare the empirical distribution of ZN futures contract against a theoretical normal curve. To formally characterize the distribution of returns, we must examine the fourth moment of the distribution: *kurtosis*. This metric measures the "fatness" of the tails, indicating the probability of extreme return realizations. While a result of +3.00 represents a mesokurtic distribution, which is largely normal, statisticians often adjust this result to zero for simplicity in interpretation. This adjusted figure, referred to as *excess kurtosis*, allows any reading other than zero to signal a clear departure from normality [123]. Under this framework, a *leptokurtic* distribution is identified by positive excess kurtosis and is characterized by a higher peak than a normal distribution due to the clustering of data points around the mean. In financial terms, this thin shape implies that while small changes are frequent, the presence of "fat tails" signifies a higher than normal probability of extreme fluctuations. Conversely, a *platykurtic* distribution, denoted by negative excess kurtosis, appears broad and flat with extremely dispersed points along the x-axis. These distributions typically represent fewer major fluctuations and are generally considered less risky than their leptokurtic counterparts [124].

As illustrated in Figure 3.7, the 10-Year Treasury Note (ZN) exhibits a clear leptokurtic profile with a calculated excess kurtosis of 1.94.

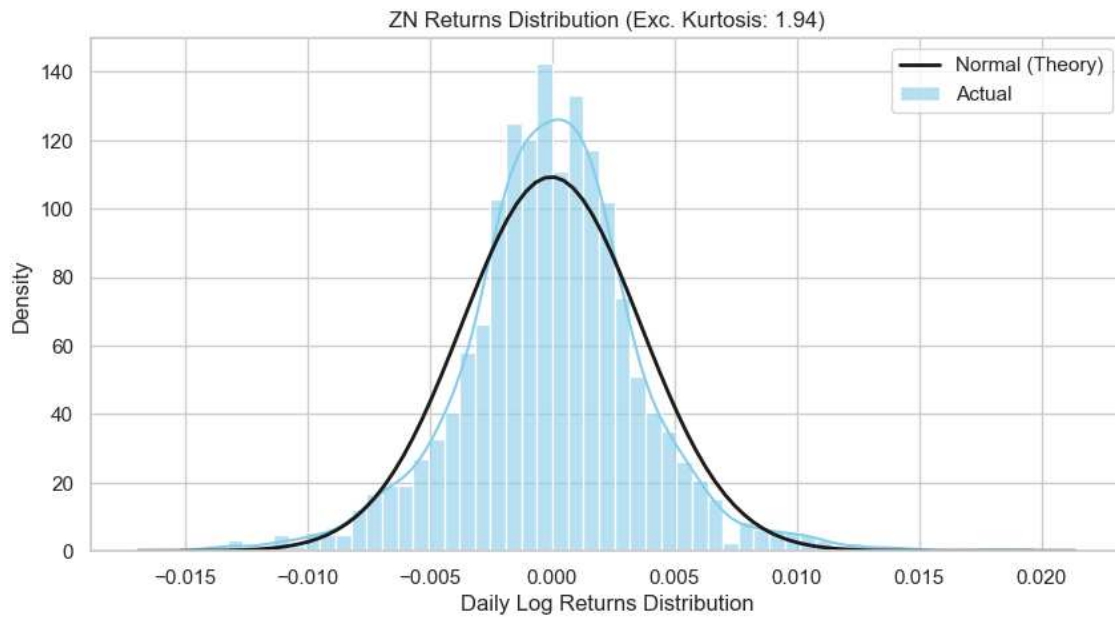


Figure 3.7: ZN Daily Returns Distribution [121]

To appreciate the practical implications of this figure, one must consider the frequency of extreme outliers. In a perfectly Gaussian world (where excess kurtosis is zero) an observation six standard deviations from the mean is a statistical impossibility in a human lifetime, however, the positive excess kurtosis found in our data shifts these probabilities by several orders of magnitude. Within the 2018–2025 period, price swings that would be dismissed as impossible under normal distribution assumptions become recurring realities, appearing multiple times a year.

Building upon the empirical analysis of the 10-year Treasury benchmark, we now expand our scope to the entire dataset. The following Table 3.2 summarizes the four fundamental moments of daily return distributions (*mean*, *standard deviation*, *skewness*, and *excess kurtosis*) providing a comprehensive statistical profile for all instruments in the sample.

Table 3.2: Descriptive Statistics of Daily Logarithmic Returns (2018–2025)

Ticker	Mean (%)	Std. Deviation (%)	Skewness	Excess Kurtosis
ZQ	-0.0012	0.05	-8.02	129.72
ZT	-0.0012	0.11	0.97	9.22
ZF	-0.0026	0.25	0.27	2.99
ZN	-0.0039	0.37	0.11	1.94
TN	-0.0058	0.48	-0.01	2.04
ZB	-0.0108	0.68	-0.00	2.57
UB	-0.0132	0.96	-0.05	4.35
ES	0.0498	1.23	-0.57	13.12
NQ	0.0705	1.53	-0.33	6.35
GC	0.0568	1.00	-0.32	3.77
6E	-0.0015	0.47	0.12	1.36
6S	0.0099	0.49	0.57	3.87
6J	-0.0156	0.58	0.45	4.47
DXY	0.0037	0.42	-0.16	1.87
VIX	0.0256	8.13	1.41	8.84
MOVE	0.0198	4.82	0.46	5.33

It can be observed that the **mean** daily returns for all instruments are nearly zero, indicating that positive and negative returns mostly balanced themselves over the sample period. However, these figures reveal distinct drifts that are consistent with the raw price trajectories previously discussed. In the Treasury complex, the means are consistently negative, aligning with the long term downtrend in prices as interest rates rose. Conversely, the stock indexes (ES, NQ) and Gold exhibit positive means, reflecting the overall uptrend witnessed in those markets.

Regarding **standard deviation** (volatility) it can be noticed that in the Treasury futures complex it grows larger as the maturity increases, mirroring the behavior seen in the price plots. While if we consider the futures complex instruments in its entirety ES, NQ, and GC possess the highest standard deviations values. At the same time the currencies maintain consistent values between 0.4% and 0.6% without significant deviation from one another, while the volatility indices (VIX and MOVE), on the contrary, present the maximum standard deviation in the dataset.

Talking about the third moment of distribution, **skewness**, it represents a measure of the deviation of each instrument's distribution from the symmetrical normal one. This asymmetry is a critical consideration for assessing return distributions, as extreme data points can significantly alter the risk profile. By definition, a normal distribution has a skewness of zero, whereas any reading other than zero signals

skewness risk. The negative skewness observed in the equity markets (ES, NQ) identifies them as negatively skewed (or left-skewed) distributions, suggesting that infrequent, large market crashes dominate the tail behavior of the distribution, even in the presence of steady daily gains. In contrast, the shorter dated Treasuries exhibit positive skewness (right-skewed), resulting in a mean value greater than the median. This indicates that the risk in these instruments is concentrated in sudden, sharp upward spikes rather than downward shocks [125].

Finally, the **excess kurtosis** results confirm that every financial instrument in the sample exhibits leptokurtic behavior. This statistical reality implies that no instrument can be properly treated as a normal Gaussian function, as they all possess a higher than normal probability of extreme positive and negative realizations. We can also notice that, while ZN, TN, 6E, and DXY appear to be the "most normal" in their behavior, ES, VIX, and ZT present significantly fatter tails.

While leptokurtosis is a common feature across the sample, its magnitude varies substantially and reveals extreme deviations for certain instruments. A prominent anomaly in the dataset is the 30-Day Fed Funds (ZQ), which serves as a massive **outlier** in both *skewness* (-8.02) and *excess kurtosis* (129.72). This can be attributed to the unique nature of the Fed Funds market, where prices often remain static for long periods while the Federal Reserve holds rates steady, only to move with violent intensity when a policy change occurs. These rare, massive jumps create a distribution that consists almost entirely of extreme tails with very little daily variation in between.

With the distributional properties of the returns established, the final requirement for ensuring the validity of the econometric framework is to formally verify the **stationarity** of the time series. To confirm this transition, an *Augmented Dickey-Fuller (ADF)* test was conducted on the daily log-returns of all sixteen instruments. The ADF test evaluates the null hypothesis (H_0) that a unit root is present in the series, signifying non-stationarity. A rejection of this hypothesis is mandatory to ensure that the subsequent regression analysis does not produce spurious results. The results of these tests are summarized in Table 3.3.

Table 3.3: Augmented Dickey-Fuller (ADF) Stationarity Test Results

Ticker	Test Statistic	P-Value	Lags	Status
ZT	-11.62	0.0000	13	STATIONARY
ZF	-27.09	0.0000	8	STATIONARY
ZN	-33.00	0.0000	1	STATIONARY
TN	-32.97	0.0000	1	STATIONARY
ZB	-33.20	0.0000	1	STATIONARY
UB	-17.46	0.0000	6	STATIONARY
ES	-13.96	0.0000	8	STATIONARY
NQ	-14.37	0.0000	8	STATIONARY
GC	-19.23	0.0000	6	STATIONARY
6E	-20.00	0.0000	5	STATIONARY
6S	-43.46	0.0000	0	STATIONARY
6J	-45.87	0.0000	0	STATIONARY
ZQ	-10.86	0.0000	10	STATIONARY
VIX	-18.47	0.0000	7	STATIONARY
MOVE	-10.91	0.0000	24	STATIONARY
DXY	-19.89	0.0000	5	STATIONARY

As shown in the table, the null hypothesis of a unit root is rejected at the 1% significance level for every instrument in the dataset, the p-values for all series are effectively zero, and the test statistics are significantly more negative than the standard critical thresholds. The Lags column indicates the number of past observations included to account for serial correlation, ensuring that the test remains robust against internal dependencies in the data. This unanimous result confirms that the return series exhibit a constant mean and variance structure, rendering them statistically sound and suitable for the empirical estimation of the following chapters.

Now the analysis proceeds to explore the interdependencies between these instruments and, to quantify the strength and direction of these relationships, we first examine the **Daily Return Correlation Matrix** (Figure 3.8), in which the primary attention is directed toward the first six columns, which represent the various maturities of the Treasury curve.

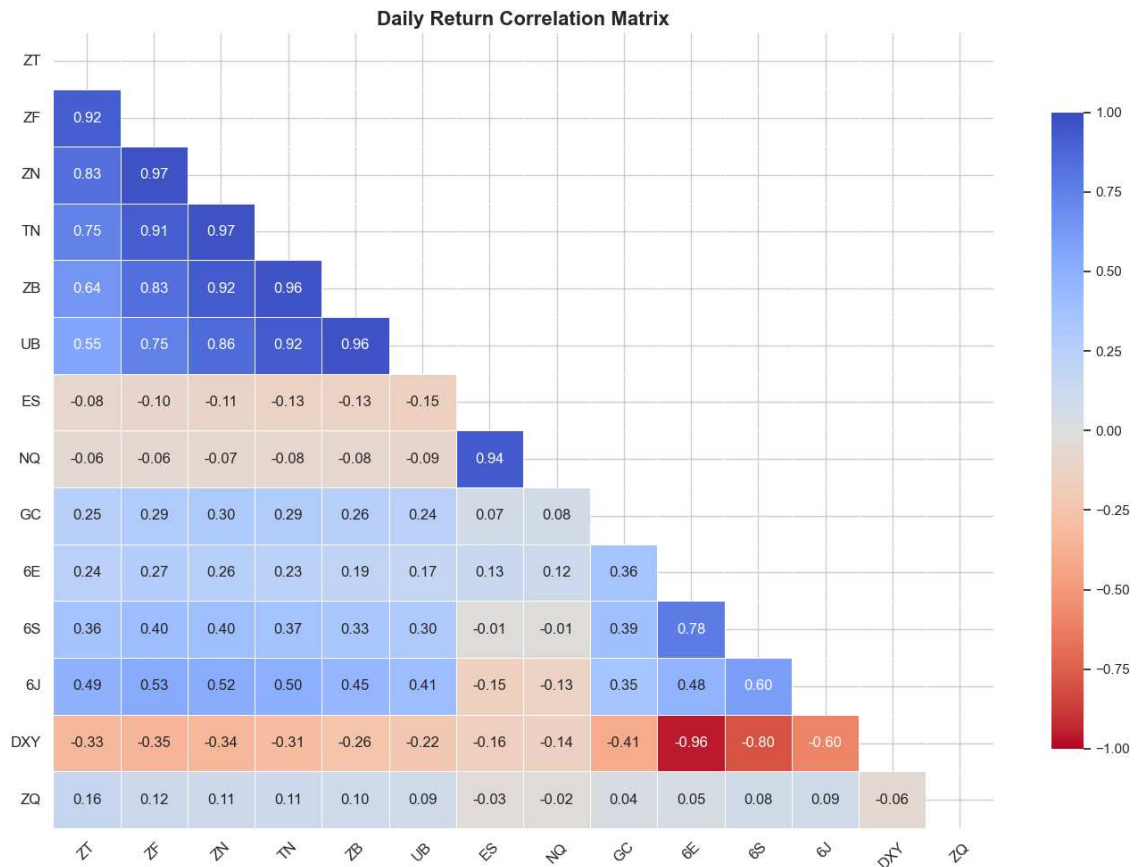


Figure 3.8: Daily Return Correlation Matrix [121]

This heatmap utilizes Pearson correlation coefficients to provide a static snapshot of pairwise dependencies across the entire sample period. Fundamentally, a correlation measures the strength of the statistical link between two nondirectional variables, expressed by a coefficient ranging from -1 to +1. A coefficient of +1 indicates a perfect positive correlation, while a coefficient of -1 represents a perfect negative correlation and a value near zero suggests the variables are not statistically linked [126].

The matrix reveals a distinct blue block in the upper-left, showing near perfect positive correlation between adjacent points on the curve within the Treasury complex. For instance, the 10-Year (ZN) and 5-Year (ZF) notes move in high synchronization with a coefficient of 0.97, but, as expected, this correlation decays slightly as the duration gap widens: 0.55 correlation between the 2-Year (ZT) and the Ultra Bond (UB).

We can also notice that Treasuries exhibit essentially zero correlation with Equity indices (ES, NQ). This lack of a statistical link suggests that, on average, the fixed income and stock markets moved independently throughout the 2018–2025 period. In contrast, Gold (GC) and the Euro (6E) maintain a slight positive correlation with the Treasury curve, while the US Dollar Index (DXY) shows a consistent negative relationship. Other currencies, such as the Swiss Franc (6S) and the Japanese Yen (6J), demonstrate even higher correlation values with Treasuries, reflecting their shared roles as traditional defensive or safe haven assets. Lastly, due to the unique characteristics of its market, the 30-Day Fed Funds (ZQ) remains a distinct outlier within the matrix, showing nearly no correlation with any other instrument in the dataset, with the exception of a marginal 0.16 correlation with the very front end of the yield curve (ZT).

While these average coefficients offer a useful structural snapshot, they can mask significant fluctuations that occur during periods of market stress or policy transitions. Consequently, it is necessary to supplement the static analysis with a rolling window approach that captures the time varying nature of asset interdependencies. In particular, to capture this evolution, Figure 3.9 tracks the 126-day **rolling correlation** for key asset pairs, utilizing a six month window that effectively filters out daily market noise while remaining responsive to fundamental shifts in monetary policy expectations.

The analysis focuses primarily on how the *10-Year Treasury Note (ZN) benchmark* interacts with critical market segments over time. By monitoring the rolling correlation of ZN against the 2-Year (ZT) and Ultra Bond (UB) futures, we can observe the coherence over time in the relationship between various maturities in the fixed income complex. While these relationships are generally robust, discrepancies emerge during periods of aggressive Fed tightening or curve inversions, where different maturities begin to price in divergent economic drivers. This is particularly evident in the relationship between the 2-Year (ZT) and the Ultra Bond (UB), where the decoupling between short term policy expectations and long term growth or inflation outlooks reaches its maximum intensity.

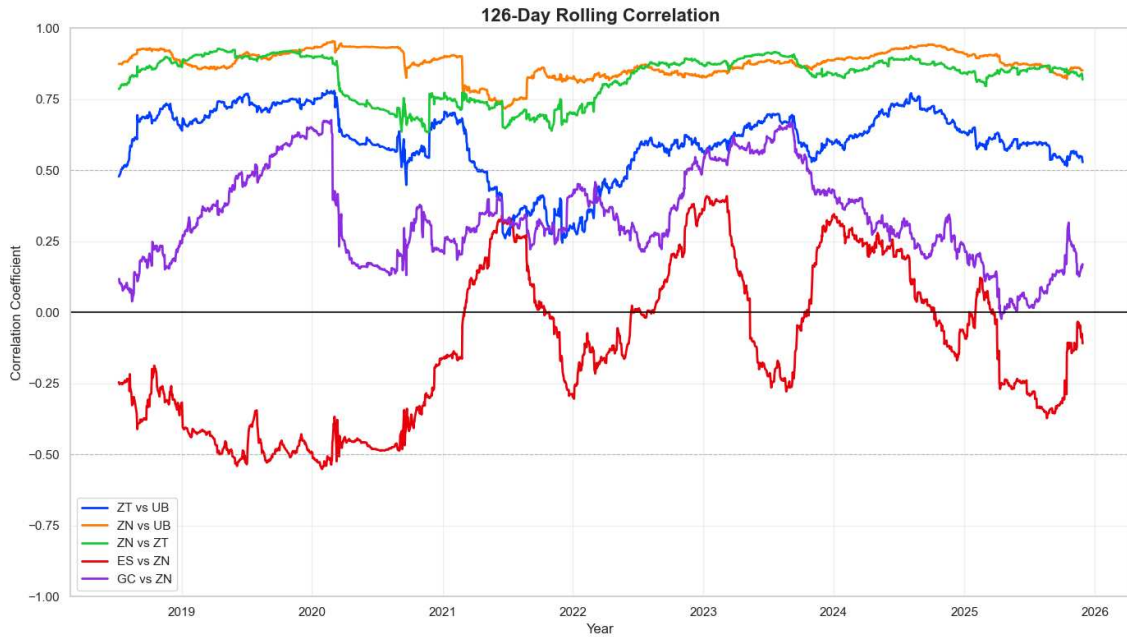


Figure 3.9: Daily Return 126-Day Rolling Correlation [121]

Even more significant is the evolution of the *stock-bond* relationship (represented by the correlation between ES and ZN) which is characterized by extreme instability. Despite the near-zero average shown in the correlation matrix (Figure 3.8), we can observe how, throughout the sample period, this correlation is not constant but oscillates frequently between negative and positive territory. Similarly, the *gold-bond* relationship (GC vs ZN) shows significant variation over time: while the correlation remains consistently in positive territory, indicating a shared defensive profile, it experienced a massive drop during the COVID-19 crisis, likely driven by a sudden shift in policy expectations and liquidity demands.

Now, to better understand the real size of market moves, we shift our focus from percentage returns to **daily tick ranges**. We start the analysis with a comparison of the *Mean*, *Median*, and *Mode* of this measure across Treasury futures contracts.

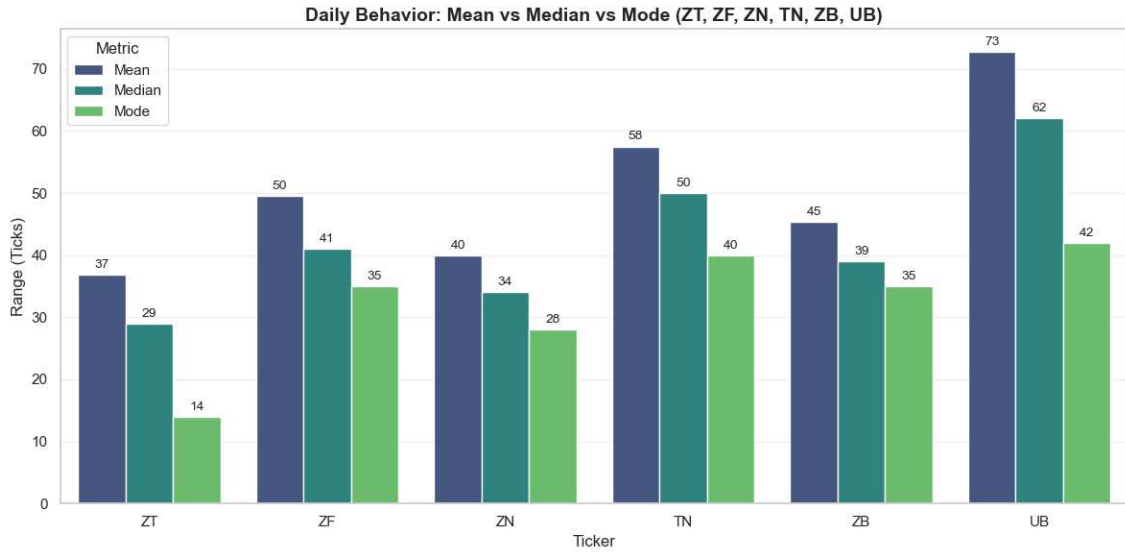


Figure 3.10: Treasury Futures Mean, Median and Mode (Daily Tick Range) [121]

This initial look at central tendency (Figure 3.10) highlights a recurring structural fact: for every instrument, the mean daily range exceeds the median and mode. This gap confirms the results found in our earlier statistical summary: leptokurtic and fat tails behavior. It indicates that while most trading days occur within a predictable normal bracket, the overall distribution is pulled higher by frequent, explosive days of activity. Additionally, the plot illustrates that while the daily tick range generally increases with maturities, with the 2-Year Note (ZT) clearly exhibiting a much lower range than the Ultra Bond (UB), the relationship is not perfectly linear across all maturities. Specifically, we observe that the 5-Year Note (ZF) maintains a higher median range than the 10-Year (ZN) and the same happens with the Ultra 10-Year (TN) and the Bond (ZB) contracts. This suggests that while duration is the primary driver of price distance, specific contract specifications or liquidity pockets in the belly of the curve can cause localized spikes in volatility that exceed those of slightly longer dated instruments.

To see the financial impact of these moves, we look at Figure 3.11, where the tick range is converted into *dollar values* (Tick Range $\times$ Dollar Value of 1 Tick). In this graph, the median is intentionally utilized over the mean to ensure that the results are less influenced by the extreme outliers, providing a more representative view

of a typical trading session.

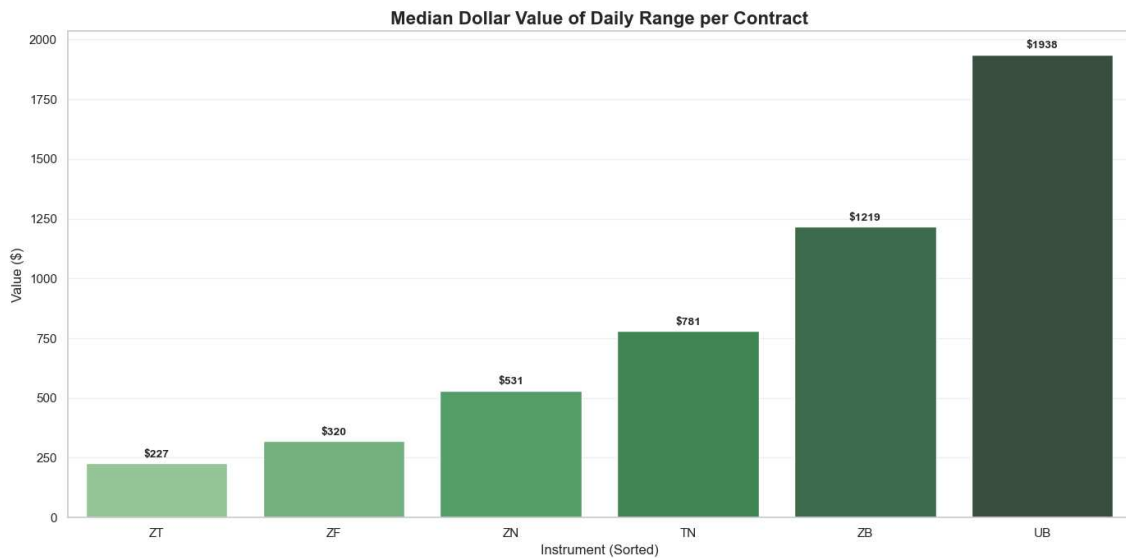


Figure 3.11: Treasury Futures Median Daily Tick Range (\$ Dollar Value) [121]

The results obtained are consistent with the earlier findings, yet they provide a much clearer picture of the risk hierarchy. Unlike the raw tick range plot, where some intermediate maturities like ZF showed higher volatility than ZN, the dollar-value range presents a perfect scale-up across the Treasury curve from ZT to UB. This progression confirms that when accounting for contract specifications and tick values, financial exposure increases linearly with maturity. This trend culminates with the Ultra Bond (UB), which presents a median daily value range of \$1,938, nearly nine times the risk of the 2-Year Note (ZT). This visualization underscores that duration remains the definitive driver of capital risk.

While the previous charts show the central tendency measures across the entire sample period, it is important to observe how these price fluctuations have developed over time. This is shown in Figure 3.12, which represents the *Evolution of Daily Median Range*, providing a dynamic perspective that simple averages cannot capture.

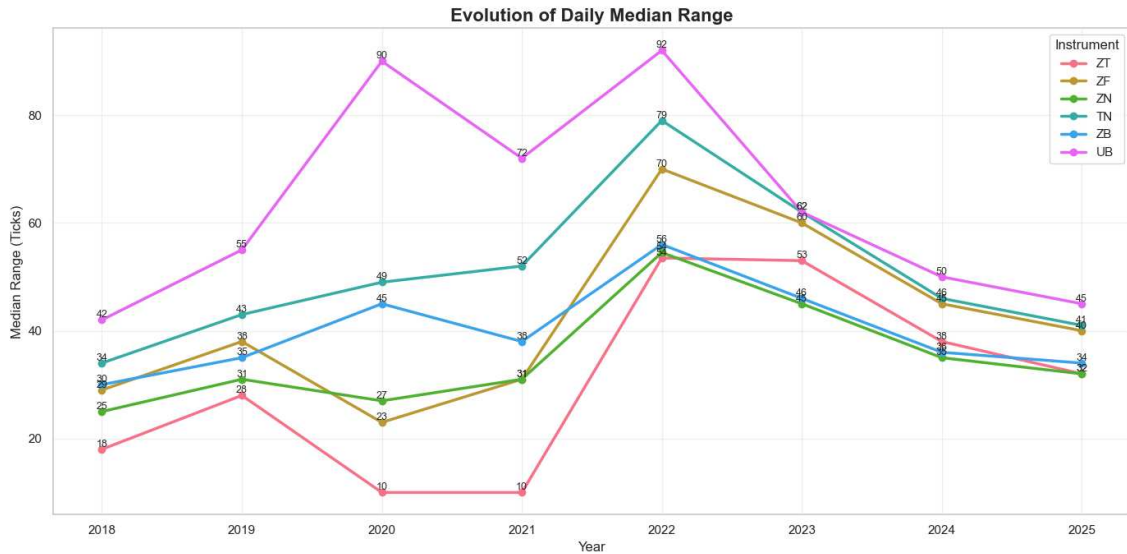


Figure 3.12: Treasury Futures Evolution of Median Daily Tick Range [121]

The yearly progression reveals two distinct volatility peaks that define the recent history of the Treasury market. The first surge occurred in 2020, as the global pandemic triggered a massive liquidity shock and a flight to safety. During this time, the Ultra Bond (UB) saw its median daily range jump to 90 ticks, nearly doubling its 2018 baseline. This highlights how extreme systemic uncertainty forces a rapid expansion in the price distance covered during a single trading session. The second peak took place in 2022 when the Federal Reserve implemented the tightening cycle to combat inflation. During this time, volatility became structurally embedded in the market and UB reached a historical median high of 92 ticks, while the Ultra 10-Year (TN) and 5-Year (ZF) contracts expanded significantly to 79 and 70 ticks, respectively. A particularly striking observation in this evolution is the behavior of the 2-Year Note (ZT) which, after remaining virtually dormant with a median range of only 10 ticks during the 2020–2021 period of near zero interest rates, it exploded to 53 ticks in 2022. This serves as a clear indicator that the front end of the curve, being more sensitive to immediate policy shifts, has been the most influenced by the Federal Reserve’s transition from an accommodative to a hawkish stance. Since the 2022 peak, the data shows a steady normalization phase continuing through 2024 and 2025. By 2025, median ranges have diminished sig-

nificantly, with the UB dropping back to 45 ticks and the ZN to 32 ticks; yet, these levels remain structurally higher than the pre-2020 environment.

The average ranges tell us what usually happens, but it is also important to look at the extremes. By examining the *maximum* and *minimum* historical ranges in Figure 3.13, we can see the full scale of price movement during the most volatile and the quietest days in our sample.

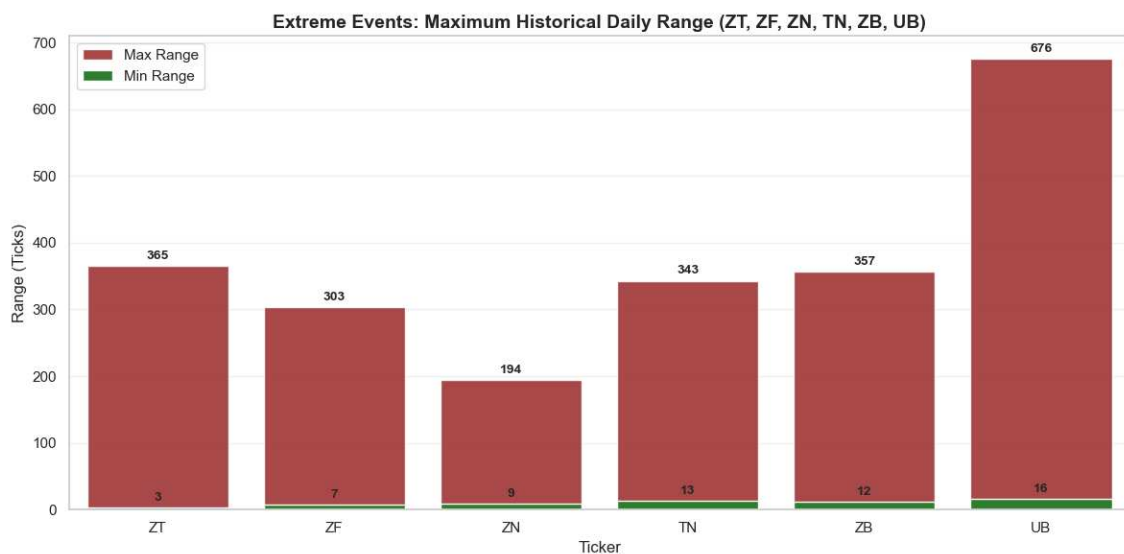


Figure 3.13: Treasury Futures Maximum and Minimum Daily Tick Range [121]

Contrary to the linear scale up seen in central tendency measures, the maximum historical expansion shows that the front end of the curve exhibits similar extremes to the long end. Specifically, the 2-Year Note (ZT) and 5-Year Note (ZF) demonstrate maximum ranges (365 and 303 ticks, respectively) that are comparable to those seen in the Bond (ZB) and Ultra 10-Year (TN) contracts. It is important to note that, within this distribution, the 10-Year Treasury Note (ZN) emerges as the most stable instrument in terms of extreme price expansion, with a maximum range of only 194 ticks. This relative stability is consistent with our previous statistical findings, where ZN was identified as one of the most normal distributions in the dataset, exhibiting fewer extreme outliers than its peers. In contrast, the Ultra Bond (UB) remains in a category of its own as it presents a staggering maximum historical range of 676 ticks, nearly doubling the extremes of the other maturities.

To finish the study of tick ranges, we analyze the timing of market volatility. We start with a look at how volatility changes from month to month. Figure 3.14 shows the *Seasonality Curve* for the median daily range, allowing us to see which parts of the year are typically the most active.

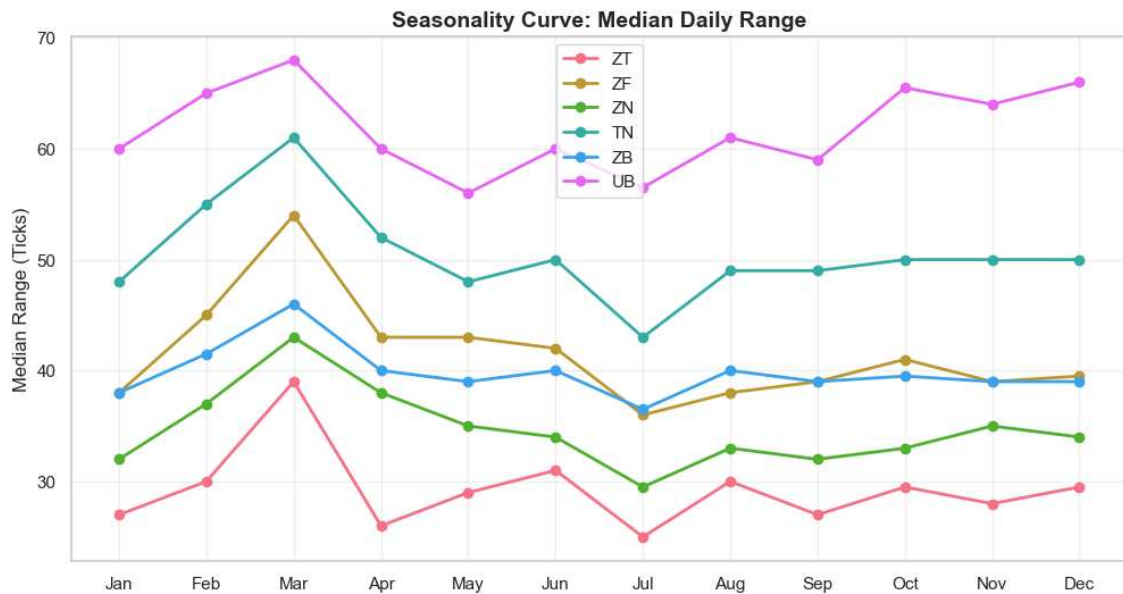


Figure 3.14: Treasury Futures Seasonality Median Daily Tick Range [121]

The data shows a clear peak in March, where volatility reaches its highest point for the year, however, it is important to note that this specific peak may be influenced by the COVID-19 market crash in March 2020, which acted as a major outlier in our sample. Following this early year high, we see a noticeable drop in July, which stands out as the quietest month for the market. For the remainder of the year, the tick ranges stay basically the same, showing very little variation. Notably, these results are consistent across all contracts, as the lines for each instrument move almost perfectly in parallel.

Next, the distribution of volatility throughout the week is examined. For this part of the study, the *Median Daily Tick Range* (Figure 3.15) is utilized.

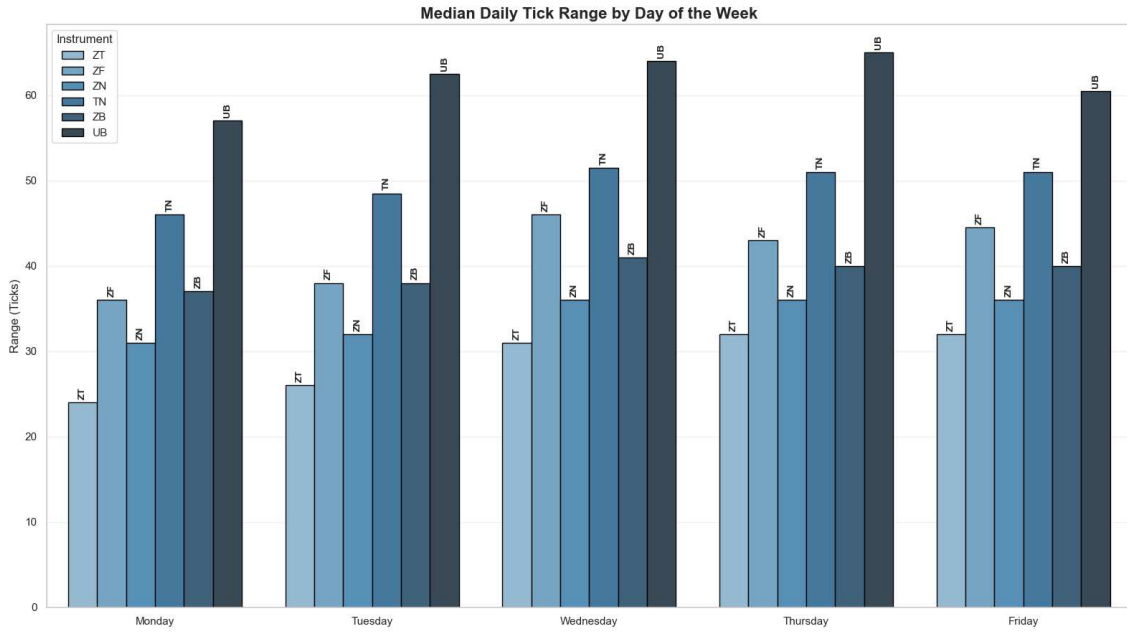


Figure 3.15: Treasury Futures Median Daily Tick Range by Day of the Week [121]

This chart shows that while volatility generally follows a slight upward trend as the week progresses, the differences between individual days are notably small, suggesting a relatively consistent distribution of intraday activity. The week typically begins with its quietest period on Monday and Tuesday, as the market often lacks major data catalysts, with Tuesday showing only a marginal increase in activity. A modest pick up in volatility is observed during the mid week session on Wednesday and this momentum carries into Thursday and Friday, which represent the peak of the weekly volatility cycle. While Friday stands as a major high point for the majority of contracts it is interesting to note that the Ultra Bond (UB) reaches its highest median range on Thursday. Ultimately, the overall stability of the bars across Figure 3.15 confirms that the baseline level of market participation and liquidity remains fairly consistent throughout the standard trading week.

After analyzing daily returns, the same statistical framework is applied to the **intraday datasets** at 15 minutes and 1 minute intervals. To formally present these findings, we examine Table 3.4, which provides the *descriptive statistics* for both intraday intervals.

The statistical analysis of the intraday data results are fundamentally analogous to

Table 3.4: Descriptive Statistics of 15 minute and 1 minute Returns

15 Minute Data					1 Minute Data				
Ticker	Mean (%)	Std Dev (%)	Skew	Kurt	Ticker	Mean (%)	Std Dev (%)	Skew	Kurt
ZT	0.000091	0.026043	0.4907	76.77	ZT	0.000004	0.003295	3.8878	723.33
ZF	0.000091	0.026043	0.4907	76.77	ZF	0.000005	0.006719	-1.4783	346.00
ZN	0.000093	0.037798	0.0979	45.40	ZN	0.000007	0.011367	-0.3780	90.98
TN	0.000069	0.046659	-0.1038	37.35	TN	0.000011	0.012340	-0.6878	105.38
ZB	-0.000046	0.071375	-0.2087	22.02	ZB	0.000011	0.022033	-0.2382	25.99
UB	-0.000161	0.091232	-0.2990	21.85	UB	0.000008	0.024433	-0.2516	27.16
ES	0.000523	0.130868	0.8730	159.82	ES	0.000077	0.020895	3.5271	316.51
GC	0.002103	0.123272	-0.4099	14.07	GC	0.000139	0.032362	0.6037	64.95
6E	0.000473	0.054566	0.1158	29.99	6E	0.000020	0.011804	1.9898	162.35
6S	0.000482	0.057248	1.2250	44.48	6S	0.000026	0.014339	8.8843	686.37
6J	-0.000054	0.064788	0.2455	31.93	6J	-0.000039	0.015202	1.6143	480.02

the daily observations. In both the 15 minutes and 1 minute datasets, the returns remain stationary, and the core risk hierarchy is preserved: volatility continues to scale with maturity across all timeframes. However, shifting from daily to intraday sampling introduces some differences in the distribution profiles. The most immediate observation is a consistently smaller *standard deviation* as sampling frequency increases. This can be explained by the fact that an instrument simply has significantly less time to cover a large distance in a single minute compared to a full trading day. Beyond the scale of movement, intraday data exhibits much greater *skewness* than is seen at the daily level, leading to a more asymmetrical distribution profile. The most dramatic transformation, however, is the explosion in *kurtosis* values as the sampling timeframe is reduced. This indicates that at high frequencies, the market typically experiences near zero movement for the vast majority of observations, yet these quiet periods are punctuated by rare and violent price jumps.

Furthermore, to provide a visual map of intraday volatility, the distribution of average volume and range for the 10-Year Note (ZN) is analyzed. While ZN serves as the primary example, these patterns are highly consistent across the entire Treasury complex.

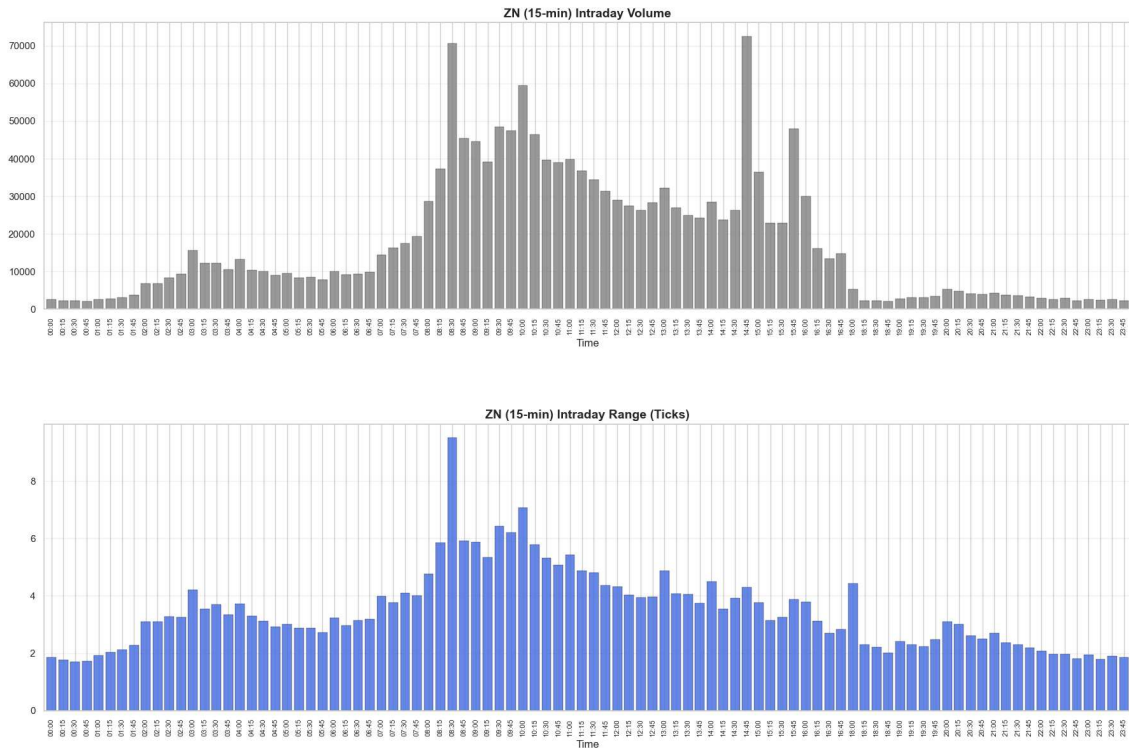


Figure 3.16: ZN Intraday Volume and Tick Range (15 minutes) [127]

The *15 minutes charts* provided by Figure 3.16 show a clear increase in activity as the market transitions from the overnight session into the regular trading hours. The distribution highlights that *Volume* and *Range* are highly correlated, as the largest price expansions are almost always backed by intense market participation. The peak for both metrics occurs in the *08:30 ET* candle, which represents the highest volatility and second highest volume of the day. A secondary, broader surge is noted between *14:30 ET* and *15:00 ET*, marking the final positioning leading into the cash market close.

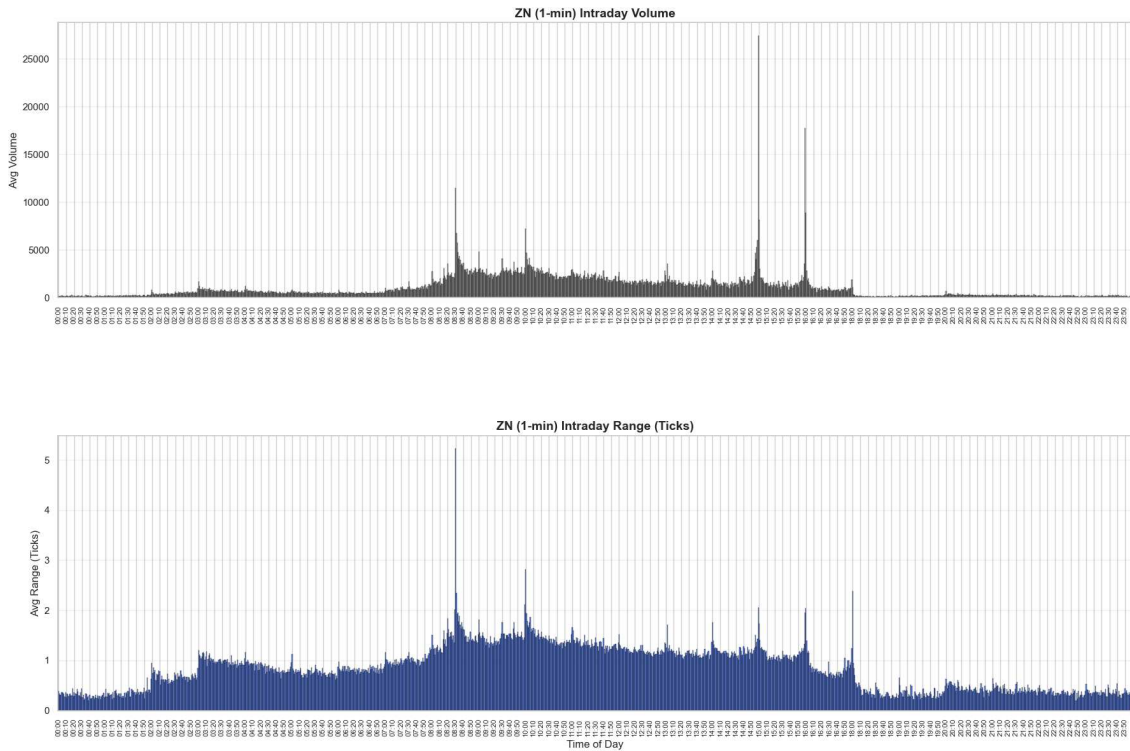


Figure 3.17: ZN Intraday Volume and Tick Range (1 minute) [127]

The *1 minute charts* (Figure 3.17) provide a more specific look at how these volatility spikes actually manifest. While the 15 minutes plots show a broad peak, the 1 minute data reveals that this activity is actually concentrated into a single, explosive spike. Indeed, at exactly *08:30 ET*, primarily driven by the news release factor, the range jumps (on average) from near zero to over 5 ticks in just sixty seconds. Following this initial shock, a synchronized spike in both volume and range occurs at *10:00 ET*, explained by the recurrent news release window for high impact indicators. As the session continues, it can be noticed a fascinating micro structural pattern: a little spike appears at almost every round hour, becoming increasingly prominent as the day progresses. Interestingly, most of these hourly events are not accompanied by significant volume, with two major exceptions that define the end of the trading day. The first exception occurs in the time between *14:59 ET* and *15:00 ET*, which records the highest volume of the entire day driven by the CME Group's Treasury Settlement window, a critical period between *14:59:30 ET* and *15:00:00 ET* where official daily settlement price is set and market participants

execute large scale orders to align with it [128]. The second exception and volume climax occurs at 16:00 ET, coinciding with the close of the US equity markets and probably caused by end of day institutional rebalancing. Finally, a notable anomaly occurs during the 18:00 ET reopening, when it can be observed one of the highest average ranges of the entire 24 hour cycle, but without significant trading volume. This divergence can be explained by the market reopening after its standard one hour daily halt: the large price range reflects the market rapidly absorbing information that arrived during the break.

To demonstrate the synchronized nature of the Treasury market, the following tables collect the most frequent 1 minute candles that appear in the top 10 range and volume rankings for each instrument.

Table 3.5: Most Frequent High Volume and High Range 1-Minute Candles (Top 10 Rankings)

Top 10 High Volume Times			Top 10 High Range Times		
Time	Count	Missing Tickers	Time	Count	Missing Tickers
08:30	6	None	08:29	6	None
08:31	6	None	08:30	6	None
08:32	6	None	08:31	6	None
10:00	6	None	09:59	6	None
14:59	6	None	10:00	6	None
15:00	6	None	14:59	6	None
15:59	6	None	18:00	6	None
16:00	6	None	08:33	5	ZB
08:33	3	UB, ZB, ZN	15:59	5	ZF
15:58	3	ZF, ZN, ZT	16:00	5	ZT

The *Count* column indicates how many of the six Treasury futures instruments (ZT, ZF, ZN, TN, ZB, UB) featured that specific timestamp in their respective top 10 lists, while the *Missing Tickers* column identifies which specific contracts did not include that minute in their ranking. The high occurrence of "perfect counts" (6 out of 6 instruments) confirms the systemic alignment of the Treasury market, suggesting that the entire yield curve moves in tandem during major liquidity and volatility shocks. Furthermore, an analysis of these temporal clusters reveals that extreme activity is not strictly confined to the round number hour. Indeed, Table 3.5 shows a consistent lead effect, with 08:29 ET and 09:59 ET intervals, alongside the 14:59 ET and 15:59 ET ones, all achieving almost perfect counts. This indicates

that the price discovery process often initiates in the seconds preceding the official news release time or round hour. Lastly, it can be noticed that the impact of the *08:30 ET* news release exhibits significant persistence: unlike other shocks that may dissipate quickly, the anomaly of high volume and range continues until *8:33 ET*, when multiple tickers still feature in the top tier rankings.

Following the identification of extreme spikes in the intraday futures data, this part transitions to an exploratory analysis of the **economic release dataset**. The scheduling of US macroeconomic data serves as the structural foundation for the intraday spikes identified in the intraday data exploratory analysis. As we can observe in Figure 3.18 the data confirms that the majority of high relevance events are concentrated at *08:30 ET* and *10:00 ET*, effectively explaining why the 1 minute and 15 minutes charts exhibit the greatest volatility at these moments.

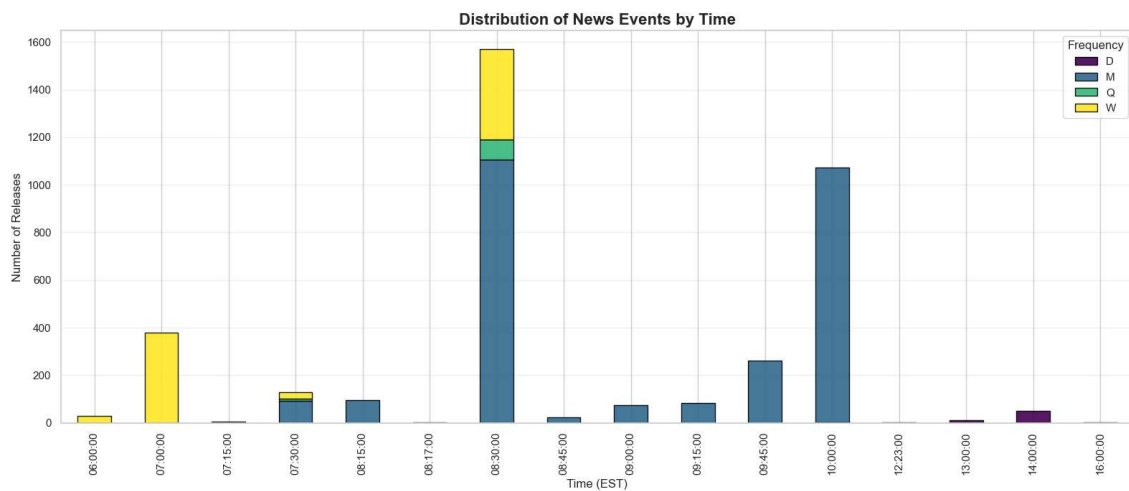


Figure 3.18: Distribution of Economic Release by Time [120]

While the timing of these events is fixed and predictable, the resulting price impact is probably driven by the deviation from market expectations, shifting the focus from the schedule itself to the magnitude of the *Surprise Factor*. This surprise is defined as the arithmetic difference between the actual realized figure and the Bloomberg survey consensus, representing the unpriced information that the market must instantaneously digest. To facilitate a rigorous comparison between disparate data types, such as thousands of non-farm jobs versus percentage points of inflation, these surprises are transformed into standardized Z-scores. A Z-score,

or standard score, serves as a statistical measure of a value's relationship to the mean in a group of values. Specifically, it quantifies how many standard deviations an individual data point, in this case a specific economic surprise, is above or below the mean of its distribution. Mathematically, the Z-score is expressed as:

$$z = \frac{x - \mu}{\sigma}$$

where x represents the raw surprise, μ is the mean surprise for that specific indicator, and σ is the standard deviation. By utilizing this formula, the *Surprise Factor* is converted from a unit dependent value into a dimensionless measure of position [129]. As illustrated in Figure 3.19, the distribution of these standardized shocks is centered at zero, confirming that the Bloomberg survey consensus is generally an efficient estimator. However, the presence of fat tails highlights the frequency of extreme informational shocks that serve as the primary catalysts for the huge price jumps observed in the Treasury data.

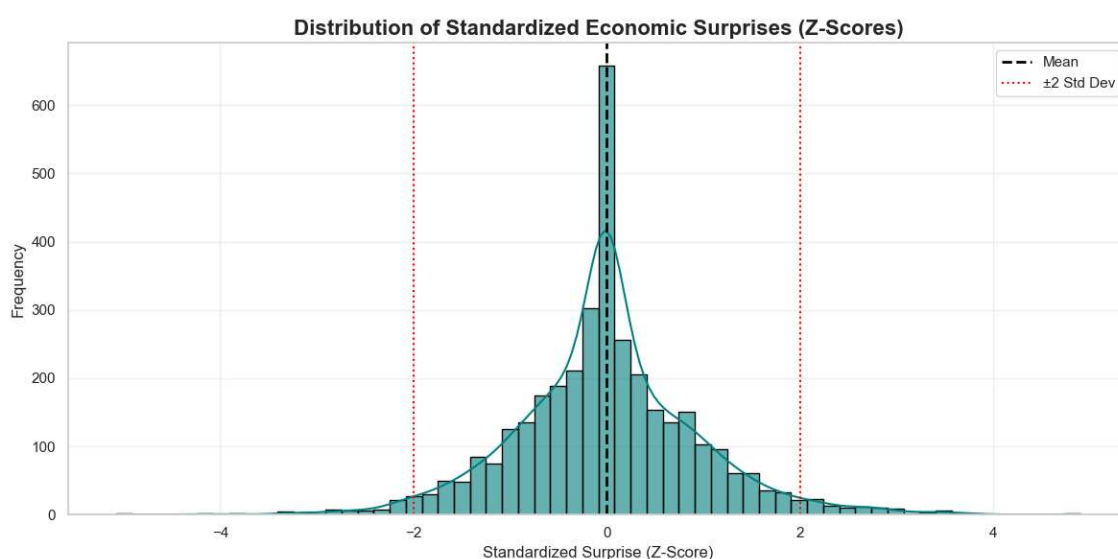


Figure 3.19: Distribution of Economic Surprise (Z-score standardization) [120]

Beyond the statistical distribution of the shocks, it is essential to categorize these indicators to understand the thematic drivers of the yield curve. While the dataset encompasses a diverse range of economic releases, as previously outlined in Section 2.3.2, these indicators can be systematically grouped into the thematic cate-

gories displayed in Table 3.6.

Table 3.6: Taxonomy of Economic Indicators by Theme

Category	Economic Indicators
Labor Market	Change in Nonfarm Payrolls, Unemployment Rate, Initial Jobless Claims, ADP Employment Change.
Inflation	CPI YoY, CPI MoM, PPI Final Demand MoM.
Real Economy	GDP Annualized QoQ, Retail Sales Advance MoM, Industrial Production MoM, Durable Goods Orders, Factory Orders, Personal Income, Personal Spending, Trade Balance, Construction Spending MoM, Wholesale Inventories MoM.
Sentiment & Surveys	ISM Manufacturing, ISM Services Index, S&P Global US Manufacturing PMI, Conf. Board Consumer Confidence, U. of Mich. Sentiment, Empire Manufacturing, MNI Chicago PMI, Leading Index.
Housing	Existing Home Sales, New Home Sales, Housing Starts, MBA Mortgage Applications.
Monetary Policy	FOMC Rate Decision (Upper Bound).

This taxonomy allows the study to move beyond a generic news effect and isolate which specific economic themes exert the most pressure on various maturities of the Treasury complex.

To complement the categorical overview in Table 3.6 a historical visual plot has been generated for all releases in the dataset. However, for the sake of brevity, this section presents the specific results for the *Change in Nonfarm Payrolls (NFP)* and the *Consumer Price Index (CPI) YoY*, which are widely recognized as two of the most influential and significant market mover economic announcements. As illustrated in Figure 3.20 and 3.21 it is visually evident that the survey consensus generally tracks well the actual measures, but, particularly in the Non-Farm Payrolls (NFP) data, it frequently tends to underestimate the realized figures. Furthermore, the NFP chart clearly highlights the extreme magnitude of the COVID-19 unemployment shock, which produced an unprecedented outlier that significantly deviates from the standard historical range.

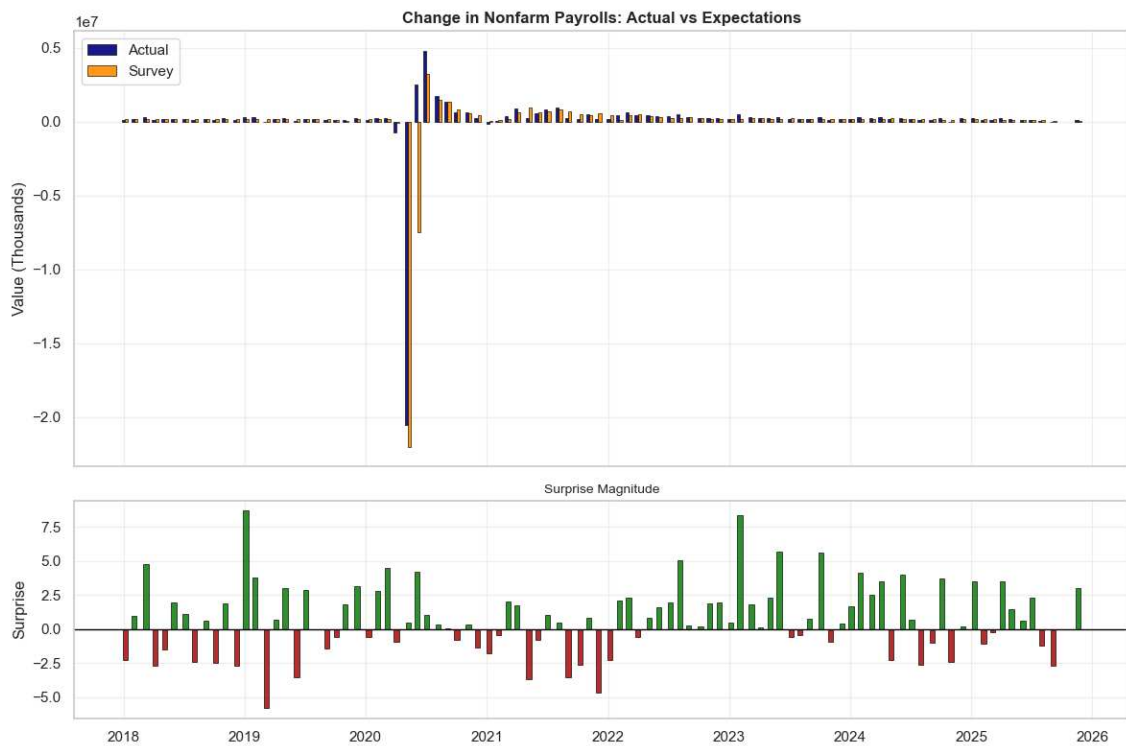


Figure 3.20: Change in Nonfarm Payrolls (NFP) [120]

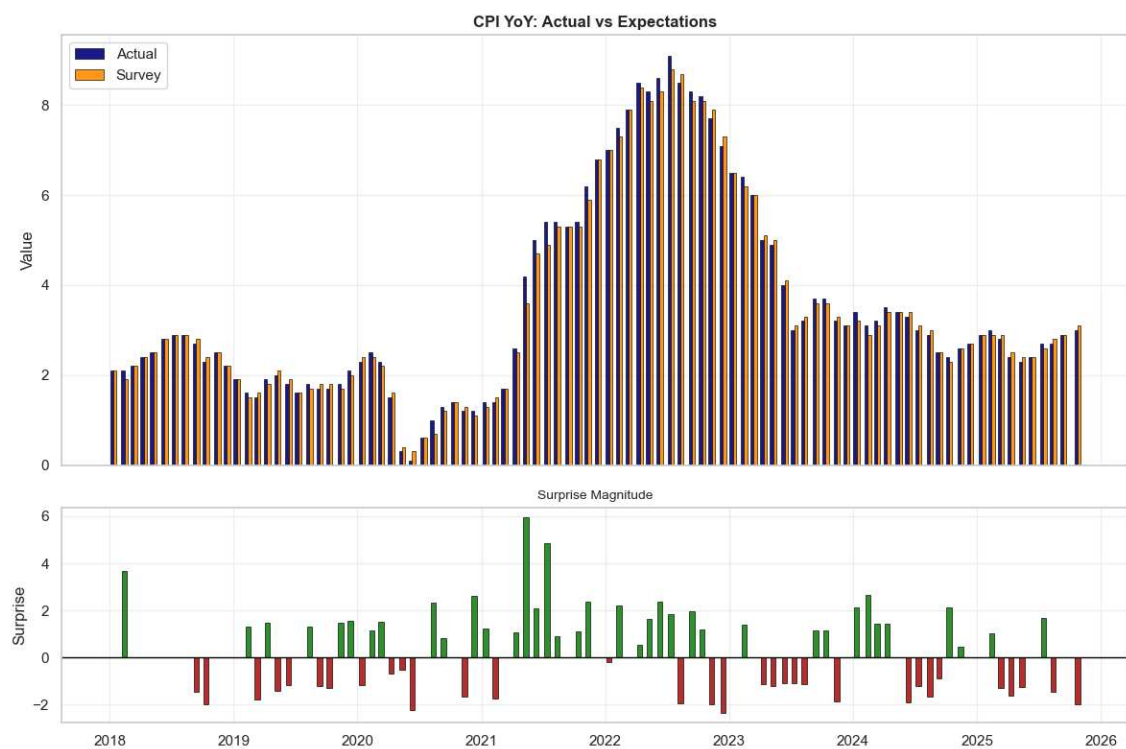


Figure 3.21: Consumer Price Index (CPI) YoY [120]

3.3 Model Specification and Empirical Results

Building upon the statistical properties and market characteristics identified in the Exploratory Data Analysis, this section transitions from descriptive observation to predictive modeling. The primary objective is to evaluate the extent to which daily volatility can be anticipated using the engineered dataset. To ensure a robust analysis, the empirical strategy follows a progressive structure, evolving from linear regression frameworks attempting to forecast exact price ranges to more flexible classification algorithms designed to detect volatility regimes. By evaluating these models across different performance metrics, the study aims to define the limits of predictability in highly efficient fixed income markets.

3.3.1 Linear Regression Models

The initial phase of the empirical analysis focuses on the direct prediction of the daily trading range for Treasury futures contracts. Before exploring complex non-linear methods, it is necessary to establish a baseline using **Linear Regression models (OLS)**, which represent one of the most simple, yet fundamental, econometric tools. To contextualize this approach, we first define the theoretical structure of the model. A *Linear Regression model* is a fundamental statistical method used to quantify the relationship between a dependent (or response) variable (y) and one or more independent (or predictor) variables (X). Its primary objective is to find the "line of best fit" that minimizes the error between predicted and actual values. Mathematically, a multiple linear regression model is expressed as:

$$y_i = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_p X_{ip} + \varepsilon_i$$

where:

- y_i is the target response variable (e.g., Daily Range);
- β_k are the coefficients representing the weight or impact of each predictor;
- X_{ij} are the input features (predictors);

- ε_t is the error term (noise) not captured by the model.

Crucially, the term “*linear*” refers to the coefficients (β), not necessarily to the variables themselves. This implies that the model assumes the target variable to be a weighted sum of the inputs, making it highly interpretable but limited in its ability to capture complex, non-linear market behaviors [130].

Translating this theoretical framework to empirical analysis, the linear regression model was first applied to the 10-Year Treasury Note (ZN) and, in this specification, the dependent variable y_t is defined as the Daily Range (High minus Low prices) in ticks for day t , while the vector of predictors X_t is drawn from the engineered feature set described in Section 3.2. The initial model adopted an unrestricted approach, incorporating the complete set of variables:

$$\text{Range}_t = \alpha + \sum_{i=1}^n \beta_i \text{CurveLags}_{t,i} + \sum_{j=1}^m \gamma_j \text{MacroVol}_{t,j} + \sum_{k=1}^p \delta_k \text{NewsImpact}_{t,k} + \varepsilon_t$$

The input features included:

- *Curve Lags*: Previous day’s range for the entire yield curve (ZQ, ZT, ZF, ZN, TN, ZB, UB) and cross-asset classes (ES, NQ, GC, 6E, 6S, 6J).
- *Macro Volatility*: Lagged absolute values of the MOVE and VIX Indexes.
- *News Impact*: Granular dummy variables for high-impact economic events.

While the calculation of lagged price ranges and volatility indices is straightforward, the *News Impact* variable requires an explanation. To classify the economic events, the study used 1-min intraday data and, in particular, it computed the Average 1-Minute Tick Impact of the 1-minute bar coincident with the release time. Based on these impact scores, economic events were segmented into four distinct tiers: *Very High (VH)*, *High (H)*, *Medium (M)*, and *Low (L)*. The resulting classification is presented in Table 3.7 below.

Table 3.7: Economic News Categorization

Event	Avg. Tick Impact	Tier
Change in Nonfarm Payrolls	34.20	Very High
Unemployment Rate	34.20	Very High
CPI YoY	31.47	Very High
CPI MoM	31.47	Very High
PPI Final Demand MoM	17.57	High
Initial Jobless Claims	17.39	High
Trade Balance	15.33	High
FOMC Rate Decision (Upper Bound)	12.63	High
ADP Employment Change	11.36	High
GDP Annualized QoQ	10.79	High
Retail Sales Advance MoM	10.67	High
Construction Spending MoM	8.57	Medium
Personal Income	7.71	Medium
Personal Spending	7.71	Medium
ISM Manufacturing	7.62	Medium
ISM Services Index	7.31	Medium
Factory Orders	5.77	Medium
Empire Manufacturing	5.50	Medium
Durable Goods Orders	5.38	Medium
Wholesale Inventories MoM	3.85	Low
Conf. Board Consumer Confidence	3.31	Low
U. of Mich. Sentiment	3.08	Low
S&P Global US Manufacturing PMI	2.78	Low
Existing Home Sales	2.78	Low
Housing Starts	2.38	Low
Leading Index	2.33	Low
MNI Chicago PMI	2.06	Low
Industrial Production MoM	1.92	Low
New Home Sales	1.42	Low
MBA Mortgage Applications	0.80	Low

To incorporate these categorical tiers into the linear regression model, a binary dummy encoding logic was applied. Rather than summing the events, the model tests for the presence of a specific risk tier on any given day. For example, the variable $News_VH$ is defined as:

$$News_VH_t = \begin{cases} 1, & \text{if at least one "Very High" event is scheduled on day } t, \\ 0, & \text{otherwise.} \end{cases}$$

This logic applies similarly to $News_H$, $News_M$, and $News_L$. This binary approach avoids the assumption that two "High" events result in exactly double the volatility of one, instead isolating the regime of the day based on the most significant scheduled event.

The calibration of the **unrestricted linear model** on the in-sample period (Jan

2018 – Dec 2024) brings the results presented in Table 3.8.

Table 3.8: OLS Regression Results (Full Specification)

Dependent Variable: ZN Daily Range (Ticks) In-Sample Period (2018-2024)				
Metric	Value			
R-squared	0.236			
Adj. R-squared	0.227			
AIC	15,260			
BIC	15,370			
Variable	Coef.	Std. Err.	t	P> t
const	17.710	1.864	9.502	0.000
News_VH	3.573	0.844	4.233	0.000
News_H	2.533	0.635	3.990	0.000
News_M	-0.196	0.582	-0.337	0.736
News_L	-0.216	0.527	-0.410	0.682
MOVE_Lag	0.175	0.019	9.230	0.000
VIX_Lag	0.168	0.099	1.701	0.089
ZT_Range_Lag	0.071	0.053	1.334	0.182
ZF_Range_Lag	0.189	0.115	1.648	0.100
ZN_Range_Lag	-0.386	0.206	-1.876	0.061
TN_Range_Lag	0.320	0.124	2.573	0.010
ZB_Range_Lag	-0.273	0.101	-2.697	0.007
UB_Range_Lag	0.063	0.041	1.534	0.125
ES_Range_Lag	-0.007	0.009	-0.823	0.411
NQ_Range_Lag	0.002	0.002	0.916	0.360
GC_Range_Lag	-0.011	0.003	-3.265	0.001
6E_Range_Lag	-0.007	0.009	-0.784	0.433
6S_Range_Lag	-0.000	0.000	-0.286	0.775
6J_Range_Lag	-0.000	0.000	-0.957	0.339
ZQ_Range_Lag	0.009	0.116	0.073	0.942

The model achieves an Adjusted- R^2 of 0.227, implying that nearly 23% of the daily range variance can be explained by the selected factors [131]. However, the high values for the *Akaike Information Criterion (AIC)* and *Bayesian Information Criterion (BIC)*, which heavily penalize the inclusion of non predictive variables, suggest significant model inefficiency [132]. Despite the inefficiency, the coefficients confirm distinct market drivers. The *News_VH* and *News_H* dummies are highly significant ($P < 0.001$) and positive, validating the classification methodology. Similarly, the *MOVE_Lag* ($t = 9.23$) emerges as the strongest continuous predictor, confirming that implied volatility is a reliable precursor to realized price expansion. However, the results also reveal critical structural issues, particularly *multicollinearity*² within the Yield Curve. Theoretically, volatility in the 10-Year

²Multicollinearity denotes when independent variables in a linear regression equation are correlated. Multicollinear variables can negatively affect model predictions on unseen data [133].

(ZN) should be positively autocorrelated, yet, the *ZN_Range_Lag* coefficient is negative (-0.38) and marginally insignificant ($P = 0.06$), while the neighboring Ultra 10-Year (*TN_Range_Lag*) is positive (+0.32). This conflicting sign attribution is a hallmark of redundancy: the model cannot distinguish between the highly correlated signals of the ZN and TN contracts, rendering individual coefficients unreliable [133].

As illustrated in Figure 3.22, the limitations of the full specification model become undeniable when applied to the out-of-sample test period (2025).

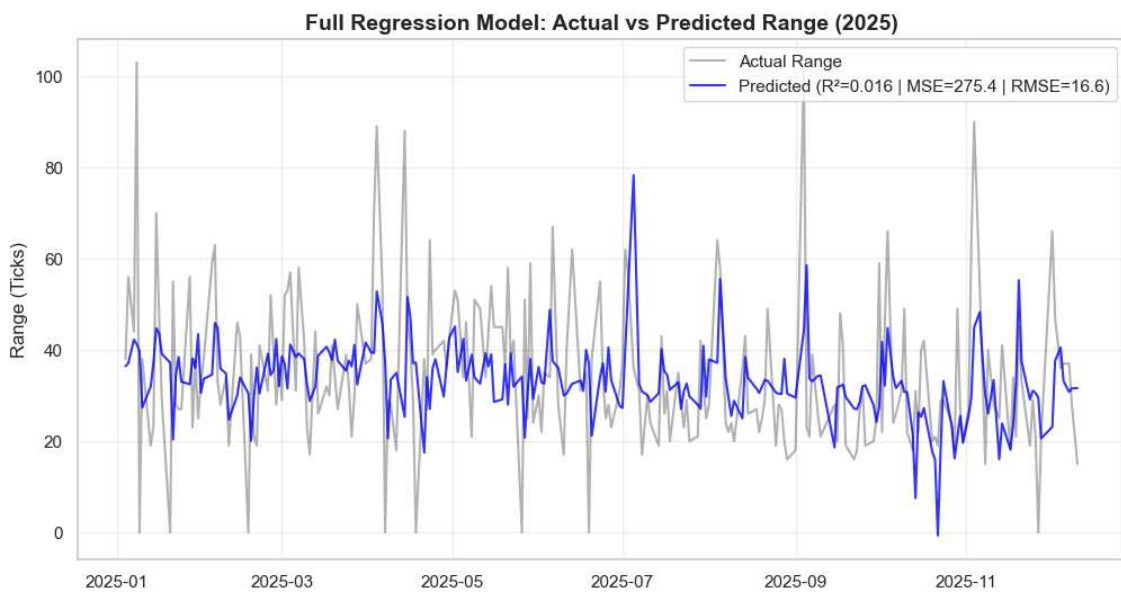


Figure 3.22: Out-of-Sample Full Model Results [121]

We can notice that, while the in-sample R^2 was nearly 24%, the out-of-sample R^2 drops precipitously to 1.6%. This collapse confirms that the unrestricted model failed to generalize, having effectively memorized the noise of the training data rather than learning robust structural relationships. To address this overfitting problem and isolate the true market signal, a refined **Parsimonious Model** was constructed through three methodological modifications:

- All variables failing to meet the significance threshold of $p < 0.05$ are removed.
- To solve the redundancy observed in the coefficients, all collinear variables

are discarded, maintaining only ZN_Range_Lag to capture the asset's own autoregressive memory without interference.

- The granular news dummies are consolidated into a unified variable, called $News_Score$, computed using the following weighted summation:

$$NewsScore_t = 5 N_{VH,t} + 3 N_{H,t} + 1 N_{M,t} + 0.5 N_{L,t}$$

Applying these selection criteria results in a model that retains only the most robust drivers of volatility: the asset's own memory ($ZNrange_{t-1}$), the broad market fear gauge ($MOVE_{t-1}$), the aggregated economic calendar ($News_Score_t$), and the cross-asset spillover from Gold ($GCrangle_{t-1}$). The resulting parsimonious regression model is defined as follows:

$$Range_t = \alpha + \beta_1 ZNrange_{t-1} + \beta_2 GCrangle_{t-1} + \gamma_1 MOVE_{t-1} + \delta_1 News_Score_t + \varepsilon_t$$

The statistical results of this refined model are presented in Table 3.9.

Table 3.9: OLS Regression Results (Parsimonious Specification)

Dependent Variable: ZN Daily Range (Ticks) In-Sample Period (2018-2024)				
Metric	Value			
R-squared	0.217			
Adj. R-squared	0.215			
AIC	15,280			
BIC	15,300			
Variable	Coef.	Std. Err.	t	P> t
const	16.175	1.243	13.008	0.000
ZN_Range_Lag	0.190	0.025	7.513	0.000
MOVE_Lag	0.192	0.016	12.001	0.000
News_Score	0.677	0.129	5.253	0.000
GC_Range_Lag	-0.010	0.003	-3.219	0.001

The transition to a parsimonious framework yields a mixed outcome. From a statistical perspective, the model is significantly cleaner: every variable possesses a highly significant p-value ($p \leq 0.001$). However, the predictive power has not improved: the Adjusted R^2 remains marginally lower than the full specification, and the information criteria (AIC and BIC) show no substantial reduction. This indi-

cates that while we successfully eliminated noise, the remaining linear signal is simply insufficient to explain the majority of the variance in daily price ranges. Crucially, the out-of-sample performance (Figure 3.23) mirrors the failure of the full model. The parsimonious specification continues to compress predictions toward the mean, failing to capture the tail events that define market risk.

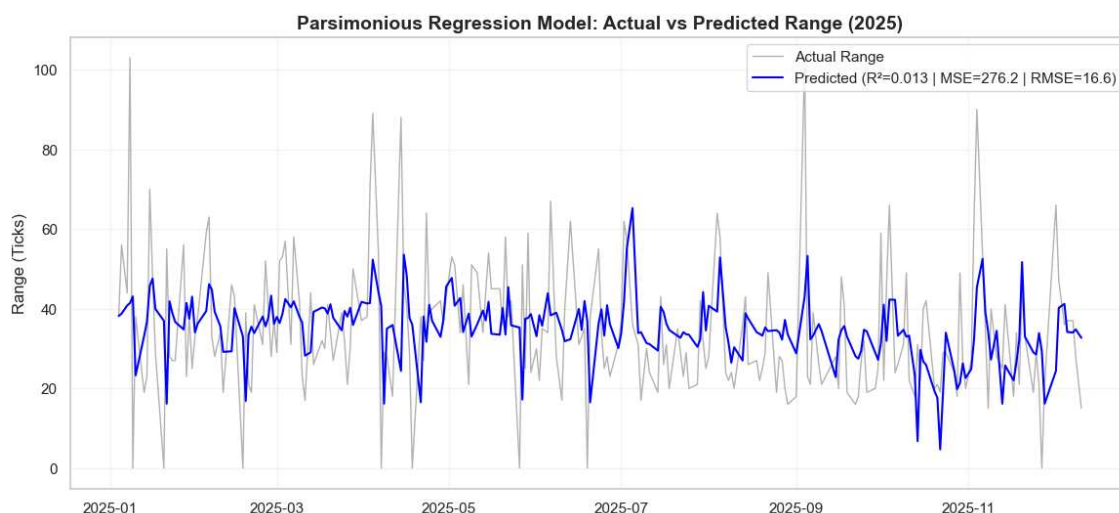


Figure 3.23: Out-of-Sample Parsimonious Model Results [121]

The persistent inability of both the full and parsimonious specifications to forecast the exact daily range suggests that the limitations are probably rooted in both the input variables and the rigidity of the linear methodology itself, indicating that exact point forecasting is computationally intractable under these constraints. We hypothesize two primary drivers for this failure. First, daily volatility is frequently catalyzed by exogenous shocks, such as geopolitical headlines, which are, by definition, absent from a pre-scheduled economic calendar. Second, a significant portion of range expansion is likely endogenous, driven by intraday microstructure inefficiencies. Consequently, the linear framework, which assumes a direct and proportional relationship between yesterday's closing data and today's range, proves insufficient to capture the complex, non-linear interactions that define modern market volatility.

3.3.2 Classification Models

In light of the limitations observed in linear point forecasting, the second phase of this empirical analysis shifts the analytical objective from continuous regression to probabilistic classification. Therefore, we redefine the forecasting problem from a continuous task to a discrete classification task: determining whether the upcoming session will fall into a 'High' or 'Low' volatility cluster. In particular, the models aim to predict whether the daily trading range will exceed or not the asset's average historical range. To address this binary classification problem, we selected four distinct learning algorithms, chosen to represent a spectrum ranging from rigid parametric methods (which trade flexibility for stability) to complex non-parametric ones (which maximize predictive power at the cost of interpretability).

The analysis begins with **Linear Discriminant Analysis (LDA)**, which serves as our robust baseline. LDA approaches the problem indirectly by modeling the distribution of the predictors X separately for each class and then using Bayes' theorem³ to estimate the probability of the class given the predictor. The model relies on the assumption that the predictors within each class are drawn from a Gaussian (Normal) distribution and, crucially, that all classes share a common covariance matrix. While financial variables often exhibit non-Gaussian features, such as fat tails, we employ LDA specifically for its stability [135]. Building on this, we employ **Quadratic Discriminant Analysis (QDA)** to extend the LDA framework by relaxing the assumption of homoscedasticity. Indeed QDA allows each class to have its own distinct covariance matrix rather than forcing a pooled estimate, however, this flexibility comes with a trade-off: estimating a separate covariance matrix for each class requires more parameters, which can introduce instability if the data is noisy [135]. Shifting from rigid parametric models to flexible algorithmic learning, we employ **Random Forests** model: this algorithm builds hundreds

³Bayes' theorem states that:

$$P(A | B) = \frac{P(B | A)P(A)}{P(B)},$$

where $P(A | B)$ is the conditional probability of event A given that event B has occurred, $P(B | A)$ is the conditional probability of event B given event A , $P(A)$ denotes the marginal probability of event A , and $P(B)$ denotes the marginal probability of event B [134].

of deep, unpruned trees using random samples of the data (bootstrapping) and random subsets of predictors at each decision node. This randomness ensures that the individual trees are diverse and de-correlated, preventing the model from overfitting to any single dominant feature. By aggregating the predictions of these diverse trees, the model can approximate complex decision boundaries that linear models often miss. Furthermore, this method offers a unique advantage in interpretability by measuring feature importance: it calculates the degradation in predictive accuracy when a specific variable is randomly permuted, allowing us to quantify exactly which drivers are most critical for regime classification [136]. Finally we apply **Gradient Boosting Decision Tree (GBDT)**, which, unlike Random Forest that builds independent trees in parallel to reduce variance, builds them sequentially. What happens in detail is that, during each iteration, the model calculates the error of the current ensemble and fits a new learner (tree) to minimize this error, providing a final model which is the additive sum of these sequentially improved trees [137].

Now, after having specified the classification models that we are going to use, it is time to specify the predictor variables. To ensure the feature set is robust, we exploit the work done in the regression models and take the variables that resulted statistically significant: the range of the previous day for ZN (*ZN_Range_Lag*) and Gold (*GC_Range_Lag*), together with the variable for the economic calendar (*News_Score*) and the proxy for volatility in the treasury market, the previous day closing value of the MOVE index (*MOVE_Lag*). Beyond these variables, we also added a new metric calculated as the previous day's range divided by its 10-day simple moving average (*Vol_Ratio*). The reason for this inclusion is to ensure the model does not look solely at the absolute value of the previous day's range, but also if the volatility is expanding or contracting.

Before analyzing the specific empirical performance of the candidate models, it is essential to establish the mathematical definitions of the evaluation metrics that we're going to use. The foundation of these metrics is the *confusion matrix*, which categorizes the classifier's predictions into four distinct states based on the align-

ment between the predicted class and the actual class. A *True Positive (TP)* occurs when the model correctly predicts the positive class (high volatility), conversely, a *True Negative (TN)* represents a correct prediction of the negative class (low volatility). On the other hand errors are captured as either a *False Positive (FP)*, where the model incorrectly predicts the positive class, or a *False Negative (FN)*, where the model fails to detect an actual positive instance [138]. From these four fundamental outcome states, we derive five key performance indicators to quantify the model's utility:

- **Accuracy:** is the most intuitive metric and is calculated as the ratio of correctly classified samples to the total number of samples [138].

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} = \frac{TP + TN}{P + N}$$

- **Precision:** it focuses on the reliability of positive predictions and it is defined as the ratio of True Positives (TP) to the total number of positive predictions [138].

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall:** also known as *Sensitivity*, it measures the model's completeness by calculating the ratio of True Positives (TP) to the total actual positive cases. High recall indicates that the model successfully captures most of the high volatility events, minimizing missed opportunities [138].

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{TP}{P}$$

- **F1-Score:** it is used to balance the often inverse relationship between Precision and Recall, and it is defined as the harmonic mean of the two metrics. It is particularly useful to ensure that neither false positives nor false negatives are disproportionately ignored [138].

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \text{ Recall}}{\text{Precision} + \text{Recall}}$$

- Finally, we examine the **ROC-AUC Score** (*Receiver Operating Characteris-*

tic - Area Under the Curve), which indicates the probability that a randomly selected positive instance is ranked higher than a randomly negative instance and shows how good the model is in ranking predictions [138].

Applying this evaluation framework to the 10-Year Treasury Note (ZN) for the 2025 out-of-sample period brings the results summarized in Table 3.10.

Table 3.10: ZN Classification Model Performance Metrics [121]

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
LDA	0.719	0.655	0.339	0.447	0.695
QDA	0.623	0.443	0.482	0.462	0.635
Random Forest	0.641	0.471	0.589	0.524	0.670
Gradient Boosting	0.683	0.541	0.357	0.430	0.687

We can notice that, although *Linear Discriminant Analysis* is the simplest of the four algorithms, it confirms itself as the superior performer regarding both Accuracy (0.719) and Precision (0.655). This result indicates that when LDA predicts a high volatility session, the signal is highly reliable. However, this reliability comes at the cost of Recall (0.339), the lowest among the group: this reveals that the model fails to recognize a significant portion of the actual high volatility sessions, effectively acting as a conservative filter that prioritizes safety over opportunity. Conversely, *Quadratic Discriminant Analysis* fails to improve upon this baseline: despite the theoretical advantage of using separate covariance matrices, it suffers from poor Precision (0.443) and the lowest overall Accuracy (0.623). This underperformance suggests that the additional flexibility of this model led to overfit stochastic noise rather than capture structural signal. The most unique behavior among the classifiers is observed in the *Random Forest* as it excels at identifying volatile days, evidenced by the Recall of 0.589, but fails to do so reliably, with a Precision dropping to 0.471. This means that, operationally, this model presents significant risks, since, in forecasting high volatility days, the false alarms actually outnumber accurate predictions. Lastly, *Gradient Boosting* offers a equilibrium: it filters out the excessive noise found in Random Forest and, although less precise than LDA (0.541 vs 0.655), detects more signal than the ultra conservative linear approach. The distinct characteristics emerging from the performance metrics in

Table 3.10 are visually confirmed by the **Confusion Matrices** in Figure 3.24.

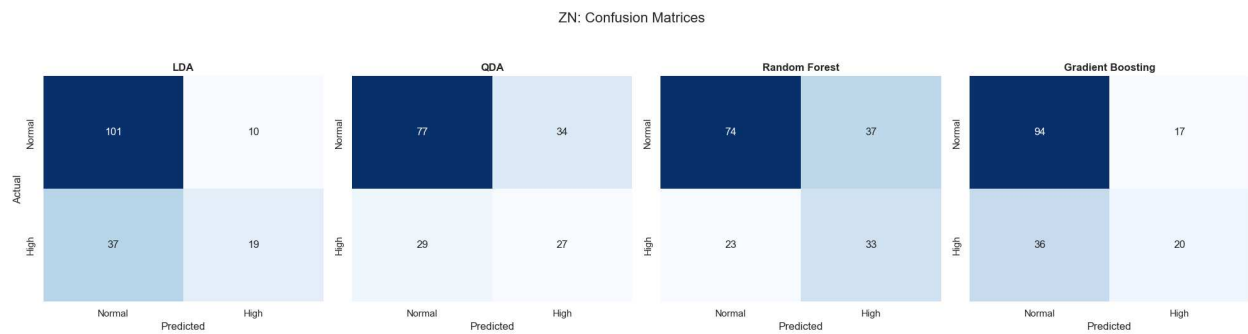


Figure 3.24: ZN Confusion Matrices [121]

These plots reaffirm LDA as the most reliable yet conservative model, minimizing false positives while missing some opportunities. At the same time Random Forest and QDA are characterized by a lot of high volatility predictions that often result in noise. Between these extremes, Gradient Boosting represents the balance between the conservative linear approach and the noisier one.

As far as the **ROC-AUC** metric is concerned, the LDA model is still the best with a value of 0.695, followed closely by Gradient Boosting (0.687), Random Forest (0.670), and QDA (0.635). To interpret this, an AUC of 0.50 represents a random guess, while 1.0 represents a perfect prediction. Therefore, LDA's score implies that if we were to pick one actual high volatility day and one actual normal day at random, the model would correctly identify which is which about 70% of the time. However, as we can see in Figure 3.25 where the ROC curves of all the models are plotted, the LDA model is only marginally better since the curves are closely clustered, indicating that no single model stands out particularly as a superior classifier.

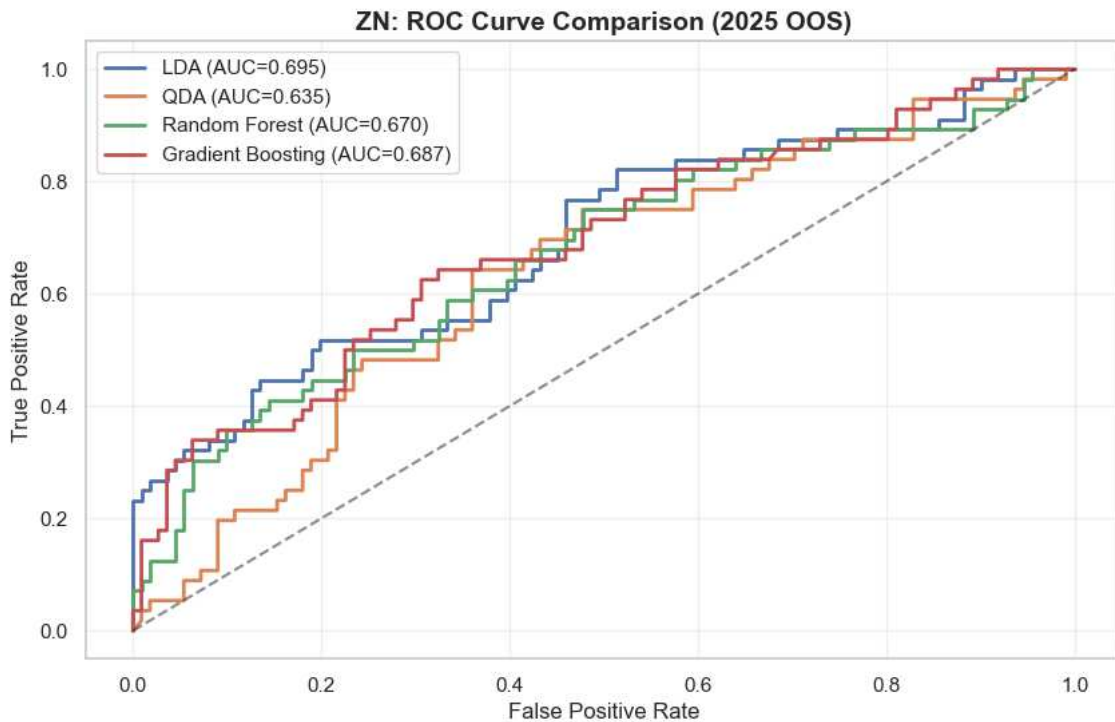


Figure 3.25: ZN ROC/AUC Comparison by Model [121]

Finally, to understand the economic logic behind these results, we look at the Feature Importance in Figure 3.26.

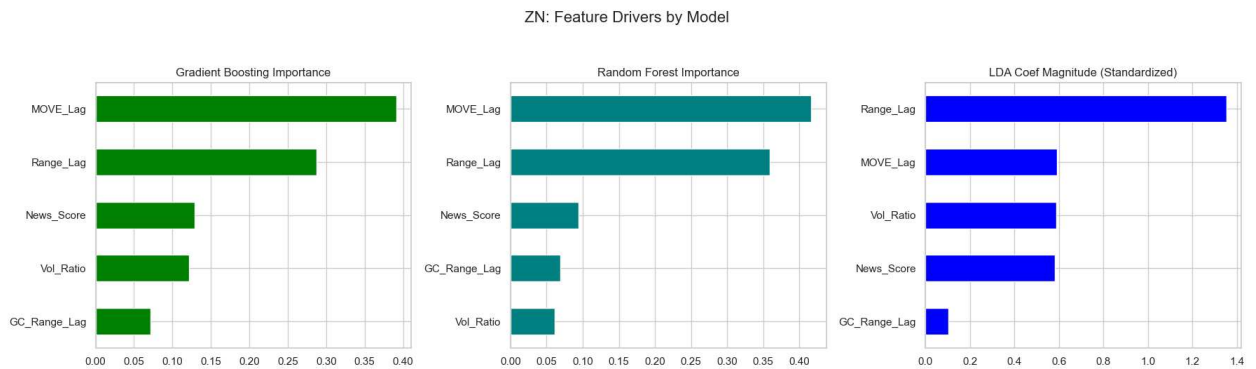


Figure 3.26: ZN Feature Drivers by Model [121]

All models agree that *Range_Lag* and *MOVE_Lag* are the most critical predictors, however, the weighting differs: LDA prioritizes the autoregressive term, while the other models lean more heavily on the macro sentiment provided by the MOVE index. Furthermore, Gradient Boosting extracts more signal from the *News_Score* variable than the LDA model do, implying that the impact of economic releases is

likely non linear.

We now expand the analysis across the entire maturity spectrum of the US Treasury futures curve. The performance metrics for the ZN contract clearly designated Linear Discriminant Analysis (LDA) as the robust baseline, offering the highest reliability and structural stability. Simultaneously, Gradient Boosting (GBDT) distinguished itself as the superior non-linear alternative. Consequently, we discard the Random Forest and QDA models due to their tendency to overfit stochastic noise, and we advance with LDA and GBDT as our candidate algorithms to test the 2-Year (ZT), 5-Year (ZF), 30-Year (ZB), and Ultra-Bond (UB) contracts. Table 3.11 details the classification performance for both LDA and Gradient Boosting across the full maturity spectrum.

Table 3.11: Yield Curve Classification Performance by Asset and Model

Asset	Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
2Y (ZT)	LDA	0.731	0.760	0.328	0.458	0.735
	Gradient Boosting	0.671	0.523	0.586	0.553	0.709
5Y (ZF)	LDA	0.701	0.654	0.293	0.405	0.708
	Gradient Boosting	0.653	0.500	0.414	0.453	0.645
10Y (ZN)	LDA	0.719	0.655	0.339	0.447	0.695
	Gradient Boosting	0.683	0.541	0.357	0.430	0.687
Ultra 10Y (TN)	LDA	0.808	0.833	0.250	0.385	0.732
	Gradient Boosting	0.808	0.700	0.350	0.467	0.755
30Y (ZB)	LDA	0.814	0.692	0.250	0.367	0.690
	Gradient Boosting	0.766	0.448	0.361	0.400	0.702
Ultra Bond (UB)	LDA	0.904	0.750	0.167	0.273	0.753
	Gradient Boosting	0.886	0.444	0.222	0.296	0.757

The results confirm that the trade-off between the models observed in the 10-year contract is not an isolated case but a consistent feature across the entire Treasury maturity spectrum. Indeed LDA systematically prioritizes reliability, consistently achieving higher Accuracy and Precision, while GBDT adopts a riskier profile, consistently delivering higher Recall. In the short end of the curve, and in particular in 2-Year note (ZT), this trade-off is more pronounced: LDA achieves a very high Precision (0.760), ensuring that when it signals volatility, it is highly likely to be correct, while Gradient Boosting achieves the best Recall of the study (0.586), although its Precision drops to 0.523. Moving to the belly of the curve, the metrics

narrate a similar story for the ZF, ZN, and TN contracts, however, the most interesting observation corresponds to the Ultra 10Y (TN). Indeed TN contract, despite maintaining the characteristically low Recall of LDA, obtained the best Precision (0.833) of the entire study and a remarkably high Accuracy (0.808). This implies that for the Ultra 10Y, the models (and particularly LDA) become extremely selective in triggering a high volatility signal, but when they do, the signal is very likely to be correct. As we extend to the 30-Year (ZB) and Ultra Bond (UB), the cautious nature of LDA reaches its extreme. In the Ultra Bond, LDA achieves an astonishing Accuracy of 90.4%, but, as we can see more clearly in the confusion matrices below (Figures 3.27 and 3.28), this is largely because it predicts almost exclusively low volatility signals, resulting in the lowest Recall of the group (0.167). Similarly, for this part of the curve, the Gradient Boosting model achieved comparable Accuracy and Recall, yet it failed to match the high Precision of the LDA baseline. Furthermore, if we look at the *F1-scores* across the curve, they suggest a distinct narrative: as we move toward longer maturities, the scores consistently exhibit lower values. This signifies that the reliability of the forecasts diminishes with duration, even though, at first glance, we observe the highest Accuracy values at the long end of the curve. This contrast suggests that, given our specific dataset, the factors driving the longer maturities bonds are significantly harder to capture than the underlying drivers of the short end.

Confusion Matrices: Short & Intermediate End (ZT, ZF, ZN, TN)

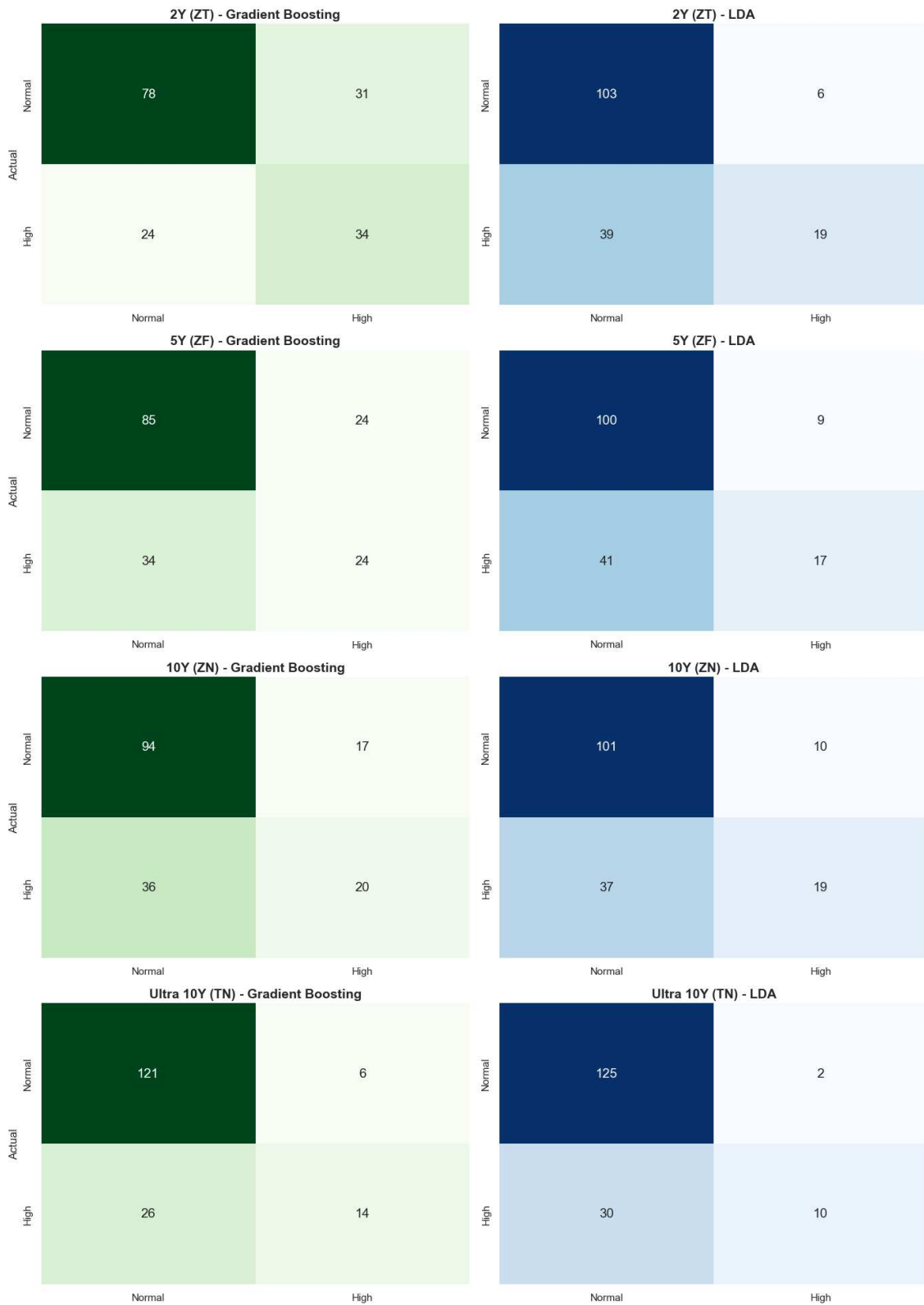


Figure 3.27: Treasuries Confusion Matrices (*1st part*) [121]

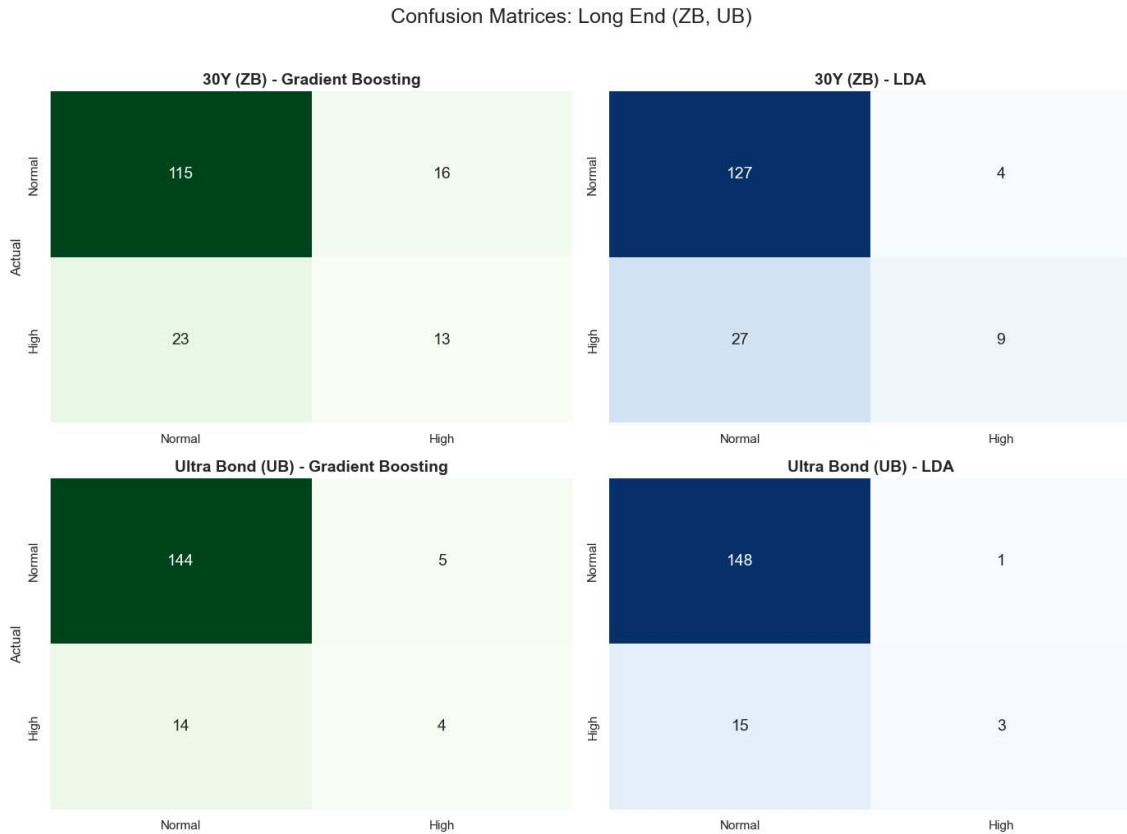


Figure 3.28: Treasuries Confusion Matrices (*2nd part*) [121]

The *confusion matrices* displayed in Figure 3.27 and Figure 3.28 tell basically the same story as the aggregate metrics, but they clarify the specific nature of the errors. For instance, in the 2-year note (ZT), the matrix reveals the true cost of Gradient Boosting’s high Recall: the model generated 31 False Positives compared to just 6 for LDA. This disparity highlights a noisy operational environment where, to capture the majority of volatility spikes, the GBDT model is forced to trigger false alarms nearly five times more often than its linear counterpart. While at the long end of the curve (UB), the confusion matrices expose a structural collapse in the models’ predictive capability. In particular, the LDA model failed to actively discriminate between regimes, effectively retreating into a passive state where it signaled high volatility on only four occasions throughout the entire test set.

We now turn our attention to the *ROC-AUC metrics* displayed below in Figure 3.29. We can notice that, although the historical range (left panel) exhibits significant differences between maturities, the ROC-AUC scores (right panel) remain remarkably

constant across the entire curve, showing high consistency between both the LDA and Gradient Boosting models. Indeed, the AUC values settle between a minimum of 0.64 in the ZF contract to a maximum of 0.76 in the UB contract (both in GBDT model). This indicates that, based on this metric, both the classifiers demonstrate a robust capacity to distinguish between different regimes, successfully ranking a volatile day higher than a quiet day approximately three out of four times.

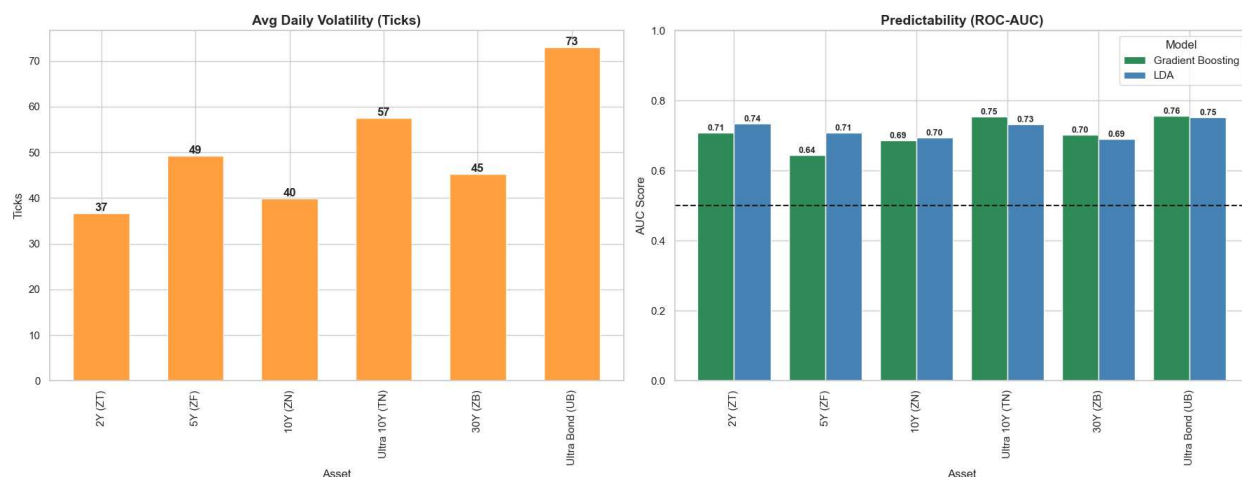


Figure 3.29: Treasuries Average Daily Range & ROC/AUC by Model [121]

Finally, we examine the *Feature Importance heatmaps* in Figure 3.30. The most consistent finding is the dominance of the previous day's volatility variable (*Range_Lag*) across both models and all maturities, confirming that volatility is highly sticky and autoregressive. We also notice that the specific dynamic found in the 10-Year (ZN) analysis, where Gradient Boosting model ranked *MOVE_Lag* variable as more critical than *Range_Lag*, proves to be an isolated case. Nevertheless, *MOVE_Lag* remains the second most significant driver overall, exhibiting slightly higher weights in the GBDT model than in LDA. Crucially, however, its importance diminishes as we extend toward the longest maturities, dropping to just 0.10 and 0.07 in the Ultra Bond, implying that the broad fear gauge fails to capture the specific volatility dynamics inherent to the extreme long end of the curve. Beyond the primary drivers, looking at *Vol_Ratio* variable, we can observe the inverse: especially in the GBDT context, the importance scales linearly with the duration reaching a maximum of 0.23 in the Ultra Bond (UB). On the other hand the News variable (*News_Score*)

remains remarkably stable across all the maturities, however it retains higher importance in the LDA model (ranging from 0.14 to 0.21) compared to the Gradient Boosting model (0.07 to 0.13). At the lower end of the predictive spectrum we observe that the previous day's range of Gold (*GC_Range_Lag*) holds negligible relevance in both models. Despite the theoretical safe haven correlation between Treasuries and commodities, this feature consistently registers as the least significant predictor across the entire curve.

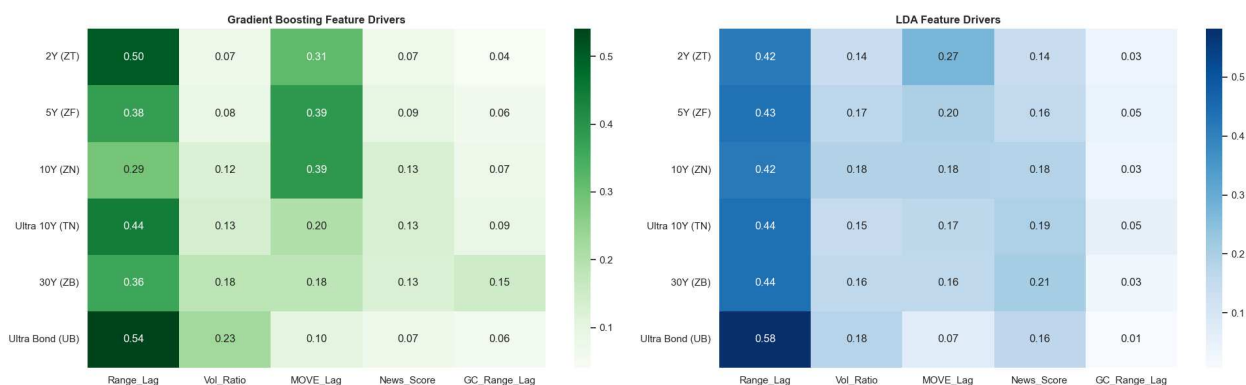


Figure 3.30: Treasuries Feature Drivers Matrices by Model [121]

Now, to bridge the gap between statistical theory and market practice, we can analyze how these models can be exploited into an operational framework. The divergence in performance metrics between Linear Discriminant Analysis (LDA) and Gradient Boosting (GBDT) essentially offers two distinct point of view: one conservative and precise (LDA), the other more sensitive and aggressive (GBDT). This dichotomy allows to assign specific mandates to each algorithm based on the risk profile:

- *LDA as a conservative tool for market entry*: characterized by its structural reluctance to issue false alarms, the model functions as a confirmation filter for opening new positions. When this conservative model triggers a high volatility signal, it provides the statistical confidence necessary to enter the position, minimizing the transaction costs of false breakout signals.
- *GBDT as a risk management tool for market exit*: contrarily this model performs better as a mechanism for defense or risk reduction, because it prior-

itizes sensitivity and it acts as a early warning system. For instance, if the model triggers a high volatility signal, even if it might be a false positive, the prudent action is to tighten stop-loss orders or partially hedge the position in order to minimize the risk of a tail event.

However, the application of these algorithms is not uniform across the yield curve. The empirical evidence, particularly the structural decay observed in F1-scores as duration increases, establishes a clear hierarchy for capital allocation. With the 2-Year Note (ZT) exhibiting a robust Precision of 0.760, the short end of the curve validates itself as the optimal domain for the LDA model, where it can be confidently utilized for active positioning. However, the analysis reveals a significant operational opportunity also in the belly of the curve, specifically within the Ultra 10-Year (TN), which achieves the study's highest recorded Precision of 0.833, offering a signal even cleaner than the short-term notes. In contrast, the long end (ZB,UB) dictates a fundamental shift from speculation to preservation, indeed, in this part of the curve, the predictive utility of the models significantly deteriorates. Consequently, in this sector the operator should employ different strategies to enter the market, utilizing the Gradient Boosting model solely for defensive hedging rather than as a tool to generate active returns.

Conclusions

4.1 Theory and Practice: Confirmations and Contradictions

The primary objective of this thesis was to investigate the nature of the US Treasury market and to assess the predictability of volatility across the yield curve. By juxtaposing the theoretical foundations established in Chapter 2 with the empirical results obtained in Chapter 3, we can extract some critical insights. It is important to note that these findings are derived from the specific dataset and methodology used in this study, and should not be interpreted as absolute truths. In Chapter 2, we delineated how the short end of the yield curve is primarily anchored by the Federal Reserve's monetary policy stance. Given that central bank communication has become increasingly transparent through forward guidance and dot plots, it follows theoretically that this sector should be the most efficiently priced and easiest to model, and our empirical results, which show a superior predictability in the short term notes, validate this logic. On the other hand, economic theory suggests that the long end of the curve should be driven by major macroeconomic variables, such as long term inflation, employment, and growth. However, our results do not fully support this expectation, since the news impact feature, which tracks scheduled economic releases, showed a similar level of importance across the entire curve, rather than becoming more important for long term bonds as expected. This result can be interpreted as evidence that the long end of the curve is not driven solely by the scheduled economic releases included in our dataset, but likely also by unscheduled factors such as geopolitical news and instability. Consequently, while both the short and long ends of the curve react to scheduled news, the long end is probably more sensitive to the broader market narrative, which is harder to quantify. This interpretation provides also an explanation for the reduced pre-

dictability observed at the back end of the curve. Another contradiction emerged regarding the role of Safe Haven assets. Theory suggests that US Treasuries should be strongly linked to other defensive assets like Gold, the Japanese Yen, and the Swiss Franc and, while our initial data exploration (EDA) seemed to show a partial connection between these markets, the statistical models failed to confirm it. In particular, in the regression models, the currencies (JPY and CHF) were not statistically significant and Gold, which showed significance in the regression, when tested in the classification models, it demonstrated very low feature importance. This proves that, while a cross asset correlation might exist over the long term, it is not strong enough to be a useful predictor for daily volatility.

4.2 Limitations of the Study and Future Research Directions

While this study successfully identified key patterns in Treasury volatility, it has specific limitations regarding the data used and the scope of the predictions. These limitations, however, point towards clear opportunities for future research. The most significant limitation of this study is that the models relied exclusively on daily data, indeed by defining volatility strictly as the daily range, the analysis inevitably hides the complex dynamics that occur within a single trading session. In reality, volatility is rarely uniform throughout the day, instead, the market often experiences sudden bursts of volatility caused by liquidity events or news, as well as distinct shifts in behavior as global trading sessions open and close. Because our models aggregate everything into a single daily bar, they are blind to these intraday changes and cannot capture these dynamics. To address this, future studies should apply these models to intraday data or even tick-by-tick data: by analyzing the market at a higher resolution researchers could detect these specific intraday bursts and liquidity shifts. This would allow for a much more granular approach, turning the models into tools for real time risk monitoring rather than just a daily summary. Another significant limitation, as previously cited, lies in how we defined the News variable, which, in this study, was strictly limited to scheduled economic releases found on the standard economic calendar (such as CPI or Non-

Farm Payrolls). Consequently, the models were effectively blind to unscheduled events, such as sudden geopolitical shocks, central bank and president speeches, or rapid shifts in global sentiment. Future research should try to expand the input data to include breaking news from major financial journals and social media platforms like X (formerly Twitter) and, by analyzing the sentiment of real time headlines and tweets and converting them into quantitative scores, researchers could test whether this unstructured data improves predictive performance. This addition would effectively allow the models to read the real time market narrative, potentially capturing the surprise, unscheduled events that our current dataset missed. It is also important to note that the scope of this thesis was strictly defined to forecast the magnitude of the move (volatility), rather than the direction but, while focusing on volatility provides essential insights for risk management, a useful evolution for future research would be to examine and explore the possibility of forecasting the direction of the price. By adapting the models to predict trend rather than just range, researchers could see if these algorithms can generate actionable trading signals. Additionally, future studies should try to expand the historical dataset back before 2018: this would be particularly valuable for the daily analysis, as it would provide a larger sample size for the models to learn from. Testing on older data would also help verify if the patterns observed are consistent over the long term, or if they are specific only to the recent years. Furthermore, there is significant room to expand the type of data analyzed, for instance future research could include unexplored assets like Bitcoin to test for emerging correlations with the Treasury market. It would also be very interesting to analyze not only the Futures market, but also the Options market, which directly reflects volatility expectations, and the underlying Spot market. Moreover, this study did not deep dive into liquidity and primary market metrics: future researchers could exploit Volume and Open Interest data, as well as Treasury Auction results, to see if these variables add predictive power to the models. Lastly, the models and algorithms themselves can be further improved: while this study compared LDA model with Gradient Boosting, future research could try to apply more advanced techniques like Deep Learning and Neural Networks architectures.

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