Digital Bonds: The Role of Costs and Document Information on Trading Volume

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Abstract

This paper examines digital bonds issued on blockchain platforms, classifying them as native or non-native (tokenized) based on issuance architecture. Using a dataset of 7,719 transactions in tokenized treasury products backed by U.S. government securities, we analyze how transaction costs, management fees, macroeconomic conditions, and regulatory structures affect trading volume. Higher transaction costs are associated with lower trading activity, while management fees exhibit a positive association conditional on documentation quality. To measure disclosure content, we apply large language models to quantify the informativeness of legal, financial, and technological product documentation. Financial disclosures increase trading volume, while legal disclosures reduce it. Interaction effects show that financial information attenuates investor sensitivity to management fees, whereas legal and technological clarity amplify it. Instrumental variable estimation, placebo simulations, and heterogeneity analysis confirm the robustness of the results. Our findings contribute to the literature on digital finance and tokenized assets by identifying how cost structures and documentation quality jointly influence participation in decentralized fixed-income markets.

Keywords: Digital Bonds, Tokenized Treasury Products, Trading Volume, Decentralized Finance (DeFi), Investor and Product Information
JEL Codes: G12, G23, O33

1 Introduction

The progressive digitalization of financial markets has created new channels for issuing and investing in bonds. Leveraging distributed ledger technology (DLT), digital bonds have been developed with the potential to enhance transparency, streamline processes such as issuance and interest payments, and reduce transaction costs (Chen, Cheng, and Luo 2024). By 2024, several commercial banks, government entities, and supranational institutions, including the United Bank of Switzerland (UBS), European Investment Bank (EIB), Hong Kong Monetary Authority (HKMA), and the World Bank, had issued digital bonds using DLT to improve issuance efficiency and lower costs. Industry estimates suggest that blockchain technology can generate cost savings of 35 to 65 percent in bond issuance[1].

Digital bonds can be categorized into two types based on their issuance method: native digital bonds and non-native digital bonds (tokenized bonds). Native digital bonds are issued and settled entirely on DLT platforms from inception[2]. In contrast, non-native digital bonds represent conventional bonds that are transferred into the digital environment, where they are recorded as digital tokens on blockchain platforms. Trading on public blockchain platforms, such as decentralized exchanges (DEXs), reduces entry barriers and facilitates broader access to assets traditionally available only to institutional investors (Lehar and Parlour 2025, Makridis et al. 2023). These features make non-native digital bonds particularly attractive to retail investors seeking exposure to real-world assets (RWA) within digital asset markets. Among these products, tokenized bonds backed by conventional United States Treasury securities are the most prominent, combining the security and liquidity of traditional fixed income instruments with the operational efficiency enabled by blockchain technology.

Although digital bonds have attracted growing interest, empirical evidence on their ability to improve the slow and costly process of debt issuance remains limited (Brugler, Comerton-Forde, and Martin 2021). This study addresses this gap by documenting the life cycle of digital bonds, comparing native and non-native (tokenized) digital bonds to conventional bonds, and analyzing the determinants of trading activity in tokenized bond markets. We compare non-native digital bonds, conventional bonds, and native digital bonds across bond-, investor-, deal-, and post-deal-level characteristics to provide a comprehensive framework for understanding their design and market behavior.

Our empirical analysis relies on a dataset of 7,719 transactions involving 22 tokenized treasury products issued on the Ethereum and Polygon blockchain platforms. We examine the determinants of trading volume and develop novel measures of product documentation informativeness using generative artificial intelligence (AI). Following Becht, Franks, and Wagner (2024), we employ the ChatGPT-4o model to simulate investor interpretation of product documentation, assessing disclosures from legal, financial, and technological perspectives. We find that financial and technological information are associated with higher trading volume, whereas extensive legal disclosure is associated with reduced trading activity.

We further analyze investor sensitivity to transaction costs and management fees. Given that tokenized treasury products primarily generate returns from highly liquid, low-risk assets such asU.S. Treasury securities and repurchase agreements, we hypothesize that trading volume is sensitive to cost structures. Consistent with this expectation, we find that higher transaction costs are associated with lower trading volume, with a 1% increase in daily average transaction costs leading to a 0.87% decrease in daily trading volume. Management fees, however, exhibit a positive association with trading volume in baseline models. Interaction analyses between management fees and documentation informativeness indicate that the positive effect is primarily driven by financial disclosures, consistent with theories suggesting that higher-quality information reduces

[1] See Financial Times article: `https://www.ft.com/content/3717fe36-1536-43ef-ace4-b63e5efe778e`

[2] Throughout this study, the terms DLT and blockchain are used interchangeably, although blockchain is technically a subset of DLT. For a detailed discussion, see Liu, Farahani, and Firouzi (2020).

uncertainty, facilitates both informed and uninformed trading, and improves market liquidity(Bloomfield, O'Hara, and Saar 2009, Choi, Huh, and Seunghun Shin 2024).

To address endogeneity concerns and strengthen causal interpretation, we exploit variation in blockchain network congestion by using daily average block size as an instrument for transaction costs. Two-stage least squares (2SLS) estimates confirm the negative relationship between transaction costs and trading volume, although with slightly reduced magnitude and statistical significance compared to ordinary least squares (OLS) results. We validate the robustness of the AI-based informativeness measures across multiple models trained by OpenAI and DeepSeek, and further implement placebo tests using simulated management fee and informativeness variables. Finally, we document substantial heterogeneity in investors' sensitivity to cost structures and fees, depending on incorporated regions, investment accessibility, investor restrictions, and other bond characteristics.

This study makes three contributions to the literature. First, it provides a systematic analysis of digital bonds by documenting their life cycle and comparing native and non-native digital bonds with conventional bonds. While prior studies have described specific digital bond issuances, such as the green bond issuance discussed in Malamas et al. (2024), there has been no comprehensive framework for classifying digital bonds based on issuance method and evaluating their broader characteristics. By distinguishing between native and non-native structures and empirically analyzing a representative subgroup of tokenized treasury products, this study contributes to the understanding of digital bond markets and their implications for bond market practices.

Second, this study extends the empirical literature on blockchain applications in financial markets by examining how cost structures and documentation quality jointly shape trading activity in tokenized debt securities. Prior research has primarily focused on tokenized assets such as real estate (Kreppmeier et al. 2023, Swinkels 2023), green and energy tokens, and cryptocurrencies and initial coin offerings (Cong et al. 2021, Howell et al. 2020, Momtaz 2020), with limited attention to sovereign debt markets. While Chen, Cheng, and Luo (2024) documents how blockchain reduces information asymmetries in asset-backed securities (ABS) and lowers financing costs, empirical evidence on tokenized sovereign bonds remains scarce. By analyzing tokenized United States Treasury products, this study provides the first systematic evidence on how transaction costs and product documentation affect liquidity in blockchain-based government debt markets. The findings underscore the economic importance of transparent cost structures and high-quality disclosure in promoting trading activity and suggest that blockchain-based innovations in public debt markets may depend critically on both technological and informational factors.

Third, this study advances the literature on financial disclosure and investor behavior by applying generative artificial intelligence to quantify the informativeness of product documentation in the context of digital financial assets. Prior work has assessed disclosure quality using traditional text analysis techniques based on readability, complexity, or specific linguistic features (Bao and Datta 2014, Dyer, Lang, and Stice-Lawrence 2017, Lawrence 2013, Loughran and McDonald 2014, Wei, Ma, and Wang 2023). Recent studies have begun to explore the use of large language models to interpret corporate filings and policy documents (Becht, Franks, and Wagner 2024, Jha et al. 2024, Kim, Muhn, and Nikolaev 2023), but applications to structured financial products remain limited. Building on these advances, we develop an AI-based framework that simulates investor processing of product documentation across legal, financial, and technological dimensions and link these measures to actual trading behavior in tokenized treasury products. This approach provides new empirical evidence on how the depth and clarity of disclosures affect investor participation and liquidity in decentralized financial markets, and demonstrates the potential of generative AI as a tool for evaluating financial communication in emerging asset classes.

The remainder of this paper is organized as follows. In Section 2, we make a systematic introduction to digital bonds, compare them with conventional bonds, and introduce tokenized treasury products. Then, we

present the hypotheses, data sources of our empirical analysis, and method to calculate the informativeness of documentation in Section 3. Section 4 examines the determinants of trading volume in tokenized treasury. Section 5 conducts a robustness check and heterogeneity analysis. Finally, Section 6 makes conclusions and policy implications.

2 Digital Bonds: An Overview

2.1 Introduction of Digital Bonds

Typically, digital bonds are debt securities issued, traded, and managed exclusively through digital platforms using blockchain, serving similar fundamental functions in raising capital for corporations or specific projects. According to OECD (2020), the World Bank issued a blockchain-operated debt instrument denominated in AUD 110 million in 2018, referred to as the *bond-i*, which marked a milestone as the first legally binding bond to be created, allocated, transferred, and managed throughout its life cycle using blockchain. Since 2018, numerous blockchain-based debt securities have been issued and traded on public and private blockchain platforms[3]. Since then, several international commercial banks, such as Société Générale, Kreditanstalt für Wiederaufbau (KfW), Bank of China Hong Kong, and UBS, have issued digital bonds. In parallel, multinational and regional sovereign institutions, including the World Bank, International Bank for Reconstruction and Development (IBRD), EIB, HKMA, and the Canton of Basel-City and Zurich, have progressively increased their participation in issuing digital bonds. The EIB[4] and KfW[5] emerged as the leading institutions in digital bond issuance. According to preliminary statistics, the cumulative market value of digital bonds issued on blockchain platforms has reached 1.6 billion dollars from mid-2023 to the end of 2024[6], underscoring the growing market interest and participation in blockchain-based digital bonds.

The life cycle of digital bonds follows a comparable pattern to that of conventional bonds. Figure 1 provides an overview of the digital bond life cycle, detailing the actions of participants at each stage. The life cycle of digital bonds commences with the onboarding of participants, including investors, issuers, and the Central Market Unit (CMU). CMU functions as a clearing and custodian entity for digital bonds. To onboard the digital platform, investors must provide the necessary identification and financial information and undergo Know-Your-Customer (KYC) and Anti-Money Laundering (AML) procedures to comply with regulatory requirements. Issuers, in turn, register on the digital platform, supplying comprehensive information about the bond issuance and ensuring adherence to relevant regulatory standards. CMU facilitates the onboarding process by conducting compliance checks and verifying the identities and eligibility of both investors and issuers. This stage is critical in ensuring that all participants are properly vetted and authorized to engage on the digital bond market.

After the onboarding and compliance checking, the following 5 stages transition to the blockchain-based digital platform. Stage 1 - Bond pricing: Before the tokenization process, the bond pricing and subscription

[3]**Public Blockchains**: Open and decentralized networks where anyone can participate as a node, validate transactions, and interact with the system (e.g., Bitcoin, Ethereum). These blockchains are highly transparent and secure, but often face scalability and regulatory challenges. **Private Blockchains**: Restricted networks controlled by a single entity or a consortium (e.g., Hyperledger, Corda). Access is limited to approved participants, offering greater control, efficiency, and privacy, but at the cost of decentralization.

[4]By the end of 2024, EIB has issued six digital bonds on the blockchain. See EIB website: `https://www.eib.org/en/investor-relations/press/all/fi-2024-14-eib-2nd-digital-bond-eurosystem-explanatory-work`

[5]By January of 2025, KfW has issued four sets of digital bonds on the blockchain with an accumulated value of 17.5 billion Euro. See Ledger Insights report: `https://www.ledgerinsights.com/state-owned-kfw-issues-another-e9-billion-in-digital-bonds-using-clearstreams-d7/`

[6]Preliminary statistics from BNP Paribas, see website: `https://globalmarkets.cib.bnpparibas/digital-bonds-blockchain-vs-traditional/`

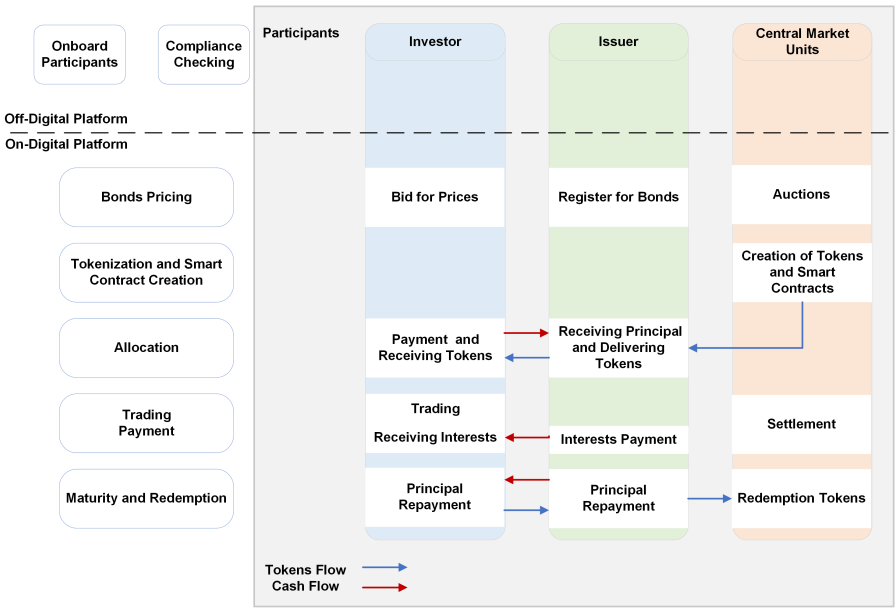

Figure 1: Full Life Cycle of Digital Bonds

Notes. This figure illustrates the full life cycle of digital bonds, presenting key processes across both off-digital and on-digital platforms. It shows how participants, including investors, issuers, and central market units, interact at each stage of the bond's life. The flow of tokens and cash is depicted through blue and red arrows, respectively, representing transactions such as price bidding, payment and receipt of tokens, principal and interest payments, and redemptions of tokens.

are conducted based on market demand, prevailing interest rates, and other financial metrics. Investors engage in the price discovery process by participating in auctions to establish the issuance price. Issuers register the issuance of bonds and set preliminary pricing terms based on financial metrics and current market conditions. CMU oversees and manages the auction or pricing mechanism, ensuring transparency and fairness while facilitating communication between investors and issuers. This stage is pivotal for setting a fair and accurate price that reflects the bond's risk and return profile.
Stage 2 - Tokenization and smart contracts: Once the bonds are priced, the next stage involves tokenization and the creation of smart contracts. The smart contract is a self-executing computer program on the blockchain that automates and enforces the terms of financial agreements. In collaboration with CMU, issuers initiate the tokenization process by issuing digital tokens to represent ownership of digital bonds on the blockchain, embedding the terms of interest payments, maturity dates, and other relevant conditions within smart contracts. CMU plays a crucial role in developing and deploying these digital tokens, ensuring that the smart contracts accurately represent the bond's terms and automate its management throughout the life cycle. Smart contracts enhance transparency and efficiency by encoding and automating the execution of all contractual obligations.
Stage 3 - Allocation: Following tokenization, the bonds are allocated to investors. Smart contracts facilitate the automated distribution of digital tokens according to the allocation plan. CMU ensures the secure and accurate transfer of tokens to investors, recording all allocations on the blockchain to maintain a transparent ledger. This stage signifies the successful completion of the issuance process and transitions the bonds into the trading phase.
Stage 4 - Trading: During the trading phase, investors can trade digital bonds on the digital platform, with all transactions governed by blockchain-based smart contracts. These contracts automate and secure trade execution, ensuring real-time settlement while recording every transaction on the blockchain that participants can access and verify to uphold transparency and accuracy. Besides managing trading, smart contracts are programmed to handle periodic coupon payments, distributing interest payments directly to investors' digital wallets according to the bond's stipulated terms. Throughout this process, CMU supervises trading activities and payment settlements, ensuring compliance with regulatory standards and maintaining the integrity and security of the market.
Stage 5 - Maturity and redemption: The final stage in the digital bond life cycle is maturity and redemption, where the bond reaches its end. At maturity, the smart contract automatically triggers the repayment of the bond's principal directly to investors' digital wallets. Issuers ensure the timely fulfillment of all financial obligations, while CMU oversees the repayment and redemption of digital tokens to verify compliance and accuracy.

In summary, the life cycle of digital bonds integrates blockchain technology and smart contracts to streamline processes, enhance transparency, and ensure compliance. From onboarding and compliance checks to tokenization, trading, and maturity, each stage leverages blockchain to automate key functions, such as price discovery, token allocation, trade settlement, coupon payments, and principal redemption. CMU plays a vital role throughout this life cycle, acting as custodians, compliance overseers, and facilitators of secure and efficient market operations. This comprehensive framework not only reduces operational inefficiencies but also fosters trust and accessibility in the digital bond market, paving the way for broader adoption of tokenized financial instruments.

2.2 Comparison of Digital Bonds to Conventional Bonds

We classify digital bonds into two types based on their issuance method: native and non-native digital bonds. Native digital bonds are created, issued, and managed entirely on the blockchain platform, while non-native

digital bonds are digital tokens of pre-existing conventional bonds that are later transferred and traded on the blockchain with the help of securitization. Similarly, conventional bonds can be classified into direct and indirect bonds. Direct bonds are standard bonds issued and managed within conventional financial systems, whereas indirect bonds incorporate additional structuring elements such as securitization, pooling, conversion features, and other financial enhancements. Table1 provides a comparative analysis of the four characteristics of bond structure, investors, deal, and post-deal of native and non-native digital bonds versus direct and indirect conventional bonds.

Table 1: Comparison between Digital and Conventional Bonds

	Native Digital Bonds	Non-Native Digital Bonds	Direct Conventional Bonds	Indirect Conventional Bonds
Panel A: Bond Characteristics				
Issuance	Directly on blockchain	Tokenized on blockchain	Traditional financial systems	Traditional financial systems
Intermediaries	Minimal reliance	Less intermediaries	High reliance on intermediaries	High reliance on intermediaries
Transparency	High due to blockchain	Improved via tokenization	Lower transparency	Variable in transparency
Settlement	Fully on-chain	Both on-chain and off-chain	In central registration system	In exchange or by bilateral agreement
Panel B: Investor Characteristics				
Investors	Institutional investors	Tech-oriented, retail and pseudo-anonymous investors	Institutional investors	Investors seeking tailored solutions
Motivation	Technology adoption and efficiency	Technology adoption and enhanced liquidity	Financing	Diversification and tailored profiles
Panel C: Deal Characteristics				
Market Cap	Relatively small	Relatively small	Big	Complex and big
Market Entry	High, fewer participants in digital bond	Low due to access to blockchain platforms	High, intermediaries and entry barriers	High, complex structuring and pooling
Regulation	Evolving blockchain-specific	Evolving	Well-established	Complex due to multilayered structures
Panel D: Post-Deal Characteristics				
Interest Payments	Automated via smart contracts	Automated and manual	Manual	Manual or through financial engineering
Principal Repayment	Automated via smart contracts	Automated and manual	Manual	Manual or through financial engineering
Record Keeping	Immutable blockchain records	Blockchain and traditional records	Central registration system	Complex due to layered structures

Notes. This table compares four types of bonds: Native Digital Bonds, Non-Native Digital Bonds, Direct Conventional Bonds, and Indirect Conventional Bonds, across various characteristics in four panels. Panel A (Bond Characteristics) shows the differences in issuance methods, reliance on intermediaries, transparency, and settlement methods. Panel B (Investor Characteristics) contrasts the investor base and motivation. Panel C (Deal Characteristics) compares market capitalization, market entry barriers, and regulation. Panel D (Post-Deal Characteristics) looks at the mechanisms for interest payments, principal repayment, and record-keeping.

Panel A: Bond Characteristics Panel A of Table 1 outlines the bond characteristics distinguishing digital and conventional bonds. Native digital bonds are issued directly on blockchain platforms, reducing the number of intermediaries required. This direct issuance structure provides high levels of transparency through immutable records and real-time transaction settlement. In contrast, non-native digital bonds originate as conventional bonds or other debt-financing instruments and are subsequently tokenized for trading and settlement on blockchain platforms. While non-native digital bonds involve traditional intermediaries during issuance because of the manually tokenized process, they benefit from increased automation after tokenization with the help of smart contracts (Watsky et al. 2024).

Direct conventional bonds are fully managed within the traditional financial system, relying on intermediaries such as custodians, clearinghouses, and brokers, resulting in a higher dependency on manual processes for trading and settlement. Indirect conventional bonds, encompassing structured, securitized, syndicated, convertible, exchangeable, dual-currency, and revenue bonds, are characterized by complex structures and advanced financial engineering. These bonds typically rely on intermediaries and may offer or reduce transparency and functionalities through pooling, securitization, and other mechanisms.

Panel B: Investor Characteristics Panel B highlights the investor characteristics across digital and conventional bonds. Investors in native digital bonds are predominantly institutional investors. Even though some leading institutions mention that digital bonds bring greater accessibility to bond markets[7], most of these bonds are traded on private or consortium blockchain platforms linked to stock exchanges and centralized trading platforms, limiting access for individual and retail investors. Conversely, non-native digital bonds are more attractive to a broader audience, including technology-oriented, individual, and retail investors, due to their accessibility on public blockchain platforms like Ethereum, Stellar, Polygon, etc. These investors are often drawn to the potential economic benefits of cryptocurrency markets and other tokenized assets.

Direct conventional bonds primarily appeal to institutional investors who value the stability and familiarity of well-established financial systems. Retail investors typically face entry barriers, such as minimum investment requirements. With their structured and securitized features, indirect conventional bonds cater to sophisticated investors seeking diversification, tailored risk/return profiles, and potential for higher returns through complex financial engineering. These investors are attracted by the ability of indirect bonds to provide customized solutions that align with specific investment strategies.

Panel C: Deal Characteristics Panel C compares deal characteristics across the four bond categories. Native digital bonds generally have a smaller market capitalization than conventional bond markets due to the nascent adoption of blockchain technology and ongoing regulatory developments. Non-native digital bonds, while also limited in market size, benefit from lower market entry barriers due to the availability of public tokenization platforms, but they face evolving regulatory scrutiny as native digital bonds. In contrast, direct conventional bonds, with market capitalization in hundreds of trillions of dollars, encounter high entry barriers owing to the involvement of multiple intermediaries and reliance on manual processes, operating under mature regulatory frameworks. Indirect conventional bonds, due to their complex structures, have large market caps and potentially reduced entry barriers through mechanisms such as structuring and pooling while being governed by multi-layered regulatory standards.

Panel D: Post-Deal Characteristics Panel D further compares the post-deal characteristics, such as interest payments, principal repayments, and record-keeping for each bond category. Native digital bonds leverage smart contracts to automate interest payments and principal repayments, ensuring high efficiency and transparency in managing these transactions. Non-native digital bonds are likely to employ a hybrid approach, combining automated processes with traditional manual methods, depending on the extent of integration with blockchain technology (Watsky et al. 2024). Direct conventional bonds rely on manual processes for interest and principal payments, resulting in inefficiencies and potential delays. Indirect

[7] See BNP Paribas `https://globalmarkets.cib.bnpparibas/digital-bonds-blockchain-vs-traditional/`

conventional bonds, while typically using manual or semi-automated processes, may benefit from more sophisticated financial engineering solutions that optimize payment mechanisms due to their structured nature. Record-keeping for native digital bonds is maintained entirely on an immutable blockchain ledger, enhancing transparency and security. Non-native digital bonds utilize a mixed record-keeping system that integrates blockchain and traditional documentation, improving overall data integrity. Direct conventional bonds depend on conventional record-keeping methods, whether paper-based or electronic, while indirect conventional bonds face additional complexity in record management due to their layered.

2.3 Tokenized Products

Tokenized products refer to financial, physical, or virtual assets that are digitized and represented as tokens on a blockchain or distributed ledger (Cong et al. 2021). Tokenization involves creating digital tokens that confer ownership or rights linked to an underlying asset, enabling these tokens to be traded on digital platforms with automated execution through smart contracts (Abakah et al. 2024, Swinkels 2024). By utilizing blockchain technology, tokenized products facilitate fractional ownership, improve liquidity, and enhance trading and settlement efficiency. The range of tokenized assets has expanded to include real estate, equities, commodities, and other asset classes (Kreppmeier et al. 2023, Swinkels 2023).

Public blockchain platforms such as Ethereum and Polygon have become central infrastructures for tokenized products. Ethereum, one of the earliest and most widely used blockchain networks, supports tokenization through its smart contract architecture, allowing for programmable, automated transactions without reliance on centralized intermediaries (John et al. 2025). Polygon, designed as a layer-2 scaling solution for Ethereum, offers higher transaction throughput and lower costs while maintaining compatibility with Ethereum's protocols. The use of public blockchains enables fractionalization of assets, thereby increasing market accessibility and liquidity, particularly for traditionally illiquid asset classes such as real estate and fixed income securities. Smart contract functionality further facilitates peer-to-peer trading, enforces compliance protocols, and improves transparency in asset ownership and transfer (Chen et al. 2022, Hu et al. 2021).

In the context of bond markets, tokenization introduces several potential improvements over conventional structures, including real-time settlement, reduced transaction costs, and enhanced transparency (Watsky et al. 2024). Tokenized bonds, categorized as non-native digital bonds, can be subdivided into smaller units, lowering investment thresholds and broadening access to retail and smaller institutional investors. Smart contracts embedded within blockchain platforms can automate key bond functions, such as compliance verification, interest payments, and redemption, thereby improving operational efficiency relative to traditional custodial and settlement systems.

Tokenized treasury products represent a specific category of tokenized bonds, where the underlying assets consist primarily of U.S. Treasury securities, repurchase agreements, fiat currencies, or stablecoins. By enabling fractional ownership of high-grade government securities, tokenized treasury products expand access to treasury markets for investors who may not otherwise participate. These products are traded on blockchain platforms, allowing investors to allocate capital into yield-generating assets while maintaining custody on-chain. As of June 2024, over 20 tokenized treasury products are actively traded on public blockchains, with a total market capitalization of approximately USD 1.7 billion. Ethereum hosts the largest share, accounting for around USD 1.2 billion in market value[8].

[8]RWA.xyz provides the list of tokenized treasury products on blockchain, see `https://app.rwa.xyz/treasuries`

3 Hypotheses, Data, and Methods

3.1 Hypotheses Development

This section develops hypotheses concerning the key factors expected to influence the trading volume of tokenized treasury products. Based on prior literature, we categorize the determinants into five dimensions: (i) cost and fee structures, (ii) the informative effects of product documentation, (iii) macroeconomic conditions, (iv) equity, commodity, and cryptocurrency market dynamics, and (v) the regulatory framework. Each hypothesis addresses how these factors are expected to shape trading activity in tokenized treasury markets.

Prior research on asset tokenization suggests that higher transaction costs can negatively impact capital raising and trading efficiency. For instance,Kreppmeier et al. (2023) finds that elevated transaction costs in real estate tokenization extend funding periods and lower fundraising success rates. We hypothesize that higher transaction fees are expected to deter trading in tokenized treasury products by reducing their net expected returns.

The impact of management fees on trading volume is theoretically ambiguous. On one hand, higher fees may discourage investor participation by reducing net returns, particularly in markets where investors are fee-sensitive (Khorana and Servaes 1999, Adams, Mansi, and Nishikawa 2012). On the other hand, management fees may serve as signals of higher service quality, stronger governance, or better liquidity provision, which can attract investors even at higher cost levels (Choi, Laibson, and Madrian 2009, Hu, Chao, and Lim 2016). Moreover, empirical evidence from mutual fund markets shows mixed results regarding investor sensitivity to fees, reflecting differences in financial literacy and perceived service value. In the context of tokenized treasury products, where information asymmetries and investor sophistication vary considerably, the relationship between management fees and trading volume may depend on how effectively product characteristics and value propositions are communicated to investors. Based on these considerations, the following hypotheses are proposed:

- *Hypothesis 1a: Higher transaction costs, proxied by gas fees, are associated with lower trading volume of tokenized treasury products.*
- *Hypothesis 1b: Management fees are associated with trading volume in tokenized treasury products, with the direction of the effect depending on investor perceptions of service quality and cost sensitivity.*

Prior research highlights the critical role of information availability in influencing trading activity. Noise trader models suggest that the dissemination of information increases participation by both informed and uninformed traders, thereby enhancing trading volume and market liquidity (Bhushan, Brown, and Mello 1997, De Long et al. 1990). Even when reacting to non-fundamental signals, noise traders contribute positively to market volume through increased trading activity (Bloomfield, O'Hara, and Saar 2009, Shleifer and Summers 1990). Applied to tokenized treasury products, these frameworks imply that the availability of clear and detailed documentation may encourage broader investor participation, leading to higher trading volume.

Liquidity provision theory further emphasizes the value of information in reducing market uncertainty and facilitating liquidity provision. Greater information transparency improves the ability of market participants to assess asset value, enabling tighter spreads and deeper markets (Choi, Huh, and Seunghun Shin 2024, Adrian, Boyarchenko, and Shachar 2017). In the context of tokenized markets, where liquidity is often thinner than in traditional financial markets, the provision of high-quality information through product documentation may enable more efficient trading and attract both liquidity providers and investors (Bianchi, Babiak, and Dickerson 2022).

While prior literature often measures disclosure quality using text-based metrics such as document length or readability indices (Huang et al. 2018, Kostovetsky and Warner 2019), these proxies may not capture the substantive informational content relevant for investment decisions. Recent advances in generative artificial intelligence (AI) offer new tools to assess the perceived informativeness of financial documents at a more granular level (Becht, Franks, and Wagner 2024, Jha et al. 2024, Kim, Muhn, and Nikolaev 2023). Leveraging these technologies allows for a more nuanced evaluation of disclosure quality as perceived by investors.

In the case of tokenized treasury products, two main forms of documentation exist: (i) the prospectus, a formal regulatory filing containing detailed investment disclosures, and (ii) the product documentation website, a less formal presentation providing general information on the tokenized product, technological protocols, and legal terms. Both sources contribute to shaping investors' perceptions of the product's risks, returns, and operational mechanisms. We define documentation informativeness as the perceived clarity, depth, and relevance of product disclosures in supporting investor understanding and decision-making. To capture distinct informational dimensions relevant to tokenized markets, we classify informativeness into three categories:

- Legal informativeness reflects disclosures concerning regulatory compliance, investor protection mechanisms, and contractual rights and obligations. Prior research suggests that comprehensive legal frameworks reduce investment uncertainty and strengthen investor confidence (Qian and Strahan 2007, Demirgüç-Kunt and Maksimovic 1998).

- Financial informativeness encompasses disclosures related to yield characteristics, fee structures, collateral arrangements, and risk-return profiles. Transparent financial information can enhance investors' ability to assess asset value and investment attractiveness (Loughran and McDonald 2014).

- Technological informativeness pertains to descriptions of blockchain architecture, smart contract functionality, and tokenization processes. Given the technical complexity of blockchain finance, the clarity of technological disclosures may be particularly important in attracting or deterring participation among different types of investors.

Although greater documentation informativeness may generally reduce uncertainty and promote participation, the impact of each information type on trading activity is theoretically ambiguous. Legal disclosures may improve perceived legitimacy but increase complexity and potential investor hesitation. Financial disclosures may facilitate valuation but also reveal cost structures that dampen demand. Technological disclosures may attract digitally proficient investors while alienating those less familiar with blockchain protocols. We therefore propose the following hypotheses:

- *Hypothesis 2a: Legal informativeness in product documentation is associated with the trading volume of tokenized treasury products.*

- *Hypothesis 2b: Financial informativeness in product documentation is associated with the trading volume of tokenized treasury products.*

- *Hypothesis 2c: Technological informativeness in product documentation is associated with the trading volume of tokenized treasury products.*

Macroeconomic conditions and monetary policy are fundamental determinants of investor behavior in fixed income markets, including tokenized treasury products. During periods of economic expansion, risk appetite tends to increase, leading investors to reallocate capital toward higher-yielding or riskier assets. As a result, demand for safe assets such as tokenized treasury products may decline. This relationship can be

proxied by the Aruoba-Diebold-Scotti (ADS) Business Conditions Index, which provides a high-frequency measure of real-time economic conditions (Aruoba, Diebold, and Scotti 2009, Aruoba and Diebold 2010). The ADS index aggregates indicators of employment, production, income, manufacturing, and sales to produce a daily measure of economic activity, with a mean value normalized to zero. Positive values reflect periods of economic growth, while negative values indicate economic contraction. Prior research suggests that during periods of economic prosperity, investors tend to reduce allocations to lower-yielding, safer assets in favor of equities and alternative investments (Wan 2019). Accordingly, trading volume in tokenized treasury products is expected to decline when the ADS index indicates stronger economic conditions.

Interest rate policy, particularly adjustments to the Federal Reserve's target rate, also plays a critical role in shaping the yield environment for treasury securities. Under the expectations theory of the term structure of interest rates, short-term rates influence investor expectations about future interest rates and asset yields. Changes in the Federal Reserve target rate directly affect the returns available on short-term government securities, including those underlying tokenized treasury products. An increase in the target rate raises yields on these products, potentially making them more attractive to yield-sensitive or risk-averse investors. However, tokenized products involve additional costs, such as blockchain transaction fees and management fees, which may partially offset their attractiveness relative to traditional treasury securities. As a result, the overall effect of changes in the Federal Reserve target rate on trading volume in tokenized treasury markets is theoretically ambiguous. Based on these considerations, we formulate the following hypotheses:

- *Hypothesis 3a: Economic prosperity, proxied by the ADS business index, is negatively associated with trading volume in tokenized treasury products.*
- *Hypothesis 3b: Changes in the Federal Reserve target rate are associated with the trading volume of tokenized treasury products.*

The performance of broader financial markets may influence investor behavior in tokenized treasury products. Given that tokenized treasuries are backed by U.S. Treasury securities, they are inherently sensitive to monetary market conditions, including changes in interest rates and government bond returns. The U.S. Treasury Securities Index, which measures the returns on government debt instruments, serves as a benchmark for evaluating the relative yield and valuation of tokenized treasuries. Changes in this benchmark may alter the attractiveness of tokenized treasury products, particularly among investors seeking stable returns within digital asset platforms. In addition, prior research indicates that the supply of Treasury securities can affect liquidity across broader financial markets, underscoring the interconnectedness of safe asset supply and financial market dynamics(Krishnamurthy and Vissing-Jorgensen 2015).

Spillover effects across asset classes also play an important role in shaping portfolio allocation decisions. Behavioral finance and asset pricing research suggests that investors' participation in one asset class is influenced by the relative performance of other asset classes (Corbet, Larkin, and Lucey 2020, Gil-Alana, Abakah, and Rojo 2020, Koch and Dimpfl 2023, Lahiani, jeribi, and Jlassi 2021). When traditional markets, such as equities (e.g., S&P 500), commodities (e.g., gold and crude oil), or fixed-income securities, perform strongly, investors may reallocate capital away from low-risk instruments such as tokenized treasuries toward higher-yielding assets. Conversely, during periods of market volatility or heightened uncertainty, demand for safe assets typically increases (Liu, Longstaff, and Pan 2003), potentially boosting trading volume in tokenized treasury products.

The performance of cryptocurrencies, particularly Ethereum, the native token of the blockchain infrastructure supporting many tokenized products, may also affect trading activity. Strong performance in cryptocurrency markets may enhance investor risk appetite and divert attention toward higher-risk digital assets, reducing demand for stable instruments such as tokenized treasuries. Alternatively, poor performance

or elevated volatility in cryptocurrency markets may prompt investors to shift toward safer blockchain-based assets. Based on these considerations, we formulate the following hypotheses:

- *Hypothesis 4a: The performance of traditional financial assets (e.g., Treasury Bond Index, S&P 500, gold, and crude oil) is associated with trading volume in tokenized treasury products.*
- *Hypothesis 4b: The performance of major cryptocurrencies, particularly Ethereum, is associated with trading volume in tokenized treasury products.*

The regulatory and structural characteristics of tokenized products play an important role in shaping investor behavior and trading activity. While blockchain-based markets offer features such as transparency, immutability, and decentralized verification, these technological attributes alone may not be sufficient to establish investor trust, particularly in emerging asset classes (Cong et al. 2023, Amiram, Lyandres, and Rabetti 2025). Clear and enforceable regulatory frameworks are critical for enhancing investor protection, reducing information asymmetry, and supporting market integrity (Augustin, Rubtsov, and Shin 2023).

Theoretical and empirical research suggests that a robust regulatory framework can increase the credibility and attractiveness of financial instruments, particularly for institutional and risk-averse investors (Bhojraj, Jun Cho, and Yehuda 2012, Khorana, Servaes, and Tufano 2005). In the United States, mutual funds are subject to stringent disclosure and registration requirements under SEC Forms N-1A and N-2, which mandate transparency regarding investment risks, management structures, and fee arrangements. Applying similar regulatory standards to tokenized treasury products may enhance their perceived legitimacy and broaden their appeal among more traditional investor bases.

However, the regulatory framework may also introduce higher compliance costs, increased documentation requirements, and reductions in transaction anonymity that may be valued by blockchain-native investors (Griffith and Clancey-Shang 2023, Shanaev et al. 2020). Empirical evidence suggests that stricter regulation can discourage participation from investors who prioritize privacy or seek to avoid extensive regulatory scrutiny (Van Der Linden and Shirazi 2023, Cuervo, Morozova, and Sugimoto 2020). Thus, while regulation may improve formal credibility, it may also reduce trading activity among segments of the investor population sensitive to the frictions imposed by regulatory frameworks. Based on these considerations, we formulate the following hypothesis:

- *Hypothesis 5: The application of SEC N-1A or N-2 regulatory frameworks is negatively associated with trading volume in tokenized treasury products.*

3.2 Method

We mainly run different multivariate analyses using ordinary least squares (OLS) and two-stage least squares (2SLS) to identify the connection between the previously described potential influencing factors on trading volume described by our main dependent variable, the trading volume of tokenized treasury products.

In addition to the previously described potential influencing factors, we also analyze how the information availability to investors may impact the trading volume. Large Language Models (LLMs) and Generative Pre-trained Transformers (GPTs) have revolutionized business research by providing powerful tools for processing and analyzing vast amounts of unstructured data. LLMs, such as OpenAI's GPT series, are designed to understand unstructured information by leveraging extensive datasets and sophisticated machine-learning algorithms. In business research, LLMs and GPT models play a crucial role in transforming how researchers and analysts handle textual data, whether in analyzing customer feedback, generating insights from financial reports, or monitoring trends from news sources and social media. In this research, we mainly

Table 2: Large Language Model Prompts

You are an expert assisting in structuring data into a table format. Given product documents with various information pieces, your task is to analyze and output the data in a CSV-friendly format.
The uploaded documents are Prospectus or Documentation Websites of some tokenization treasury products, that are some treasury bills, notes, and bonds which have been tokenized, issued, traded and managed on blockchain platform such as Ethereum. All of these documents have been cleaned, and when investor reading these documents, they are potentially obtaining different types of information.
Based on the documents, if you are an investor and want to purchase tokenized treasury products, how much information from the documents may you find informative for your investment decision from the Legal, Financial, and Technological perspectives (0 to 100)?
These scores should be based on the clarity, depth, and relevance of the information provided in each document to an investor making an informed decision.

Notes. This table presents the prompts used for calculating the informative effects of tokenized treasury products' documentation. The prompts are based on (Becht, Franks, and Wagner 2024). The LLM model used to calculate the informative effects is ChatGPT-4o. The model performs better on text, reasoning, and coding intelligence than previous models.

follow the prompts from Becht, Franks, and Wagner (2024) and adopt the ChatGPT-4o model to evaluate the informative effects of product documentation of tokenized treasury products. Specifically, we adopt prompts in Table 2 and ask ChatGPT to simulate the human reading process to quantify how investors perceive information and assess the clarity, depth, and relevance of information provided from legal, financial, and technological perspectives. Legal information refers to disclosures related to regulatory compliance, investor protection mechanisms, and contractual terms governing the tokenized product. Financial information includes details on yield, fee structures, collateral backing, and risk-return characteristics. Technological information captures explanations of the underlying blockchain infrastructure, smart contract mechanisms, and tokenization processes. Each document is rated for its informativeness on these three dimensions, allowing us to assess documentation quality and its potential influence on investor decision-making.

3.3 Data and Descriptive Statistics

Our primary data sources are Etherscan and Polygonscan, which are blockchain explorers and analytics platforms for the Ethereum and Polygon networks, respectively. Etherscan, established in 2015, provides application programming interfaces (APIs) that enable detailed access to Ethereum blockchain data. Polygonscan offers equivalent functionality for the Polygon network, supporting data extraction and analytics with a structure closely aligned with Etherscan. At the time of data collection, 30 publicly available tokenized treasury products were identified on these platforms. We focus on a subset of 22 tokenized treasury products with reported positive market capitalizations and observable trading records. The remaining eight products are excluded due to missing market value information or an absence of recorded transactions during the sample period.

Tokenized treasury products primarily consist of tokenized representations of U.S. Treasury Bills, fiat cash, and repurchase agreements recorded on Ethereum and Polygon. These products are typically structured to maintain a stable value per token by leveraging the price stability of underlying government securities

while integrating blockchain settlement mechanisms. Several products facilitate financing and transactions through stablecoins, such as USD Coin (USDC) and Tether (USDT), thereby linking traditional financial assets to the broader digital asset ecosystem.

The regulatory frameworks governing tokenized treasury products exhibit considerable variation across products and jurisdictions. Most products are incorporated in the United States or the British Virgin Islands, with additional representation from the European Economic Area (EEA), the Cayman Islands, and Seychelles. Some products comply with stringent regulatory standards, including registration under the U.S. Investment Company Act of 1940, the U.S. Securities Act via Forms N-1A or N-2, or the Swiss Financial Market Supervisory Authority (FINMA) Framework. Other products operate under exemptions or lighter regulatory regimes, such as the U.S. Securities Act Regulation D exemption, the Singapore Securities and Futures Act Section 275 exemption, or the Cayman Islands Mutual Funds Act.

Investor eligibility requirements vary across products, ranging from offerings open to accredited individual investors to those restricted to institutional participants. Documentation practices also differ: some products provide comprehensive prospectuses, while others supply detailed but less formal documentation through dedicated informational websites. This diversity in regulatory compliance, investor eligibility, and disclosure standards enables the analysis of heterogeneity in investor preferences and trading behaviors across tokenized treasury products.

Transaction-level data is extracted directly from the respective smart contracts on Ethereum and Polygon. For each transaction, we collect timestamps, transaction quantities, counterparty wallet addresses, and unique transaction hashes. Utilizing these hashes and the API functionality provided by the platforms, we retrieve additional information, including transaction-specific gas fees and other related metadata. The final dataset covers transactions occurring between January 1, 2023, and June 10, 2024.

The descriptive statistics for the determinants of trading volume in tokenized treasury products are presented in Table 3. Panel A reports the product-level characteristics. The average annual management fee across the sample is 0.34%. The informativeness of product documentation is evaluated across three dimensions—legal, financial, and technological—using AI-based assessments. The average legal informativeness score is 83.41, while the financial and technological informativeness scores are 75.91 and 72.50, respectively. These results indicate that, as measured by the AI model, financial disclosures tend to exhibit greater perceived informativeness compared to legal and technological content. A significant proportion of the sampled products support stablecoin purchases and impose accredited or professional investor restrictions. Most products directly hold U.S. Treasury Bills as their underlying assets and set minimum investment thresholds, reflecting a focus on high-net-worth and sophisticated investors.

Panel B of Table 3 presents descriptive statistics on transaction and market data. The total number of valid transactions recorded is 7,719, with substantial variance observed in transaction quantities and gas fees. The average transaction cost is 56.47 Gwei (1 Gwei = $1x10^9$ ETH or POL). The returns on monetary, equity, and commodity assets show stability over the observed period, reflecting the relatively low volatility in the market for tokenized treasury products.

4 Main Analysis

4.1 Concentration of Ownership

We begin our empirical analysis by examining the distribution of ownership across participants in tokenized treasury products. Ownership concentration is a critical market characteristic that can influence trading volume, liquidity, price discovery, and investor participation. In traditional financial markets, higher ownership concentration has been associated with reduced liquidity and impaired market functioning (Huang,

Table 3: Descriptive Statistics

	N	Mean	SD	Min	p25	Median	p75	Max
Panel A: Product Characteristics								
Mgmt_fee	22	0.34	0.27	0	0.15	0.3	0.5	1
Legal_informative	22	83.41	7.77	70	75	82.5	90	95
Fin_informative	22	75.91	7.81	60	70	75	80	90
Tech_informative	22	72.5	11.62	50	65	80	80	85
SEC_Regulation	22	0.32	0.48	0	0	0	1	1
SEC_N1_Regulation	22	0.09	0.29	0	0	0	0	1
SEC_D_Exemption	22	0.23	0.43	0	0	0	0	1
Prospectus	22	0.32	0.48	0	0	0	1	1
Stablecoin	22	0.73	0.46	0	0	1	1	1
US_incorporate	22	0.32	0.48	0	0	0	1	1
EU_incorporate	22	0.23	0.43	0	0	0	0	1
US_investor	22	0.09	0.29	0	0	0	0	1
T-bill	22	0.73	0.46	0	0	1	1	1
Min-invest	22	0.73	0.46	0	0	1	1	1
Panel B: Transaction and Market Variables								
Vol	7719	286826.87	2046685.90	0	20	990.73	20005.42	79307546
Gas_fee	7719	56.47	75.54	6.86	22.8	33.27	54.74	2033.24
ADS-index	7719	-0.18	0.23	-0.81	-0.33	-0.14	-0.02	0.43
Federal-rate	7719	5.27	0.18	4.33	5.33	5.33	5.33	5.33
T-bond-5-year-index	7719	0	0.01	-0.02	0	0	0.01	0.04
Gold_price	7719	0.01	0.02	-0.05	-0.01	0	0.02	0.06
Crudeoil_price	7719	0	0.04	-0.14	-0.03	0	0.02	0.1
S&P500_price	7719	0	0.02	-0.05	-0.01	0	0.01	0.06
Ethereum	7719	0.02	0.08	-0.23	-0.03	0	0.05	0.27

Notes. This table reports the descriptive statistics on the variables used in the analysis of trading volume. The full sample includes 7,719 transactions of 22 tokenized treasury products between January 1, 2023, and June 10, 2024. Panel A presents the product-level information and variables of tokenized treasury products on Ethereum and Polygon, including management fees, informative effects from generative AI based on product documentation, regulation status, and other unique features of tokenized products. *Mgmt_fee* measures the annual management fee rate charged by the fund issuer. *Legal_informative*, *Fin_informative*, and *Tech_informative* are informative effects generated by ChatGPT-4o for measuring informative effects in legal, financial, and technological perspectives, respectively. *SEC_Regulation* is a dummy variable indicating whether the tokenized product is under the U.S. Securities and Exchange Commission (SEC) regulatory framework, which both include N1 and N2 Regulation and D Exemption. *SEC_N1_Regulation* is a dummy variable indicating whether the tokenized product is under SEC N1 or N2 regulatory framework. *SEC_D_Exemption* is a dummy variable indicating whether the product relies on Regulation D exemption from registration for offering and selling securities. *Prospectus* is a dummy variable indicating whether the tokenized treasury product has a registered prospectus. If the tokenized product has no registered prospectus but a documentation website, the variable *Prospectus* will take value in 0. *Stablecoin* is an indicator of whether the product supports using stablecoin (e.g., USDC, USDT, etc.) for investment. *US_incorporate* and *EU_incorporate* are dummy variables that represent whether the issuer of the tokenized product is incorporated in the U.S. and EU/EEA, respectively. *US_investor* is a dummy variable set to one if a tokenized product only allows investors from the U.S. to invest in the product. *T-bill* is a dummy variable that takes value in 1 when the product directly holds treasury securities as primary assets and takes value in 0 otherwise. *Min_invest* indicating whether the tokenized product has a requirement in minimal investment amount. The product characteristics data is collected from https://app.rwa.xyz/treasuries and the websites of each tokenized treasury product. Panel B presents transaction-level variables and market conditions, such as trading volume, gas fees, and key economic indicators. *Vol* is the trading volume of each transaction in the number of shares. *Gas_fee* records the actual transaction cost of each transaction. *ADS-index* is the Aruoba-Diebold-Scotti (ADS) Business Index, which is designed to track real business conditions at high observation frequency (daily level), published and adjusted by the Federal Reserve Bank of Philadelphia. *Federal-rate* is the Federal Funds Effective Rate, which is the interest rate at which depository institutions trade federal funds (balances held at Federal Reserve Banks) with each other overnight. The data here is collected from the website of the Federal Reserve Bank of St. Louis. *T-bond-5-year-index* is the weekly return of the five-year treasury note index. *Gold_price* is the weekly return of the gold price. *Crudeoil_price* is the weekly return of crude oil price. *S&P500_price* is the weekly return of S&P 500 index. *Ethereum* is the weekly return of cryptocurrency Ethereum.

Wang, and Wang 2024). In the context of tokenized assets, where products are recorded on decentralized infrastructures but often issued by centralized entities, the ownership structure may reflect the degree of decentralization, investor diversity, and institutional involvement. Understanding ownership concentration provides insights into the maturity of tokenized treasury markets and the potential barriers to broader investor participation, which may ultimately affect market liquidity and trading activity.

To quantify ownership concentration, we compute the Herfindahl-Hirschman Index (HHI) for each tokenized treasury product. The HHI, commonly used in real estate tokenization studies (Swinkels 2023), is calculated by summing the squares of ownership shares across all investors. Higher HHI values indicate more concentrated ownership, while lower values reflect broader distribution among participants. Analyzing HHI distributions allows us to assess whether tokenized treasury products are predominantly held by a small number of investors or whether ownership is more evenly dispersed, with implications for market resilience and efficiency.

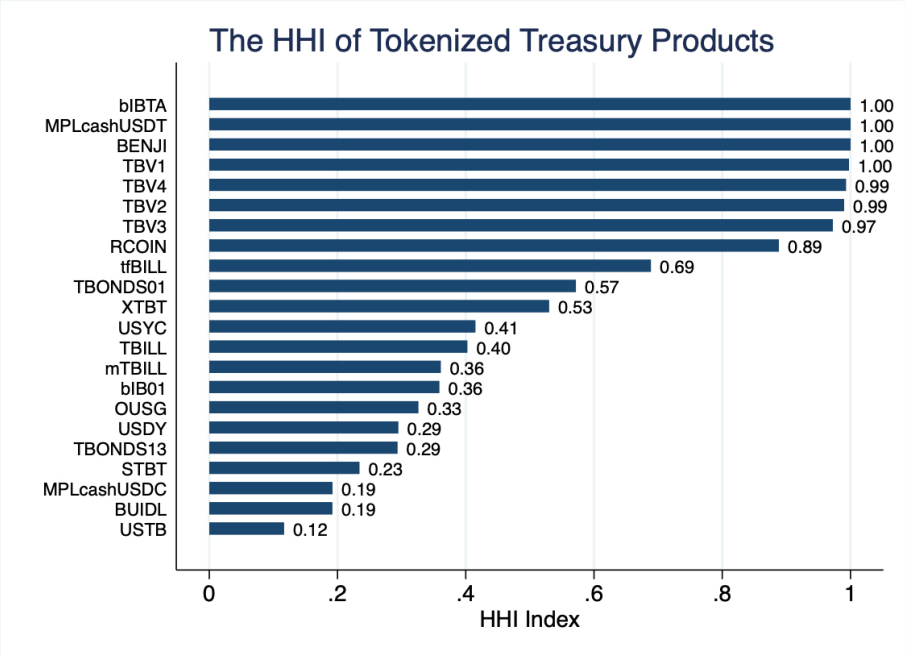

Figure 2: HHI of Tokenized Treasury Products

Notes. This figure displays the Herfindahl-Hirschman Index (HHI) of the ownership structure of tokenized treasury products in a bar chart. The tokenized treasury products are sorted in descending order based on their HHI values to highlight the products with the greatest market concentration on top. The ownership structure is based on June 10, 2024.

The HHI values for the 22 tokenized treasury products in our sample are presented in Figure 2. Ownership concentration exhibits substantial heterogeneity across products, with HHI values ranging from 0.12 to 1.00. Thirteen products display HHI values between 0.1 and 0.6, indicating moderately concentrated ownership structures. For example, USTB (HHI = 0.12) and BUIDL (HHI = 0.19) exhibit relatively dispersed ownership patterns. In contrast, products such as RCOIN (HHI = 0.89) and tfBILL (HHI = 0.69) display significantly higher concentration, suggesting dominance by a small number of large holders. Notably, six products, including BENJI (HHI = 1) and MPLcashUSDT (HHI = 1), exhibit near-complete concentration, with

ownership effectively monopolized by single or very few entities.

The comparison with traditional markets further highlights the distinct ownership patterns of tokenized treasury products. In U.S. bond mutual funds, the average HHI is approximately 0.20(Huang, Wang, and Wang 2024), substantially lower than the concentration observed in several tokenized products. This evidence suggests that the tokenized treasury market remains at an early developmental stage, characterized by high issuer or sponsor holdings and limited broader investor participation. Such concentration is consistent with patterns observed in nascent financial markets, where institutional sponsors and early adopters retain significant ownership stakes until broader market access and investor diversification evolve.

4.2 Analysis of Product Transaction

We begin the multivariate analysis by estimating cross-sectional regressions to examine the relationship between trading volume and key explanatory variables. The dependent variable is the natural logarithm of transaction quantity, $\log(Vol_{i,s})$, where i indexes transactions and s indexes time. The baseline empirical specification is as follows:

$$\begin{aligned}\log(Vol_{i,s}) = \alpha + \beta_1 Gas_{i,s} + \beta_2 Fee_i \\ + \beta_3 Info_{i,j} + \beta_4 X_{i,s} + \varepsilon_{i,s}.\end{aligned} \tag{1}$$

where $Gas_{i,s}$ denotes the transaction cost (gas fee) for transaction i at time s, Fee_i is the associated management fee, $Info_{i,j}$ captures the informativeness of the corresponding product documentation across dimension j (legal, financial, or technological), and $X_{i,s}$ represents a vector of control variables, including product characteristics, regulatory frameworks, and asset market performance indicators. $\varepsilon_{i,s}$ is the error term.

Regression results are presented in Table 4. Column (1) reports the baseline specification, which includes transaction costs, management fees, and the three dimensions of documentation informativeness. Column (2) extends the baseline model by incorporating macroeconomic conditions, proxied by the ADS Business Conditions Index and the Federal Reserve target rate. Column (3) adds controls for monetary, equity, and commodity market performance. Column (4) further includes Ethereum market returns, reflecting conditions in the underlying blockchain network supporting many tokenized products. Column (5) introduces regulatory variables related to SEC registration frameworks. Column (6) presents the full specification, combining all independent variables into a comprehensive model.

In Column (1), a 1% increase in the daily average gas fee is associated with an estimated 1.1% decrease in trading volume, consistent with Hypothesis 1a. This negative association supports the view that transaction costs discourage trading activity in blockchain-based financial markets. However, the magnitude and statistical significance of the gas fee coefficient decline in Columns (5) and (6) as macroeconomic and regulatory variables are introduced, suggesting that part of the gas fee effect may be mediated by broader market conditions.

The measurements of documentation informativeness exhibit statistically significant associations with trading volume, with distinct effects across legal, financial, and technological dimensions. These findings provide empirical support for Hypotheses 2a to 2c. Specifically, the financial informativeness score is positively and strongly associated with trading volume across all specifications. This suggests that financial disclosures that are perceived as clear and relevant, such as those describing yield characteristics, fee structures, or collateral backing, enhance investors' ability to assess product value and risk, thereby encouraging participation. The technological informativeness score is also positively related to trading activity, albeit

Table 4: Determinants of Trading Volume at Transaction-level

	Dependent variable:					
	log(Vol)					
	(1)	(2)	(3)	(4)	(5)	(6)
log_Gas_fee	−1.1000***	−1.1224***	−1.1440***	−1.1213***	−0.0274	−0.1243
	(0.0860)	(0.0861)	(0.0864)	(0.0858)	(0.0807)	(0.0818)
Mgmt_fee	3.8270***	3.5819***	3.8420***	3.8211***	3.7969***	3.6096***
	(0.2346)	(0.2331)	(0.2359)	(0.2342)	(0.2290)	(0.2268)
Legal_informative	−0.1185***	−0.1267***	−0.1144***	−0.1152***	−0.2166***	−0.2167***
	(0.0125)	(0.0126)	(0.0126)	(0.0125)	(0.0109)	(0.0111)
Fin_informative	0.0892***	0.0965***	0.0879***	0.0864***	0.1896***	0.1907***
	(0.0089)	(0.0089)	(0.0088)	(0.0089)	(0.0080)	(0.0080)
Tech_informative	0.0539***	0.0447***	0.0593***	0.0536***	0.0511***	0.0469***
	(0.0082)	(0.0084)	(0.0083)	(0.0082)	(0.0077)	(0.0080)
ADS-index		−0.1157				−0.3134
		(0.2243)				(0.2154)
Federal-rate		−2.7965***				−2.3299***
		(0.3257)				(0.3233)
T-bond-5-year-index			2.7627			−4.3603
			(9.1286)			(8.7399)
Gold_price			15.8118***			10.9493***
			(2.9551)			(2.7981)
Crudeoil_price			0.1719			1.6577
			(1.5696)			(1.5166)
S&P500_price			−5.1003			−5.6440
			(3.7935)			(3.6647)
Ethereum				2.5824***		1.9440***
				(0.6326)		(0.6242)
SEC_N1_regulation					−7.5894***	−7.3579***
					(0.2863)	(0.2850)
Observations	7,719	7,719	7,719	7,719	7,719	7,719
R^2	0.192	0.201	0.197	0.194	0.261	0.270
Adjusted R^2	0.192	0.200	0.196	0.193	0.260	0.269

Notes. This table reports the regression results from cost and fee structures, informative effects, and other control variables on investor participation (*log(Vol)*) in tokenized treasury products on transactional level data. The sample period is January 1, 2023, to June 10, 2024. All variables are defined in Table 3. Standard errors are in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

with smaller coefficients, indicating that transparency regarding blockchain protocols and smart contract mechanisms may improve product credibility, particularly among technologically sophisticated investors.

In contrast, the legal informativeness is negatively and significantly associated with trading volume. While comprehensive legal disclosures may reduce informational asymmetries, they may also introduce complexity or signal restrictive terms and may deter investors' participation. This result is consistent with the notion that legal content, although important for regulatory compliance, may impose cognitive or interpretive burdens that lower transaction volume in decentralized markets.

Macroeconomic and market condition variables are also meaningfully related to trading volume. Higher Federal Reserve target rates are associated with significantly lower trading activity, consistent with Hypothesis 3b, potentially reflecting investor reallocation toward conventional treasury securities in a rising interest rate environment. Gold price performance is positively associated with trading volume, suggesting that demand for safe-haven assets may increase investor engagement in tokenized treasuries during periods of market uncertainty. Ethereum returns also show a positive relationship, indicating that broader sentiment in crypto markets may influence activity in tokenized financial products.

Finally, regulatory variables show a strong association with trading behavior. In particular, the adoption of the SEC N-1A or N-2 regulatory framework is associated with a statistically significant reduction in the trading volume. This finding supports Hypothesis 5 and aligns with prior research suggesting that a stricter regulatory framework, while enhancing credibility, may deter participation from blockchain-native or pseudonymous investors who are sensitive to identity verification and compliance requirements (Chod, Trichakis, and Yang 2022, Cong et al. 2023). As noted by Cong et al. (2023), regulated crypto exchanges exhibit lower trading volumes and reduced user traffic relative to unregulated counterparts, a pattern partly explained by strategic wash trading practices used to simulate liquidity on less regulated platforms.

Taken together, these findings highlight the multifaceted determinants of trading activity in tokenized treasury markets. They underscore the importance of cost structures, perceived informativeness of disclosures, macroeconomic conditions, and regulatory design in shaping investor behavior. To further examine these dynamics, the next section turns to panel regression models using daily aggregated transaction-level data.

4.3 Analysis of Market Participation

To complement the cross-sectional analysis, we next estimate panel regressions using daily aggregated transaction data. The panel is structured at the product-day level, allowing us to account for both product-level heterogeneity and time-varying factors. The baseline specification is as follows:

$$\begin{aligned}\log(Dvol_{p,t}) = \alpha + \beta_1 Gas_{p,t} + \beta_2 Fee_p \\ + \beta_3 Info_{p,j} + \beta_4 X_{p,t} + \xi_{p,t}\end{aligned} \tag{2}$$

where $\log(Dvol_{p,t})$ denotes the natural logarithm of the total trading quantity for product p on day t. $Gas_{p,t}$ captures the average daily transaction cost (gas fee), Fee_p represents the product's annual management fee, and $Info_{p,j}$ denotes the informativeness score in dimension $j \in$ legal, financial, technological. $X_{p,t}$ is a vector of control variables, including product features, regulatory status, and market condition indicators. $\xi_{p,t}$ is the idiosyncratic error term.

Table 5 presents the results. Column (1) includes transaction costs, management fees, and documentation informativeness. Columns (2) through (5) sequentially introduce macroeconomic variables, asset market returns, cryptocurrency indicators, and regulatory controls. Column (6) reports the full specification, incorporating all covariates.

Table 5: Determinants of Trading Volume at Daily-level

	Dependent variable:					
	log(DVol)					
	(1)	(2)	(3)	(4)	(5)	(6)
log_Gas_fee	−1.6219***	−1.6423***	−1.6393***	−1.6310***	−0.8263***	−0.8742***
	(0.1200)	(0.1199)	(0.1205)	(0.1205)	(0.1385)	(0.1407)
Mgmt_fee	2.5028***	2.4427***	2.5152***	2.5091***	1.9108***	1.8873***
	(0.3266)	(0.3285)	(0.3267)	(0.3259)	(0.3225)	(0.3242)
Legal_informative	−0.2108***	−0.2195***	−0.2094***	−0.2102***	−0.3085***	−0.3112***
	(0.0213)	(0.0217)	(0.0212)	(0.0212)	(0.0229)	(0.0229)
Fin_informative	0.0484***	0.0545***	0.0476***	0.0478***	0.1282***	0.1300***
	(0.0136)	(0.0140)	(0.0136)	(0.0135)	(0.0155)	(0.0156)
Tech_informative	0.0156	0.0119	0.0159	0.0152	−0.0058	−0.0076
	(0.0165)	(0.0166)	(0.0166)	(0.0166)	(0.0164)	(0.0165)
ADS-index		1.0496***				0.7059*
		(0.3802)				(0.3647)
Federal-rate		−0.7287				−0.5274
		(0.5368)				(0.5167)
T-bond-5-year-index			5.1621			−0.2962
			(15.0358)			(14.5907)
Gold_price			4.9810			4.0210
			(4.7892)			(4.5984)
Crudeoil_price			1.4728			0.2791
			(2.3696)			(2.3403)
S&P500_price			3.2318			2.5733
			(5.7050)			(5.5715)
Ethereum				1.1944		0.3386
				(1.1038)		(1.0866)
SEC_N1_regulation					−4.2798***	−4.1781***
					(0.2962)	(0.2976)
Observations	1,581	1,581	1,581	1,581	1,581	1,581
R^2	0.329	0.333	0.330	0.330	0.375	0.377
Adjusted R^2	0.327	0.330	0.326	0.327	0.372	0.372

Notes. This table reports the regression results from cost and fee structures, informative effects, and other control variables on investor participation (*log(Dvol)*) in tokenized treasury products on daily level data. The daily panel transaction data of each product is aggregated from transaction-level data. The sample period is January 1, 2023, to June 10, 2024. All variables are defined in Table 3. Standard errors are in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Across all specifications, the coefficient on gas fees remains negative and statistically significant, consistent with Hypothesis 1a. This result reinforces the finding that higher transaction costs reduce daily trading activity by raising the marginal cost of participation, even when controlling for time-varying macroeconomic and financial conditions. Management fees continue to exhibit a positive and significant association with trading volume, consistent with the interpretation that higher-fee products may signal better quality, stronger governance, or more efficient operations in the context of tokenized financial assets.

The documentation informativeness variables reveal patterns partially consistent with the cross-sectional results. Financial informativeness remains positively and significantly associated with trading volume across all model specifications, supporting Hypothesis 2b. This finding suggests that clear and well-structured financial disclosures improve investor understanding of product yield, risk, and fee structures, thereby promoting participation. Legal informativeness is negatively and significantly related to trading volume in all models, consistent with Hypothesis 2a. While legal disclosures may enhance transparency, they may also signal regulatory complexity or restrictiveness, which could discourage some investor types. In contrast, technological informativeness is not statistically significant in any specification, suggesting that disclosures related to blockchain protocols or token mechanics do not materially influence daily trading behavior on average. This finding does not support Hypothesis 2c in the panel setting.

Turning to macro-financial variables, the coefficient of ADS Business Conditions Index is positive but marginally significant in Column (6), implying that improved macroeconomic conditions may coincide with increased activity in tokenized treasury products. Other asset market indicators, including the Federal Reserve target rate, Treasury bond returns, commodity prices, and Ethereum returns, do not exhibit statistically significant or consistent associations in the panel regressions. These null results may reflect limited daily variation in investor reallocation behavior or a muted short-term response to broader financial market movements in this market segment.

Finally, the indicator for SEC N-1A/N-2 regulatory requirements remains negatively and significantly associated with trading volume across specifications. This result is consistent with Hypothesis 5 and reinforces the evidence from the cross-sectional regressions, suggesting that stricter regulatory frameworks may reduce participation, particularly among blockchain-native or pseudonymous investors who are more sensitive to compliance burdens and identity verification requirements.

4.4 Interaction Between Management Fees and Documentation Informativeness

The regression results in both the cross-sectional (Table 4) and panel (Table 5) specifications show a positive and statistically significant relationship between annual management fees and trading volume in tokenized treasury products. This finding contrasts with conventional expectations in traditional asset markets, where higher fees are typically associated with lower investor participation due to reduced net returns (Khorana, Servaes, and Tufano 2005). In the context of tokenized financial assets, however, this relationship may reflect distinct market dynamics.

One potential explanation is the demand-side frictions. The number of tokenized treasury products available to crypto-market participants remains limited, and the elasticity of demand for these products may be relatively low. Issuers may price management fees based not only on cost structures but also on perceived scarcity and investor willingness to pay for access to blockchain-native treasury exposures, as in traditional markets (Christoffersen, Evans, and Musto 2005). A second explanation is based on investor segmentation and information asymmetry. Tokenized treasury products combine blockchain infrastructure with traditional fixed-income instruments and may attract investors with technological expertise but limited experience in bond markets. Prior research suggests that asset managers may extract higher fees in contexts where investors are less equipped to evaluate cost structures or investment alternatives (Houge and Wellman 2007).

To examine the channels through which management fees influence trading volume, we introduce interaction terms between annual management fees and documentation informativeness across legal, financial, and technological dimensions. These results are reported in Table 6. The inclusion of interaction terms modifies the interpretation of the management fee coefficient: its main effect now reflects the marginal influence when all informativeness scores are equal to zero, while the interaction terms capture the marginal impact of informativeness on the fee–volume relationship.

Table 6: Mechanism of Management Fee and Informative Effect

	Dependent variable:
	log(DVol)
log_Gas_fee	−0.8323***
	(0.1416)
Mgmt_fee	86.5698***
	(27.5855)
Legal_informative	−0.0816
	(0.0570)
Mgmt_fee × *Legal_informative*	−0.6361***
	(0.1791)
Fin_informative	−0.0166
	(0.0460)
Mgmt_fee × *Fin_informative*	0.3276**
	(0.1553)
Tech_informative	0.2541***
	(0.0414)
Mgmt_fee × *Tech_informative*	−0.7730***
	(0.1155)
Controls	Yes
Observations	1,581
R^2	0.409
Adjusted R^2	0.403

Notes. This table reports the mechanism of joint effects of management fee and informative effects using daily-level data of tokenized treasury products. The daily panel transaction data for each product is aggregated from transaction-level data. The control variables include: *ADS-index*, *Federal-rate*, *T-bond-5-year-index*, *Gold_price*, *Crude_oil_price*, *S&P500_price*, *Ethereum*, *SEC_N1_regulation*, and Constant. The sample period is January 1, 2023, to June 10, 2024. All other variables are defined in Table 3. Standard errors are in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results show that documentation informativeness significantly moderates the association between

management fees and trading volume. Specifically, the interaction between financial informativeness and management fees is positive and statistically significant, suggesting that higher levels of financial disclosure increase investor tolerance for higher fees. This finding is consistent with the interpretation that clear and relevant financial information enhances perceived value and facilitates informed investor evaluation, thereby reducing fee sensitivity in trading decisions.

By contrast, legal informativeness significantly weakens the positive association between management fees and trading volume. Although the main effect of legal informativeness is not statistically significant in this model, its negative interaction with management fees suggests that more detailed legal disclosures may heighten investor scrutiny or signal greater regulatory complexity. As a result, higher fees may be viewed less favorably when accompanied by extensive legal language, potentially due to perceived rigidity, legal risk, or cost-inefficiency.

Technological informativeness presents a distinct pattern. Its main effect is positive and statistically significant, indicating that greater transparency around blockchain protocols and token mechanics is associated with higher trading activity. However, the interaction between technological informativeness and management fees is negative and significant, implying that investors who value technological clarity may become more fee-sensitive. This result may reflect elevated expectations for cost-efficiency and automation among technologically sophisticated participants, who may penalize fee structures that appear misaligned with the operational advantages of blockchain-based finance.

Taken together, these findings underscore that the informativeness of product documentation plays a central role in conditioning the effect of management fees on investor behavior. Rather than acting independently, fee structures and disclosure content interact in economically meaningful ways that influence trading volume. This result highlights the importance of considering how product-level transparency complements or offsets cost-based frictions in emerging digital financial markets.

5 Robustness and Further Analysis

5.1 Robustness Check

5.1.1 Removal of Outliers

To assess the sensitivity of our baseline panel regression results in Table 5 to potential outliers, we winsorize the dependent variable, trading volume, at the 1st and 99th percentiles. Table 7 reports the results. The estimated coefficients on gas fees, management fees, and documentation informativeness remain qualitatively and quantitatively consistent with our main findings, indicating that the observed relationships are not driven by extreme trading activity and that the results are robust to the presence of high-leverage observations.

5.1.2 Alternative AI Tool Measurement

To evaluate the robustness of our AI-based informativeness measures, we replicate the analysis using multiple LLMs. While our baseline results are based on the ChatGPT-4o model, we extend the analysis using ChatGPT-4, GPT-o1, GPT-o3-mini, DeepSeek-V3, and DeepSeek-R1. These models differ in architecture, parameter tuning, and training data, which allows us to assess the stability of our informativeness metrics across alternative language models.

The results, presented in Table 8, show that the key empirical findings are robust across models. The coefficient on gas fees remains negative and statistically significant in all specifications, reaffirming Hypothesis 1a. Management fees continue to exhibit a positive association with trading volume, particularly in models

Table 7: Winsorized Regression Results on Daily Dataset

	Dependent variable:					
	log(Dvol_win)					
	(1)	(2)	(3)	(4)	(5)	(6)
log_Gas_fee	−1.5454***	−1.5647***	−1.5612***	−1.5540***	−0.7478***	−0.7910***
	(0.1087)	(0.1084)	(0.1084)	(0.1089)	(0.1258)	(0.1265)
Mgmt_fee	2.5571***	2.5002***	2.5683***	2.5631***	1.9636***	1.9410***
	(0.3225)	(0.3243)	(0.3229)	(0.3218)	(0.3177)	(0.3196)
Legal_informative	−0.1977***	−0.2059***	−0.1966***	−0.1971***	−0.2956***	−0.2983***
	(0.0198)	(0.0201)	(0.0198)	(0.0197)	(0.0215)	(0.0216)
Fin_informative	0.0377***	0.0435***	0.0371***	0.0372***	0.1177***	0.1195***
	(0.0118)	(0.0122)	(0.0119)	(0.0118)	(0.0140)	(0.0141)
Tech_informative	0.0156	0.0122	0.0159	0.0153	−0.0058	−0.0075
	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0162)	(0.0163)
ADS-index		0.9951***				0.6544*
		(0.3747)				(0.3591)
Federal-rate		−0.6906				−0.4882
		(0.5281)				(0.5070)
T-bond-5-year-index			4.4869			−0.8125
			(14.7782)			(14.3404)
Gold_price			4.5059			3.5092
			(4.7016)			(4.5063)
Crudeoil_price			1.5156			0.3298
			(2.3401)			(2.3029)
S&P500_price			2.5788			1.9822
			(5.4276)			(5.2953)
Ethereum				1.1228		0.2938
				(1.0872)		(1.0701)
SEC_N1_regulation					−4.2907***	−4.1981***
					(0.2889)	(0.2892)
Observations	1,581	1,581	1,581	1,581	1,581	1,581
R^2	0.332	0.335	0.333	0.332	0.381	0.384
Adjusted R^2	0.329	0.332	0.329	0.330	0.379	0.378

Notes. This table reports the regression results from cost and fee structures, informative effects, and other control variables on winsorized investor participation *log(Dvol_win)* in tokenized treasury products on daily level data. The trading volume is winsorized at 1% and 99%. The sample period is January 1, 2023, to June 10, 2024. All variables are defined in Table 3. Standard errors are in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Alternative LLM Models Results

	Dependent variable:					
	log(Dvol)					
	Baseline	GPT4	GPTo1	GPTo3-mini	DeepSeek-V3	DeepSeek-R1
log_Gas_fee	−0.8742***	−0.7031***	−1.5530***	−0.6648***	−1.5394***	−1.3962***
	(0.1407)	(0.1604)	(0.1734)	(0.1557)	(0.1690)	(0.1653)
Mgmt_fee	1.8873***	9.1984***	4.3194***	4.4218***	0.2944	0.7324
	(0.3242)	(0.6260)	(0.3234)	(0.3646)	(0.7634)	(0.5846)
Legal_informative	−0.3112***	−0.4030***	−0.1255***	−0.3699***	−0.1612***	−0.0743***
	(0.0229)	(0.0354)	(0.0284)	(0.0386)	(0.0375)	(0.0175)
Fin_informative	0.1300***	0.6215***	0.0632**	0.1173***	0.0259	−0.0016
	(0.0156)	(0.0377)	(0.0315)	(0.0238)	(0.0169)	(0.0091)
Tech_informative	−0.0076	0.0568**	0.0745***	−0.0140	−0.0196	0.0240***
	(0.0165)	(0.0233)	(0.0248)	(0.0149)	(0.0137)	(0.0085)
ADS-index	0.7059*	0.2512	0.5468	0.5118	0.3688	0.4551
	(0.3647)	(0.3829)	(0.3929)	(0.3714)	(0.4033)	(0.3876)
Federal-rate	−0.5274	−0.7193	−0.5625	0.8229	0.2487	0.1727
	(0.5167)	(0.5392)	(0.5726)	(0.5179)	(0.6095)	(0.5811)
T-bond-5-year-index	−0.2962	9.3010	15.0659	−0.5204	12.4242	8.0787
	(14.5907)	(15.2579)	(16.0867)	(14.8224)	(16.7467)	(16.1341)
Gold_price	4.0210	1.2960	3.4384	4.4229	5.9007	6.3993
	(4.5984)	(4.7977)	(5.0432)	(4.6437)	(5.1165)	(5.0553)
Crudeoil_price	0.2791	0.7313	2.4642	0.0643	1.4982	0.7988
	(2.3403)	(2.4829)	(2.4889)	(2.4008)	(2.6104)	(2.5170)
S&P500_price	2.5733	4.2624	3.3483	4.2341	6.2790	5.8795
	(5.5715)	(5.8338)	(5.9780)	(5.6860)	(6.1948)	(6.0252)
Ethereum	0.3386	0.4562	1.4231	0.9131	2.1423*	1.6308
	(1.0866)	(1.1168)	(1.2006)	(1.1171)	(1.2168)	(1.1955)
SEC_N1_regulation	−4.1781***	0.4375	−1.4190***	−1.6808***	−0.5918	−1.5394***
	(0.2976)	(0.4504)	(0.3352)	(0.3124)	(0.3635)	(0.3584)
Observations	1,581	1,581	1,581	1,581	1,581	1,581
R^2	0.377	0.322	0.254	0.352	0.215	0.247
Adjusted R^2	0.372	0.317	0.247	0.346	0.209	0.241

Notes. This table reports the regression results from cost and fee structures, informative effects, and other control variables on investor participation (*log(Dvol)*) in tokenized treasury products on daily level data. The informative effects in this table are generated by different LLMs using the same prompts shown in 2. The baseline model is the ChatGPT-4o model which we adopt in our empirical analysis. The testing date is March 26, 2025, and we adopted the newest version of each LLM. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

based on GPT variants. Regarding documentation informativeness, legal informativeness consistently shows a negative and statistically significant effect on trading volume across all LLMs. Financial informativeness remains positively associated with trading activity in most specifications, especially under ChatGPT-4 and GPT-o3-mini. Results for technological informativeness are more heterogeneous: some models, including ChatGPT-4, GPT-o1, and DeepSeek-R1, produce positive and significant coefficients, while others do not. These variations suggest that the interpretation of technological documentation may be more sensitive to model architecture and training context. Coefficients on control variables related to macroeconomic conditions, market performance, and regulatory status remain directionally consistent and statistically robust. These findings strengthen the reliability of our informativeness metrics and confirm the validity of our textual analysis across model environments.

5.1.3 Instrumental Variable Approach

To address concerns about potential endogeneity, particularly regarding transaction fees, we estimate a two-stage least squares (2SLS) model using an instrumental variables (IV) strategy. Our identification relies on blockchain-level congestion as a source of exogenous variation in gas fees. Specifically, we construct an instrument using the natural logarithm of the average daily block size on Ethereum and Polygon. Average block size reflects network congestion and is a key determinant of gas fees, but it is plausibly exogenous to short-term trading volume in individual tokenized treasury products. While average block time remained stable throughout the sample period, block size varied substantially, providing sufficient variation for identification.

Table 9 presents the 2SLS estimation results. Consistent with our OLS findings, gas fees remain negatively associated with trading volume across specifications. While the magnitude of the coefficient is attenuated and statistical significance somewhat reduced, particularly in less saturated models, the effect remains statistically significant in Columns (5) and (6), supporting Hypothesis 1a. The results confirm that the observed negative relationship between gas fees and trading activity is not solely driven by omitted variables or reverse causality. Other explanatory variables—such as management fees, financial informativeness, and legal informativeness—retain their sign, magnitude, and significance levels, indicating that the main findings are robust to endogeneity concerns.

Notably, the positive relationship between management fees and trading volume, and the negative association between legal informativeness and trading activity, are preserved under the IV estimation. Results for technological informativeness remain directionally consistent but statistically weaker, consistent with prior specifications. Overall, the IV analysis provides additional support for the causal interpretation of our findings and reinforces the conclusion that transaction costs, documentation quality, and regulatory structure are central determinants of market participation in tokenized treasury products.

5.1.4 Placebo Test

To assess whether the relationships identified in our main analysis could plausibly arise from random variation rather than reflecting systematic associations, we implement a placebo test as an additional robustness check. Specifically, we focus on four key explanatory variables: the management fee and the informativeness scores derived from legal, financial, and technological content. In the placebo design, we generate random variables that preserve the marginal distributional properties (e.g., mean, standard deviation, and range) of the original variables, but break any underlying correlation with trading volume.

We then re-estimate our main panel specification 1,000 times, each time replacing the true variables with these randomly generated placebo counterparts. This approach yields empirical distributions of placebo coefficients under the null hypothesis of no true relationship. The resulting distributions are presented in Figure 3, alongside the actual coefficients from the baseline model in Table 5 for reference.

Table 9: Instrumental Variable Approach Results

	Dependent variable:					
	log(Dvol_win)					
	(1)	(2)	(3)	(4)	(5)	(6)
log_Gas_fee	−0.7522	−0.4455	−0.7960	−0.7705	−0.9751**	−0.7300*
	(0.5039)	(0.4469)	(0.4953)	(0.5145)	(0.4339)	(0.3757)
Mgmt_fee	3.0047***	3.1548***	2.9964***	2.9995***	1.8865***	1.9115***
	(0.4157)	(0.4039)	(0.4105)	(0.4175)	(0.3258)	(0.3272)
Legal_informative	−0.1890***	−0.1873***	−0.1890***	−0.1891***	−0.3053***	−0.3141***
	(0.0251)	(0.0256)	(0.0247)	(0.0251)	(0.0251)	(0.0247)
Fin_informative	0.0435***	0.0458***	0.0431***	0.0433***	0.1241***	0.1338***
	(0.0146)	(0.0154)	(0.0145)	(0.0145)	(0.0201)	(0.0193)
Tech_informative	0.0424*	0.0497**	0.0412*	0.0418*	−0.0077	−0.0057
	(0.0231)	(0.0226)	(0.0227)	(0.0234)	(0.0169)	(0.0170)
ADS-index		0.8888**				0.6780*
		(0.3946)				(0.3707)
Federal-rate		−0.4338				−0.4864
		(0.5202)				(0.5106)
T-bond-5-year-index			8.7476			0.1107
			(15.2597)			(14.5588)
Gold_price			1.4510			3.5236
			(5.0246)			(4.6184)
Crudeoil_price			1.4502			0.1987
			(2.3782)			(2.3442)
S&P500_price			1.6363			2.4648
			(5.8716)			(5.5639)
Ethereum				0.5481		0.2193
				(1.1982)		(1.1109)
SEC_N1_regulation					−4.0289***	−4.4220***
					(0.7639)	(0.6744)
Observations	1,581	1,581	1,581	1,581	1,581	1,581
R^2	0.304	0.286	0.307	0.305	0.374	0.377
Adjusted R^2	0.302	0.283	0.303	0.303	0.372	0.372

Notes. This table reports the second stage of 2SLS regression results from cost and fee structures, informative effects, and other control variables on investor participation *log(Dvol)* in tokenized treasury products on daily level data. The instrumental variable is the average block size of the blockchain platform. The sample period is January 1, 2023, to June 10, 2024. All variables are defined in Table 3. Standard errors are in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The placebo distributions are centered tightly around zero, as expected in the absence of systematic effects. In contrast, the actual coefficients for the management fee and financial informativeness fall well outside the 95th percentile range of the placebo distributions, indicating that the observed relationships in the main analysis are highly unlikely to have arisen by chance. For the legal informativeness variable, the actual negative coefficient also lies in the extreme left tail of the placebo distribution. While the results for technological informativeness are closer to the distribution center, they remain outside the interquartile range in some specifications.

Overall, the placebo test provides further evidence that the core explanatory variables in our analysis—particularly management fees and financial documentation quality—exhibit robust associations with trading volume in tokenized treasury products. These findings help mitigate concerns that the primary results are driven by statistical artifacts or spurious correlation.

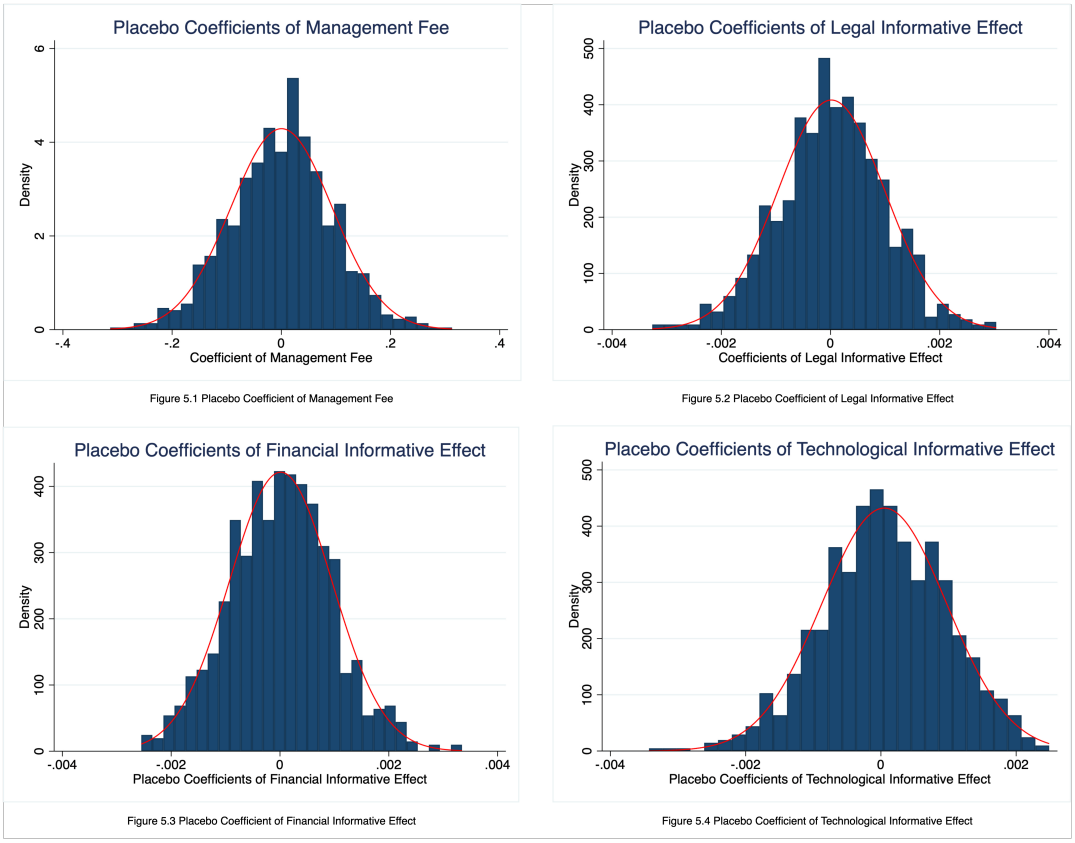

Figure 5.1 Placebo Coefficient of Management Fee

Figure 5.2 Placebo Coefficient of Legal Informative Effect

Figure 5.3 Placebo Coefficient of Financial Informative Effect

Figure 5.4 Placebo Coefficient of Technological Informative Effect

Figure 3: Distribution of Placebo Coefficients

Notes. In this figure, we display the distribution of coefficients in the placebo test. We randomly generate values on management fees and three informative effects of tokenized treasury products, adopt randomly generated values for regression in Table 5, repeat one thousand times, and depict the distribution of coefficients and compare them with normal distribution. Vertical and horizontal axes represent the density of the regression coefficient and the value of the tested variable, respectively. The red curve is the probability density function of the normal distribution with the same mean and standard deviation as the dataset of placebo coefficients.

5.2 Heterogeneity Analysis

While the baseline results establish that trading volume in tokenized treasury products is influenced by transaction costs, management fees, and documentation quality, the magnitude and direction of these effects may vary depending on product design, investor access, and jurisdictional characteristics. To account for this, we conduct a heterogeneity analysis by estimating a fully interacted panel regression model. This framework allows us to examine how the relationships between cost structures and trading activity differ across key product subgroups. The results are reported in Table 10.

In Panel A, we explore whether the effects of gas fees and management fees differ across regions of incorporation. The interaction between management fees and the EU/EEA region is negative and statistically significant, suggesting that investors in products incorporated in the EU/EEA exhibit greater sensitivity to management costs. While the main effect of the management fee remains positive and consistent with baseline estimates in U.S.- and offshore-incorporated products, the negative marginal effect in the EU/EEA indicates that higher fees are less tolerated in this regulatory environment, possibly reflecting stricter disclosure standards or more fee-aware investor segments. The interaction terms involving gas fees are statistically insignificant across regions, implying that the average effect of transaction costs on trading volume is relatively stable across jurisdictions. However, the main effect for EU/EEA incorporation is positive and significant, suggesting that—conditional on other controls—tokenized products domiciled in the EU/EEA tend to experience higher average trading volumes. This may reflect region-specific demand factors, regulatory credibility, or investor base composition.

Panel B analyzes whether the ability to purchase tokenized products using stablecoins influences the cost–volume relationship. The main effect of the stablecoin dummy is negative, indicating that, on average, products supporting stablecoin purchases exhibit lower trading volumes. However, the interaction between stablecoin support and gas fees is strongly positive and significant. This result suggests that while products with stablecoin functionality attract more crypto-native users, these users are particularly sensitive to transaction costs, likely due to their familiarity with fee-efficient platforms and expectation of low execution frictions. Specifically, the estimated marginal effect of gas fees in products that support stablecoin purchases is significantly negative (-3.5241, combining coefficient of 2.3775 and -5.9016), indicating that higher transaction costs disproportionately reduce trading activity in these products. This result highlights the importance of cost efficiency in attracting and retaining crypto-oriented participants. In contrast, the interaction between management fees and stablecoin support is negatively significant, and the overall management fee effect remains positive across both subgroups, consistent with the full-sample results in Table 5.

Panel C evaluates whether the nature of the underlying asset—specifically, whether the product directly holds U.S. Treasury bills or instead invests via exchange-traded funds (ETFs) that track T-bill performance—modifies the relationship between costs and trading volume. The interaction between the gas fee and the T-bill indicator is positive and statistically significant, indicating that the negative effect of transaction costs on trading volume is attenuated when the underlying asset consists of directly held government securities. One possible interpretation is that direct T-bill backing may be perceived as more transparent or efficient, thereby reducing investors' sensitivity to trading frictions. The interaction between management fees and the T-bill indicator is negative but not statistically significant, suggesting that the positive association between management fees and trading volume is not systematically affected by whether the product holds T-bills directly or via ETFs. The main effect of the T-bill holding indicator is positive and significant, consistent with the notion that products with direct exposure to Treasury securities attract more investor participation, potentially due to their perceived simplicity, lower risk, or improved informational clarity.

Panel D explores whether imposing a minimum investment threshold alters investor sensitivity to costs and fees. The interaction between the minimum investment indicator and the management fee is negative

and statistically significant, indicating that the positive relationship between management fees and trading volume weakens for products with higher entry barriers. This may reflect greater price sensitivity among retail or smaller investors, who are more likely to be excluded or deterred by both fee structures and participation constraints. In contrast, the interaction between gas fees and minimum investment requirements is statistically insignificant, suggesting that transaction cost sensitivity does not vary systematically based on minimum investment thresholds. The main effect of the minimum investment indicator is positive and significant, implying that products targeting institutional or high-net-worth investors—those typically subject to minimum investment conditions—tend to experience higher trading activity, even in the presence of fees.

Panel E examines the effect of geographic access constraints, focusing on whether products are restricted to U.S.-based investors. The main effect of the U.S.-only restriction is negative and statistically significant, suggesting that limiting participation to domestic investors is associated with lower trading volume. This may reflect reduced market reach, smaller addressable investor pools, or less participation from the global crypto-investor community. Interestingly, the interaction between the U.S.-only restriction and the management fee is positive and significant. This finding implies that among products restricted to U.S. investors, higher management fees are more positively associated with trading volume. One possible explanation is that U.S.-based investors may be more accustomed to traditional fee structures or may associate higher fees with product quality, particularly when operating in a more regulated environment. The interaction between gas fees and the U.S.-only restriction is not significant, indicating that transaction cost sensitivity is broadly similar across open and restricted products.

Taken together, these findings underscore that the impact of cost structures on trading volume is not homogeneous across tokenized treasury products. Instead, it is shaped by a combination of structural design features, jurisdictional considerations, and investor eligibility criteria. The observed heterogeneity highlights the importance of accounting for market segmentation and regulatory variation when evaluating investor behavior in blockchain-based fixed income markets.

Table 10: Heterogeneity Analysis

Panel A: Incorporated Region			
Variable	America	EU/EEA	Other Regions
log_Gas_fee	-0.8289***		
	(0.1754)		
Region		6.1253***	0.9257
		(1.6886)	(1.5336)
log_Gas_fee × *Region*		0.0916	0.6654**
		(0.4885)	(0.3392)
Mgmt_fee	5.5493***		
	(0.6712)		
Mgmt_fee × *Region*		-59.1913***	-1.9617
		(9.0283)	(2.0371)
Controls		Yes	
N		1581	
adj. R^2		0.400	
Panel B: Supporting Stablecoin Purchase			
Variable	Not Support		Support
log_Gas_fee	-2.2156***		
	(0.3092)		
Stablecoin			-5.9016***
			(1.8932)

Table 10 continued from previous page

log_Gas_fee × *stablecoin*		2.3775***
		(0.3494)
Mgmt_fee	6.9296***	
	(1.9731)	
Mgmt_fee × *stablecoin*		-5.3370***
		(2.0243)
Controls	Yes	
N	1581	
adj. R^2	0.402	
Panel C: Holding T-bills Directly		
Variable	Not Directly Hold T-bills	Directly Hold T-bills
log_Gas_fee	-2.2548***	
	(0.2799)	
T-bills		-1.5844
		(1.1044)
log_Gas_fee × *T-bills*		1.0006***
		(0.3567)
Mgmt_fee	4.0344***	
	(0.9979)	
Mgmt_fee × *T-bills*		-0.7748
		(0.9221)
Controls	Yes	
N	1581	
adj. R^2	0.332	
Panel D: Having Minimal Investment		
Variable	Not Have Minimal Investment	Have Minimal Investment
log_Gas_fee	-0.3940*	
	(0.2216)	
minimal_invest		13.2638***
		(1.9078)
log_Gas_fee × *minimal_invest*		-0.0765
		(0.2794)
Mgmt_fee	42.7345***	
	(4.9806)	
Mgmt_fee × *minimal_invest*		-42.3845***
		(4.9851)
Controls	Yes	
N	1581	
adj. R^2	0.416	
Panel E: Only Available for US Citizen		
Variable	No Limit for US Citizen/Entity	Only Limit for US Citizen/Entity
log_Gas_fee	-0.7824***	
	(0.1643)	
only_US		-10.6212***
		(0.9012)
log_Gas_fee × *only_US*		0.9278***
		(0.1974)
Mgmt_fee	1.6084***	
	(0.3614)	

Table 10 continued from previous page

Mgmt_fee × *only_US*	7.1625***
	(1.2429)
Controls	Yes
N	1581
adj. R^2	0.375

Notes. In this table, we report the heterogeneity of different unique characteristics of tokenized treasury products using the same data as in Table 5. The dimensions we consider include incorporated region (where the variable $Region$ is coded as 0 for products incorporated in the U.S., 1 for incorporated in the EU/EEA, and 2 incorporated in other regions), support for stablecoin purchases (dummy variable $Stablecoin$ equals 1 for products that facilitate stablecoin purchases and 0 otherwise), asset holdings (dummy variable *T-bills* equals 1 for products directly holding T-bills as the primary underlying asset and 0 otherwise), minimum investment requirement (dummy variable Min_invest equals 1 for products requiring a minimum investment amount and 0 otherwise), and investor regional limitations (dummy variable $only_US$ equals 1 for products accessible only to U.S. citizens or entities and 0 otherwise). The control variables are *ADS-index*, *Federal-rate*, *T-bond-5-year-index*, $Gold_price$, $Crudeoil_price$, $S\&P500_price$, $Ethereum$, $SEC_N1_regulation$, $Accredited_investor$, and $Constant$. The sample period is January 1, 2023, to June 10, 2024. Standard errors are in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Conclusion

Digital bonds, supported by distributed ledger technology (DLT), represent a structural innovation in fixed-income markets. By enabling programmable execution, faster settlement, and greater transparency, DLT reduces reliance on financial intermediaries and lowers transaction costs. Smart contract automation allows for the streamlining of processes such as coupon payments and redemptions, reducing operational risk and enhancing settlement efficiency. These features position digital bonds as a potentially important alternative to conventional fixed-income instruments, particularly in market environments that prioritize liquidity, cost-efficiency, and auditability.

This paper provides one of the first comprehensive empirical studies of digital bonds by documenting their full life cycle and systematically comparing digital and conventional bonds across issuance, trading, and investor access dimensions. We distinguish native digital bonds—issued and settled entirely on blockchain—from non-native digital bonds, or tokenized bonds, which are blockchain representations of traditional debt instruments. Our empirical focus is on tokenized treasury products, a prominent subset of non-native digital bonds backed by U.S. government securities and transacted via public blockchain infrastructure.

Using a dataset of 7,719 transactions across 22 tokenized treasury products, we estimate a series of regression models—including OLS, instrumental variable (2SLS), placebo, and heterogeneity frameworks—to analyze the determinants of trading activity. Our core findings indicate that higher transaction costs, proxied by blockchain gas fees, are negatively associated with trading volume. Product documentation quality, particularly in the financial dimension, is positively associated with trading activity, while legal documentation informativeness is negatively associated, potentially reflecting complexity or participation constraints.

Interaction analyses show that documentation characteristics condition the effect of fee structures on trading volume. Specifically, the legal and technological informativeness of disclosures moderates the positive association between management fees and trading activity, while financial documentation appears to increase investor tolerance for higher fees. We also find that stricter regulatory requirements, such as U.S. SEC Form N-1A compliance, are associated with lower trading volumes, suggesting that formal investor protections may discourage participation in decentralized markets that value flexibility or pseudonymity.

This study contributes to the growing literature on digital finance, tokenized assets, and market microstructure in several ways. First, it provides a structured framework for analyzing digital bonds by distinguishing

native and non-native instruments based on issuance architecture. Within this framework, we examine tokenized treasury products as a well-defined subset of non-native digital bonds, linking their structure to trading dynamics in blockchain-based fixed-income markets. Second, we offer one of the first empirical assessments of how transaction costs and documentation characteristics jointly shape trading activity in tokenized debt markets. Our results emphasize the importance of cost efficiency and disclosure quality in driving investor participation, even when the underlying asset, U.S. Treasury securities, is traditionally considered risk-free. Third, we advance methodological tools in financial research by applying generative AI to quantify perceived informativeness in product documentation. By leveraging large language models, we assess legal, financial, and technological content at scale, offering a replicable approach for future studies seeking to analyze disclosure effects in digital or tokenized settings.

One limitation of our analysis is the relatively narrow scope of the sample: our dataset includes 22 tokenized treasury products currently traded on major public blockchain platforms. While this sample reflects the vast majority of publicly available products as of the study period, the limited number of observations may constrain generalizability. To address this, we implement a set of robustness and heterogeneity tests, including interaction models based on regulatory incorporation, investment thresholds, and investor restrictions, to assess the internal consistency of our findings. Future research could expand the analysis to cover additional products and jurisdictions, particularly as adoption of tokenized debt markets continues to grow and platform-level data becomes more standardized and accessible.

The findings also carry practical and policy implications. Although tokenized treasury products are backed by U.S. government securities, the assets are widely viewed as highly liquid and creditworthy, the structure and trading environment of these digital instruments introduce new risks and frictions. Notably, our results suggest that regulatory design influences investor behavior: products subject to stricter regulatory regimes, such as SEC registration under Form N-1A, experience lower trading volume, potentially due to reduced appeal among pseudonymous or crypto-native participants. This highlights a fundamental tension between regulatory rigor and market inclusiveness. Policymakers must consider how to calibrate oversight frameworks in ways that preserve investor protection while enabling innovation in blockchain-based financial markets. As tokenized debt instruments evolve, aligning market integrity with technological efficiency will remain a central challenge for regulators and market participants alike.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT 4o in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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