Tax-Loss Harvesting with Cryptocurrencies*

Lin William Cong† Wayne Landsman‡ Edward Maydew§ Daniel Rabetti¶

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Abstract

We study investors' responses to increasing tax reporting awareness and scrutiny in the crypto markets. We document significant taxation effects on investors' behavior and preferences for crypto exchanges using novel data on retail investors' trading. In relation to international peers, U.S.-based investors decrease taxable events while exploiting tax-loss harvesting to balance portfolio losses. We further examine billions of trades on the trading books of large crypto exchanges and discover widespread tax-loss harvesting trades on U.S.-based crypto exchanges, amounting to billions of dollars in tax revenue losses for the government. Finally, we discuss ongoing anti-tax-loss harvesting proposals in anticipation of traders' likely reactions.

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†Cornell University, will.cong@cornell.edu.
‡University of North Carolina, wayne_landsman@unc.edu.
§University of North Carolina, edward_maydew@unc.edu.
¶Corresponding author: rabetti@mail.tau.ac.il. Coller School of Management, TAU. Ramat Aviv, 6997801, Israel.

1 Introduction

The market for cryptocurrencies and other crypto assets has grown from near non-existence in 2009 to almost $2 trillion of market capitalization in early 2022. Thirty-one percent of Americans aged 18-29 claim to have invested, traded, or used a cryptocurrency.[1] The rise and innovation of the crypto sector and decentralized finance (DeFi) have created a growing awareness and need for regulatory oversight. Nowhere is this oversight more pressing than in crypto transaction taxation because—against the backdrop of regulatory uncertainty—crypto assets provide significant tax planning opportunities for investors and significant challenges for tax authorities. Existing tax laws and regulations have been, and in many respects still are, ill-suited to deal effectively with the rise of cryptocurrencies. Policymakers are therefore proposing and enacting tax regulations with significant ramifications for crypto markets and investors. Yet, there is little empirical research to inform their decision-making.

To this end, we study one controversial yet widespread practice concerning crypto taxation, a form of "tax-loss harvesting" in which investors sell cryptocurrency that has decreased in value to "harvest" the losses for tax purposes, only to buy the same or a similar cryptocurrency shortly before or afterwards. What makes tax-loss harvesting in cryptocurrency particularly attractive to investors (during the period of our study) is the absence of the celebrated "wash sale" rule in crypto asset transactions that disallows losses for tax purposes from the sale of certain assets when the taxpayer has purchased the same asset within 30 days before or after the sale.[2] Although legislation

[1] Pew Research Center, see https://www.pewresearch.org/fact-tank/2021/11/11/16-of-americans-say-they-have-ever-invested-in-traded-or-used-cryptocurrency/

[2] Internal Revenue Code Sec. 1091. The wash sale tax rules apply to sales of stock and securities. Although there have been proposals to apply the wash sale rules to cryptocurrency, they have not made it into law by early 2022. For example, the act commonly referred to as the Build Back Better Act contained a provision that would subject digital assets to the wash sale rules, but the bill stalled in Congress.

has been introduced in response to anecdotal reports of tax-loss harvesting, there has been no study documenting tax-loss harvesting in crypto markets to date.[3] We provide, therefore, the first empirical evidence of systematic tax-loss harvesting and analyze how investors are likely to respond to changes in tax reporting, both of which are important to the development and implementation of effective anti-tax-loss-harvesting regulation.

To illustrate the usage of cryptocurrency in tax-loss harvesting, consider an investor facing a tax liability related to US $30,000 of gains from the sales of various investments in 2020. Included among the investor's unsold positions are ten Bitcoin purchased in February 2021 when it was trading at $10,000, for a total investment of $100,000. By April, when Bitcoin's price declined to $7,000, the investor decided to sell the ten Bitcoin for $70,000, "harvesting" a $30,000 tax loss, which can then be used to eliminate the tax liability from the investor's other investment gains. Afterwards, the investor immediately repurchases ten Bitcoin for $70,000, restoring the long position in the asset. Unlike other securities markets, the absence of wash sale rule for transactions in crypto markets enables crypto investors to "have their cake and eat it too," thereby harvesting their tax losses while maintaining their exposure to the asset.

To systematically analyze this phenomenon, we examine proprietary data on trading reports of large retail traders in crypto markets. We use a series of actions by tax authorities in recent years, such as enhanced regulation of crypto exchanges, clarification of tax treatment, the release

[3]Tax-loss harvesting can, and does, take place in assets (i.e., stocks and securities) that are subject to the wash sale rules, but doing so requires that investors reduce their exposure to the stock at a time when the investor may feel it is particularly undervalued. For example, suppose that instead of Bitcoin, the investor held Tesla stock, which was originally acquired in February 2020 at $180 per share, and was trading at only $150 per share by April 20, 2020. The investor can sell the Tesla stock, harvesting the $30 per share tax loss. However, because of the wash sale rule the investor would not be able to purchase Tesla stock during the 61-day period from March 21, 2020 to May 20, 2020. If the investor purchased Tesla stock in the first place believing it was undervalued, and regarded the $30 price drop as temporary, the investor may be reluctant to sell and remain out of the position when the price falls. Essentially, a "buy high, sell low" strategy may not be attractive to some investors, despite the tax benefits of harvesting the tax loss.

of educational material, and issuance of tax misreporting letters to U.S.-based traders (domestic) as exogenous shocks to traders' tax reporting awareness. We begin our assessment by comparing the responses of domestic traders to their international peers in the period before and after increased tax scrutiny. The results of these difference-in-differences regressions are the following. First, domestic traders decrease taxable events by reducing the quantity and volume traded while engaging more in tax-motivated trades towards the end of the tax year. Additionally, consistent with the tax-loss harvesting motive, domestic traders move from exchanges located in "crypto-friendly" (i.e., less regulated) and tax haven countries to U.S.-based crypto exchanges. Moreover, a portfolio composition analysis documents that harvesting trading (i.e., positions sold and bought within a month), rather than regular trading (i.e., positions sold and bought in more than a month), is the primary source of domestic traders' activities around the year-end.

We continue our analysis by assessing billions of trades on the trading books of large crypto exchanges to estimate the size of tax-loss harvesting in the United States. We use data provided by Kaiko, a digital assets data provider, that have been used in several recent studies (e.g., Amiram, Lyandres, and Rabetti, 2022; Makarov and Schoar, 2020). Whereas other studies examine wash trading as a tool used by crypto exchanges to create fake volume (e.g., Cong, Li, Tang, and Yang, 2022; Aloosh and Li, 2021; Amiram et al., 2022), we establish wash trading as a market outcome of tax-loss harvesting activity. Tax-loss harvesting activity, i.e., the sale and immediate repurchase of a losing position so that the loss can be used for tax purposes, is nothing but a wash trade where prices are unlikely to be affected (if executed at the mid-range price).

We focus our exchange data analysis on a highly liquid pair, Bitcoin (BTC), to either Tether (USDT) or U.S. Dollars (USD), to mitigate the incentives of endogenous wash trading (fake volume).[4] Less liquid coins are more likely to be the subject of fake volume to attract demand (Amiram et al., 2022). Similarly, we expect wash trades to work as a proxy for tax-loss harvesting in regulated exchanges because these exchanges are less likely to engage in volume inflation (Cong et al., 2022). Our findings corroborate these predictions: Regulated exchanges show spikes in wash trade activities during periods of significant Bitcoin devaluation. Using 2018 as our period for BTC price devaluation (approximately 70 percent relative to the previous year), we estimate nearly a hundred billion dollars in tax-loss harvesting volumes arising from trades on regulated and U.S.-based crypto exchanges. Applying a BTC price devaluation during 2018 and an average capital gains tax rate of 30%, we estimate the 2018 tax revenue loss of the U.S. Treasury to be between $10.02 and $16.20 billion dollars.

Beyond conventional cryptocurrencies, investors may also respond to increased tax reporting awareness and scrutiny by trading innovative products, such as NFTs (non-fungible tokens) and DeFi tokens, because the tax authorities have not yet provided clarification regarding the tax rules for these assets. We provide initial insights and believe they constitute interesting future research. Analyzing the largest NFT marketplace in the period, we find that the total number of sales, the value in dollars of these sales, and the number of sales in the secondary market are significantly larger in December than in other periods of the year, which is consistent with NFTs and secondary markets activities offering an additional layer of obfuscation to tax reporting.

Finally, the dynamics of decentralized lending rates on major DeFi lending platforms offer complementary evidence. By staking at the lending pool, traders can lock short-term positions into long-term positions by receiving synthetic tokens or shares from the lending pool as interest payments (yield). Some traders may assert that the strategy converts what would be higher-taxed

[4] Extant literature investigates exchanges incentives to fake volume. See our detailed discussion on Section 4.2.

short-term gains to lower-taxed long-term gains if the trader holds into the position. Consistent with this strategy, we find lending rates significantly increase at the end of the year. These results suggest that tax considerations potentially also affect decentralized lending activities.

Our findings have immediate relevance for recent anti-tax-loss-harvesting proposals for raising additional tax revenue. Such proposals may have unintended effects because their static estimates of the potential tax revenue gains assume away traders' endogenous responses, which are likely unrealistic in light of our empirical observations. For instance, because traders may lose a considerable incentive to trade on regulated exchanges, they might choose to move their trades to unregulated exchanges located overseas or decentralized exchanges (DEX)—a move that would make it difficult for authorities to enforce tax reporting.[5] Additionally, these markets' fast pace of innovation offer several alternatives, such as NFTs and DeFi, for traders to hide returns in gray areas of current taxation. Consequently, the effects of a particular tax law change on overall tax revenue are difficult to assess when considered in isolation in these rapidly changing markets.

Our contribution to the literature is threefold. First, we add to the taxation literature by conducting arguably the first study on crypto taxation. Prior studies (e.g., Landsman and Shackelford, 1995; Graham, 1996; Lang and Shackelford, 2000; Dai, Maydew, Shakelford, and Zhang, 2008; Blouin, Hail, and Yetman, 2009; Sialm, 2009; Hanlon and Heitzman, 2010; Li, Lin, and Robinson, 2016; Yost, 2018; He, Jacob, Vashishtha, and Venkatachalam, 2022) on the effects of taxation in other markets for fungible, easily tradable assets (e.g., securities markets), document important effects that taxes have on asset markets, including lock-in (i.e., capital gains taxes decrease supply) and tax capitalization (i.e., capital gains taxes decrease demand). These findings are unlikely to

[5]For instance, Binance is currently under investigation by the SEC and IRS, which are seeking information about possible for money laundering and tax offenses (https://www.bloomberg.com/news/articles/2021-05-13/binance-probed-by-u-s-as-money-laundering-tax-sleuths-bore-in).

extend to crypto assets for at least two reasons. The securities markets in the prior literature are subject to explicit tax rules against tax-loss harvesting using wash sales and are also subject to high levels of regulation and reporting, including required third party reporting by brokerages to the tax authorities, whereas the crypto markets are subject to neither. Thus, our study not only sheds light on the role of tax-motivated trading in crypto markets, but also examines a "counterfactual setting" to other securities markets in which key tax rules are, at least for the time being, absent.

Second, notwithstanding increasing empirical research on cryptocurrencies in the economics and finance literature, accounting research on crypto assets is in its infancy. Cao, Cong, and Yang (2019) and Cao, Cong, Han, Hou, and Yang (2020) examine blockchain design and impact for financial reporting and auditing. Empirically, Bourveau, De George, Ellahie, and Macciocchi (2021) examines the role of analysts in mitigating information asymmetries in the unregulated initial coin offering (ICO) markets. Lyandres, Palazzo, and Rabetti (2021) examines the role of disclosure on the ICO-success and post-ICO operating performance. Amiram, Jørgensen, and Rabetti (2022) exploits the blockchain transparent accounting system to detect terrorist-associated transfers. Tang (2022) examines country-level regulation effects on crypto adoption. Chang and Cong (2022) document how on-chain data growth nowcasts and forecasts firm fundamentals and stock returns. Our study is, to our knowledge, the first study of crypto markets from a tax perspective.

Finally, our study adds to a growing literature examining the economics of crypto exchanges and decentralization (e.g., Cong, He, and Li, 2021; Capponi and Jia, 2021; Lehar and Parlour, 2021). Although wash trading has previously been treated by other studies as an endogenous tool to inflate volume to attract demand (Cong et al., 2022; Fusaro and Hougan, 2019; Aloosh and Li, 2021) or respond to market competition (Amiram et al., 2022), our paper complements these studies by documenting wash trades as an outcome from intense tax-loss harvesting activities.

Moreover, our estimated size of tax-loss harvesting activities is of potential interest to tax authorities, regulators, and policymakers. Therefore, we dedicate a significant portion of our discourse on ongoing efforts for effective cryptocurrency regulation.

The remainder of the study is organized as follows. Section 2 explains the institutional background, covering crypto taxation, tax authority's actions, and new crypto products. Section 3 describes the data. Section 4 contains the empirical analyses, including our quantification of tax-loss harvesting and discussion of the upcoming regulation. Section 5 concludes.

2 Institutional Background

Cryptocurrencies, such as Bitcoin and Ethereum, are treated as property under federal tax law in the United States.[6] The same general tax principles applicable to property transactions are also applicable to cryptocurrencies. Cryptocurrency transactions are thus subject to tax when they generate gains. Beyond some general principles, however, the taxation of cryptocurrency quickly becomes murky and uncertain. Many tax rules (e.g., rules against using losses from wash sales) apply to specific kinds of property (e.g., securities). Because cryptocurrency and related digital assets have only existed for a relatively short period, there has been considerable uncertainty about how they are—and should be—treated for tax purposes.

2.1 Like-kind Exchange

A major source of confusion concerning cryptocurrency tax reporting comes from crypto-to-crypto trading being a taxable event. Before the end of 2017, many traders believed that this type

[6] See IRS Notice 2014-21 at https://www.irs.gov/pub/irs-drop/n-14-21.pdf.

of transaction was a "like-kind" exchange. Like-kind exchanges allow for the exchange of property without creating a taxable event on the condition that the property exchange is "like kind," or of the same nature.[7]

Following the exponential increase in trading Bitcoin and other cryptocurrencies, the Treasury Department's Inspector General issued a report on virtual currencies in late 2016 recommending that the IRS more clearly define its policy.[8] The report called for additional actions by tax authorities to ensure taxpayer compliance as the use of virtual currencies in taxable transactions became more evident. Some of the actions include providing taxpayers with clarity on which type of cryptocurrency activity is a taxable event. Until then, the only crypto tax guidance provided by the IRS was from guidance provided in 2014.[9] The lack of guidance on crypto taxation prompted the American Institute of CPAs to request further clarification from the tax authority.[10] An article for practitioners clearly states tax professionals' confusion as of November 2017: "IRS guidance is silent on which section of the tax code cryptocurrency falls into. For instance, IRC ξ1031 allows for the like-kind exchange of certain property. ξ1031 exchanges typically are done with real estate or business assets. However, with the classification of cryptocurrency as property by the IRS, many tax professionals will argue that cryptocurrency can be exchanged using IRC ξ1031."[11]

Despite the confusion and requests for further clarification, nearly four years passed before the tax authority provided further guidance in the form of several releases throughout 2018. In March, the IRS reminded taxpayers that income from virtual currency transactions is reportable on their

[7] These are also called "1031 exchanges" because they are governed by IRC Sec. 1031. See https://www.irs.gov/businesses/small-businesses-self-employed/like-kind-exchanges-real-estate-tax-tips.

[8] See https://www.treasury.gov/tigta/auditreports/2016reports/201630083fr.pdf

[9] See https://www.irs.gov/pub/irs-drop/n-14-21.pdf

[10] See http://docplayer.net/43122378-June-10-internal-revenue-service-attn-cc-pa-lpd-pr-notice-room-5203-p-o-box-7604-ben-franklin-station-washington-dc-20044.html

[11] See http://www.cpapracticeadvisor.com/tax-compliance/news/12380583/the-classification-of-bitcoin-and-cryptocurrency-by-the-irs.

income tax returns.[12] The IRS also cautioned in this release that taxpayers that do not report virtual currencies returns can be audited by the tax authority and liable for penalty and interest. Additionally, taxpayers may also be subject to criminal prosecution in more extreme situations. In July, the IRS announced a compliance campaign targeting cryptocurrency as one of five large business and international compliance campaigns.[13] The crypto-tax-compliance campaign related to withholding virtual currencies internationally (i.e., in non-American crypto exchanges) and stated that U.S. persons are subject to tax on worldwide income from all sources, including transactions involving virtual currency. The campaign also disclosed IRS efforts to provide education and future guidance to the taxpayers. To some extent, the IRS began signalling its compliance campaign as early as 2016, when the IRS served a "John Doe" summons to a leading crypto exchange, demanding information on trading by U.S. persons.[14] Finally, the Tax Cuts and Jobs Act of 2017 limited the use of like-kind exchanges to real estate transactions starting in 2018. However, whether pre-2018 cryptocurrency exchanges could qualify for like-kind treatment was still being unresolved as of late 2021.[15]

2.2 Capital Gains and Taxable Events

Because cryptocurrency is a new asset and its properties vary depending on its usage, there has been a general confusion regarding which type of crypto transactions are subject to capital tax gains and when such are to be reported, in part, for issues discussed above. The context of

[12] See https://www.irs.gov/newsroom/irs-reminds-taxpayers-to-report-virtual-currency-transactions.

[13] See https://www.irs.gov/businesses/irs-lbi-compliance-campaigns-july-2-2018.

[14] See https://www.justice.gov/opa/pr/court-authorizes-service-john-doe-summons-seeking-identities-us-taxpayers-who-have-used.

[15] See https://www.irs.gov/newsroom/like-kind-exchanges-now-limited-to-real-property and https://www.irs.gov/pub/irs-wd/202124008.pdf.

the transaction matters. For instance, donating cryptocurrencies to tax-exempt charities, transferring cryptocurrencies among wallets a trader owns, purchasing cryptocurrencies with fiat currency, and gifting cryptocurrencies to someone else (under $15k), do not trigger capital gains. However, trading crypto-to-fiat, crypto-to-crypto and even purchasing goods are all now considered taxable events. Crypto investors are also required to report fiat funds above $10,000 in any foreign exchange (e.g., Binance) per Report of Foreign Bank and Financial Accounts (FBAR) and Foreign Account Tax Compliance Act (FATCA). With the ease of access to international crypto exchanges, which are primarily web-based platforms, the transactions and balances on traders' addresses must be meticulously pieced together to trace which cryptocurrency unit belongs to each type of activity. Finally, cryptocurrencies resulting from mining, hard forks, and airdrops must be reported if generating income, even though the trader does not purchase the asset.[16] The tax reporting issue is even more complicated if the trader uses several cryptocurrency accounts to operate all the activities mentioned above.

To understand the implications of these issues on cryptocurrency trading, consider how capital gains are calculated. If a purchased cryptocurrency appreciates, the profits generated from its disposal are treated as a capital gain. Conversely, if a purchased cryptocurrency decreases in value, the losses incurred upon disposal can be deducted against other capital gains to minimize tax obligations.[17] Capital losses can be deducted against any capital gains, not just those from cryptocurrencies. To this end, traders need to keep an accurate record of every cryptocurrency transaction (date, amount, fees, cost) to calculate the capital gains correctly. This procedure is usually the most challenging part of cryptocurrency tax reporting. The increasing demand for

[16]Mining is the process of creating a new cryptocurrency (e.g., Bitcoin) by solving a computational puzzle needed to add transactions to a new block in the chain. A hard fork is a chain split, where a new chain is born from an old chain (e.g., Bitcoin Cash). Airdrops are the giveaway of cryptocurrencies to users, usually through marketing campaigns.

[17]See https://www.irs.gov/pub/irs-pdf/i1040sd.pdf.

proper tax reporting culminated in a rise of firms specialized in cryptocurrency tax services (such as the one that provided the data used in this study) and the proliferation of online crypto tax software.[18]

The amount of tax due depends on how long a cryptocurrency position is being held. Cryptocurrency sold within one year of purchase is subject to short-term capital gains tax. Short-term gains (losses) are added (deducted) to income for tax purposes and are subject to ordinary income tax rates (currently from 10% to 37% depending on income tax brackets). Cryptocurrency sold after one year is subject to long-term capital gains tax (currently 0%, 15%, or 20%, depending on thetaxable income and filing status). Capital gains are calculated by subtracting the purchase price (i.e., cost-basis) from the selling price. However, the calculation becomes increasingly complex as traders engage in more frequent trading and trading among several cryptocurrency pairs.

For example, consider a trader who buys three Bitcoins in three separate transactions of one Bitcoin, each with a different cost-basis. The trader later sells one Bitcoin. How does the trader determine which of the three initial Bitcoins was sold? The IRS suggests traders report capital gains following a FIFO method, or in other words, to account first for the oldest inventory of Bitcoins. The LIFO method, which accounts for the newest inventory, and a method called Specific Identification, which identifies each Bitcoin in the trading report according to users' addresses, can also be used. The method selected can significantly affect transaction returns if prices increase (decrease) rapidly in a short time. To illustrate the issue, consider the following example: Mary buys 1 BTC for $1,000, another 1 BTC for $3,000, and 1 more BTC for $5,000 (on different dates). Later she sells 1 BTC for $2,000. If Mary uses the FIFO method, the cost basis when selling 1 BTC will be $1,000, and her capital gain is a $1,000 profit (= $2,000 (selling price) - $1,000 (cost-

[18]See https://www.forbes.com/advisor/investing/cryptocurrency-taxes/.

basis)). If Mary uses the LIFO method, her cost-basis would instead be \$5,000, and the capital gain is now a \$3,000 loss (=\$2,000 (selling price) - \$5,000 (cost-basis)). Finally, suppose she had used specific identification, where the three crypto transactions were made in separated Bitcoin wallets (addresses on the blockchain). In that case, she can match the coin sold to the coin bought and get the exactly matched cost-basis for that transaction.

As the above example illustrates, the method used to calculate the transaction returns determines whether a trader reports capital gains or capital losses. However, an additional element provides more complexity to these calculations, which stems from the fact that trading crypto-to-crypto also generates a taxable event. Thus, even if the trader exchanges Bitcoins to other cryptocurrencies and the new position loses value – the trader is still liable for tax on any capital gains from sale of the Bitcoin. To illustrate the issue, consider the following example. Mary bought 1 BTC for \$1,000 in 2016. At the beginning of 2018, she decides to trade her BTC (which was worth \$5,000) for 10 ETH. A few months later, ETH's value decreases to \$5 per ETH. Mary believes the decrease is temporary and decides to hold the position. Consequently, Mary has a capital gain of \$4,000 from the sale of the Bitcoin, on which she needs to pay tax, even though the 10 ETH that she still holds are worth just \$50. Had Mary instead sold her ETH position – perhaps to another cryptocurrency – at the end of 2018 and repurchased it at the beginning of 2019, she would turn this transaction into a loss that she potentially can used to minimize her general tax obligations, while keeping the same ETH position in the beginning of the following year.

On one hand, the crypto-to-crypto taxable event may lead users to report taxes incorrectly because accounting for several transactions across several cryptocurrency pairs and several types of cryptocurrencies usage can be extremely difficult.[19] On the other hand, users may intentionally

[19]Note that a user may not necessarily be a trader, as the purchase of goods is also considered a taxable event.

exploit the system to benefit from tax planning or, in more extreme cases, tax evasion. Because the room for improper tax reporting is seemingly large, the IRS has started to question crypto holders in recent years.[20] In 2021, the IRS national fraud counsel warned that by analyzing blockchains and removing anonymity, the IRS can "track, find, and work to seize crypto in both a civil and criminal setting..."[21]

2.3 Crackdowns

In 2016, the IRS summoned the largest American crypto exchange, Coinbase, to provide data on over 10,000 U.S.-based users.[22] Although the IRS provided no further guidance until early 2018, the move was perceived as the tax authority increasing efforts to address improper tax reporting and tax evaders. The IRS did not act alone; tax regulation on cryptocurrencies appeared all over the world. Following the IRS's move, the U.K.'s tax authority requested the names of U.K.-based clients to popular crypto exchanges, such as Coinbase, eToro, and CEOX.io.[23]

In 2019, the IRS sent letters to over 10,000 U.S.-based crypto investors whose information was provided to the IRS by crypto exchanges such as Coinbase. The IRS sent three types of letters, one of which stated that, based on IRS assumptions, the recipient potentially failed to report crypto income or file returns for the years 2013 to 2017. The letter required a response or a request for extension within 30 days. The second type of letter stated that the IRS is aware the recipient

[20]See https://www.irs.gov/newsroom/irs-has-begun-sending-letters-to-virtual-currency-owners-advising-them-to-pay-back-taxes-file-amended-returns-part-of-agencys-larger-efforts

[21]See https://www.taxnotes.com/tax-notes-federal/cryptocurrency/irs-hunt-uncover-crypto-tax-fraud/2021/03/15/3k5qy?entity=3k5qy-0000001%2C3k5qy-0000007%2C3k5qy-0000012

[22]There was some question as to whether the IRS summons was enforceable. In late 2017 a federal court ruled that Coinbase had to comply with the IRS summons. See https://techcrunch.com/2017/11/29/coinbase-internal-revenue-service-taxation/.

[23]See https://koinly.io/blog/hmrc-crypto-tax-avoiders/ for more information on the matter.

holds cryptocurrency accounts and provides a detailed explanation of how to file tax reports. The third type of letter also requires the recipient to correct tax reporting in the event of previous misreporting. The purpose of these letters is to ensure taxpayers are aware of all the forms that they may be required to file. “Taxpayers should take these letters very seriously by reviewing their tax filings and when appropriate, amend past returns and pay back taxes, interest and penalties,” said IRS Commissioner Chuck Rettig at the time.[24]

Beginning with tax year 2020, the IRS included a question for each individual taxpayer on Form 1040: “At any time during 2020, did you receive, sell, or otherwise acquire any financial interest in any virtual currency?” Responding to taxpayers’ confusion about the implications of merely buying and holding cryptocurrency, the IRS modified the question for tax year 2021 to be “At any time during 2021, did you receive, sell, exchange, or otherwise dispose of any financial interest in any virtual currency?” In 2021, the IRS announced that its Fraud Enforcement Office had initiated “Operation Hidden Treasure” to detect unreported cryptocurrency income.[25]

2.4 Non-fungible tokens (NFTs)

From crypto punks to digital artists, new digital assets and popular figures are being tokenized on Ethereum platform in the form of collectible non-fungible tokens (NFTs).[26] See https://www.larvalabs.com/cryptopunks. As indicated by major media outlets reporting on digital art NFT releases and auctions, the market has been growing at a phenomenal pace.[27] Several marketplaces have been trading NFTs since the issuance of CryptoKitties issuance in late 2017,

[24] See the complete report at https://dailyhodl.com/2019/08/03/youre-a-us-crypto-investor-and-you-received-an-irs-letter-dont-panic/.

[25] See https://news.bloombergtax.com/daily-tax-report/irss-operation-hidden-treasure-focusing-on-crypto-fraud.

[26] Crypto punks are unique collectible characters with proof of ownership stored on the Ethereum blockchain.

[27] See https://fortune.com/2021/03/18/nft-art-crypto-marketplace-opensea-amazon/.

and even Amazon has recently announced that it will allow users to buy NFTs on its platform.[28] The most prominent market tracker (https://nonfungible.com/) registered over $12 billion in sales in 2021, with one fourth of it coming from primary markets (issuance) and the remaining from secondary markets (trading). NFTs are ownership tokens on blockchains linked to unique (digital) items exhibiting distinct return dynamics from cryptocurrencies used as means of payment (Cong and Xiao, 2021; Cong, Karolyi, Tang, and Zhao, 2022). NFTs may appear in the form of collectibles, art, card games, metaverse assets and sports. CryptoPunks for instance, are 10,000 unique collectible characters with proof of ownership stored on the Ethereum blockchain.[29] Because no two punks are alike, they are considered non-fungible assets and can be officially owned only by a single person on the blockchain. An interested user can buy, sell and trade NFTs in marketplaces or directly in the Ethereum blockchain.

Although the IRS has not yet released specific tax guidance for non-fungible tokens, some of its features can be anticipated as taxable events. For instance, purchasing NFTs with cryptocurrencies, trading NFTs to other NFTs, and disposing NFTs for other fungible cryptocurrencies likely are taxable events. For example, if Mary purchases a CryptoPunk for 1 ETH when ETH is US $1,000, but later sells it for 2 ETH when ETH is US $1,500, she should recognize a taxable gain of US $2,000. Unlike other fungible crypto assets, if Mary trades an NFT to another NFT, that cannot be interpreted as a “like-kind” exchange transaction because an NFT is considered unique. As with cryptocurrency, NFTs are not subject to the wash sale rules so long as they are not considered stock or securities, which allows traders to once again engage in tax-loss harvesting. Despite the

[28]Crypto kitties are unique collectible and breedable characters whose ownership is tracked via a smart contract on the Ethereum blockchain. See https://www.cryptokitties.co/.

[29]For example, crypto Punk number 3011 was first sold at US $7,831.73, last sold at US $1,764,108.28, and accumulating a total of 2,509,136.09 in total sales as of April 2022 (https://nonfungible.com/market-tracker/cryptopunks/%CF%BE/3011.

lack of guidance, some believe that the IRS likely views NFTs as collectibles. Collectibles held longer than a year are a special segment of capital assets that are taxed at 28 percent, a higher rate than typical capital assets.[30] However, certain NFTs may be taxed as ordinary income rates, which are generally higher than capital gains rates. For instance, a digital art dealer, for whom NFTs are essentially inventory, may not be subject to or be eligible for favorable capital gains tax treatment.

2.5 The Rise of Decentralized Financing (DeFi)

The rise of DeFi in the summer of 2020 and subsequent growth in 2021, especially in the Ethereum ecosystem, has taken the blockchain community by storm. According to `defimarketcap.io`, the top 25 DeFi protocols ranked by market capitalization sums to over $105 billion (as of May 2021).[31] The most prominent services are decentralized exchanges, known as liquidity pools, and decentralized lending protocols. Because the IRS has not yet provided clear guidance for DeFi markets, traders again may take advantage of the ambiguity in labeling taxable events.

Taxable events from decentralized lending potentially come in two forms. If the cryptocurrency is lent to another trader or pooled into a platform that generates fees back to the lender, then the receipt of fees triggers income taxes. The platform may pay interest yield to the lender by providing synthetic crypto tokens as exchange.[32] These tokens are of similar version and have the same proprieties as the lent token. For instance, if a trader lends, she receives Compound USDC or simply cUSDC—if the trader holds onto the lending position.[33] The issue from the

[30]The IRS defines collectible capital assets as: any work of art, rug or antique, metal or gem (with exceptions), stamp or coin (with exceptions), alcoholic beverage, or other tangible personal property that the IRS determines is a "collectible" under IRC Section 408(m).

[31]See `https://defimarketcap.io/protocols`.

[32]DeFi protocols feature various staking and locking programs, which have impacts on token prices. Cong, He, and Tang (2022) provide more discussion.

[33]USD Coin (USDC) is a digital stablecoin that is pegged to the United States dollar. Compound USDC (cUSDC) is a record of USDC deposited to the Compound protocol in form of tokens. Anyone who holds cUSDC or any other

tax regulatory perspective is whether both tokens should be regarded as distinct. The other form entails less uncertainty and consists of capital gains from either converting or withdrawing tokens from the liquidity pool or lending platform. By doing so, the trader likely triggers a taxable event and must report capital gains. The rise of DeFi lending and liquidity pools products provide new opportunities for traders to convert short-term positions to long-term positions while still making money from interest payments or acquiring a share for supplying the pool. For example, Figure 1 illustrates how traders lend tokens to the pool and lock into long-term interest payments acquired by holding a share of the pool token or swapping to similar synthetic token. Some traders may argue that such a strategy converts what could be a more costly short-term taxable gain into a less costly long-term gain.[34]

3 Data and Summary Statistics

We use two data sources in our analyses. The first dataset comprises of proprietary full-detailed trading reports for 500 large retail traders. The second dataset is based on information extracted from the trading book of dozens of major crypto exchanges provided by a large crypto exchange data provider. The trading report data of the first dataset is quite granular, which provides some advantages. However, the behavior we document using the first dataset may not generalize beyond large retail traders. The trading book data in second dataset is less granular but has the advantage of reflecting essentially all trading activity on the major crypto exchanges, enabling us to generalize to the entire market and make estimates of aggregate tax revenue losses.

cTokens earns the prevailing market interest rate. Interest payments are not remitted to depositors but are expressed via the cTokens exchange rate.

[34] A trader that supplies liquidity to the pool (i.e., lending his tokens) receives a share of the liquidity pool token in exchange. See Uniswap (https://uniswap.org/) and Balancer (https://balancer.fi/) for more information.

3.1 Trading Reports

We obtain proprietary data from a tax firm that has been operating in the cryptocurrency field since 2012. The data covers the trading activities in the form of trading reports for the tax firm's 500 largest retail traders.[35] Approximately one-third of the traders are U.S.-based taxpayers, and the remaining traders are internationally domiciled.[36] Although the firm did not provide details about the traders to protect clients' privacy, the data on traders' activity are very granular, including information about inbound and outbound transfers, cryptocurrency pairs, fees collected, transaction size, prices in Bitcoins and U.S. dollars, and the crypto exchange used for each transaction between April 2011 to September 2019.

The data provided to us are very similar to the trader's report obtained from popular trading platforms for tax purposes, such as Binance and Coinbase. However, an important variable, returns, is not provided because it is up to the tax firm to calculate returns according to each trader's needs. Estimating the returns for each trading position is a difficult task for two reasons. First, it involves decisions regarding which crypto asset unit is being sold. Also, returns depend on the accounting method for inventory flow, i.e., whether FIFO, LIFO, or the specific identification approach is used. For generalization and comparison purposes, we implement the FIFO method, which assumes that the first unit of a crypto asset bought. i.e., the oldest one, is the first one to be sold. However, although the method is beneficial for empirical examinations in that it makes returns across traders comparable, it may not be the method used by traders when reporting their

[35]Measured by activity (e.g., number of trades and volume) during the period of 2017 to 2019.

[36]For international peers in which a local FX trade exists, 38.21% (14.63%, 9.76%, 7.32%, 5.69%, 4.88%, 4.07%, 4.07%, 3.25%, and 2.44%) are located in Europe (Bahamas, Solomon Islands, Brazil, South Korea, China, Malaysia, UK, Vietnam, and Chile).

activity to tax authorities.[37]

Panel A in Table 1 reports the summary statistics for 500 large retail traders obtained from the trading reports database. An average trader engages in over \$66 thousand worth of cryptocurrency trades daily. The median volume per daily transaction is only \$4.5 thousand, which indicates that the distribution is right-tailed or that most of the transactions consist of small values. Similarly, an average trader engages in 23 transactions per day and a median trader, 4 transactions. The standard deviation for daily volumes and transactions varies widely, with over 450 thousand in daily volumes and 150 in daily transactions. A large standard deviation is not surprising because the crypto markets are quite volatile—for instance, the presence of hot markets driven by skyrocketing Bitcoin price, such as at the end of 2017. Traders typically trade on more than one crypto exchange, succeed in having more winning trades than losing trades, and are profitable most of the time (as indicated by mean and median daily average returns of 6.35% and 0.28%.[38] Finally, traders' preference toward tokens issued in ICOs dominates trading activities, where these trades occur 62 percent of the time. The greatest portion of trading activity in the dataset, 60 percent, relates to a period where traders perceived cryptocurrency taxation as a like-kind exchange event, i.e., a taxable event occuring when converting cryptocurrency back to fiat money, as opposed to what the IRS later clarified—that a taxable event also occurs in crypto-to-crypto conversions.

[37] Refer to Section 2 for the implications of different reporting methods.

[38] Note that these traders likely represent a portion of successful traders, as perceived by large daily returns, thus providing a sample of traders more likely to be sensitive to increased tax scrutiny. Although generalization is limited, the results on this sample motivate a more generalized examination later in this paper (i.e., tax-loss harvesting inferences based on the trading books of several crypto-exchanges).

3.2 Trading Books

We access the trading books of dozens of large crypto exchanges through `kaiko.com`, a digital assets data provider used in several studies (e.g., Amiram et al., 2022; Makarov and Schoar, 2020). The raw data are at the exchange-pair-millisecond level and contain information on each trade executed during the pair life in a given exchange. For each transaction, information on the direction (sell or buy), date, amount, and price are provided.

Extant literature uses several techniques to detect wash trading. For instance, Bitwise's report to the SEC plotted the densities of crypto exchanges' volume series to infer for volume inflation Fusaro and Hougan (2019). Cong et al. (2022) implements the first set of statistical measures such as deviations from the Benford's law. Amiram et al. (2022) further combines statistical and machine learning measures. In this study, we use a more straightforward measure of wash trading. We access the historical trading data at each exchange-pair level and flag trades in which buy and sell orders are executed at the same price within 60 seconds.[39] We then scale this measure by the total number of trades and aggregate it daily. The scaling is important to make this variable comparable among different pairs within an exchange and the same pair between exchanges. We focus our analysis on Bitcoin (BTC) to either U.S. dollars (USD) or Tether (USDT).[40]

Panel B in Table 1 reports the summary statistics for the trading books of 34 crypto exchanges in the period from August 2011 to May 2021. A typical exchange in our sample has an average daily trading volume (*TotalVolume*) of \$103 million, median volume of \$7.83 million, and a stan-

[39]Using such a tight window to estimate wash trades is conservative and likely understates the extent of loss harvesting using wash trades. Aloosh and Li (2021) similarly construct direct measures using internal data of Mt. Gox exchange leaked by hackers.

[40]Besides being the most liquid trading pair in the period, it also helps us develop a proxy for tax-loss harvesting that is less likely to be affected by crypto-exchanges incentives to inflate volume. See our section 4.2 for the details.

dard deviation of $333.79 million. These figures suggest that, although the volume distribution is skewed towards small values, the presence of hot markets drastically increases volume. For instance, the maximum daily volume is a staggering $13.4 billion. The total amount of trades (*TotalTrades*) follows a similar volume pattern, but the respective figures are smaller. Finally, the BTC price (*PriceClose*) increased drastically from about $10 (early days) to around $60 thousand (late days). Price is volatile, as indicated by a mean of near $12 thousand relative to a standard deviation of $14.6 thousand.

We find that 8.75% of the daily volume (*WashVolumePercTota*) and 18.12% of the daily number of trades (*WashPercTotal*) are potentially washed trades, i.e., those for which a buy and sell order occurs at the same exchange, pair, price, and within a minute). Consistent with Cong et al. (2022), wash trade percentage varies significantly across the exchanges and time episodes, ranging from zero to 100 percent in the sample. Wash trades are also sizable; on average, they correspond to $6.65 million per day (*WashVolume*) and can reach over billions of dollars during moments of prolonged price devaluation, such as the end of 2018. Finally, about 23 percent of the sample's crypto exchanges are regulated (*Regulated*), including major U.S.-based crypto exchanges such as Coinbase and Kraken.[41]

4 Empirical Analyses and Discussion

We first document the effects of increasing tax reporting awareness on traders' trading behavior and exchanges preferences. We expect U.S.-based traders to decrease the number of taxable

[41]Following Cong et al. (2022), we classify exchanges as regulated if they have been licensed by either the U.S., U.K., or Japanese financial authorities.

events following increases in tax awareness and scrutiny (i.e., crypto exchange crackdowns, taxable events clarification, and IRS letters to investors). We also expect U.S.-based traders to respond to increased tax awareness and scrutiny by increasing their tax-loss harvesting using wash trades, taking advantage of cryptocurrency not being subject to the wash sale rules. Finally, we expect traders to concentrate their activities on regulated U.S.-based crypto exchanges where reported information is verifiable by the U.S. authorities.

4.1 Traders' Responses to Increasing Tax Reporting Awareness

4.1.1 Trading behavior

To assess empirically the effects of increasing tax reporting awareness on traders trading activities, we estimate the following equation:

$$Y = \alpha + \beta(IRS \times Domestic) + \gamma IRS + \delta Domestic + \Lambda + \epsilon, \tag{1}$$

where Y is one of five response variables: (i) *Trades*, the number of trades reported in log plus one; (ii) *Volume*, the number of trades times price reported in log plus one; (iii) *Diversity*, the number of unique cryptocurrencies traded reported in log; (iv) *Profit*, the total profit made in a sold position reported in positive scale log plus one; and (v) *Harvest*, the number of trades whose asset sold is bought within 30 days. All response variables are at the trader-daily level. The explanatory variables are: (i) *IRS*, a binary indicator switching on for the period of increasing tax awareness (post-2017), and zero otherwise; (ii) *Domestic*, a binary indicator switching on if a trader is U.S.-based, and zero otherwise; (iii) the interaction *IRS* $\times$ *Domestic*. Λ is a trader fixed effect, and ϵ is the error term. β, our coefficient of interest, reflects the differences in responses between U.S.-based and international investors during the period of increasing tax reporting awareness. As such, Equation (1) is essentially a differences-in-difference model. Because trader's data are obtained in a time series format, serial correlation may affect the error term in the pooled regression. To mitigate this concern, we report heteroskedastic robust standard errors clustered at the trader level. To mitigate possible selection concerns, we also estimate Equation (1) using propensity score matched samples.[42]

Panels A and B in Table 2 report summary statistics of Equation (1) based on unmatched and matched samples. When accounting for trader fixed effects, the daily trading level regressions reflect that increased tax reporting awareness significantly impacts trading behavior. Relative to international peers, as indicated by the significantly negative $IRS \times Domestic$ coefficients in panel A, -0.09 and -0.41, U.S.-based traders decrease their number of daily trades and substantially reduce their volume traded while increasing their portfolio diversification (i.e., number of unique pairs traded).[43] Interestingly, tax reporting awareness does not affect profits, i.e., the $IRS \times Domestic$ coefficient in the profit model is near zero. However, U.S.-based traders respond by engaging more in tax-loss harvesting activities than international peers, as indicated by the significantly positive coefficient of 0.06 in the tax harvesting model. These results suggest that in response to increasing tax reporting awareness, U.S.-based traders attempt to minimize taxable events by reducing the quantity and volume traded while harvesting losses in their portfolios through wash trades.

4.1.2 Exchange preferences

Table 3 reports the differences-in-differences results for changes in exchange preferences. We use the same specification as Equation (1), but replace the response variables with: (i) *Exchanges*,

[42]See Appendix 1 for statistics assessing the improvements in matching achieved using propensity matching.

[43]Because inferences are generally the same based on unmatched and matched estimations, for the sake of brevity we limit our discussion of the Tables 2 and 3 findings to those in panel A

the number of unique crypto exchanges the trader uses, (ii) *Trusted*, the sum of trades in trusted crypto exchanges according to CoinGecko trusted score – exchanges not listed in CoinGecko receive a trust score of zero,[44](iii) *Lax*, the sum of trades in crypto exchanges located in crypto-friendly countries (e.g., Estonia, Singapore, and Hong Kong); and (iv) *TaxHaven*, the sum of trades in crypto exchanges located in tax haven countries (e.g., British Virgin Islands, Malta, and Seychelles).

The results suggest that, relative to international peers, U.S.-based traders reduce the number of exchanges they use, particularly exchanges located in crypto-friendly and tax haven locations following the increase in tax awareness and scrutiny, i.e., the *IRS* $\times$ *Domestic* coefficients in the *Exchanges*, *Lax*, and *Tax Haven* estimations, -0.02, -0.27, and -0.34, are significantly negative. In contrast, U.S.-based traders increase their use of trusted exchanges following the increase in tax awareness and scrutiny, i.e., the *IRS* $\times$ *Domestic* is 0.07 in the Trusted estimation. The results also suggest a migration from decentralized exchanges, i.e., the *IRS* $\times$ *Domestic*, -0.09, is significantly negative in the DEX model. However, this effect should be interpreted with caution because our trading reports' period does not include the decentralized exchange boom in 2021. Overall, these findings suggest that U.S.-based traders seek to use the services of crypto exchanges whose credentials are verifiable to the tax authorities, consistent with an increased emphasis on harvesting tax-losses.[45]

[44] CoinGecko is one of the largest cryptocurrency price and data providers. The trusted score considers several parameters shown to be correlated with the overall quality of a crypto exchange. For instance, whether a crypto exchange has know-your-customer and anti-money laundering provisions in place. See more at https://blog.coingecko.com/trust-score-explained/.

[45] Although increased scrutiny also leads foreign exchanges to avoid Americans in the long-term, U.S.-based traders can easily bypass weak compliance measures aimed to prevent their access (https://www.wsj.com/articles/u-s-crypto-traders-evade-offshore-exchange-bans-11627637401).

4.1.3 End-of-the-year trading strategy

If non-tax-related channels account for the changes in trading behavior and exchange preferences documented in the previous section, we should not observe tax-motivated trading in periods sensitive for tax considerations. To assess the veracity of this conjecture, we next examine whether retail traders disaggregate their winning and losing portfolios around the turn of the year, the period more likely to reflect the effects of increased tax reporting awareness. We thus estimate:

$$\begin{aligned} Y = \alpha + \beta_1(IRS \times Domestic \times Dec) + \beta_2(IRS \times Domestic \times Jan) + \\ \gamma IRS + \delta Domestic + \zeta Jan + \omega Dec + \Lambda + \epsilon, \end{aligned} \tag{2}$$

where Y is the cumulative daily number of trades. To further assess traders' strategies, we disaggregate the number of trades relating to winning (losing) positions and whether the losing trades occur through regular or harvesting strategies. Winning positions are determined by the cumulative returns (estimated using FIFO method) being positive when the position is sold whereas losing positions, by the cumulative returns being negative. Harvesting (regular) trades are defined by whether the asset sold is bought within (after) 30 days. In addition to the variables specified in Equation (1), Equation (2) includes the following indicator variables: *Jan* is an indicator variable that equals one for trades during in the first two weeks of January and zero otherwise; and, *Dec* is an indicator variable that equals one for trades during the last two weeks of December and zero otherwise. Therefore, our coefficients of interest, β_1 and β_2, reflect the triple differences effects of a U.S.-based trader in the period of increased tax-awareness for moments of the year most and least sensitive for tax-motivated trading.

Table 4 reports the regression summary statistics for Equation (2). The findings reveal that U.S.-based traders started selling more losing positions in the last two weeks of December and less of them in the first two weeks of January than their international peers after the increase in tax awareness and scrutiny, as indicated by the significantly positive and negative *IRS* × *Domestic* × *Dec* and *IRS* × *Domestic* × *Jan* coefficients of 0.39 and -0.42. Because we can identify winning and losing positions and their respective buybacks at the traders' portfolio level, we further investigate whether the turn-of-the-year activity is affected by tax-loss harvesting that would be disallowed if cryptocurrency were subject to the wash sale rules, i.e., when the position sold is subsequently bought back within 30 days, relative to regular trading. Tax-loss harvesting dominates the end-of-the-year trading strategies for U.S.-based traders, as indicated by larger positive coefficients—in terms of both magnitude and statistical significance—on *IRS* × *Domestic* × *Dec* in the loss harvesting sub-sample relative to the regular trading sub-sample, 0.59 vs. 0.24, as well as compared to the negative coefficient on *IRS* × *Domestic* × *Jan*, -0.39, in the loss harvesting sub-sample.

Overall, we document in this section several channels through which U.S.-based traders respond to increased tax reporting awareness. First, U.S.-based traders react to tax clarification, guidance, and scrutiny by decreasing taxable events. Second, these traders move away from unregulated exchanges and exchanges located in crypto-friendly or tax haven countries, consistent with registering tax losses on exchanges in which reporting is verifiable to the authorities. Third, U.S.-based traders significantly increase their sales of losing cryptocurrency positions in the last weeks of December, culminating in turn-of-the-year effects. Moreover, portfolio composition analysis demonstrates that the turn-of-the-year activity is largely influenced by increased tax-loss harvesting.

4.2 Tax-Loss Harvesting at Crypto Exchanges

The previous analyses document 500 large retail traders' responses to increased tax reporting awareness and scrutiny, including the exploitation of tax-loss harvesting rules. We now expand our examination to billions of trades on the trading books of several major crypto exchanges. In addition, we estimate the size of tax-loss harvesting activity and discuss the results in light of the current regulatory debate. However, because there is no direct measure of tax-loss harvesting in the trading data of crypto exchanges—doing so requires traders' IDs for a proper matching—we start our analysis by discussing the choice of our proxy.

4.2.1 Wash trades

A race for receiving the SEC permission to list Bitcoin futures turned out to be a surprising outcome, a 200-page document filed by Bitwise suggesting that 95 percent of crypto exchanges volume was fake (Fusaro and Hougan, 2019). Following the episode, several academic studies examined the issue more scientifically.

Cong et al. (2022) introduces statistical measures to document deviations from expected patterns on volume data. One of the measures employed is based on the deviation of a given series from Benford's law (Benford, 1938). This law describes expected frequencies of the first digit equaling one through nine for datasets obtained by drawing observations from random samples of varying magnitudes. Departures from Benford's Law indicate potential data manipulation or misstatements (e.g., Michalski and Stoltz, 2013; Amiram, Bozanic, and Rouen, 2015).

4.2.2 Tax-loss harvesting proxy

This study uses wash trades as a proxy for potential tax-loss harvesting because tax-loss harvesting activities involve selling a losing position and buying it immediately back. The loss information can be used for tax purposes, but the trader still retains the asset. The execution of this trade is nothing but a wash trade where prices are unlikely to be affected, but the process generates large volumes. Unlike extant literature examining wash trade by crypto exchanges to fake volume (e.g., Aloosh and Li, 2021; Amiram et al., 2022; Cong et al., 2022), we examine wash trades as a tax-loss harvesting maneuver by individuals. This distinction is essential because the statistical measures used in the literature are unlikely to serve our purposes given that the data-generating process from tax-loss harvesting is not the outcome of manipulation.

Therefore, our proxy for wash trade is based on whether a buy-sell order is placed in the same crypto exchange, at the same pair, price, and quantity, and within 60 seconds. Because wash trades derived from tax-loss harvesting are likely to be confounded with wash trades originating endogenously (e.g., volume inflation), we expect our measure to be a cleaner proxy under the following circumstances: (i) During periods where tax-loss harvesting is more likely to be accentuated and the intense tax-loss harvesting activity likely boosts overall wash trade measures. (ii) When trades are in highly liquid pairs such as BTC-USDT because volume inflation is more likely to occur in illiquid pairs to attract demand. (iii) Wash trades likely incorporate tax-loss harvesting on regulated exchanges because regulatory oversight makes these exchanges less likely to engage in volume inflation. For instance, Figure 2, Panel A, shows that wash trades are decreasing on exchanges level of compliance, where high (low) compliance indicates whether measures to certify users' identity and anti-money laundering procedures are (not) in place. Panel B shows that wash trades are higher for unregulated (Bibox), than regulated (Binance) and U.S.-based (Kraken) exchanges.

We exploit the extreme BTC price drop throughout 2018 as a potential period of intense tax-loss harvesting activities. BTC price achieved an all-time high in the 2017 end – about $20 thousand. Figure 3 shows that BTC price then dropped nearly 70 percent throughout 2018, potentially leaving many traders with unrealized losses. These unrealized losses could have been realized at the year-end, as suggested by a further sharp decline around mid-November. Therefore, the last months of 2018 are potentially beneficial for tax-loss harvesting.

Spikes in wash trade patterns among several regulated exchanges reinforce our assumption for market-driven (i.e., tax-loss harvesting) effects. Figure 4 depicts wash trades measures for regulated and U.S.-based (Coinbase and Kraken), regulated internationally (Binance), and an unregulated (Okex) exchanges. The trading activity highlighted by the green circle indicates spikes in the wash trades activities in the period beneficial for traders to sell losing positions. The documented wash trades for a highly liquid pair in regulated exchanges, such as Coinbase, Kraken, and Binance, are persistent across exchanges, suggesting exogenous causes. However, the documented pattern is smaller in the unregulated exchange, Okex. Additionally, although the spike is also observed in unregulated exchanges, our proxy also reflects volume inflation in later periods of the BTC-USDT wash trade series—as documented by the increasing wash trade activity only on Okex. The latter result increases our confidence in the reliability of the proposed measure.

4.2.3 Estimating tax-loss harvesting revenue

We start our analysis by estimating the following regression at the exchange-Bitcoin level:

$$Y = \alpha + \beta(Regulated \times HarvestPeriod) + \gamma Regulated + \delta HarvestPeriod + \Lambda Controls + \epsilon, \quad (3)$$

where Y is our proxy for wash trade and is reported as a percentage of total daily volume. We focus on BTC to either USD or USDT as this pair is the most liquid cryptocurrency—thus providing fewer incentives for endogenous wash trading as discussed before. The right-hand side of Equation (3) includes the following variables: *Regulated*, an indicator variable that equals one if an exchange is regulated, and zero otherwise. We replace this variable with an indicator for *Binance*, *Coinbase* and *Kraken*, to estimate tax-loss harvesting activity on exchanges of interest (i.e., regulated or U.S.-based exchanges). *Harvest Period*, an indicator variable that equals one for trades made from September to December 2018, and zero otherwise. *Controls*, a vector of market-based variables used as controls for other characteristics likely to affect wash trade, such as price, price volatility, and volume. We expect price to be inversely correlated with wash trade because tax-loss harvesting occurs on price drops. We expect price volatility to be inversely correlated with wash trade because it makes re-buying a sold asset at the same price more difficult. Finally, we expect volume to be positively correlated with wash trade because of the intensification of tax-loss harvesting activities. Standard errors are clustered at the crypto exchange level.

The Equation (3) regression summary statistics presented in Table 5 confirm our expectations. On average, regulated exchanges have lower wash trades than unregulated exchanges during regular periods, i.e., the *Regulated* variable coefficient, -0.12, is significantly negative. However, wash trades in regulated exchanges increase dramatically during tax-loss harvesting periods. In particular, the interaction *HarvestPeriod* coefficients, which range from 0.12 to 0.45, are all significantly positive. Thus, wash trades are about one-third larger in regulated exchanges than unregulated exchanges during the harvesting period. These results suggest that wash trade spikes on regulated exchanges are influenced by tax-loss harvesting activities on both large crypto exchanges such as Binance and the U.S.-based crypto exchanges Coinbase, Gemini, and Kraken.

We continue our analysis by estimating the size of tax-loss harvesting in the following way. First, we calculate the median average wash trade as a percentage of total trades during the harvesting and regular periods. We focus on regulated exchanges because these exchanges are less likely to be subject to endogenous volume inflation that can affect our estimates. Because the volume size across regulated exchanges varies widely, we calculate both volume-weighted and equally-weighted tax-loss harvesting estimates. Table 6, Panel A, reveals that volume-weighted (equal-weighted) estimate of wash trades is 21.56% (19.34%) for the harvesting period, and 4.25% (5.24%) for the regular period. We next estimate wash volume figures. First, we take the differences between wash trades estimates in the harvest and regular period. Then, we multiply it by the total volume during the harvesting period. Finally, we estimate the revenue loss to the government by first estimating traders reported losses as the product of estimated wash volume to the average BTC price devaluation in 2018, 70%, and then multiplying the estimated traders reported losses by an average capital loss rate of 30%.

Table 6,Panel B, reports the estimated wash volume and revenue loss to the government.[46] For the BTCUSDT pair, we estimate a value-weighted (equal-weighted) wash volume of $25.52 ($20.80) billion and revenue of $5.36 ($4.37) billion across all exchanges. These figures reduce slightly to a wash volume of $19.37 ($15.78) billion and revenue of $4.07 ($3.31) billion if only regulated exchanges are used. Across all BTC pairs, we estimate a wash volume of $77.14 ($62.85) billion and revenue of $16.20 ($13.20) billion across all exchanges. These figures reduce to a wash volume of $58.53 ($47.69) billion and revenue of $12.29 ($10.02) billion for regulated exchanges. Taken together, the results suggest a total loss of revenue in 2018 to the government between $10.02 and $16.20 billion.

[46]Our estimates ignore fee costs, which typically range between 1% and 3%.

4.2.4 Anti tax-loss harvesting bill

The wash sale rules in the U.S. tax code dictate that investors must wait at least 30 days before purchasing another security that is "substantially identical" to the security that was sold at a loss for the loss to be allowed for tax purposes.[47] Cryptocurrency traders have so far taken advantage of a loophole in the rule because the wash sale rules apply to sales of stock or securities, not to property more generally. However, a proposed bill intends to extend the wash sale rule to cryptocurrencies.[48] Assuming there is no market reaction, the bill is expected to bring larger revenues to the IRS. In a similar figure to our estimated Bitcoin tax income in 2018, the move could generate a 10 to 15 percent tax-revenue increase to the authority.

However, the no-market reaction assumption is quite unrealistic. As shown in this study, traders are likely to accommodate for the tax-rule change in their trading behavior and crypto exchange preferences. Therefore, the bill may pose unintended consequences to crypto tax reporting. The lack of incentives to report trading activity may worsen due to innovative crypto products, such as NFTs and DeFi, where clear guidance has not yet been provided. Moreover, traders may have incentives to evade taxation by moving from regulated exchanges to unregulated exchanges (e.g., decentralized exchanges), making it more challenging for the tax authority to implement enforcement procedures, such as crackdowns to obtain traders' identities.

[47] Internal Revenue Code Section 1091. IRS Publication 550: Investment Income and Expenses, Pages 56-57 (https://www.irs.gov/pub/irs-pdf/p550.pdf).

[48] See https://rules.house.gov/sites/democrats.rules.house.gov/files/Section$_{b}y_{S}ection_{B}BB.pdf$

4.3 FinTech Innovations and Gray Areas of Taxation

The previous subsections' results suggest challenges for regulators to match the complexity and fast pace of innovation in the crypto markets. Although some of the issues, such as tax-loss harvesting, are currently subject to regulatory debate, other areas of crypto trading, such as non-fungible tokens and decentralized financing, remain disregarded. Therefore, this subsection provides some initial insights regarding traders' potential incentives to exploit the lack of guidance in these more innovative crypto markets. However, given that these markets are still in their infancy, our inferences are primarily descriptive, serving as a starting point for future research.

4.3.1 Non-fungible tokens (NFTs)

CryptoKitties, a non-fungible token for a unique digital cat collection, launched in late 2017 and rapidly captured the crypto community's attention. More than 300 thousand crypto kitties were sold in primary and secondary markets in the brief period before the end of 2017. After CryptoKitties, several other NFTs products have been launched, and, accompanied by skyrocketing BTC prices, the market gained traction yet again in 2021. Figure 5 plots the evolution of the market. From 2018 to 2021, the sales pattern in Panel A suggests a peak around the end of the year, which is consistent with tax motivations. Panel B indicates that in 2021, the NFT market amassed over $12 billion in sales, with sales peaking around Bitcoin's all-time high price in the period covered.[49] The sales are mostly dominated by NFTs Collectibles (such as Crypto Kitties). Other segments, however, such as arts, games, and metaverse, started trending in mid of 2021,

[49]Bitcoin price reached around $20,000 at the end of 2017.

suggesting an increase in diversification of the NFT market.[50]

NFTs, as explained earlier, may be considered as an investment in collectibles by the IRS. However, because the tax guidance on NFTs is lacking, some traders lock into NFTs as a long-term investment to avoid paying tax on short-term cryptocurrency positions, at least until new guidance arrives. To assess the demand for NFTs around year-end we estimate the following fixed effect model:

$$Y = \alpha + \beta Jan + \delta Dec + \Lambda + \epsilon, \tag{4}$$

where Y is one of five response variables including (i) *Total Sales*, the total number of sales made during the period; (ii) *Sales (USD)*, the total USD spent on completed sales; (iii) *Primary Mkt*, the total number of primary-market sales made during the period; (iv) *Secondary Mkt*, the total number of secondary-market sales made during the period; and (v) *Ownership*, the number of unique wallets which bought or sold an asset. All response variables are at the trader-daily level and reported in logarithmic values. *Jan* and *Dec*, our variables of interest, are indicator variables that equal one for trades falling in the first two weeks of January or two last weeks of December, and zero otherwise. The omitted category relates to rates from February to November. Λ is a year fixed effect and ϵ is the error term.

Table 7 reports Equation (4) regression summary statistics.[51] The motivation for these regressions is to assess whether the demand for NFT assets in December is likely greater than

[50] *Art* is a marketplace, project or individual artist who produces, sells or generates content in the form of an NFT which is considered to be a work of art or relates directly to an art form whether manual or generative. *Collectibles* is a project whose primary function is to issue tokens intended to be collected. These tokens can be part of a system that includes gamification or a set of interactions between collectibles themselves or between the collectors and players. *Games* is video game using the NFT standard. This can be trading card games (TCG) strategy role-playing games (RPG) or any other electronic gaming experience incorporating NFT. *Metaverse* is a parallel digital universe which offer a set of unique experiences to users. These virtual worlds are accessible via a computer, virtual reality headset, or a smartphone.

[51] The variables were extracted from a popular NFT market tracker (https://nonfungible.com/).

other months suggesting tax-motivated investments. All market variables are significantly larger (smaller) in December (January) than other months of the year. The December (January) coefficients for the total number of sales, the value in dollars of these sales, and the number of sales in secondary markets are all significantly positive (negative). These findings suggest that the demand for non-fungible tokens at the year-end could in part be tax motivated.[52] However, the scope of this analysis does not permit us to establish causation as the demand for NFTs around the year may also capture wash trade activities intended to stimulate demand to pressure the price of these assets upwards.[53] Therefore, future research mapping off-chain sales (i.e., on marketplaces) and on-chain transactions (i.e., on NFTs blockchain addresses) can potentially advance the understanding of the driving forces behind the results at hand.

4.3.2 Decentralized financing (DeFi)

Another developing market in which traders can potentially exploit gray areas of taxation is decentralized finance, or simply, DeFi. The development of smart-contract based applications, such as decentralized exchanges and decentralized lending, led the DeFi market to experience a booming growth 2021.[54] DeFi markets use Ethereum-based smart contracts to create protocols that replicate existing financial services, such as exchanges, liquidity pools, and lending platforms, in a peer-to-peer ecosystem governed by a set of predetermined rules (smart contracts).[55] DeFi

[52] A robustness test excluding crypto-kitties December's launch, results into similar effects.

[53] The NFT market, like other crypto markets, is also subject to intense wash trade activities. See https://www.nbcnews.com/tech/security/nft-sales-show-evidence-wash-trading-researchers-say-rcna14535, https://blog.chainalysis.com/reports/2022-crypto-crime-report-preview-nft-wash-trading-money-laundering/, and a recent study by von Wachter, Jensen, Regner, and Ross (2022).

[54] According to a report by CoinGecko, the market cap across the decentralized finance protocols grew by 7.5x from $20 billion to $150 billion in 2021 (https://cryptopotato.com/defi-and-nft-scaled-to-new-heights-in-2021-coingecko-report/).

[55] Ethereum pioneered the market for smart contracts, but recent developments in the crypto space gave birth to several other platforms such as Polygon and Avalanche.

protocols account for $216 billion in total value locked as of march 2022.[56]

Some services, such as decentralized lending, offer smart solutions for traders attempting to avoid short-term taxes. By supplying the lending pool or lending tokens to the platform, traders lock short-term positions into long-term positions by staking cryptocurrencies and receiving synthetic tokens or shares from the lending pool in the long term (i.e., interest). Some traders may take the position that the strategy exchanges considerably higher short-term taxes for long-term taxes, if the trader holds into the position.

As explained in section 2, the IRS has not provided specific guidance on decentralized financing platforms. Therefore, the strategy of receiving synthetic alike tokens, for instance, USDC to cUSDC, may again lead investors to misreport, claim ignorance, or simply take an aggressive interpretation on the matter by exploiting this gray area of crypto tax reporting.

Compound, a leading DeFi lending platform that offers decentralized borrowing and lending for 12 cryptocurrency pairs, is evaluated in over $21.4 billion market capitalization. Figure 6 shows the evolution of on-chain smart-contracts transfers for the Compound token and its two main assets, a synthetic token for USDC (cUSDC) and DAI (cDAI) stable coins. cUSDC and cDAI correspond to more than nine billion dollars in locked assets or roughly half of Compound market capitalization. The evolution of Compound's contracts suggests a peak in activities at the 2020 year-end. Most evident, cUSDC (Panel B) presents high levels of activities in November and December 2020, suggesting that investors engage in tax-motivated lending activities.

To document whether lending rates increase at the end of the year, which is consistent with locking short-term positions into long-term synthetic tokens, we collect the information on interest rates in both lending and borrowing contracts for a composite index that is based on several lending

[56]See https://defillama.com/.

platforms, and in the main lending platforms, Compound and Aave.[57] To assess the demand of Defi lending during the year we estimate the following regression:

$$Y = \alpha + \beta Jan + \delta Dec + \Lambda + \epsilon, \tag{5}$$

where Y is either a decentralized lending rate or a decentralized borrowing rate for three assets including (i) Index, the weighted average rates across several Defi protocols; (ii) Compound, the average rates for Compound protocol; and (iii) Aave, the average rates for Aave protocol. *Jan* and *Dec*, our variables of interest, are indicator variables that equal one for trades falling in the first two weeks of January or two last weeks of December, and zero otherwise. The omitted category relates to rates from February to November. Λ is a year fixed effect and ϵ is the error term. The interest rates are annualized, and the terms of the loan are open-ended. Returns are annualized and reported on a monthly frequency. We estimate Equation (5) for both the most used Ethereum-based stable coins (USDC and DAI) from October 2019 to January 2022.

Table 8 reports the mean differences between February through November in relation to December and January for the annualized monthly lending and borrowing rates. Considerably large lending and borrowing rates indicate that the market demand for synthetic products is greater than the supply.[58] The coefficients for lending and borrowing rates across the two most relevant pairs (USDC and DAI) indicate that December and January rates are substantially larger than other months. Especially USDC for Aave's platform and DAI for Compound's platform. These findings suggest that the significant increase in the demand for decentralized lending at the year-end may be tax motivated.

[57] Aave being the second largest lending platform.

[58] In the decentralized markets, the lending and borrowing rates move together as the decentralized lending platform matches demand and supply synthetic tokens.

5 Conclusion

Accounting research on blockchain and cryptocurrencies is a nascent but vibrant field with an enormous potential for significant contributions. This study documents how investors in crypto assets respond to increased tax reporting awareness and scrutiny. More specifically, relative to their international peers, U.S.-based traders alter trading behaviors and crypto exchange choices to a greater extent as tax policies in the U.S. tighten. The response is consistent with traders seeking to minimize taxable events while exploiting tax-loss harvesting trades around year-end to balance portfolio losses.

We further examine billions of trades in several crypto exchanges to provide broad sample evidence on tax-loss harvesting activities. We document a spike in wash trade activities in regulated crypto exchanges during the harvesting period of year-long price devaluations. The wash trade behavior is persistent across exchanges, suggesting intense and profound tax-loss harvesting in the market. We estimate billions of dollars in tax-loss harvesting concentrated in regulated and U.S.-based crypto exchanges.

Tax-loss harvesting is not socially desirable, but given the easy-to-avoid and hard-to-enforce nature of crypto trading, simply extending rules designed for traditional securities, as recent proposals do, may prove ineffective. Additionally, traders may continuously exploit gray areas of taxation by trading innovative products such as non-fungible tokens (NFTs) and decentralized finance (DeFi). Moreover, the bill may incentivize selective reporting of their activities by moving from regulated to unregulated exchanges. Consequently, the expected tax revenue may decline in the post-bill period.

5.1 Future Research

Crypto markets continue expanding and evolving rapidly, challenging tax authorities and policymakers to quickly develop and implement sensible and effective regulations. The dearth of research on crypto taxation does not help matters and suggests a pressing need for more researchers to contribute their insights and empirical evidence. We call for further research using a variety of datasets, approaches, and research questions to shed light on this $2 trillion innovative market.

Given the easy-to-evade nature of crypto markets, studies looking into how traders evade taxes, exploit gray areas of taxation, and lock-in returns on innovative products, are interesting angles for exploration. Additionally, studies using proprietary data, from sources such as data aggregators (e.g., coinmarketcap.com), specialized accounting and auditing firms, and governmental agencies (e.g., IRS), may provide unique settings to examine these questions. Moreover, as regulation develops, accounting research has the potential to provide key insights to market players, regulators, and policymakers.

Research questions related to crypto reporting and disclosure are equally promising. Accounting researchers may consider exploring firms' strategies to minimize reported taxable events, as well as report and disclose crypto holdings and the different forms in which crypto holdings are classified (e.g., inventory, intangible assets, or investment).

Finally, the valuation of crypto assets and how that affects the overall valuation of holders (e.g., firms) also provides a potential avenue for future research—especially considering the recent migration of Bitcoin miners from China to Texas, the increasing number of publicly listed blockchain-based firms, and the boom of decentralized financing businesses.

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Table 1. Summary. The table reports summary statistics. Panel A reports statistics for trading reports of 500 retail traders in the period from 2011 to 2019. Panel B reports statistics for trading books of 34 crypto exchanges in the period of 2011 to 2021. The statistics Minimum, Maximum, Median, Mean and Standard Deviation, are reported at the daily frequency and winsorized at one percent. See Appendix 2 for all variable definitions.

Panel A: Trading reports (500 retail traders)

	min	**max**	**median**	**mean**	**sd**	**obs**
Volume (Million)	0.00	37.57	0.0045	0.066	0.45	47,666
Trades	1.00	9,539.00	4.00	23.00	150.61	47,666
Diversification	1.00	8.00	1.00	1.60	0.80	47,666
Exchange	1.00	8.00	1.00	1.31	0.70	47,666
Returns	-12.62	63.99	0.28	6.35	17.16	47,666
Winning	0.00	6,245.00	2.00	12.04	90.78	47,666
Losing	0.00	3,398.00	0.00	8.56	66.54	47,666
Domestic	0.00	1.00	0.00	0.27	0.44	47,666
ICO	0.00	1.00	0.80	0.62	0.42	47,666
IRS	0.00	1.00	0.00	0.40	0.49	47,666

Panel B: Trading books (34 crypto exchanges)

	min	**max**	**median**	**mean**	**sd**	**obs**
TotalTrades (Million)	0.00	5.89	0.01	0.06	0.19	50,590
TotalVolume (Million)	0.00	13,410.00	7.83	103.60	333.79	50,590
PriceClose	10.30	66,245.10	8,205.10	11,991.10	14,623.40	50,590
WashTrades	0.00	3.36	0.00	0.01	0.05	50,590
WashPercTotal	0.00	100.00	13.14	18.12	17.33	50,590
WashVolume (Million)	0.00	2,184.00	0.36	6.65	28.15	50,590
WashVolumePercTotal	0.00	100.00	5.38	8.75	12.55	50,590
Regulated	0.00	1.00	0.00	0.23	0.42	50,590
HarvestPeriod	0.00	1.00	0.00	0.03	0.18	50,590

Table 2. Trading behavior. This table reports the effects of increased tax reporting awareness on trading behavior. While Panel A reports the regression results to the full sample, Panel B reports to matched samples. *IRS* is an indicator variable switching on for the period of 2018 to 2020, and off otherwise. *Domestic* is an indicator variable switching on for whether the trader's main local currency is USD, and off otherwise. *Trades* is the amount of trades reported in log plus one. *Volume* is the price times traded amount reported in log plus one. *Diversity* is the number of unique cryptocurrencies traded reported in log. *Profit* is the total profit made in a sold position reported in positive scale log plus one. *Harvest* is the number of trades whose asset sold is bought within 30 days. All variables are aggregated daily. All regressions have trader fixed effects. Standard errors are heteroskedastic robust and clustered at the trader level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Panel A: Trading behavior (unmatched)

	Trades	**Volume**	**Diversity**	**Profit**	**Harvest**
IRS	0.08 ***	0.13 ***	-0.05 ***	0.00	-0.07 ***
	(0.02)	(0.04)	(0.01)	(0.00)	(0.01)
Domestic	-0.93 ***	-1.74 ***	-0.26 ***	0.00	-0.27 **
	(0.22)	(0.47)	(0.07)	(0.01)	(0.11)
IRS × Domestic	-0.09 ***	-0.41 ***	0.05 ***	0.00	0.06 ***
	(0.03)	(0.07)	(0.01)	(0.00)	(0.02)
Trader FE	yes	yes	yes	yes	yes
Obs	47,666	47,666	47,666	47,666	47,666
Adj.r^2	0.29	0.44	0.23	0.02	0.34

Panel B: Trading behavior (matched)

	Trades	**Volume**	**Diversity**	**Profit**	**Harvest**
IRS	0.10 ***	0.35 ***	-0.05 ***	0.00	-0.06 ***
	(0.03)	(0.06)	(0.01)	(0.00)	(0.01)
Domestic	-0.85 ***	-1.23 **	-0.34 ***	0.01	-0.34 ***
	(0.26)	(0.54)	(0.09)	(0.02)	(0.13)
IRS × Domestic	-0.12 ***	-0.63 ***	0.05 ***	0.00	0.05 ***
	(0.04)	(0.08)	(0.01)	(0.00)	(0.02)
Trader FE	yes	yes	yes	yes	yes
Obs.	26,004	26,004	26,004	26,004	26,004
Adj.r^2	0.25	0.39	0.21	0.01	0.29

Table 3. Exchange preferences. This table reports the effects of increased tax reporting awareness on exchange preferences. While Panel A reports the regression results to the full sample, Panel B reports to matched samples. *Exchanges* captures the number of unique crypto exchanges used reported in log. *Trusted* captures the sum of trades in trusted crypto exchanges according to CoinGecko trusted score - exchanges not listed in CoinGecko receive a trust score of zero. *Lax* captures the sum of trades in crypto exchanges located in crypto friendly countries (e.g., Estonia, Singapore, and Hong Kong). *TaxHaven* is the sum of trades in crypto exchanges located in tax haven countries (e.g., British Virgin Islands, Malta, and Seychelles). All variables are aggregated daily. All regressions have trader fixed effects. Standard errors are heteroskedastic robust and clustered at the trader level. *** p < 0.01; ** p < 0.05; * p < 0.10.

Panel A: Exchange preferences (unmatched)

	Exchanges	**DEX**	**Trusted**	**Lax**	**TaxHaven**
IRS	0.01 *	0.08 ***	-0.29 ***	0.54 ***	0.70 ***
	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)
Domestic	-0.04	-0.93 ***	-1.22 ***	-0.12	0.28 *
	(0.04)	(0.22)	(0.27)	(0.17)	(0.17)
IRS × Domestic	-0.02 ***	-0.09 ***	0.07 *	-0.27 ***	-0.34 ***
	(0.01)	(0.03)	(0.04)	(0.02)	(0.02)
Trader FE	yes	yes	yes	yes	yes
Obs.	47,666	47,666	47,666	47,666	47,666
Adj.r^2	0.23	0.29	0.45	0.44	0.44

Panel B: Exchange preferences (matched)

	Exchanges	**DEX**	**Trusted**	**Lax**	**TaxHaven**
IRS	0.01	0.00	-0.25 ***	0.55 ***	0.75 ***
	(0.00)	(0.00)	(0.03)	(0.02)	(0.02)
Domestic	-0.06	0.00	-1.23 ***	-0.12	0.30
	(0.05)	(0.01)	(0.31)	(0.20)	(0.21)
IRS × Domestic	-0.02 ***	0.00	0.03	-0.28 ***	-0.39 ***
	(0.01)	(0.00)	(0.05)	(0.03)	(0.03)
Trader FE	yes	yes	yes	yes	yes
Obs.	26,004	26,004	26,004	26,004	26,004
Adj.r^2	0.21	0.14	0.38	0.40	0.42

Table 4. Trading strategy (EoY). This table reports difference-in-differences regression results on the trading activity of U.S.-based traders and international traders, and for the period of increased tax reporting awareness. The response variable is the cumulative daily number of trades and is reported in logarithm plus one. Winning (losing) positions are determined by whether the cumulative returns are positive (negative) at the time the position is sold. Returns on sold positions are calculated using the FIFO method. *IRS* is an indicator variable switching on for the period of 2018 to 2020, and off otherwise. *Domestic* is an indicator variable switching on for whether the trader's main local currency is USD, and off otherwise. *Jan* is an indicator variable switching on for trades falling in the first two weeks of January, and off otherwise. *Dec* is an indicator variable switching on for trades falling in the last two weeks of December, and off otherwise. *Harvesting* are trades in which the asset sold is bought within 30 days. *Regular* are trades in which the asset sold is bought in more than 30 days. All variables are aggregated daily. All regressions have trader fixed effects. Standard errors are heteroskedastic robust and clustered at the trader level. *** p < 0.01; ** p < 0.05; * p < 0.10.

	Selling positions		**Harvesting (<30 days)**		**Regular (>30 days)**	
	Winning	**Losing**	**Winning**	**Losing**	**Winning**	**Losing**
IRS	-0.22 ***	0.29 ***	-0.23 ***	0.34 ***	-0.09 ***	0.26 ***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Jan	0.08 ***	-0.20 ***	0.13 ***	-0.29 ***	0.17 ***	-0.17 ***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
Domestic	-0.65 ***	0.16	-1.22 ***	-0.15	-0.58 ***	0.13
	(0.21)	(0.20)	(0.37)	(0.37)	(0.20)	(0.17)
Dec	-0.22 ***	0.08	-0.48 ***	-0.03	-0.16 ***	0.06
	(0.06)	(0.05)	(0.10)	(0.10)	(0.06)	(0.05)
IRS × Jan	-0.20 **	0.59 ***	-0.49 ***	0.82 ***	-0.34 ***	0.40 ***
	(0.09)	(0.08)	(0.11)	(0.11)	(0.10)	(0.08)
IRS × Domestic	0.11 ***	-0.20 ***	-0.04	-0.33 ***	0.08 **	-0.18 ***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
Jan × Domestic	0.11 *	0.13 **	0.19 **	0.13 *	0.08	0.02
	(0.06)	(0.05)	(0.08)	(0.08)	(0.07)	(0.06)
IRS × Dec	0.27 ***	0.04	0.62 ***	0.16	0.19 ***	-0.01
	(0.07)	(0.06)	(0.11)	(0.11)	(0.07)	(0.06)
Domestic × Dec	-0.13	-0.15	-0.04	-0.18	-0.22 *	-0.15
	(0.13)	(0.12)	(0.20)	(0.20)	(0.13)	(0.11)
IRS × Domestic × Jan	-0.03	-0.42 ***	-0.02	-0.39 **	-0.21	0.01
	(0.14)	(0.13)	(0.20)	(0.20)	(0.16)	(0.14)
IRS × Domestic × Dec	-0.06	0.39 ***	0.03	0.59 ***	0.27 *	0.24 *
	(0.14)	(0.14)	(0.22)	(0.22)	(0.15)	(0.13)
Trader FE	yes	yes	yes	yes	yes	yes
Obs	36,974	36,974	23,276	23,276	24,390	24,390
Adj.r^2	0.24	0.29	0.26	0.31	0.19	0.25

Table 5. Wash trades during tax-loss harvesting periods. This table reports difference-in-differences regression results for wash trades between regulated (Binance, Coinbase, and Kraken) and unregulated exchanges for tax-loss harvesting periods. The response variable is the daily number of wash trades scaled to total trades and is reported in percentage. *Harvesting Period* is an indicator variable switching on for October to December 2018, and off otherwise. *Indicator* is our variable of interest and takes the following values: *Regulated*, an indicator variable switching on for Regulated exchanges located in the United States; *Binance*, an indicator variable switching on for Binance exchange; *Coinbase*, an indicator variable switching on for Coinbase exchange; and *Kraken*, an indicator variable switching on for Kraken exchange; and off otherwise. *Price Close* is the daily close BTC price in either USD or USDT reported in log. *Price Volatility*, is the standard deviation of the intraday prices reported in log plus one. *Volume* is the total daily volume (number of trades time price) reported in log. All variables are aggregated daily. Standard errors are heteroskedastic robust and clustered in time. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

	Wash Trades (BTC)			
Indicator:	**Regulated**	**Binance**	**Coinbase**	**Kraken**
Indicator	-0.12 ***	-0.06	0.00	-0.28 ***
	(0.03)	(0.06)	(0.04)	(0.05)
Harvest Period	0.64 ***	0.75 ***	0.75 ***	0.76 ***
	(0.13)	(0.18)	(0.18)	(0.18)
Price Close	-0.00 ***	-0.00 ***	-0.00 ***	-0.00 ***
	(0.00)	(0.00)	(0.00)	(0.00)
Price Close Square	0.00 ***	0.00 ***	0.00 ***	0.00 ***
	(0.00)	(0.00)	(0.00)	(0.00)
Price Volatility	-0.04 **	-0.04 **	-0.04 **	-0.03 **
	(0.02)	(0.02)	(0.02)	(0.02)
Volume	0.03 ***	0.03 ***	0.03 ***	0.03 ***
	(0.01)	(0.01)	(0.01)	(0.01)
Regulated ×	0.35 **	0.31 ***	0.39 ***	0.12 *
Harvest Period	(0.17)	(0.09)	(0.14)	(0.07)
Obs	50,570	50,570	50,570	50,570
Adj.r^2	0.06	0.05	0.05	0.06

Table 6. Estimating tax-loss harvesting revenue. This table reports estimates for tax-loss harvesting revenue. Panel A reports the tax-harvesting estimates based on volume-weighted and equally-weighted median estimates for the harvest and regular periods. Panel B reports the estimated wash volume and revenue loss to the government. Wash volume is calculated as the differences between tax-loss harvesting and regular periods (in percent) multiplied by the total volume during tax-harvesting periods (in billions). We estimate the revenue loss to the government by first estimating traders reported losses as the product of estimated wash volume to the average BTC price devaluation in 2018, 70%, and then multiplying the estimated traders reported losses by an average capital loss rate of 30%. [1] Using total BTC volume as per coinmarketcap.com. [2] Using regulated exchanges share of BTC-USDT to derive regulated exchanges share of the entire BTC market.

Panel A - Tax-Loss Harvesting Estimates

Volume-Weighted		Equally-Weighted	
Harvest	**Regular**	**Harvest**	**Regular**
21.56	4.25	19.34	5.24

Panel B - Estimated Loss to the Government

Exchanges	Pair	Volume-Weighted		Equally-Weighted	
		Wash	**Revenue**	**Wash**	**Revenue**
All	BTC-USDT	25.52	5.36	20.80	4.37
Regulated	BTC-USDT	19.37	4.07	15.78	3.31
All[1]	ALL	77.14	16.20	62.85	13.20
Regulated[2]	ALL	58.53	12.29	47.69	10.02

Table 7. Non-fungible tokens demand. This table reports the demand for non-fungible tokens. The data in this table has been collected from the largest and oldest NFT trading platform (https://nonfungible.com/) from June 2017 to January 2022. The variables used in this analysis are described as follow: *Total Sales* is the total number of sales made during the period, *Sales (USD)* is the total USD spent on completed sales, *Primary Mkt* is the total number of primary-market sales made during the period, *Secondary Mkt* is the total number of secondary-market sales made during the period, and *Ownership* is the number of unique wallets which bought or sold an asset. All other explanatory variables report marginal coefficients for a specific month in logarithmic value. The omitted category relates to logarithmic amounts for January. Standard errors are heteroskedastic robust. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

	Total Sales	**Sales (USD)**	**Primary Mkt**	**Secondary Mkt**	**Ownership**
Dec	1.59 ***	2.10 ***	1.60 ***	1.58 ***	1.46 ***
	(0.11)	(0.13)	(0.12)	(0.11)	(0.09)
Jan	-0.21 *	-0.84 ***	-0.27 **	-0.07	-0.28 ***
	(0.12)	(0.14)	(0.13)	(0.12)	(0.09)
Year FE	yes	yes	yes	yes	yes
Obs	1,690	1,690	1,690	1,90	1,690
Adj.r^2	0.69	0.82	0.70	0.67	0.77

Table 8. Decentralized lending rates. This table reports decentralized lending and borrowing rates for a composite index, Compound, and Aave platforms based on rates retrieved from https://loanscan.io/. The Decentralized Lending columns report rates for the weighted average rates (Composite Index) and the two of the most popular Defi-lending products (Compound and Aave). The interest rates are annualized and terms of loans are open-ended. Returns are annualized and reported in the monthly frequency. For each rate (lending and borrowing) the table reports returns for the two most used Ethereum-based stable coins (USDC and DAI) from October 2019 to Jan 2022. The omitted category relates to rates in the period of February to November. Standard errors are heteroskedasticity robust. *** p < 0.01; ** p < 0.05; * p < 0.10.

USDC

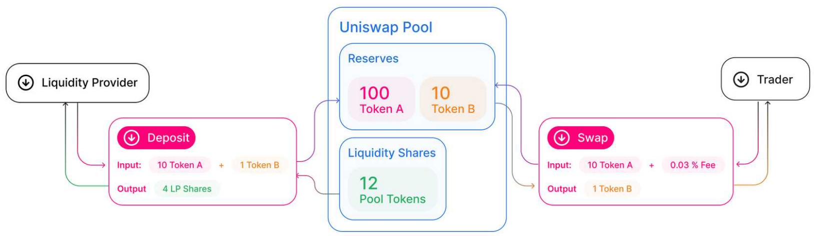
	Index		**Compound**		**Aave**	
	Lend	**Borr**	**Lend**	**Borr**	**Lend**	**Borr**
Dec	4.42 **	1.94	1.83	1.51	8.74 ***	7.38 **
	(1.88)	(2.06)	(1.41)	(1.57)	(2.52)	(3.27)
Jan	3.06 *	2.41	2.97 *	3.79 *	1.40	0.10
	(1.75)	(2.41)	(1.65)	(1.84)	(2.35)	(3.82)
Year Fe	yes	yes	yes	yes	yes	yes
Obs	27	27	27	27	27	27
Adj.r^2	0.18	0.07	0.11	0.25	0.26	0.05

DAI

	Index		**Compound**		**Aave**	
	Lend	**Borr**	**Lend**	**Borr**	**Lend**	**Borr**
Dec	2.48	3.03	2.06 *	2.50 *	4.30	6.07
	(2.41)	(2.93)	(1.18)	(1.43)	(3.69)	(4.45)
Jan	9.38 ***	8.99 **	3.86 **	4.03 **	0.64	0.04
	(2.81)	(3.43)	(1.38)	(1.67)	(4.30)	(5.20)
Year Fe	yes	yes	yes	yes	yes	yes
Obs	27	27	27	27	27	27
Adj.r^2	0.24	0.17	0.21	0.17	0.10	0.08

Figure 1. Liquidity pool's schematics. This figure shows the schematics for two popular liquidity pools. Traders lend tokens to the pool and lock into long-term interest payments acquired by holding a share of the pool token or swapping to similar synthetic token.

Panel A: Uniswap



Panel B: Balancer

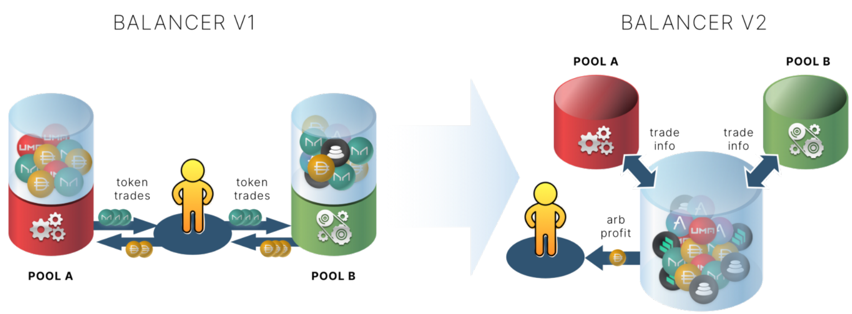
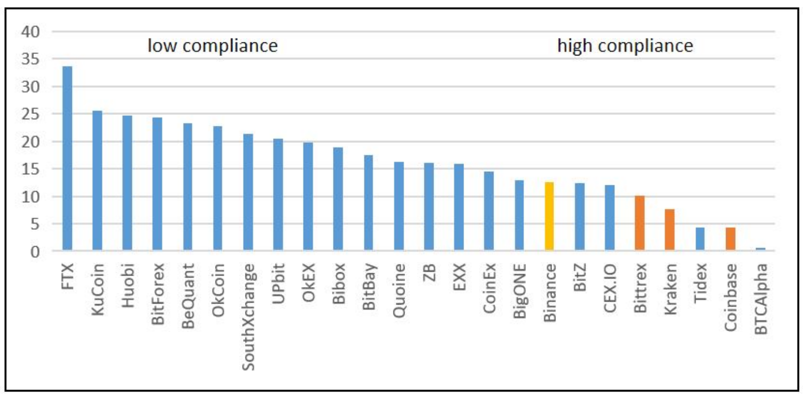


Figure 2. Compliance and regulation effects. This figure shows compliance (Panel A) and regulation (Panel B) effects on wash trades. A wash trade is measured as a buy-sell order occurring in the same pair, price and quantity, and within 60 seconds. The Y-axis reports the daily wash trade measure in percentage of total trades. Panel A plots the average wash trade per exchange. The left-hand (right-hand) side of the plot is composed by exchanges with low (high) level of compliance in place (e.g., know-your-customer and anti-money laundering procedures). Panel B plots the evolution of wash trades for Bibox (unregulated), Binance (regulated) and Kraken (regulated in the U.S.).

Panel A



Panel B

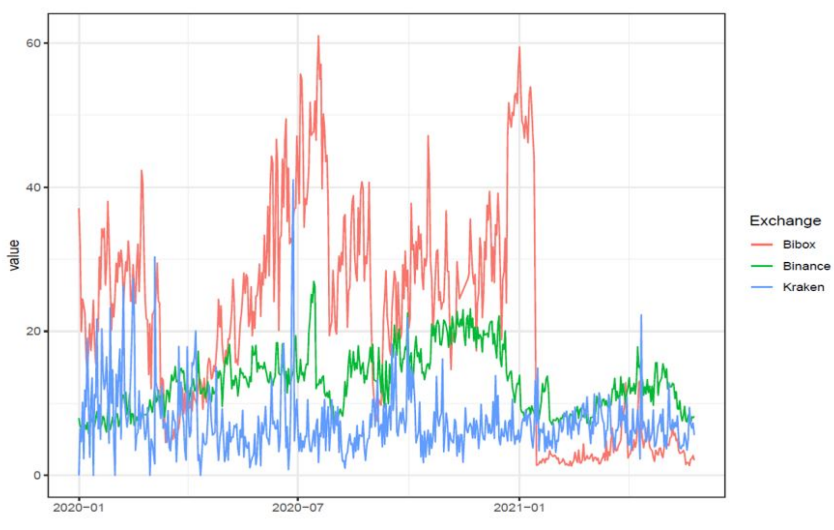


Figure 3. Tax-loss harvesting period. This figure plots Bitcoin price scaled by all-time high (20,000 USD) from 2017-end to mid-2020. The Y-axis reports BTC price devaluation in percent. As perceived by the graph, BTC price declined about 70 percent throughout 2018. The green square indicates the harvesting period.

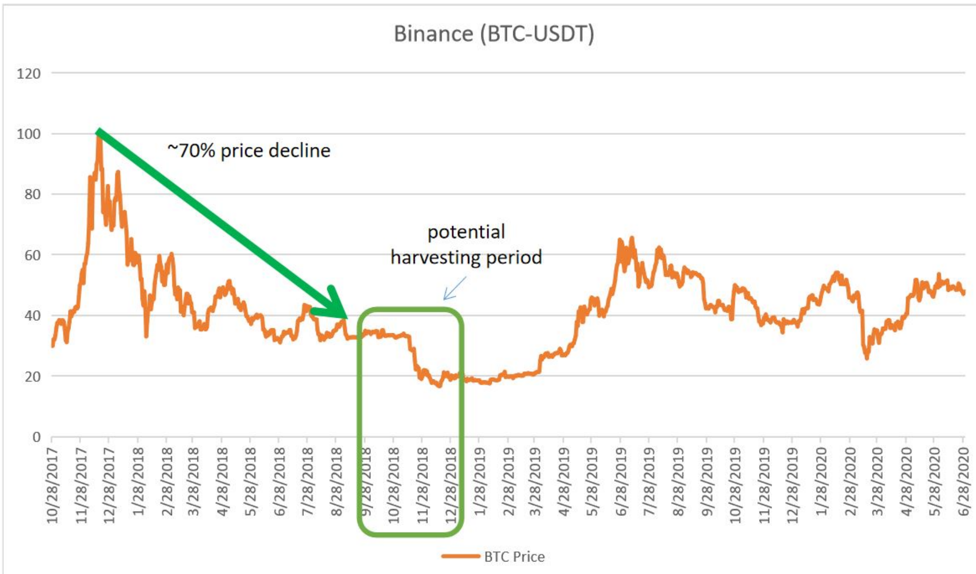


Figure 4. Tax-loss harvesting evidence. This figure shows the wash trade evolution for U.S.-based exchanges (Coinbase and Kraken), the largest international exchange (Binance), and an unregulated exchange (Okex). A wash trade is measured as a buy-sell order occurring in the same pair, price and quantity, and within 60 seconds. The Y-axis reports the daily wash trade measure in percentage of total trades. The green circle indicates wash trades potentially driven by tax-loss harvesting activities (exogenous effects). The red square indicates wash trades potentially driven by volume inflation (endogenous effects).

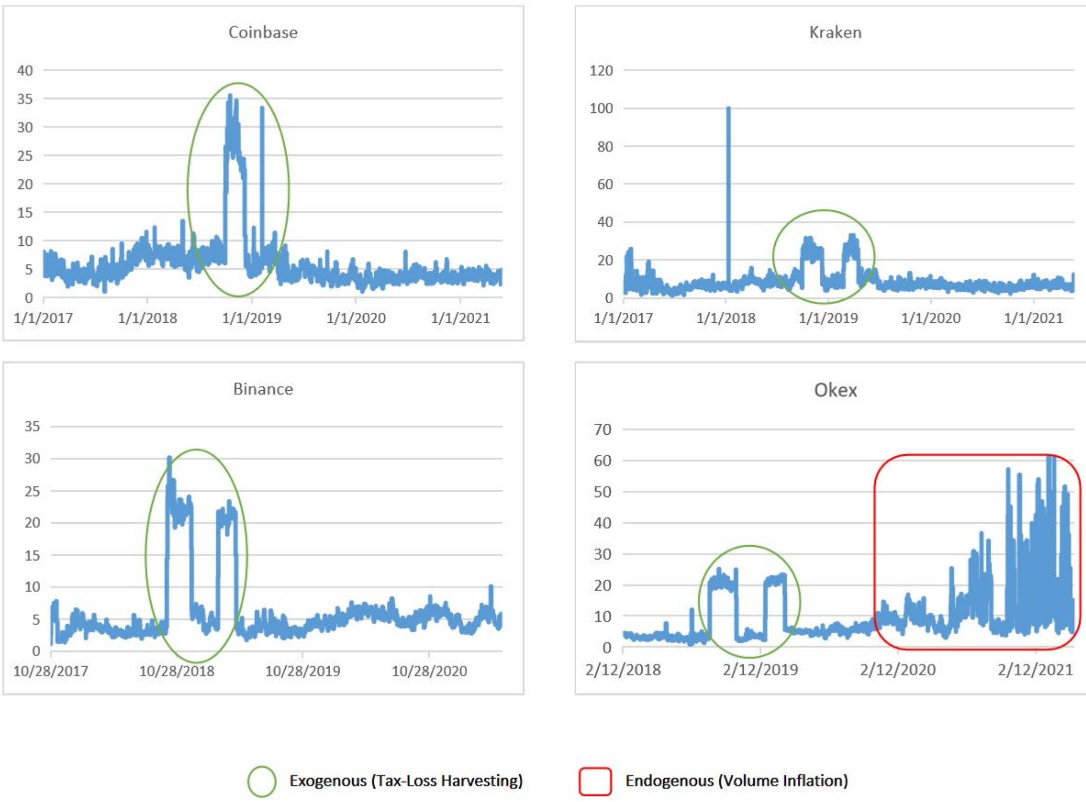
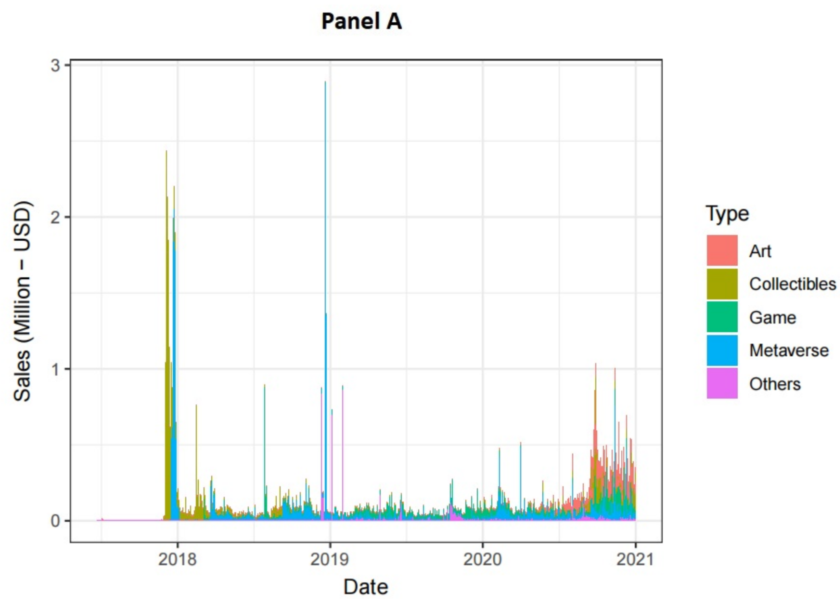


Figure 5. Non-fungible tokens demand. This figure plots the demand for non-fungible tokens from 2018 to 2021 (Panel A) and in 2021 (Panel B). *Art* is a marketplace, project or individual artist who produces, sells or generates content in the form of an NFT which is considered to be a work of art or relates directly to an art form whether manual or generative. *Collectibles* is a project whose primary function is to issue tokens intended to be collected. These tokens can be part of a system that includes gamification or a set of interactions between collectibles themselves or between the collectors and players. *Games* is video game using the NFT standard. This can be trading card games (TCG) strategy role-playing games (RPG) or any other electronic gaming experience incorporating NFT. *Metaverse* is a parallel digital universe which offer a set of unique experiences to users. These virtual worlds are accessible via a computer, virtual reality headset, or a smartphone. The data used in this plot was obtained from the largest and oldest NFT market https://nonfungible.com/.



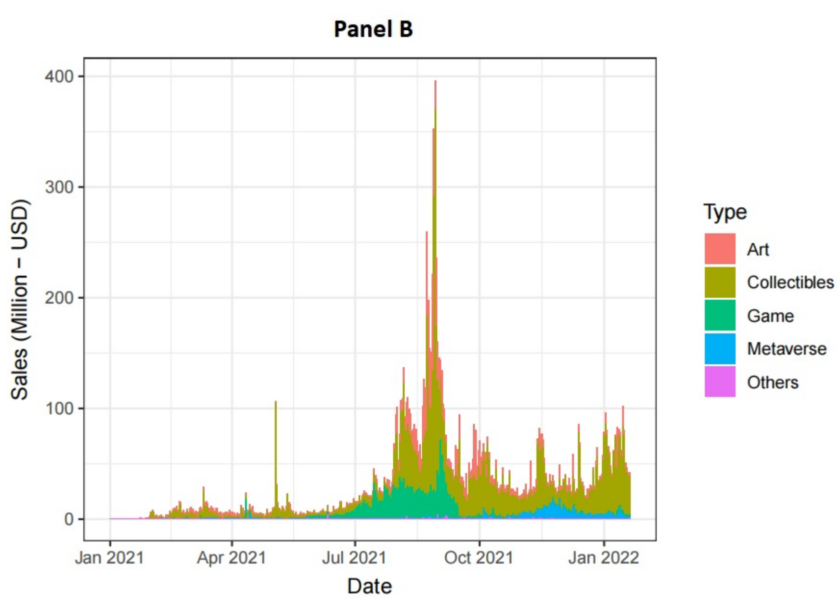
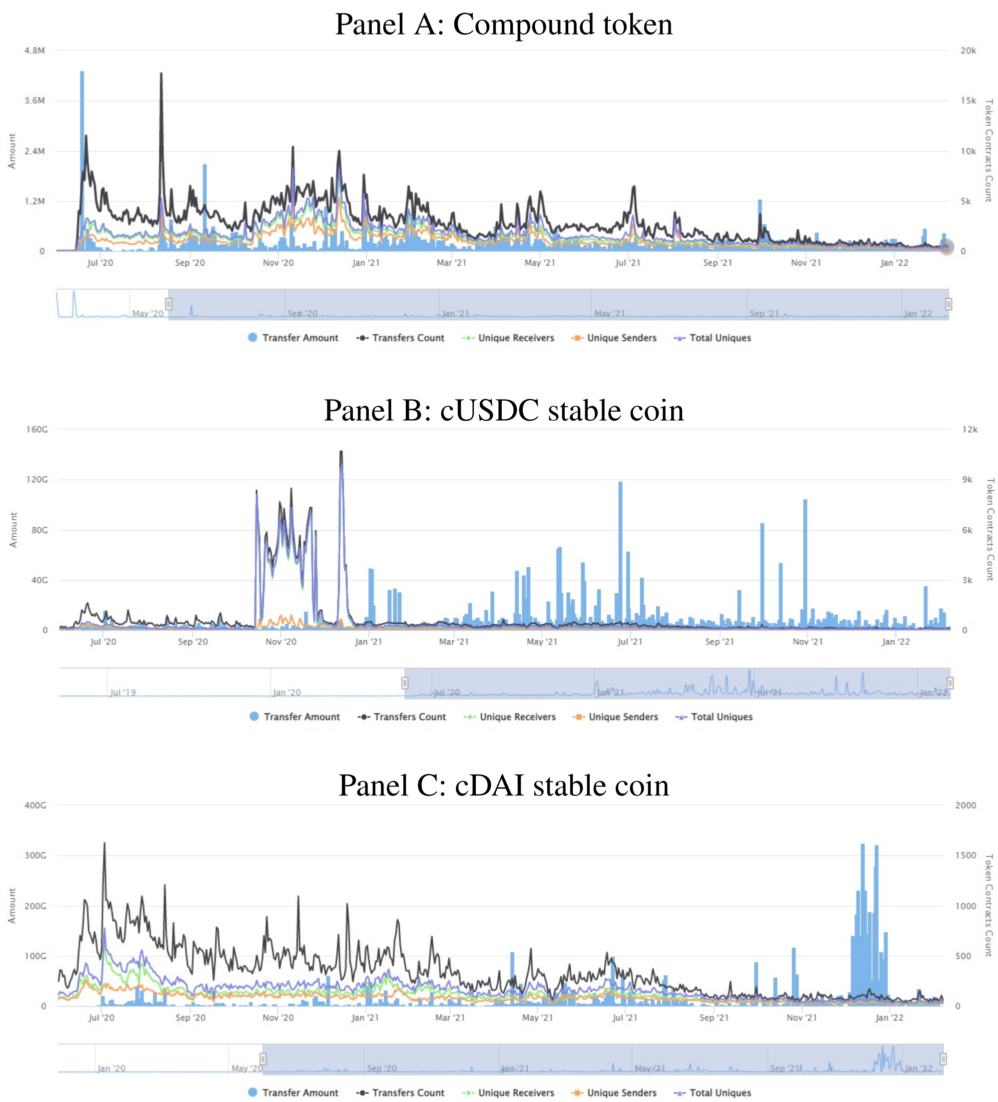


Figure 6. Decentralized lending contracts evolution. This figure shows the evolution of Ethereum-based smart contracts written for Compound token, and Defi protocol leading products (cUSDC and cDAI). The plots were generated with data from Ethereum based smart contracts (`https://etherscan.io/`), from June 2020 to January 2022.



Appendix 1. Matching results. This table reports the matching results between treated (U.S.-based traders) and control (international traders). Panel A reports the sample sizes. Panel B reports the summary of balance for unmatched and matched samples. Panel C reports the percent of balance improvement in the matching procedure. *Volume* is the price times traded amount reported in log plus one. *Trades* is the number of trades reported in log plus one. *Diversity* is the number of unique cryptocurrencies traded reported in log. *Exchanges* is the number of unique exchanges used reported in log. All variables are aggregated daily.

Panel A: Sample sizes

	Treated	**Control**
All	13,002	34,664
Matched	13,002	13,002
Unmatched	0	21,662
Discarded	0	0

Panel B: Summary of balance

	Unmatched		**Matched**	
	Treated	**Control**	**Treated**	**Control**
Distance	0.28	0.27	0.28	0.28
Volume	8.01	7.72	8.01	8.21
Trades	1.49	1.56	1.49	1.56
Diversity	0.41	0.36	0.41	0.42
Exchanges	0.20	0.18	0.20	0.21

Panel C: Percent balance improvement

	Std. Mean Diff.	**Var. Ratio**	**eCDF Mean**	**eCDF Max**
Distance	97.30	-38.50	99.60	78.50
Volume	31.00	-196.00	-39.70	-1.00
Trades	2.30	43.90	-1.90	-43.90
Diversity	81.70	88.30	58.20	62.20
Exchanges	76.90	-415.10	19.00	64.00

Appendix 2. Variable Definition. This table describes all variables used in the summary statistics reported in Table 1. Panel A describes variables used in the trading reports summary. We report all variables in this panel at the daily trader level. Panel B describes variables used in the trading books summary. We report all variables in this panel at the daily exchange-pair level—BTC to USD or BTC to USDT.

Panel A: Trading reports

variable	**quantity**	**description**
Volume	($) Million	The trading volume
Trades	Integer	The number of trades
Diversification	Integer	The number of unique pairs traded
Exchange	Integer	The number of unique exchanges used
Returns	Continuous	The return on a trading position using FIFO method
Winning	Integer	The number of winning positions (positive returns)
Losing	Integer	The number of losing positions (negative returns)
Domestic	Indicator	Takes the value of one if a trader is located in the U.S.
ICO	Indicator	Takes the value of one if a coin is issued in an initial coin offering
IRS	Indicator	Takes the value of one for the period after 2017

Panel B: Trading books

variable	**quantity**	**description**
TotalTrades	Integer	The total number of trades
TotalVolume	Continuous	The total volume
PriceClose	Continuous	Bitcoin close price
WashTrades	Integer	The total number of wash trades
WashPercTotal	Percent	Total number of wash trades to total number of trades
WashVolume	($) Million	The total amount of wash trades
WashVolumePercTotal	Percent	Total amount ($) of wash trades to total amount ($) of trades
Regulated	Indicator	Takes the value of one if an exchange is regulated in the U.S., U.K., or Japan
HarvestPeriod	Indicator	Takes the value of one for trades executed in the last quarter of 2018