Tax Planning, Illiquidity, and Credit Risks: Evidence from DeFi Lending

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Abstract

This study establishes a plausible causal link between tax-planning-induced illiquidity and credit risks in lending markets. Exploiting an exogenous tax shock imposed by the Internal Revenue Service (IRS) on cryptocurrency gains, along with millions of transactions in retail-dominated Decentralized Finance (DeFi) lending, we document that tax-motivated borrowing strategies—intended to defer capital gains taxes—significantly reduce market liquidity, as borrowers become more reluctant to trade to avoid taxable events. This effect is particularly pronounced among individuals borrowing in stablecoins (a way to monetize returns), those with higher loan-to-value ratios (more risk-averse towards new regulations and typically with larger taxable gains), those with high returns in the underlying asset (representing larger taxable gains), and those holding locked-in assets for over a year (i.e., converting high short-term to lower long-term capital gains tax rates). Using instrumental variable analysis, we demonstrate that tax-planning-induced illiquidity significantly increases the incidence of credit risks. A standard deviation increase in tax-induced illiquidity leads to a more than twofold increase in the value of defaulted loans. Our results remain robust across a battery of checks, including alternative model specifications and analyses of subsamples of highly tax-sensitive borrowers. Furthermore, they align with well-documented tax awareness periods, such as the year-end deferral effect. Overall, our insights are relevant to market participants, assist in estimating revenue losses for tax authorities, and inform emerging policies on the tax treatment of digital assets.

Keywords: DeFi lending, tax planning, illiquidity, credit risk, digital assets regulation.

JEL classification: G15, G18, G23, M41, M48, K22, K34.

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1 Introduction

Tax planning plays a pivotal role in shaping financial decisions.[1] Although a substantial literature focuses on taxes and asset prices (Landsman and Shackelford, 1995; Klein, 1999, 2001; Jin, 2006; Dai, Maydew, Shackelford, and Zhang, 2008), individual tax deferral strategies are less well understood (Ivkovic, Poterba, and Weisbenner, 2005), especially related to borrowing behavior.[2] Nevertheless, growing anecdotal evidence indicates that individuals, particularly the wealthy, benefit from borrowing against pledged assets to preserve their holdings, meet liquidity or leverage needs, and defer tax payments on capital gains triggered by the sale of such assets, as borrowed funds are not subject to taxation. For example, Elon Musk leveraged his SpaceX stock holdings to secure financing for the acquisition of Twitter.[3] This strategy not only garners media attention and academic interest but also raises significant regulatory concerns.[4]

To address this gap, our study leverages a unique setting in decentralized finance (DeFi) lending where traders' portfolios, borrowing and pledging decisions, and high-frequency trading activities are transparently available at the individual level.[5] We exploit an exogenous increase in tax scrutiny on cryptocurrency gains brought about by the Internal Revenue Service (IRS) imposing increased third-party reporting requirements on crypto brokers in November 2021. Following this shock, we document that U.S. borrowers, on average, reduce triggering taxable transactions compared to their international peers. This effect is pronounced among borrowers with high leverage and returns, and those borrowing stablecoins to

[1]For example, at the corporate level, tax benefits can influence the use of debt in capital structure decisions (DeAngelo and Masulis, 1980; Graham, 2000; Jacob and Jacob, 2013; Heider and Ljungqvist, 2015).

[2]This gap primarily arises from 1) limited access to data on individual traders' borrowing and lending in the equity market due to stringent privacy regulations and confidentiality concerns; 2) incentives for tax-motivated borrowing are not directly disclosed—for example, Beyoncé used her financial assets to secure a substantial mortgage, financing part of her Malibu property purchase rather than paying the full amount upfront.

[3]Musk's decision to borrow against highly-appreciated assets to generate liquidity rather than selling them allows for the deferral of capital gains taxes, as borrowed funds are not subject to taxation. Alternatively, selling the stock would trigger significant capital gains taxes and could also generate signaling concerns that could depress Tesla's share price.

[4]Recently proposed regulations in the United States have targeted the so-called "buy, borrow, die" strategy, in which wealthy taxpayers with highly appreciated assets avoid paying capital gains taxes by borrowing against those assets to fund their living expenses. For example, Sen. Ron Wyden's proposed Billionaires Income Tax Act aims to address this issue. By borrowing instead of liquidating during their lifetimes, these taxpayers avoid paying capital gains taxes on their appreciated assets and can further shield their beneficiaries from taxation due to the step-up in basis upon death, as specified under IRC Sec. 1014.

[5]A nascent literature has been exploiting the transparency and relevance of the DeFi ecosystem (e.g., Rabetti, 2023; Cong, Prasad, and Rabetti, 2024; Harvey and Rabetti, 2024).

lock in profits.[6] Consequently, decreased trading activity induces market illiquidity. More importantly, we demonstrate that tax-planning-induced illiquidity amplifies the number and value of defaulted loans, suggesting a plausible causal link between tax-motivated borrowing and credit risk via the illiquidity channel. Our conclusions are supported by various robustness checks, alternative specifications, and empirical strategies addressing endogeneity concerns.

Analyzing individuals' tax planning is inherently challenging due to the limited accessibility and completeness of their trading information (e.g., confidentiality concerns and/or the inability to observe borrowers' tax incentives). Traditional datasets used for tax analysis, for example, capture only the outcomes of investor trades and fail to account for the full spectrum of assets available to individuals (Feldstein, Slemrod, and Yitzhaki, 1980; Poterba, 2002; Carrillo, Pomeranz, and Singhal, 2017; Alstadsæter, Johannesen, and Zucman, 2018). In contrast, decentralized finance (DeFi) markets, defined by minimal regulation, decentralization, and anonymity, offer a unique quasi-laboratory setting to study traders' responses to tax policies (Marian, 2013; Auer, Cornelli, and Frost, 2020). Additionally, publicly available, granular retail-based transaction and portfolio data enable unprecedented empirical insights on individuals' borrowing behavior.

Another advantage of our setting is that tax planning holds particular appeal in less regulated markets (Hanlon, Maydew, and Saavedra, 2015). Cryptocurrency markets with loose regulations have seen explosive growth in recent years (Makarov and Schoar, 2020; Harvey and Rabetti, 2024) and are becoming increasingly integrated with traditional financial systems (Cong et al., 2024). With Bitcoin recently reaching the $100,000 mark and with a crypto-friendly U.S. administration on the horizon, the stage appears set for continued activity in cryptocurrency markets.[7] Although prior literature demonstrates that crypto traders harvest losses during periods of price declines (Cong, Landsman, Maydew, and Rabetti, 2023),

[6] Stablecoins, which are pegged to the U.S. dollar, provide a low-volatility medium of exchange and are widely used in DeFi for liquidity and collateralization. Thus, borrowing stablecoins against other crypto assets is a potential method for monetizing paper profits while deferring tax payments. Investors can lock in returns by borrowing stablecoins, either to generate liquidity or as a strategy to defer tax payments.

[7] For instance, Donald Trump suggested that the Federal Reserve will stock $15 Trillion cryptocurrencies under his upcoming presidential mandate (See https://www.forbes.com/sites/digital-assets/2024/12/14/trump-confirms-bitcoin-reserve-plans-15-trillion-price-boom-predicted/). Gary Gensler, known for fighting against crypto has recently stepped down as SEC commissioner (See https://apnews.com/article/sec-gensler-trump-bitcoin-12ed76558301728004741a6cb39f372).

their strategies for deferring capital gains during periods of price increases remain unexamined. Therefore, our setting not only offers data advantages to assess individuals' tax-motivated borrowing more broadly, but also provides us with timely insights into the burgeoning market of cryptocurrencies.

We conduct our analysis using DeFi lending data between 2020 and 2022 from *Venus*, the largest lending platform on the Binance Smart Chain (BSC), which accounted for 11% of the total DeFi lending market share during our research period. The dataset includes approximately 13 million transactions across the 15 most popular cryptocurrencies. After excluding accounts with low trading frequency, the dataset comprises over 1.3 million borrowers and a total of $133.34 million in defaulted loans, of which $99.27 million remains in defunct accounts.[8] Given the absence of demographic information in blockchain data, we derive three non-mutually exclusive measures for U.S. traders based on transaction timing, the holding of stablecoins regulated by U.S. authorities, and abnormal transaction behavior during U.S.-exclusive holidays.

We begin our analysis by examining the asymmetric tax implications a trader encounters when choosing between selling a high-valued asset, which constitutes a taxable event under IRS regulations, and borrowing against it, which is classified as a non-taxable event by the IRS.[9] Focusing on the IRS's announcement of increased crypto trade reporting requirements and stricter tax scrutiny on cryptocurrency brokers in November 2021, we document a notable 24.5% decline in the likelihood of trading assets among U.S. borrowers compared to their non-U.S. counterparts. This result is more pronounced under a stricter identification of U.S. taxpayers.[10] Traders borrowing stablecoins—a way to monetize profits while deferring tax payments—exhibit an additional 23.0% decline in trading activity. Furthermore, a one-percent increase in loan-to-value (LTV) ratio reduces trading by 12.0%, consistent with these traders being more risk averse to changing regulations or having larger, more profitable positions that create greater incentives to avoid taxes on their gains. A one-percent higher rate of return leads to a 16.3% decrease, consistent with these traders having larger potential taxable gains to shelter from tax.

[8] Defunct accounts are defined as those held by borrowers who cease all transactions after their loans become defaulted.

[9] It is worth noting that whether a trader borrows to address liquidity needs or leverage requirements is irrelevant in this context, as assets pledged as collateral are not taxable in either case.

[10] That is, we obtain stronger results when identifying U.S. taxpayers as a trader that trades during the U.S. daily time, has behavioral responses to U.S. exclusive holidays, and holds crypto assets pegged to U.S. dollars.

Overall, our findings suggest that U.S.-borrowers, especially those with higher leverage and higher returns, are more likely to engage in tax planning. Further, those traders borrowing stablcoins–presumably to monetize their appreciated crypto assets without triggering a tax event– exhibit greater sensitivity to stricter tax scrutiny. Noticeably, the probability of trading assets serves as a measure of market liquidity, enabling us to extend our analysis to understand how tax-motivated trading affects credit risk through the illiqudiity channel. Notwithstanding prior research examining how liquidity constraints and volatility affect credit risk, defaults, and financial instability (e.g., Acharya and Johnson, 2005; Brunnermeier and Pedersen, 2009), the role of tax-motivated borrowing to our knowledge has been so-far overlooked.

We continue our analysis by documenting a significant negative relation between illiquidity and credit risk, where credit risk is measured by the number and value of defaulted loans on the DeFi lending platform. However, this relation could be mechanical, as an increase in defaulted loans discourages traders from participating in the market, thereby exacerbating liquidity constraints. To establish causality, we leverage the IRS exogenous tax shock as an instrumental variable. This shock directly impacts market liquidity—by increasing the cost of asset trading—without directly influencing loan liquidations. As documented earlier, this shock induces U.S. borrowers to become more reluctant to trigger taxable events, thereby reducing the probability of asset trading.

Our results indicate that a one-percent increase in tax-induced illiquidity is associated with a 11.2% increase in the number of defaulted accounts and a 39.6% increase in defaulted loan values. Similarly, a one-percent increase in illiquidity is associated with a 5.6% increase in the number of defunct accounts and an 17.4% increase in the total loan value in defunct accounts. Restricting our sample to accounts with over one year of transaction history to capture tax-sensitive traders (i.e., those seeking to convert short-term capital gains positions into tax-preferenced long-term positions), we document accentuated negative effects. Results are also economically significant: a standard deviation increase in illiquidity leads to a $350.05 increase in defaulted loans for each borrower, or a 2.70-fold increase in defaulted loan value. Overall, our results are consistent with borrowers' reluctance to trigger taxable events, in response to increased tax scrutiny, increasing illiquidity, and aggravating credit risk. More importantly, we reveal a novel channel of potential market-wide consequences stemming from tax-planning-induced illiquidity.

However, our inferences hinge on the proper validation of the tax-sensitiveness of traders in our setting. We, therefore, conduct a battery of additional tests as follows. First, we observe that borrowers tend to engage in asset-trading activities more after holding a borrowing position for one year, effectively deferring tax payments from higher short-term to lower long-term capital gains tax rates. Second, borrowers with more complex portfolios are more likely to engage in trading once the one-year period has expired. Third, we examine tax-motivated year-end deferral effects (e.g., Jones, Lee, and Apenbrink, 1991; Poterba, 2002; Cong et al., 2023). Specifically, we document a notable decline in asset-trading activities during December, particularly in the final week, aligning with prior observations that investors often refrain from selling assets at year-end to defer capital gains taxes. Finally, given prevalent tax-motivated borrowing in the DeFi lending setting, we estimate potential losses of revenue to the U.S. tax authority. U.S. borrowers, on average, save $3,357.42 per year in unrealized capital gains taxes. This result is economically significant, as the total saved corresponds to 17 percent of their trading portfolios in the period. Altogether, these tests suggest prevalent tax-sensitive behavior in our setting, especially during periods when borrowers are less likely to benefit from trading.

Our study offers novel insights into the dynamics of individual tax-motivated borrowing, its impact on illiquidity, and the subsequent implications for individual credit risks, thereby contributing to at least three strands of literature. First, the paper adds to the literature on tax-motivated borrowing. Prior work has examined how corporate tax benefits influence debt usage in capital structure decisions (e.g., DeAngelo and Masulis, 1980; Graham, 2000; Jacob and Jacob, 2013; Heider and Ljungqvist, 2015) and how policies like mortgage interest deductions lower borrowing costs and encourage debt-financed homeownership (Glaeser and Shapiro, 2003; LaCour-Little, 2007; Poterba and Sinai, 2008). Although tax-motivated borrowing has been extensively studied at the corporate and household levels, its implications for individual traders remain less understood (Ivkovic et al., 2005). This paper sheds light on how tax-motivated borrowing in DeFi markets impacts liquidity and credit risk. By linking tax policy changes to investor behavior, this paper contributes to the literature on tax-driven market dynamics and provides insights for regulators addressing these inefficiencies.

Second, the paper contributes to the literature on tax arbitrage strategies and the lock-in effect of taxes, highlighting their impact on liquidity.[11] Research on the lock-in effects of taxes highlights how capital gains taxes distort investor behavior and market dynamics (Klein, 1999, 2001; Dai et al., 2008). Similar tax-induced barriers arise in other settings, such as U.S. multinational firms deferring repatriation of foreign earnings to avoid taxation, creating so-called "locked-out" profits (Foley, Hartzell, Titman, and Twite, 2007; Hanlon, Lester, and Verdi, 2015; Edwards, Kravet, and Wilson, 2016; Faulkender, Hankins, and Petersen, 2019; De Simone, Piotroski, and Tomy, 2019; Darmouni and Mota, 2024). For individuals, tax-motivated investor behavior adversely impacts market liquidity, as the lock-in effect discourages asset sales to avoid capital gains taxes, reducing immediate liquidity (Blouin, Raedy, and Shackelford, 2003; Ivkovic et al., 2005; Sialm and Starks, 2012). Poterba and Samwick (2003) and Barberis and Xiong (2009) show that tax considerations encourage holding riskier assets and deferring gains, further reducing market efficiency. Our findings extend this literature by identifying a new lock-in effect in DeFi, where investors borrow stablecoins to monetize gains while avoiding taxable swaps. This behavior significantly reduces liquidity and creates tax-driven distortions, particularly among traders with high loan-to-value ratios and returns, highlighting how tax policies shape liquidity and investor behavior.

Finally, this study examines spillover effects of tax-driven borrowing on credit risks through illiquidity channels, highlighting regulatory challenges. Prior research has linked liquidity constraints and volatility to increased credit risk, defaults, and financial instability (Acharya and Johnson, 2005; Brunnermeier and Pedersen, 2009). We establish a plausible causal link between tax-induced illiquidity and the rise of defaulted loans and defunct accounts in DeFi lending markets. Our findings show that heightened tax scrutiny exacerbates credit risks, as reduced market liquidity increases default probabilities and defunct accounts. Additionally, we provide timely insights into emerging regulatory challenges. Although current U.S. policy proposals, such as wash-sale rules and enhanced reporting, focus on centralized crypto

[11] For instance, sheltering high-tax assets in retirement accounts has been shown to enhance tax efficiency (Black, 1980; Tepper, 1981). Subsequent work examined optimal asset locations for minimizing tax burdens (Dammon, Spatt, and Zhang, 2004; Huang, 2008) and explored corporate tax planning strategies, such as the effects of tax shelters on earnings manipulation and abnormal returns (Desai and Dharmapala, 2006, 2009; Wilson, 2009; Kim, Li, and Zhang, 2011).

platforms, they may push investors toward decentralized alternatives, where enforcement is more challenging. Our analysis underscores the need for regulators to consider DeFi-specific dynamics when addressing tax-driven market inefficiencies.

Our study is structured as follows. Section 2 describes the institutional background and dataset utilized in this study. Section 3 discusses the hypotheses and conducts the empirical analysis. Section 4 estimates losses to tax authorities and discusses tax-planning dynamics. Section 5 concludes.

2 Institutional Background

2.1 Decentralized Finance (DeFi)

Decentralized Finance (DeFi) represents a rapidly evolving ecosystem of financial services and applications built on blockchain technology, governed by smart contracts deployed on platforms such as Ethereum. DeFi extends the functionality of blockchain beyond simple peer-to-peer transactions to include a wide range of complex financial activities. These include lending, borrowing, trading through decentralized exchanges (DEXs), earning returns via yield farming, and creating synthetic assets. The primary appeal of DeFi lies in its ability to offer open, permissionless, and globally accessible financial services, presenting a decentralized alternative to traditional financial systems. By eliminating intermediaries, DeFi reduces reliance on centralized authorities and mitigates barriers related to identity verification, geographical restrictions, and limited access to conventional banking infrastructure. This transformative approach democratizes finance and fosters innovation in a transparent, programmable environment.

2.2 DeFi Lending

Decentralized lending represents a cornerstone of the Decentralized Finance (DeFi) ecosystem, enabling individuals to lend and borrow funds directly through blockchain technology without reliance on traditional financial intermediaries such as banks. Operating on principles of transparency, security, and inclusivity, DeFi lending platforms use smart contracts to automate transactions, enforce lending terms, and eliminate the need for centralized oversight.

Borrowers in DeFi lending typically provide cryptocurrency collateral, which is locked in a smart contract to secure the loan. This collateral is returned upon full repayment of the loan but is subject to liquidation if the loan-to-value (LTV) ratio exceeds predefined thresholds. The LTV ratio measures the proportion of the loan's outstanding principal relative to the value of its collateral. To mitigate credit risk, DeFi loans are over-collateralized, with platforms such as Venus enforcing a maximum LTV of 0.6. When the LTV breaches this limit, the collateral may be seized and liquidated to cover the outstanding debt. Over-collateralization remains fundamental to ensuring the stability and resilience of decentralized lending platforms.

Interest rates within DeFi lending are determined algorithmically, adjusting dynamically based on real-time supply and demand for assets (details in Appendix A). This market-driven rate mechanism efficiently aligns lending capacity with borrowing needs. Additionally, some platforms offer staking rewards, providing borrowers and lenders with economic incentives to lock their assets within the ecosystem for extended periods.

Unlike traditional financial systems, DeFi lending platforms are permissionless, allowing global participation without credit checks or identity verification. All transactions are recorded on the blockchain, ensuring transparency, immutability, and auditability. This open-access framework democratizes financial services, enabling users worldwide to engage in lending and borrowing activities without the regulatory, financial, or geographic barriers that constrain access in traditional finance.

2.3 Smart Contracts

Smart contracts are self-executing agreements with the terms of the contract directly encoded into lines of code. These contracts are written in blockchain programming languages, such as Solidity for Ethereum, and operate on decentralized and distributed blockchain networks. Ethereum, as the first blockchain to pioneer smart contract functionality, remains the leading platform for smart contract applications, although this technology has expanded to several other blockchains in recent years.

Smart contracts facilitate transactions and agreements between anonymous parties without the need for centralized authorities, legal systems, or external enforcement mechanisms. They offer key benefits such as transparency, traceability, and irreversibility, ensuring that all transactions are recorded on an immutable blockchain ledger. By automating the execution of agreements once predetermined conditions are met, smart contracts reduce the reliance on traditional legal contracts, minimizing disputes and streamlining processes. This automation also reduces costs compared to conventional financial systems, making applications using smart contracts a compelling alternative in the fintech space.

By eliminating intermediaries and reducing operational inefficiencies, smart contracts hold the potential to revolutionize financial services. They enable a range of decentralized applications (dApps) across lending, trading, and insurance, providing more efficient and accessible financial solutions. As highlighted by Harvey, Ramachandran, and Santoro (2020) and Harvey and Rabetti (2024), the adoption of smart contracts represents a transformative shift in finance, promising to reshape traditional systems with lower costs, enhanced security, and improved transparency.

2.4 Data

We take Venus, the largest DeFi lending platform on the Binance Smart Chain (BSC) as our research platform. It accounts for 11% of the total market share in DeFi lending during our search period. We collected all kinds of transactions (including exchange, borrowing, lending, liquidations, repayment, transfers, etc.) on Venus from November 12, 2020, to July 31, 2022. Transactions and logs from Venus are first queried through the Binance Smart Chain (BSC) API. We then use Python and Web3 libraries to parse the retrieved logs and on-chain addresses into structured data for analysis. We focus on the top 15 tokens in Venus based on their market values.[12] Next, we exclude accounts that have never owned or borrowed any tokens and those with fewer than ten transaction records, ensuring meaningful engagement in DeFi activities and minimizing noise from insufficiently active accounts[13]

[12]See Appendix B for summary statistics of the supply and demand of these tokens in Venus.

[13]The threshold of ten transactions aligns with thresholds used in blockchain research to capture consistent activity patterns (e.g., Benkert, Gallo, and Wattenhofer (2020)). Accounts with fewer transactions may lack sufficient data for reliable behavioral or financial insights.

Table 1 reports the summary statistics and Appendix C shows the description of each variable used in this study. Our analysis includes 1,356,111 daily borrower observations, with an average of 2,275 unique borrowers on each day. About 3% of the traders on our platform experience loan defaults, leading to a total of $133.34 million in defaulted loans. About two-thirds of the defaulted traders ceased any transactions after defaulting, resulting in an aggregate $88.27 million of defunct and defaulted loans.[14] Other variables capturing trader characteristics are shown at the daily × trader level. The significant standard deviation of diversity suggests a considerable cross-sectional variation in risk appetite and financial diversification. Moreover, traders vary in profitability. Although the average trader's rate of return is extremely low, the considerable standard deviation indicates that a few traders incur substantial profits. The key outcome variable in this paper, the probability of trading assets for each borrower per day, is 5% on average.

[Table 1]

3 Hypothesis Formation and Empirical Analysis

Preferential long-term capital gains tax rates incentivize investors to hold an investment for more than one year, saving up to 17 percentage points in taxes at top federal rates. The tax-deferring investor could satisfy her liquidity needs by pledging the asset as collateral and borrowing, as borrowed funds are not taxable income to the recipient.

The crypto space provides similar tax planning opportunities. The borrowing response to capital gains taxes may be more attractive with crypto due to the lack of credit score penalties and minimal regulatory oversight. First, lending and borrowing in the crypto space are characterized by high decentralization, anonymity, and automation, with contracting conducted without financial intermediaries through a few lines of code. Defaulting on loans does not impact borrowers' credit scores like in traditional markets. The trader could abandon the defaulted account and borrow from a new account at no cost. This differs from conventional markets, where defaulted borrowers may face a higher borrowing cost. Second, unlike

[14] These total values are calculated by summing the daily outstanding loan values in the platform over the duration it remains in default, meaning a single defaulted loan could contribute multiple entries across the corresponding dates.

traditional markets, the crypto space is still highly unregulated. Although the IRS has been pushing guidance and increasing scrutiny on crypto trading tax reporting, other areas of the crypto space, such as DeFi lending, are largely outside the tax authority's radar—likely because of the fast pace of innovation in these markets and the lack of a well-defined security regulation for crypto assets.

3.1 Tax Deferring Strategy

Figure 1 depicts an example of a trader monetizing appreciated asset values within the DeFi market. Consider a trader that buys Bitcoin (BTC) at *t0*. BTC's price appreciates from *t0* to *t1*, and if this trader decides to sell her position, she would have made $10,000 in profits. However, selling crypto is taxable, so her net profit after taxes depends on her tax rate. If the sale occurs less than a year after she purchased BTC, capital gains taxes can exceed 40%.[15] Instead, this trader can monetize her paper profits by pledging her BTCs as collateral into a DeFi lending pool in exchange for stablecoins. Stablecoins are highly liquid assets with stable valuations that can easily be converted to cash. Thus, the trader successfully avoids capital gains taxes by pledging BTCs as collateral and receiving liquidity via stablecoins instead of selling the BTCs in the market.

Once she holds onto the underlying BTC for over a year, she can undo her transactions and sell her BTC at *t2*. Because she has not triggered any taxable event since *t0*, any tax due will be at long-term capital gains rates, which are lower than short-term rates.[16]

[Figure 1]

[15]The top federal short-term capital gains tax rate in 2024 is 37%. Taxpayers with incomes greater than $200,000 if filing single and $250,000 if married filing jointly additionally pay a 3.8% Net Investment Income Tax. State taxes may also apply.

[16]The top federal long-term capital gains tax rate in 2024 is 20% plus Net Investment Income Taxes of 3.8% for higher-income taxpayers. State taxes may also apply.

3.2 Hypothesis 1: Stricter Tax Reporting Requirements Increase Tax-induced Illiquidity

We test the hypothesis that stricter tax reporting requirements reduce crypto trading activity, thereby increasing tax-induced market illiquidity. To evaluate this hypothesis, we leverage an exogenous shock from the IRS's enforcement of more stringent reporting requirements for crypto gains. This hypothesis focuses on the direct impact of tax regulation on market liquidity, which we measure through the probability of asset-swapping activities, distinct from borrowing transactions. Trading activity serves as a robust proxy for liquidity, because a reduction in trading frequency or volume reflects diminished market participation and reduced ease of asset exchange.

The Infrastructure Investment and Jobs Act, enacted in November 2021, marks a significant development in U.S. tax policy, particularly for cryptocurrency markets. This legislation imposes new reporting obligations on cryptocurrency brokers, analogous to the requirements for traditional stockbrokers reporting stock trades. The primary objective is to enhance tax compliance by ensuring the U.S. tax enforcement agency—the Internal Revenue Service (IRS)—has greater visibility into cryptocurrency transactions.

Under the new provisions, cryptocurrency exchanges and wallet providers, classified as "brokers," must report customer transactions directly to the IRS. This broadens the scope of reporting beyond previous policies, which primarily focused on large-scale traders, to encompass all users of centralized finance (CeFi) platforms. U.S.-based cryptocurrency traders will now receive Form 1099-B from brokers, detailing taxable gains and losses from their transactions. This mandatory reporting reduces opportunities for traders to under-report or overlook their tax obligations, as the IRS will independently possess the same transactional data.

We assume that the Act represents a signal for a broader effort to enhance transparency and compliance of the cryptocurrency markets as a whole, driving tax-driven borrowers to take more aggressive tax planning strategies. This regulatory shift is a pivotal moment in the evolution of cryptocurrency markets in the U.S., signaling greater integration of digital assets into the traditional financial regulatory framework.

The Act compels both brokers and traders to engage with cryptocurrency in a more structured and compliant manner, reshaping the dynamics of tax reporting and transparency in the digital asset ecosystem.

We employ a difference-in-differences (DiD) approach, utilizing a logit regression model as outlined in Equation 1. The treatment group consists of U.S. traders, while traders from other countries serve as the control group because they are not subject to the new U.S. reporting rules and any consequential enforcement effects. We incorporate several control variables[17] as well as trader fixed effects to account for trader-specific characteristics. Additionally, some specifications include daily fixed effects to capture time-specific factors that may influence all traders.

$$\mathbb{I}(\text{Asset trading}_{i,t}) = \alpha_0 + \beta_1(\text{US trader}_i) + \beta_2(\text{Post}_t) + \beta_3(\text{US trader}_i \times \text{Post}_t) + \Theta_{i,t} + \Lambda_t + \epsilon_{i,t} \tag{1}$$

We classify traders as U.S. taxpayers if they conduct more than 50% of their transactions between 2 PM and 10 PM Eastern Time. During this period, it is 11 AM to 7 PM Pacific Time, 8 PM to 4 AM the next day in Central European Time (CET), and 2 AM to 10 AM in China Standard Time (CST). This method is based on the assumption that transactions happening during daylight periods in the U.S. are more likely to be US-taxable transactions.

However, we still can not distinguish U.S. taxpayers from other traders in the same time zone, such as traders in Canada and Latin America. We add two additional methods to identify U.S. taxpayers: the asset method and the holiday method. For the asset method, we select the traders who hold the stablecoins USDC or BUSD. Compared with other stablecoins, these two are heavily regulated in the US, closely linked to U.S. financial standards, and popular among U.S. traders. For the holiday method, we select traders trading abnormally during Thanksgiving in the U.S. (double or half as many transactions) while having normal transaction behavior during Thanksgiving in Canada.[18] In the following empirical analysis, we identify U.S. taxpayers as those who satisfy both the daylight and asset method or those

[17] The control variables include loan-to-value (LTV) ratio, the natural logarithm of the total value, asset diversity, asset volatility, and rate of return.

[18] Canadian Thanksgiving time is different from other countries. Although the U.S. shares the same time of Thanksgiving with other countries, most of them are not in the same time zone as the U.S.

who satisfy all three criteria. The robustness checks on U.S. taxpayers are shown in Appendix D, where we demonstrate that our definition successfully distinguishes U.S. traders from Canadian, Chinese, and Latin American traders.

To prepare for our subsequent analysis, we exclusively focus on borrowers, who not only pledge but also borrow against their pledged assets.[19] One advantage of the DeFi lending market that we leverage is its distinct tax treatment: trading is taxable, whereas borrowing and repaying a loan are not. Specifically, we examine whether these investors opt to engage in trading assets, which is taxable. Trading activities in the DeFi lending market involve exchanging, selling, and liquidating. By deferring exchanging or selling assets, these investors can benefit from postponing the taxable event, allowing for the potential classification of the capital gain as long-term, which would then be subject to preferential tax rates.

Figure 2 illustrates a parallel trend in asset-trading activities prior to the tax shock for U.S. and non-U.S. taxpayers. The figure demonstrates a notable decrease in exchange activities following the implementation of stricter crypto market disclosure requirements by the IRS.

[Figure 2]

We present the DiD result in Table 2. The estimated DiD coefficients reveal that the tax shock reduced the asset-trading probability by 1.1% to 24.3%, with the larger effects observed under a stricter definition of U.S. traders.

[Table 2]

We next analyze the heterogeneous effects of trader characteristics on the shock of stricter tax reporting. From the result shown in Table 3, traders borrowing stablecoins experience a significant additional reduction of 23.0% in their trading probability. Stablecoins, which are pegged to the U.S. dollar, are often regarded as the DeFi market's equivalent of cash. Borrowing stablecoins against other cryptocurrency assets, which account for 46.8% of all borrowings, is a common strategy for monetizing the profits of appreciated crypto assets without triggering a taxable event. This behavior seems particularly impacted

[19]Borrowers are also lenders in DeFi lending market because of the collateralization. Their assets pledged to the pool could be borrowed by others. See Appendix E for a detailed description of the borrowing mechanics.

by the regulatory changes. Similarly, traders with a one-percent higher LTV experience an incremental 12.0% decrease in trading activity. Heavily leveraged traders may become more risk-averse, particularly when faced with new regulations like stricter tax reporting on crypto gains are introduced. These traders also often have larger, more profitable positions, providing greater incentives for these traders to avoid taxes on their gains. Traders with a one-percent higher rate of return experience a 16.3% decrease in trading activity, consistent with these traders being sensitive to the higher tax costs associated with higher returns.

These results suggest that the regulatory shock disproportionately affects traders with higher LTVs and returns, for whom tax planning strategies are more advantageous. Furthermore, borrowers who are already locking in profits by borrowing stablecoins or are more likely to engage in tax planning.

[Table 3]

3.3 Hypothesis 2: Tax-induced Illiquidity Increases Credit Risk

How might an inactive crypto market impact participant welfare? Our hypothesis posits that tax-induced illiquidity, stemming from reduced asset-trading activities, increases credit risk—a key indicator of lending market stability and functionality—by raising the likelihood of borrower defaults. This dynamic not only harms lenders but also affects borrowers who, in this setting, serve as lenders by pledging collateral to secure loans and earn interest on their pledged assets.

First, we conduct an OLS regression analysis of the trading probability against defaulted loans and identify a significant negative relation. However, liquidity is endogenous to defaulted loans. An increase in defaulted loans could discourage traders from participating in the market, exacerbating liquidity constraints. Thus, to test this causal inference, we leverage an instrumental variable (IV) model, which provide consistent and asymptotically unbiased parameter estimates, offering a more robust approach to dealing with endogeneity, as presented in Equation 2.

$$
\begin{aligned}
&IV_{i,t}\text{:} \quad \text{US trader}_i \times \text{Post}_t + \text{US trader}_i \\
&\text{First Stage:} \quad \mathbb{I}(\text{Liquidity}_{i,t}) = \alpha_0 + \beta(IV_{i,t}) + \Theta_{i,t} + \Lambda_t + \epsilon_{i,t} \\
&\text{Second Stage:} \quad \text{Defaulted loans} = \alpha_i + \beta_1(\widehat{\text{Liquidity}}_{i,t}) + \Theta_{i,t} + \Lambda_t + \epsilon_{i,t},
\end{aligned} \tag{2}
$$

where instruments in our model include the treatment indicator and its interaction with the post-shock time indicator. In the second stage, we include four credit risk measures: 1) the number of defaulted loans; 2) the logarithm of the value of defaulted loans; 3) the number of defaulted loans associated with defunct accounts; 4) the logarithm of the value of defaulted loans tied to defunct accounts.

Our instruments—the U.S. trader indicator and its interaction with the post-shock time indicator—are strong and valid. The instruments are relevant because they are correlated with liquidity, which is influenced by the tax-induced illiquidity shock affecting U.S.-based traders. The joint significance test indicates that the instruments are highly relevant for predicting the endogenous variable liquidity, with an F-statistic of 25.24. The exclusion restriction holds because these instruments are unlikely to have a direct effect on borrower defaults except through their impact on liquidity. Specifically, U.S. traders do not exhibit higher default rates relative to others but significantly reduce swapping activities following the shock. The GMM models successfully pass the overidentification tests, with p-values exceeding 0.10, indicating no evidence of exclusion restriction violations.

Table 4 Panel A and Panel B explore the relation between reduced liquidity and defaulted loans. Results suggest that the absence of crypto exchange activity due to tax planning is associated with an 11.2% increase in the number of unliquidated accounts and a 39.6% increase in the value of unliquidated loans in the GMM model. The magnitudes in the IV model are different from OLS because the IV models capture the Local Average Treatment Effect (LATE), focusing on U.S. traders (compliers) who adjusted their behavior following the tax regulation. In contrast, the OLS results reflect the Average Treatment Effect (ATE) for the entire population, averaging the effects across compliers, always-takers, and never-takers (Jiang, 2017).

Moreover, the inclusion of defunct accounts in our analysis is crucial. Approximately two-thirds of defaulted accounts cease all transactions following default. These defunct accounts represent an extreme outcome of illiquidity-induced credit risk, where traders completely withdraw from the market. Understanding these cases provides valuable insights into the long-term effects of market illiquidity on trader behavior and systemic risk. The results reveal a significant effect on these accounts: the absence of crypto exchange activity due to tax planning corresponds to a 5.6% increase in the number of defunct accounts in the GMM model. A one-percent decrease in the probability of trading assets is linked to a 17.4% increase in defaulted loan value.

[Table 4 Panel A and Panel B]

The plausible mechanism behind this causal link is that stricter tax regulations, while not directly increasing loan defaults, have likely prompted more investors to delay the liquidation of these loans in order to avoid triggering a taxable event. Even when it is profitable to liquidate before taxes, if the associated tax burden of liquidation outweighs the pre-tax financial benefits, traders are unwilling to trigger this liquidation. This delay reduces market liquidity and limits arbitrage opportunities, further amplifying the negative impact on credit risk.

4 Losses to the U.S. Tax Authority and Extended Discussion

This section examines the consequences of tax-induced behaviors and market inefficiencies. First, we present validity tests to establish the presence of tax-driven borrowing within the DeFi ecosystem, analyzing how traders strategically adjust their borrowing and trading patterns to optimize tax obligations. Next, we quantify the tax revenue losses incurred by the U.S. Treasury due to deferred tax payments arising from crypto trading strategies. Finally, we explore the broader implications of market frictions, such as inefficient liquidation processes and smart-contract vulnerabilities, which amplify losses and undermine the operational stability of DeFi platforms.

4.1 Tax-Motivated Trading Behavior and Illiquidity

This section reveals the validity tests for tax-driven borrowing. The analysis is crucial as it illuminates the behavioral shifts induced by tax considerations in DeFi markets. By identifying how traders adjust their activities to optimize tax obligations—both through increased trading after transitioning to long-term tax obligations and reduced activity at year-end—the findings provide valuable insights into the interplay between tax policies and market liquidity.

First, as shown in Table 5, we find that traders increase their asset-trading activities upon holding their position for over one year. We find that once an account clearly represents a long-term capital gains tax obligation, it is associated with a 89.0% increase in the likelihood of engaging in crypto trading. This increase is more pronounced among traders with higher total portfolio value, greater asset volatility and diversity, and lower rates of return, suggesting that traders with larger and more complex portfolios are better equipped to engage in tax optimization behaviors. Those with lower returns may exhibit heightened sensitivity to tax considerations, as they seek to preserve value in the face of weaker performance. Among these borrowers, those with higher LTV ratios experience an additional 81.4% increase in the likelihood of swapping. Borrowers with greater asset values demonstrate a further 82.8% increase, while those with higher asset volatility face an additional 94.3% increase. Borrowers with greater asset diversity demonstrate a further 178.8% increase, while those with a higher rate of return face an additional 1.8% decrease. These findings suggest that traders actively adjust their strategies to leverage potential tax benefits associated with long-term positions, aligning with broader tax optimization behavior.

[Table 5]

Second, as shown in Table 6, consistent with prior literature, we observe a notable decline in trading activities among traders during December, particularly in the final week of the month, as they seek to defer tax payments to the following year. Specifically, traders execute 1.1% fewer transactions on average in December, with an additional 1.3% reduction in the last week of the month. This effect is particularly pronounced among traders with greater asset diversity and volatility, suggesting that those with more complex portfolios are better positioned to exploit these strategies effectively. The pronounced reduction in activity during the year-end aligns with existing literature (e.g., Dyl (1977); Poterba and Weisbenner (2001)) suggesting that investors often avoid selling assets at year-end to defer capital gains taxes. The interaction terms in the models further underscore how trader-specific characteristics modulate this behavior, emphasizing the impact of tax-driven motivations on trading patterns.

[Table 6]

4.2 Tax Loss Estimates for U.S. Traders

In this section, we estimate the tax revenue loss to the U.S. Treasury due to deferred tax obligations by U.S. taxpayers using the Venus platform. Our analysis focuses on accounts meeting all U.S. taxpayer criteria. To calculate tax savings, we apply the progressive tax rates for capital gains, as outlined in Table 7. We assume traders are single filers holding their positions for the historical twelve-month period. The estimated tax savings from holding crypto assets rather than selling them are summarized in Table 8.

[Table 7 and Table 8]

The tables summarize the tax savings generated by U.S. taxpayers through borrowing in a one-year period on Venus from January 1, 2021, to January 1, 2022. The tax savings are calculated based on a rolling one-year collection of profits for each account, using short- and long-term tax rates. Tax payments presented in U.S. dollars are calculated using short- and long-term tax rates respectively, with a focus on major tokens such as Bitcoin (BTC) and Ethereum (ETH).

The average annual tax saving per borrower from deferring short-term capital gains to long-term capital gains tax obligations is estimated at $3,357.42. The distribution of these savings is highly skewed, with a significant concentration among the top traders. The top 5% tax-saving traders saved on average $6,003,139.72 in taxes during this period.

To identify the cryptocurrencies contributing most to these tax savings, we focus on BTC and ETH. Our findings show that tax savings from these tokens are higher than those across all tokens during our research period, as the average returns from other tokens were close to zero or negative. This finding highlights the significant role of BTC and ETH in the estimates of tax revenue losses.

4.3 Losses to Market Frictions

In addition to the tax-induced credit risks that we analyzed, tax-deferred borrowing in DeFi lending carries inherent risks. These include potential market frictions, such as smart contract vulnerabilities, inefficient liquidation mechanisms, and exposure to high volatility in collateral assets, which can lead to substantial financial losses for borrowers and lenders alike.[20]

During our research period, Venus allowed borrowers to pledge highly volatile cryptocurrencies as collateral, creating liquidation frictions for traders unwilling to hold such assets, given their potential for dramatic overnight price drops. Risky collateralization is a main driver for under-liquidation during DeFi market downturns. As evidence, during the market crash of Venus, there were 9 profitable defaulted loans backed by stablecoins with an average market loss of $1,252, compared to 563 loans backed by depreciating tokens with an average market loss of $170,803.

Figure 3 captures the evolution of estimated market losses attributable to all defaulted loans (i.e., those loans for which the ratio of principal to pledged asset values exceeds the liquidation LTV threshold, or LTV > 0.6) and only those defaulted loans that can not be profitably liquidated (i.e., those loans for which the value of the principal exceeds pledged asset values, or LTV > 1), along with their differential, representing profitable defaulted loans, expressed in U.S. Dollars. The dashed line represents loans for which liquidation is still profitable absent taxes. Although liquidation would trigger a taxable event to the lock-in lenders, the other participants (e.g., the arbitrageurs) failed to exploit the profitable liquidation opportunities mainly due to smart contract flaws.

[Figure 3]

[20] See e.g. Harvey and Rabetti (2024), Cong et al. (2024), Adams, Wan, and Zinsmeister (2023), Campello, Jin, Rabetti, and Saleh (2024), and Capponi and Jia (2024). Traders are also exposed to other risks in the crypto space, including cyberattacks (Cong, Harvey, Rabetti, and Wu (2024)), crypto scams (Cong, Grauer, Rabetti, and Updegrave (2023)), illicit activities (Amiram, Jørgensen, and Rabetti (2022)) project failure (Lyandres, Palazzo, and Rabetti (2022)), and misinformation (Amiram, Lyandres, and Rabetti (2024)).

Notably, the market loss reached its peak during the DeFi boom, followed by a sharp contraction in the post-boom period. As the market declines further, these defaulted loans—including profitable ones—persisted on the platform, ultimately leading to permanent losses for both the platform and its participants. This trend underscores how risky collateralization, resulting in a lack of sufficient arbitrageurs, gradually erodes the profitable liquidation opportunities that over-collateralization rules are designed to facilitate.

5 Conclusion

This study empirically examines tax-motivated borrowing and its consequences in the DeFi lending market. Our findings reveal that stricter tax regulations significantly reduce market liquidity in DeFi markets, as evidenced by a decrease in the probability of asset trading of at least 1.1%, with larger effects for U.S. traders under stricter definitions and those engaging in stablecoin borrowing. This reduction in liquidity contributes to a rise in defaulted loans and defunct accounts, as demonstrated by our instrumental variable analysis: a one-percent decrease in trading probability leads to substantial increases of 5.6% the number of defunct accounts. Although tax planning does not directly increase credit risk, the tax-motivated borrowing strategy could reduce market liquidity and hinder efficient liquidations. Investors employing tax planning strategies may delay the liquidation of defaulted loans even if the liquidation is profitable before taxes, as liquidation requires asset trading and triggers costly capital gains tax payments. A liquidation could become unprofitable if not liquidated immediately because the over-collateralization status could disappear quickly in this volatile market.

Our study acknowledges several limitations. The identifications of U.S taxpayers and estimates of lost U.S. tax revenues presented herein rely on simplifying assumptions and model specifications. Moreover, as the DeFi market and crypto regulations evolve rapidly, our estimates may only represent the specific sample period we examine. Ongoing regulatory developments could significantly alter the mechanics of DeFi lending and the tax treatment of related transactions, warranting future research to assess their impact.

Despite these limitations, this study makes several important contributions to the academic literature and policy discourse. We present the first large-scale empirical analysis of tax planning in DeFi lending markets, shedding light on the prevalence and magnitude of such behavior. By doing so, we highlight how tax-motivated borrowing in DeFi reduces market liquidity, increases credit risks, and poses regulatory challenges. Tax deferral strategies, such as borrowing stablecoins to avoid taxable events, significantly distort liquidity, particularly among traders with high loan-to-value ratios and substantial returns. This behavior exacerbates defaults and defunct accounts, destabilizing lending markets. Our findings emphasize the need for tailored regulatory frameworks to address the unique inefficiencies and risks of decentralized platforms.

References

Acharya, V. V. and T. C. Johnson (2005). Liquidity risk and correlation risk: A clinical study of the general motors and ford downgrade of may 2005. *Financial Analysts Journal 63*(5), 64–75.

Adams, A., X. Wan, and N. Zinsmeister (2023). Uniswap V3 TWAP oracles in proof of stake. Working paper. Available here.

Alstadsæter, A., N. Johannesen, and G. Zucman (2018). Who owns the wealth in tax havens? macro evidence and implications for global inequality. *Journal of Public Economics 162*, 89–100.

Amiram, D., B. N. Jørgensen, and D. Rabetti (2022). Coins for bombs: The predictability of on-chain transfers for terrorist attacks. *Journal of Accounting Research 60*(2), 427–466.

Amiram, D., E. Lyandres, and D. Rabetti (2024). Trading volume manipulation and competition among centralized crypto exchanges. Forthcoming. Available here. *Management Science*.

Auer, R., G. Cornelli, and J. Frost (2020, September). Bitcoin and stablecoins: Risks and opportunities. *BIS Quarterly Review*, 55–70.

Barberis, N. and W. Xiong (2009). What drives the disposition effect? an analysis of a long-standing preference-based explanation. *Journal of Finance 64*(2), 751–784.

Benkert, R., F. Gallo, and R. Wattenhofer (2020). Detecting malicious accounts in permissionless blockchains. *Applied Network Science 5*(3).

Black, F. (1980). The tax consequences of long-run pension policy. *Financial Analysts Journal 36*(4), 21–28.

Blouin, J. L., J. S. Raedy, and D. A. Shackelford (2003). Capital gains taxes and equity trading: Empirical evidence. *Journal of Accounting Research 41*(4), 611–651.

Brunnermeier, M. K. and L. H. Pedersen (2009). Market liquidity and funding liquidity. *Review of Financial Studies 22*(6), 2201–2238.

Campello, M., P. Jin, D. Rabetti, and F. Saleh (2024). The market for crypto zombies: Under-collateralization in DeFi lending. National University of Singapore Working paper. Available here.

Capponi, A. and R. Jia (2024). Liquidity provision on blockchain-based decentralized exchanges. Working paper. Available here.

Carrillo, P., D. Pomeranz, and M. Singhal (2017). Dodging the taxman: Firm misreporting and limits to tax enforcement. *American Economic Journal: Applied Economics 9*(2), 144–164.

Cong, L., C. R. Harvey, D. Rabetti, and Z.-Y. Wu (2024). An anatomy of crypto-enabled cybercrimes. Forthcoming. Available here. *Management Science*.

Cong, L. W., K. Grauer, D. Rabetti, and H. Updegrave (2023). Blockchain forensics and crypto-related cybercrimes. Book chapters. World Scientific. Forthcoming. Available here.

Cong, L. W., W. Landsman, E. Maydew, and D. Rabetti (2023). Tax-loss harvesting with cryptocurrencies. *Journal of Accounting and Economics 76*(2–3), 101607.

Cong, L. W., E. Prasad, and D. Rabetti (2024). Financial and informational integration through decentralized oracle networks. Cornell University working paper. Available here.

Dai, Z., E. Maydew, D. A. Shackelford, and H. H. Zhang (2008). Capital gains taxes and asset prices: Capitalization or lock-in? *Journal of Finance 63*(2), 709–742.

Dammon, R. M., C. S. Spatt, and H. H. Zhang (2004). Optimal asset location and allocation with taxable and tax-deferred investing. *Journal of Finance 59*(3), 999–1037.

Darmouni, O. and L. Mota (2024). The savings of corporate giants. *The Review of Financial Studies 37*(10), 3024–3049.

De Simone, L., J. D. Piotroski, and R. E. Tomy (2019). Repatriation taxes and foreign cash holdings: The impact of anticipated tax reform. *The Review of Financial Studies 32*(8), 3105–3143.

DeAngelo, H. and R. W. Masulis (1980). Optimal capital structure under corporate and personal taxation. *Journal of Financial Economics 8*(1), 3–29.

Desai, M. A. and D. Dharmapala (2006). Corporate tax avoidance and high-powered incentives. *Journal of financial Economics 79*(1), 145–179.

Desai, M. A. and D. Dharmapala (2009). Earnings management, corporate tax shelters, and book-tax alignment. *National Tax Journal 62*(1), 169–186.

Dyl, E. A. (1977). Capital gains taxation and year-end stock market behavior. *Journal of Finance 32*(1), 165–175.

Edwards, A., T. Kravet, and R. Wilson (2016). Trapped cash and the profitability of foreign acquisitions. *Contemporary Accounting Research 33*(1), 44–77.

Faulkender, M. W., K. W. Hankins, and M. A. Petersen (2019). Understanding the rise in corporate cash: Precautionary savings or foreign taxes. *The Review of Financial Studies 32*(9), 3299–3334.

Feldstein, M., J. Slemrod, and S. Yitzhaki (1980). The effects of taxation on the selling of corporate stock and the realization of capital gains. *Quarterly Journal of Economics 94*(4), 777–791.

Foley, C. F., J. C. Hartzell, S. Titman, and G. Twite (2007). Why do firms hold so much cash? a tax-based explanation. *Journal of Financial Economics 86*(3), 579–607.

Glaeser, E. L. and J. M. Shapiro (2003). Urban growth in the 1990s: Is city living back? *Journal of Regional Science 43*(1), 139–165.

Graham, J. R. (2000). How big are the tax benefits of debt? *Journal of Finance 55*(5), 1901–1941.

Hanlon, M., R. Lester, and R. Verdi (2015). The effect of repatriation tax costs on us multinational investment. *Journal of Financial Economics 116*(1), 179–196.

Hanlon, M., E. L. Maydew, and D. Saavedra (2015). Incentives for tax planning and avoidance: Evidence from the field. *The Accounting Review 90*(3), 991–1023.

Harvey, C. R. and D. Rabetti (2024). International business and decentralized finance. *Journal of International Business Studies (Forthcoming)*.

Harvey, C. R., A. Ramachandran, and J. Santoro (2020). DeFi and the Future of Finance. Available here. *SSRN Electronic Journal*.

Heider, F. and A. Ljungqvist (2015). As certain as debt and taxes: Estimating the tax sensitivity of leverage from state tax changes. *Journal of Financial Economics 118*(3), 684–712.

Huang, J. (2008). Taxable and tax-deferred investing: a tax-arbitrage approach. *The Review of Financial Studies 21*(5), 2173–2207.

Ivkovic, Z., J. M. Poterba, and S. Weisbenner (2005). Tax-motivated trading by individual investors. *American Economic Review 95*(5), 1605–1630.

Jacob, M. and M. Jacob (2013). Taxation, dividends, and share repurchases: Taking evidence global. *Journal of Financial and Quantitative Analysis 48*(4), 1241–1269.

Jiang, W. (2017). Have instrumental variables brought us closer to the truth. *Review of Corporate Finance Studies 6*(2), 127–140.

Jin, L. (2006). Capital gains tax overhang and price pressure. *Journal of Finance 61*(3), 1399–1431.

Jones, S. L., W. Lee, and R. Apenbrink (1991). New evidence on the january effect before personal income taxes. *Journal of Finance 46*(5), 1909–1924.

Kim, J.-B., Y. Li, and L. Zhang (2011). Corporate tax avoidance and stock price crash risk: Firm-level analysis. *Journal of Financial Economics 100*(3), 639–662.

Klein, P. (1999). The capital gain lock-in effect and equilibrium returns. *Journal of Public Economics 71*(3), 355–378.

Klein, P. (2001). The capital gain lock-in effect and long-horizon return reversal. *Journal of Financial Economics 59*(1), 33–62.

LaCour-Little, M. (2007). The pricing of mortgages by brokers: An agency problem? *Journal of Real Estate Research 29*(4), 521–540.

Landsman, W. and D. Shackelford (1995). The lock-in effect of capital gains taxes: Evidence from the RJR Nabisco leveraged buyout. *National Tax Journal 48*(2), 245–259.

Lyandres, E., B. Palazzo, and D. Rabetti (2022). ICO success and post-ICO performance. *Management Science 68*(12), 8658–8679.

Makarov, I. and A. Schoar (2020). Trading and arbitrage in cryptocurrency markets. *Journal of Financial Economics 135*(2), 293–319.

Marian, O. (2013). Are cryptocurrencies super tax havens? *Michigan Law Review First Impressions 112*, 38–48.

Poterba, J. M. (2002). Taxation and portfolio structure: Issues and implications. *American Economic Review 92*(2), 360–365.

Poterba, J. M. and A. A. Samwick (2003). Taxation and household portfolio composition: Us evidence from the 1980s and 1990s. *Journal of Public Economics 87*(1), 5–38.

Poterba, J. M. and T. Sinai (2008). Tax expenditures for owner-occupied housing: Deductions for property taxes and mortgage interest and the exclusion of imputed rental income. *American Economic Review 98*(2), 84–89.

Poterba, J. M. and S. J. Weisbenner (2001). Capital gains tax rules, tax-loss trading, and turn-of-the-year returns. *Journal of Finance 56*(1), 353–368.

Rabetti, D. (2023). Auditing decentralized finance (DeFi) protocols. National University of Singapore working paper. Available here.

Sialm, C. and L. T. Starks (2012). Mutual fund tax clienteles. *Journal of Finance 67*(4), 1397–1422.

Tepper, I. (1981). Taxation and corporate pension policy. *Journal of Finance 36*(1), 1–13.

Wilson, R. J. (2009). An examination of corporate tax shelter participants. *The Accounting Review 84*(3), 969–999.

Figures

Figure 1. Mechanics of Tax Planning in DeFi Lending. The figure depicts an example of a trader monetizing appreciated asset values within the DeFi market. Consider a trader that buys Bitcoin (BTC) at *t0*. BTC's price appreciates from *t0* to *t1*, and if this trader decides to sell her position, she would have made $10,000 in profits. However, selling crypto is taxable, so her net profit after taxes depends on her tax rate. If the sale occurs less than a year after she purchased BTC, capital gains taxes can exceed 40%. Instead, this trader can monetize her paper profits by pledging her BTCs as collateral into a DeFi lending pool in exchange for stablecoins. Stablecoins are highly liquid assets with stable valuations that can easily be converted to cash. Thus, the trader successfully avoids capital gains taxes by pledging BTCs as collateral and receiving liquidity via stablecoins instead of selling the BTCs in the market.

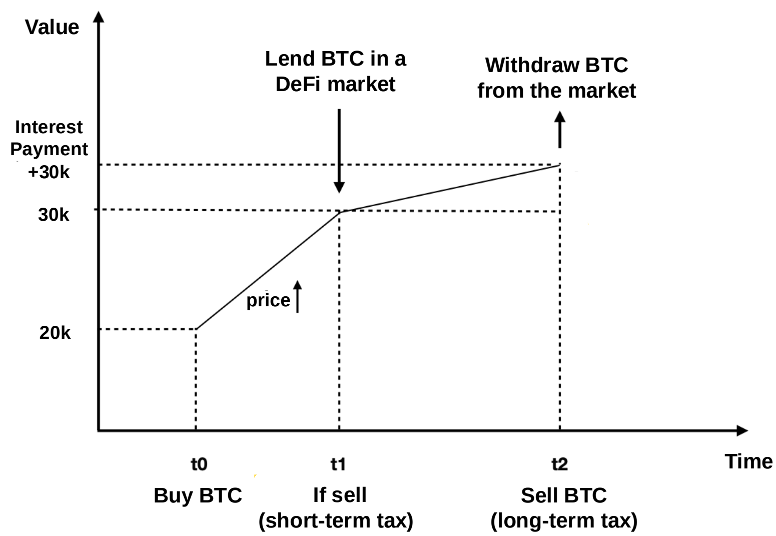


Figure 2. Time Dynamics Before and After the Tax Shock. The figure illustrates a parallel trend in asset-trading activities before and after the tax shock for U.S. and non-U.S. taxpayers. The figure demonstrates a notable decrease in liquidity following the implementation of stricter crypto market disclosure requirements by the IRS. The red vertical line indicates the timing of the tax shock.

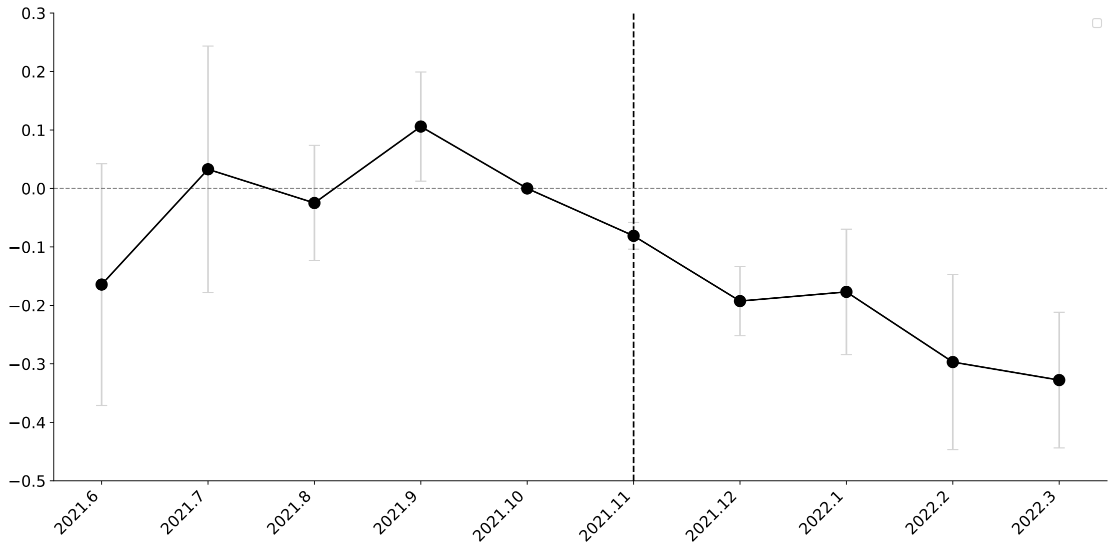
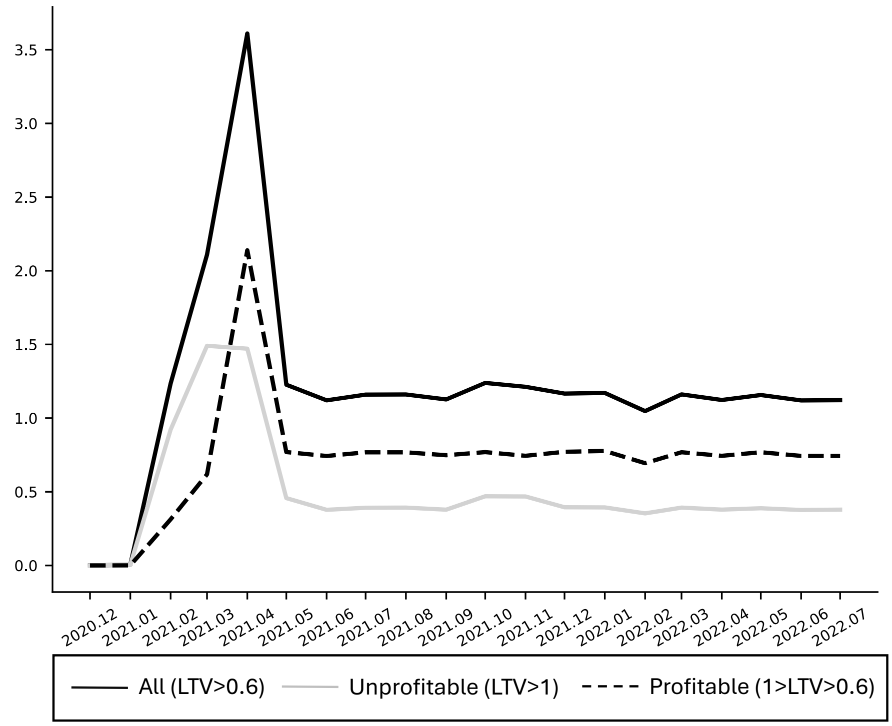


Figure 3. Market Losses Due to Defaulted Loans (in USD, Billion). The figure captures the evolution of estimated market losses attributable to all defaulted loans (i.e., the ratio of principal to pledged asset values exceeds the liquidation LTV threshold, or LTV > 0.6) and only those defaulted loans that can not be profitably liquidated (i.e., the value of the principal exceeds pledged asset values exceeds, or LTV > 1), along with their differential expressed in U.S. Dollars. The dashed line represents loans for which liquidation is still profitable absent taxes. Although liquidation would trigger a taxable event to the lock-in lenders, the other participants e.g. the arbitrageurs failed to liquidate them mainly due to smart contract flaws.



Tables

Table 1. Summary Statistics for Venus Platform and Borrower Characteristics. This table reports the summary statistics of all variables used in Venus. All variables correspond to the period from November 2020 to July 2022. We drop borrowers with fewer than ten transactions. Borrowers indicate the number of distinct borrowers per day during the research period, whereas defaulted borrowers are defined as those with an LTV exceeding 0.6 for at least seven days, with no subsequent borrowing or deposits. Thus, the total number represents not the count of unique borrowers but the count of unique borrower-occurrences. Defunct borrowers refer to inactive accounts. Defunct and defaulted borrowers are the those who stop transacting after their loans become defaulted. Defaulted loans are the total defaulted loan value of all borrowers. Defunct and defaulted loans are the total defaulted loan value of defunct borrowers. Total value represents the sum of the dollar value of all tokens held by each investor, while total borrowed value reflects the sum of the dollar value of all borrowed tokens. The loan-to-value ratio is calculated as the total borrowed value divided by the total value for each investor. Total value volatility captures the standard error of total values, respectively, over time after logarithmic transformation. Total asset diversity is calculated as the inverse of the standard deviation of the differences between individual asset values and their respective portfolio averages. The rate of return measures the daily return on all held tokens. Lastly, the trading probability per day represents the likelihood of any asset being traded for each borrower per day. LTV and rate of return have been winsorized at the 99.9th and 0.1th percentiles. Specifically, values above the 99.9th percentile are replaced with the 99.9th percentile value, and values below the 0.1th percentile are replaced with the 0.1th percentile value. See Appendix C for the description of all variables used in this study.

	Obs	Mean	St.D	Min	Median	Max
	Daily level					
Venus Platform						
Borrowers (total = 1,356,111 (#))	596	2,275.35	942.25	4.00	2,805.00	2,938.00
Defaulted borrowers (total = 43,247 (#))	590	73.18	31.77	1.00	82.00	115.00
Defunct borrowers (total = 105,155 (#))	590	178.23	138.15	1.00	157.00	428.00
Defunct and defaulted borrowers (total = 25,599 (#))	590	43.39	25.51	1.00	39.00	89.00
Defaulted loans (total = 133.34 (million ($)))	590	225,621.04	749,076.20	0.00	127,675.14	5,924,596.51
Defunct and defaulted loans (total = 88.27 (million ($)))	590	149,607.67	707,273.83	0.00	62602.35	5,823,756.75
	Daily × Trader level					
Total value ($)	1,356,111	1,039,494.19	42,412,097.21	0.00	5,385.16	2,326,000,531.92
Total borrowed value ($)	1,356,111	140,027.03	4,618,637.69	0.00	21.73	235,572,550.00
Loan-to-value ratio (%)	1,356,111	8,681.33	187,744.54	0.00	0.01	5,293,289.81
Total asset volatility ($)	1,356,111	1.29	0.84	0.09	1.08	6.25
Total asset diversity ($)	1,356,111	184,158.74	6,348,374.72	0.00	1,454.18	346,947,155.11
Rate of return (%)	1,356,111	-0.94	18.65	-515.88	0.00	1.99
Trade prob per day (%)	1,356,111	0.05	0.21	0.00	0.00	1.00

Table 2. Impact of Stricter Tax Rules on Asset Trading Probability (Liquidity): Evidence from Difference-in-Differences Analysis. This table presents the Diff-in-Diff results for Equation 1. The response variable is a binary indicator for trading asset activities. All specifications include trader fixed effects. Standard errors are clustered at the trader level. Omitted variables are excluded due to fixed effects or multicollinearity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Liquidity: Y = Prob. Asset Trading			
U.S. Trader × Post	−0.011*	−0.011*	−0.245***	−0.245***
	(0.006)	(0.006)	(0.057)	(0.057)
Post (Tax Shock)	−0.034***		−0.034***	
	(0.001)		(0.001)	
LTV	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
LN(Total Value)	0.006***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
Asset Diversity	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Rate of Return	−0.003***	−0.003***	−0.003***	−0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
U.S. Trader	Daylight, Asset		Daylight, Asset, Holiday	
Date FE	No	Yes	No	Yes
Trader FE	Yes	Yes	Yes	Yes
# Obs	762,696	762,696	762,696	762,696
Adjusted R^2	0.119	0.124	0.119	0.124

Table 3. Heterogeneous Effects of Stricter Tax Rules on Asset Trading Probability (Liquidity). This table examines the heterogeneous effects of stricter tax rules on traders' behavior, specifically focusing on borrowing stablecoins and varying levels of loan-to-value (LTV) ratios and rate of return. The response variable is a binary indicator representing trading asset activities. U.S. traders are defined based on the Daylight, Asset, and Holiday methods. All models include daily and trader fixed effects, with standard errors clustered at the trader level. Omitted variables are excluded due to fixed effects or multicollinearity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Liquidity: Y = Prob. Asset Trading		
DID × Borrow Stablecoins	−0.230***		
	(0.038)		
DID × LTV		−0.120***	
		(0.039)	
DID × Rate of Return			−0.163***
			(0.062)
DID	−0.194***	−0.242***	−0.117***
	(0.040)	(0.056)	(0.032)
LTV	−0.000*	−0.000*	−0.000
	(0.000)	(0.000)	(0.000)
LN(Total Value)	0.006***	0.006***	0.002***
	(0.000)	(0.000)	(0.000)
Asset Diversity	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
Rate of Return	−0.003***	−0.003***	0.568***
	(0.000)	(0.000)	(0.002)
U.S. Trader	Daylight, Asset, Holiday		
Date FE	Yes		
Trader FE	Yes		
# Obs	762,696	762,696	751,429
Adjusted R^2	0.124	0.124	0.501

Table 4 Panel A: Causal Relation Between Trading Asset Activities (Liquidity) and Defaulted Accounts (Credit Risk). This table examines the causal relation between crypto exchange activities and credit risk. The first three columns use the number of defaulted accounts as the response variable, while the last three columns use the defaulted loan value. U.S. traders are defined based on the Daylight, Asset, and Holiday methods. All models include daily and trader fixed effects, with standard errors clustered at the trader level. Omitted variables are excluded due to fixed effects or multicollinearity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Credit Risk					
	Y = Num. Defaulted Accounts			**Y = LN(Value of Defaulted Loans)**		
	OLS	2SLS	GMM	OLS	2SLS	GMM
Liquidity	−0.002	−0.123***	−0.112***	−0.004	−0.469***	−0.396***
	(0.002)	(0.028)	(0.026)	(0.007)	(0.172)	(0.153)
LTV	−0.000**	−0.000*	−0.000*	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LN(Total Value)	−0.000	−0.002	−0.002*	0.004	0.011*	0.009
	(0.001)	(0.001)	(0.001)	(0.003)	(0.006)	(0.006)
Asset Diversity	−0.000	−0.000	−0.000	0.000	−0.000	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset Volatility		−0.003	−0.003		−0.005	−0.005
		(0.004)	(0.004)		(0.019)	(0.019)
Rate of Return	0.000**	−0.001***	−0.001***	0.000	−0.003***	−0.003**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
U.S. Trader	Daylight, Asset, Holiday					
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Trader FE	Yes	Yes	Yes	Yes	Yes	Yes
# Obs	762,696	762,696	762,696	762,696	762,696	762,696
R-squared	0.568			0.457		
Overid p-value		0.02	0.107		0.144	0.200

Table 4 Panel B: Causal Relation Between Trading Asset Activities (Liquidity) and Defunct Accounts (Credit Risk). This table examines the causal relation between crypto exchange activities and credit risk. The first three columns use the number of defunct accounts as the response variable, while the last three columns use the defaulted value of defunct accounts. U.S. traders are defined based on the Daylight, Asset, and Holiday methods. All models include daily and trader fixed effects, with standard errors clustered at the trader level. Omitted variables are excluded due to fixed effects or multicollinearity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Credit Risk					
	Y = Num. Defunct Accounts			**Y = LN(Value of Defunct Accounts)**		
	OLS	2SLS	GMM	OLS	2SLS	GMM
Liquidity	−0.004***	−0.060***	−0.056***	−0.012**	−0.209***	−0.174***
	(0.001)	(0.013)	(0.012)	(0.005)	(0.071)	(0.063)
LTV	−0.000***	−0.000*	−0.000*	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LN(Total Value)	−0.001***	−0.001	−0.001	−0.001	0.005	0.004
	(0.000)	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)
Asset Diversity	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset Volatility		−0.001	−0.001		0.005	0.004
		(0.003)	(0.003)		(0.012)	(0.012)
Rate of Return	0.000	−0.000***	−0.000***	0.000	−0.002***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
U.S. Trader	Daylight, Asset, Holiday					
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Trader FE	Yes	Yes	Yes	Yes	Yes	Yes
# Obs	762,696	762,696	762,696	762,696	762,696	762,696
R-squared	0.396			0.324		
Overid p-value		0.03	0.095		0.148	0.148

Table 5: Liquidity Changes After Transition to Long-term Account Status. This table analyzes the relation between changes in account status (from short-term to long-term) and asset trading activities. The response variable is the likelihood of asset trading activities. All models incorporate daily and daily and trader fixed effects, with standard errors clustered at the trader level. Omitted variables are excluded due to fixed effects or multicollinearity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Liquidity: Y = Prob. Asset Trading					
Switch to Long-term	0.890***					
	(0.003)					
Switch × LTV		0.814***				
		(0.003)				
Switch × LN(Total Value)			0.828***			
			(0.003)			
Switch × Asset Volatility				0.943***		
				(0.004)		
Switch × Asset Diversity					1.788***	
					(0.007)	
Switch × Rate of Return						−0.018***
						(0.000)
LTV	−0.000**	−0.000**	−0.000**	−0.000**	−0.000**	−0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LN(Total Value)	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset Diversity	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rate of Return	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Trader FE	Yes	Yes	Yes	Yes	Yes	Yes
# Obs	674,422	674,422	674,422	674,422	674,422	665,804
Adjusted R^2	0.121	0.121	0.121	0.121	0.121	0.121

Table 6: Year-End Deferral Effect on Trading Asset Activities (Liquidity). This table analyzes the relation between the December dummy, or the dummy for the final week of December, and asset trading activities. The response variable is the likelihood of asset trading activities. All models include trader fixed effect, with standard errors clustered at the trader level. Omitted variables are excluded due to fixed effects or multicollinearity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Liquidity: Y = Prob. Asset Trading					
	(1)	(2)	(3)	(4)	(5)	(6)
December	−0.011***	−0.034***	−0.011***	−0.011***	−0.013***	−0.012***
	(0.001)	(0.004)	(0.001)	(0.001)	(0.002)	(0.001)
Last week of December	−0.013***	0.008**	−0.013***	−0.013***	−0.009***	−0.013***
	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)
December × LN(Total Value)		0.003***				
		(0.000)				
Last Week × LN(Total Value)		−0.002***				
		(0.000)				
December × LTV			0.000			
			(0.000)			
Last Week × LTV			0.000***			
			(0.000)			
December × Asset Diversity				−0.000***		
				(0.000)		
Last Week × Asset Diversity				−0.000***		
				(0.000)		
December × Asset Volatility					0.002	
					(0.001)	
Last Week × Asset Volatility					−0.003*	
					(0.002)	
December × Rate of Return						−0.000
						(0.000)
Last Week × Rate of Return						−0.000
						(0.000)
LTV	−0.000*	−0.000*	−0.000*	−0.000*	−0.000*	−0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LN(Total Value)	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset Diversity	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rate of Return	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trader FE	Yes	Yes	Yes	Yes	Yes	Yes
# Obs	762,696	762,696	762,696	762,696	762,696	762,696
Adjusted R^2	0.112	0.112	0.112	0.112	0.112	0.112

Table 7: Tax Rates for U.S. Traders: Short-term vs. Long-term Capital Gains. The short-term capital gain tax rates are aligned with the marginal income tax rates for various income ranges, emphasizing the progressive nature of taxation, which increases significantly for higher income levels. Conversely, the long-term capital gains tax rates are categorized into three simplified tiers: 0%, 15%, and 20%, showcasing potential tax savings for individuals who hold assets for over a year. This classification underscores the importance of strategic asset holding periods in minimizing tax liabilities. The income brackets for each category are outlined to illustrate the thresholds that determine the applicable tax rate. Traders can use this information to align their trading strategies with their financial goals and optimize their after-tax returns.

Short-term Tax	10% Up to $11,000	12% $11,000+ to $44,725	22% $44,725+ to $95,375	24% $95,375+ to $182,100
	32% $182,100+ to $231,250	35% $231,250+ to $578,125	37% Over $578,125	
Long-term Tax	0% Up to $44,625	15% $44,626 to $492,300	20% Over $492,300	

Table 8: Tax Planning Estimates for U.S. Traders. This table summarizes the total tax savings generated by U.S. taxpayers (accounts meeting all U.S. taxpayer criteria) through borrowing on the Venus platform between January 1, 2021, and January 1, 2022. Tax savings are estimated in U.S. dollars using tax rates for short- and long-term capital gains. We distinguish the tax savings from major tokens (ETH and BTC) to all tokens.

	Short-term		**Long-term**	
	Major	Total	Major	Total
Mean	14,433.387	6,422.636	6,647.862	3,065.214
SD	36,768.624	128,350.486	17,865.235	68,730.707
Min	0.000	0.000	0.000	0.000
Med	279.110	0.000	0.000	0.000
Max	343,382.201	3,152,256.810	169,637.981	1,687,948.580

Appendices for:
Tax Planning, Illiquidity, and Credit Risks: Evidence from DeFi Lending

A Interest Rate and Exchange Rate

In this section, we explain how the interest rates and exchange rates work in Venus. The borrowing interest rate and supplying interest rate are determined by the utilization rate of the vToken:

$$\begin{cases} R_{borrow,U} = aU + b \\ R_{supply,U} = R_{borrow,U} \times U \times (1 - reserve\_factor) \end{cases}$$

where $U = \frac{borrow}{supply}$ is the utilization rate, $a > 0$, $b \geq 0$, and $reserve\_factor \in [0, 1)$. a, b, and $reserve\_factor$ are set by the platform.

The exchange rate between a token and its vToken depends on the market supply and demand: $exchange\ rate = \frac{TotalAsset + TotalBorrow - TotalReserves}{TotalSupply}$. TotalAsset on the Venus platform is defined as the aggregate value of specific tokens that are locked in Venus, comprising both deposited and collateralized tokens. TotalBorrow is the summation of the borrowed tokens on the platform, while TotalReserves represents the collective amount of that particular token that is held in reserve. The exchange rate is used to calculate the value of the underlying asset when a user mints vTokens or redeems them back to the original asset. Higher demand for a particular asset on Venus can result in a higher exchange rate and interest rate, while a higher supply of an asset available for lending can result in lower rates. Thus, the platform could dynamically adjust the liquidity and avoid bank runs.

B Main vTokens at Venus platform

A distinctive feature of Venus lies in its ability to facilitate the minting of vTokens — derivative tokens that represent various cryptocurrencies. By pledging their cryptocurrency holdings, users can create vTokens (e.g. vBTC) that mirror these underlying assets (e.g. BTC). These vTokens, in turn, serve as collateral within the platform, forming the bedrock for borrowing activities. The platform's exchange, borrowing, and supplying rates are contingent on the dynamic equilibrium between demand and supply, explained earlier in this section and expanded in Appendix A. Users can set their preferred borrow-to-collateral value ratio, which ranges from 0 to 0.6. Venus also has its own governance token, XVS, which holders use to vote on governance decisions.

Table B1 reports the market values (in USD) of all liquidity transactions supplied to the lending platform by the borrowers during our research period. Panel B shows the borrowed values of each vToken. Major tokens such as vBTC and vETH have the greatest average total value and borrowed value among all tokens. The last column shows the number of lenders and borrowers of each token. Stablecoins (e.g., vUSDT, vBUSD, and vUSDC) attract the highest number of borrowers, whereas vBTC boasts the largest pool of lenders.

Table B1. Descriptive statistics of transactions of all vTokens. This table shows the descriptive statistics of the transactions of the top 15 vTokens in Venus. Panel A reports the statistics about the total values of each token of each transaction, while Panel B shows the borrowed values of each transaction. vBTC has the highest average transaction value in total and borrowed value, followed by vETH and vBNB. The last column shows the number of lenders and borrowers of each vToken in Venus during our research period. The most prevalent holding tokens are vBTC, vETH, and vXVS, followed by the stablecoins vBUSD, vUSDT, vUSDC, and vDOT. The most popular borrowed tokens are the stablecoins: vBUSD, vUSDT, and vUSDC, followed by vDOT, while the majority also borrow vBNB.

	Panel A: Total value (in USD) — Deposit Side				
	Mean (in 1k)	Std (in 10k)	Min	Max (in 100k)	Num.Lenders
vBNB	40.15	309.67	0.00	1,175.28	110,285
vXVS	4.78	22.14	0.00	650.36	90,951
vBTC	53.15	315.17	0.00	1,079.13	82,097
vETH	36.34	210.05	0.00	598.92	57,686
vUSDT	29.69	188.85	0.00	461.49	39,417
vDOT	4.84	25.88	0.00	96.99	29,805
vUSDC	17.30	164.42	0.00	878.53	20,835
vSXP	6.23	37.45	0.00	103.47	13,288
vLINK	1.64	15.99	0.00	57.91	12,697
vXRP	2.65	19.40	0.00	45.61	9,166
vLTC	0.99	6.27	0.00	16.99	6,309
vDAI	4.49	73.32	0.00	398.82	5,804
vFIL	0.52	4.21	0.00	16.25	4,961
vBCH	1.46	13.19	0.00	34.26	2,492
vBUSD	0.16	1.80	0.00	8.21	1,255

	Panel B: Borrowed value (in USD) — Demand Side				
	Mean (in 1k)	Std (in 10k)	Min	Max (in 100k)	Num.Borrowers
vUSDT	6.33	805.06	0.00	2,355.72	31,776
vUSDC	2.53	261.68	0.00	700.49	22,356
vBNB	7.50	635.00	0.00	2,186.36	20,553
vDAI	0.65	78.53	0.00	152.04	7,217
vBTC	3.58	467.80	0.00	2,300.88	3,724
vETH	1.48	148.19	0.00	371.41	3,623
vSXP	0.07	60.71	0.00	202.36	3,618
vDOT	0.15	18.63	0.00	45.94	1,967
vXRP	0.04	4.88	0.00	16.26	1,408
vLINK	0.07	7.24	0.00	14.68	1,290
vBCH	0.01	1.09	0.00	5.49	1,038
vLTC	0.02	2.48	0.00	5.77	1,010
vBUSD	0.00	0.78	0.00	2.92	852
vFIL	0.01	1.15	0.00	6.90	817
vXVS	0.00	0.97	0.00	5.50	58

C Variable Description

This section presents the variable definitions utilized in our analysis, detailing the construction and rationale behind each variable.

Table C1. The description table of variables

Variable	Description
Borrowed asset diversity ($)	The inverse of the standard deviation of the difference between individual borrowed asset value and the portfolio's overall borrowed value across time.
Borrowed value volatility ($)	The standard error of the total borrowed value of an account across time (take logarithms and then calculate std).
Defaulted traders (#)	The number of traders that have LTV>0.6 for at least 7 days, who, following the initial occurrence of this, neither borrowed additional assets nor made any further deposits.
Defunct traders (#)	The number of traders who cease any transactions after their loans become defaulted loans.
Liquidations (#)	The count of forced closures of loans due to inadequate collateral or margin requirements.
Loan-to-value ratio (%)	The ratio of total borrowed value divided by total value of each investor.
Long-term (twelve-month holding) tax (all assets ($))	The long-term tax on returns of holding all assets for twelve months.
Long-term (twelve-month holding) tax (major assets ($))	The long-term tax on returns of holding BTC and ETH assets for twelve months.
Rate of return (%)	The rate of return given all holding tokens.
Short-term (six-month holding) tax (all assets ($))	The short-term tax on returns of holding all assets for six months.
Short-term (six-month holding) tax (major assets ($))	The short-term tax on returns of holding BTC and ETH assets for six months.
Short-term (three-month holding) tax (all assets ($))	The short-term tax on returns of holding all assets for three months.
Short-term (three-month holding) tax (major assets ($))	The short-term tax on returns of holding BTC and ETH assets for three months.
Total asset diversity ($)	The inverse of the standard deviation of the difference between individual asset value and the portfolio's overall value across time.
Total borrowed value ($)	The sum of the dollar value of all borrowed tokens of each investor.
Total value ($)	The sum of the dollar value of all tokens of each investor.
Total value volatility ($)	The standard error of the total value of an investor across time (take logarithms and then calculate std).
Transaction frequency (#)	The ratio of transaction volume to the total number of days for which transactions are recorded.
Unique traders (#)	The number of unique traders in our research period.

D Validity Test on U.S. Taxpayers

To ensure the robustness of our methodology for identifying U.S. taxpayers, we utilize a strict definition of U.S. traders based on the intersection of the three identification criteria we proposed. The following subsections validate the effectiveness of our identification approach through behavioral patterns during culturally significant events.

1. Super Bowl

First, we analyze transaction behavior during the National Football League's Super Bowl. As expected, U.S. traders under our identification exhibited a significant decrease in transactions during the event compared with non-U.S. traders.

2. Canada Family Day

To test whether our identified U.S. traders can be distinguished from Canadian traders, we analyze their transaction behaviors during Canada Family Day. We find there is no significant change in their trading behaviors, suggesting that our identified U.S. traders are different from Canadian traders.

3. Chinese New Year

To validate differentiation from Chinese traders, we analyze transaction patterns during Chinese New Year (CNY). Non-U.S. traders exhibit a noticeable increase in transactions, further supporting the distinction.

4. Copa America Final

To ensure our model distinguishes U.S. traders from Latin American traders, we examine transaction patterns during the 2021 Copa America Final. There is no significant transaction change during this event, indicating successful differentiation from Latin American traders.

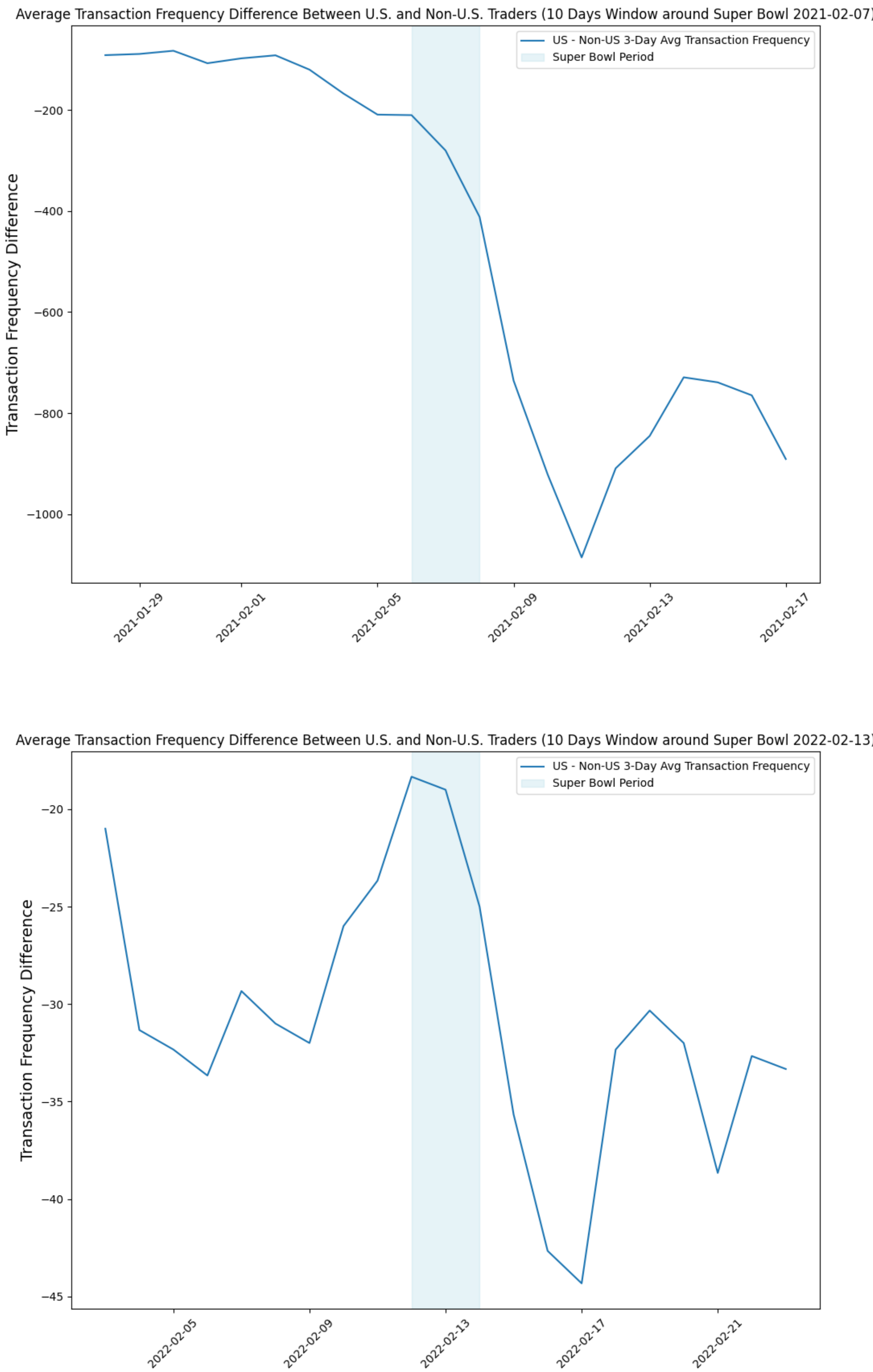
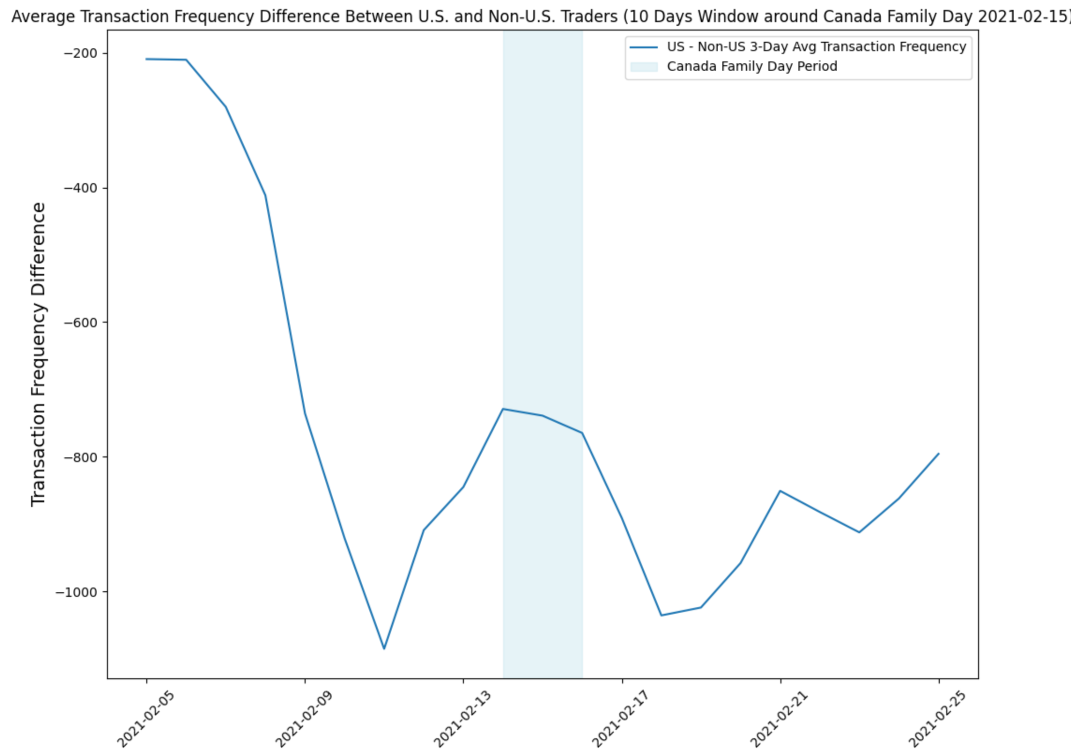


Figure A.1. Transaction patterns during the Super Bowl in 2021 and 2022.



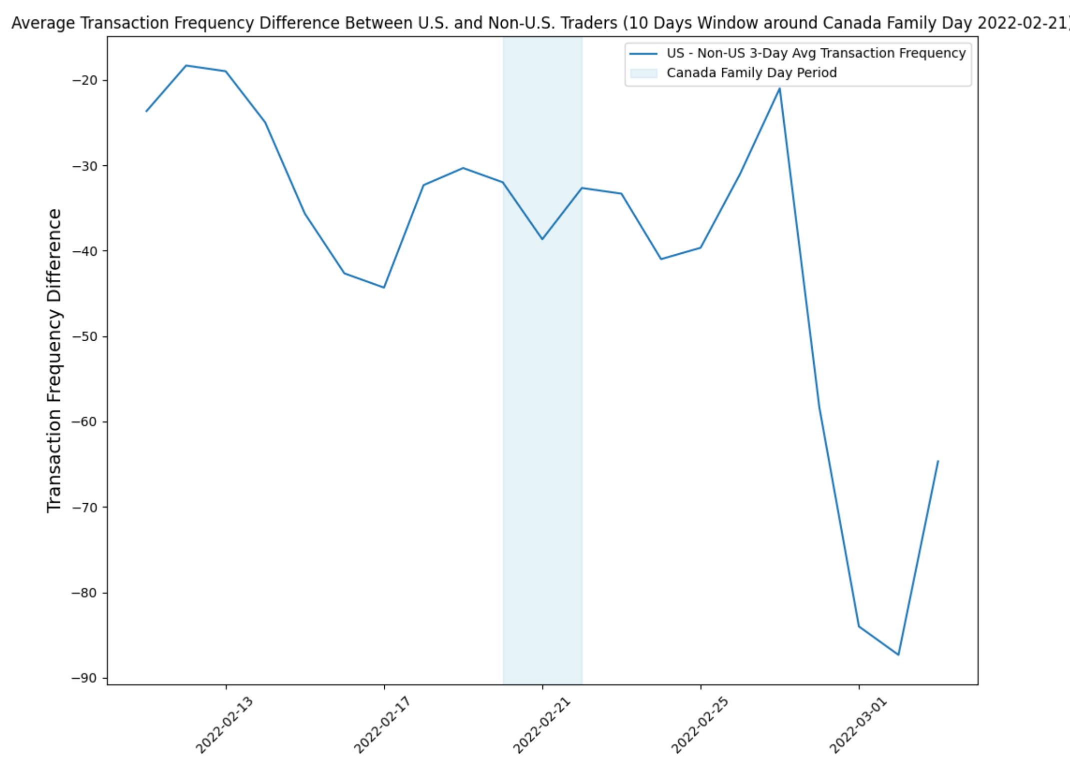


Figure A.2. Transaction patterns during Canada Family Day in 2021 and 2022.

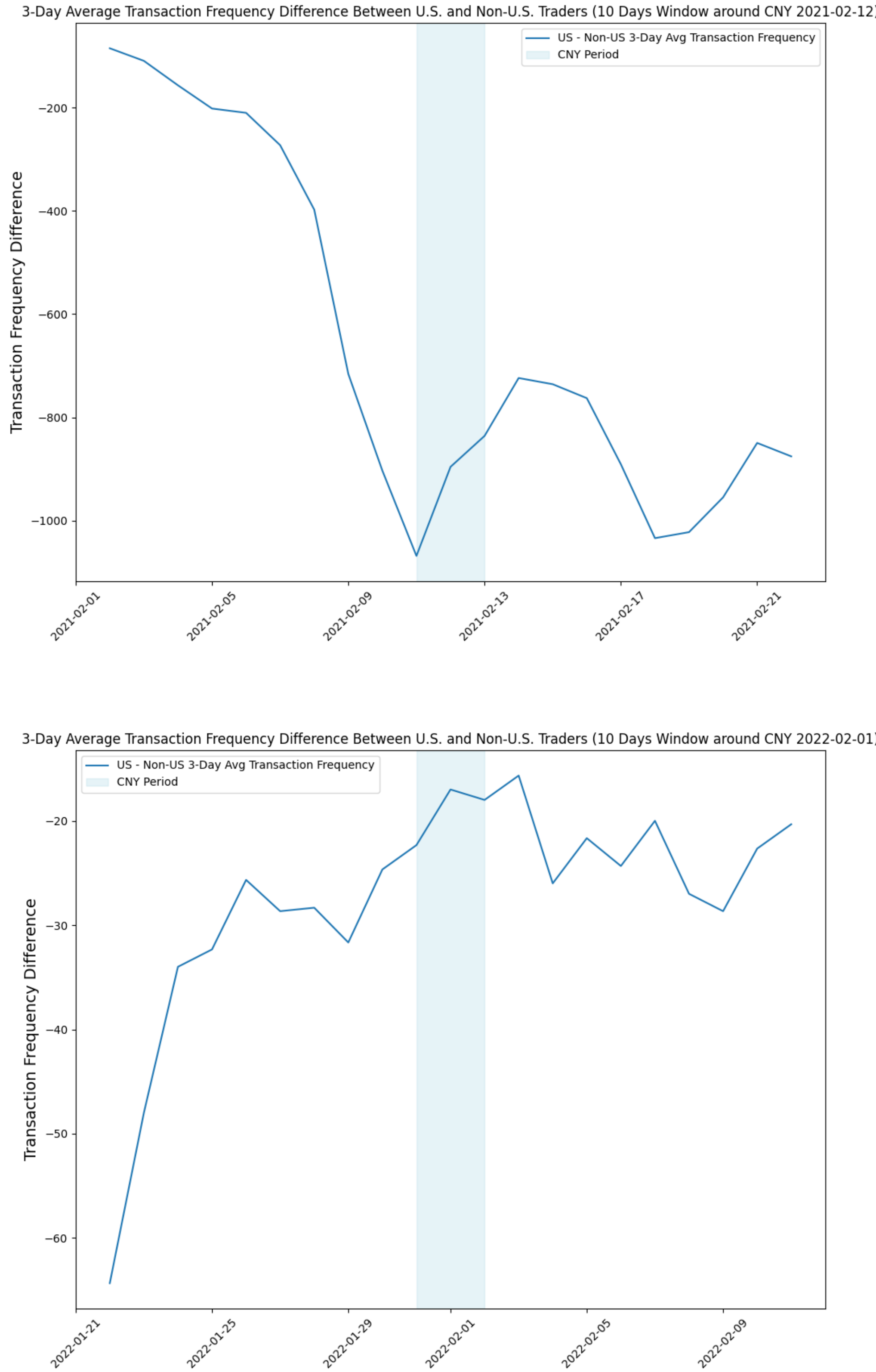


Figure A.3. Transaction patterns during Chinese New Year in 2021 and 2022.

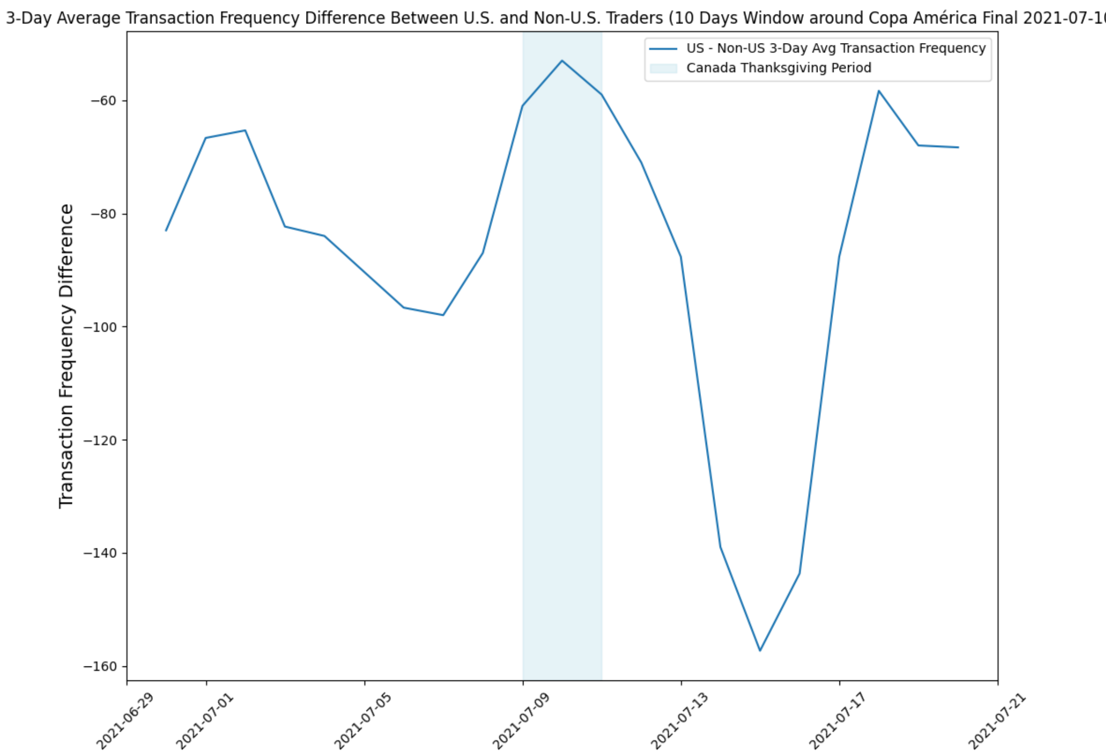
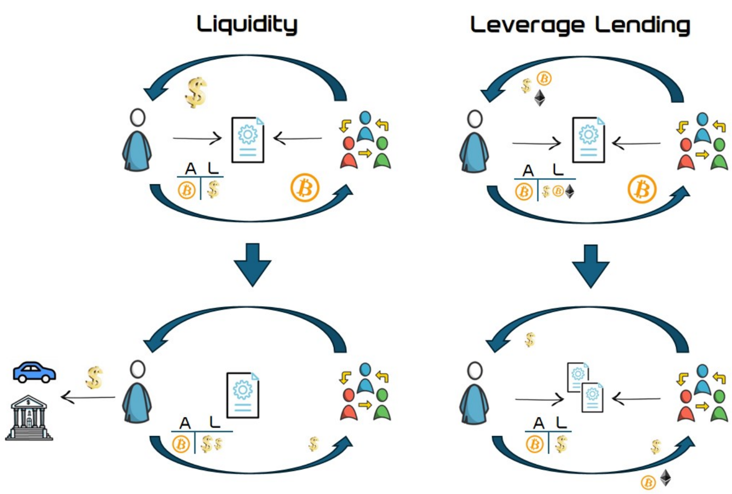


Figure A.4. Transaction patterns during the Copa America Final in 2021.

E DeFi Borrowing Strategies

Table E1 depicts two commonly used strategies by DeFi borrowers. The left-hand side of the figure illustrates a strategy known as the liquidity channel. In this strategy, the borrower pledges high-valued assets (BTC symbol) and receives stablecoins (dollar symbol). Her balance at the end of the first transaction consists of a cryptocurrency pledged as collateral as her asset, and stablecoins received from borrowing as her liability. In the second stage, this trader decides to spend her stablecoins, adding interest payments (small dollar sign) to her liability. This channel enables traders to defer the tax on a crypto gain triggered by selling while satisfying her liquidity needs at a cost of interest payment.

Table E1. Common DeFi borrowing strategies



Alternatively, if the trader wants to increase her LTV ratio or seeks to amplify her exposure to the original high-value asset to increase her rate of return, she can adopt a leveraged lending strategy. In this approach, the trader uses her high-value crypto assets as collateral to borrow a mix of other cryptocurrencies. These borrowed assets can then be lent back to the DeFi platform and earn interest.

By repeating this cycle of borrowing and lending multiple times, and considering the specific borrowing costs and lending interest rates on Venus, the interest payments and earned interest can effectively offset each other. This allows the trader to create a nearly cost-free asset-locking strategy. Ultimately, the trader achieves several objectives: she secures her original high-value asset, mitigates interest expenses, and potentially increases her exposure to other crypto assets, benefiting from any appreciation in their value.