Tax-Loss Harvesting with Cryptocurrencies*

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Abstract

This study describes the landscape of taxation in the crypto markets concerning U.S. taxpayers, and examines how recent increases in tax scrutiny have lead to changes in trading behavior by crypto traders. Using a conceptual framework, we predict and find that increased tax scrutiny leads crypto investors to utilize legal tax planning with tax-loss harvesting as an alternative to non-compliance. In particular, domestic traders increase compliance and tax-loss harvesting following the increase in tax scrutiny, and U.S. exchanges exhibit a significantly greater amount of wash trading. Additional findings suggest that broad-based and targeted changes in tax scrutiny can differentially affect crypto traders' preference for U.S.-based exchanges. We discuss new gray areas for tax regulation relating to new crypto assets such as Non-Fungible Tokens and Decentralized Finance protocols that highlight the importance of the coordination between tax policy and other regulations.

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1 Introduction

The market for cryptocurrencies and other crypto assets has grown from near non-existence in 2009 to more than a trillion U.S. dollars of market capitalization in the first half of 2022. Thirty-one percent of Americans aged 18-29 claim to have invested, traded, or used a cryptocurrency.[1] The rise and innovation of digital assets and decentralized finance (DeFi), along with their volatile markets, have created a growing need for regulatory oversight. Nowhere is the need for oversight and policy clarity more pressing than taxation because existing tax laws and regulations were not designed to deal with the rise of crypto assets. Of particular concern is the high level of noncompliance with reporting income from crypto activities, lack of transparency for tax authorities into the crypto markets, and uncertainty about how to apply tax rules to crypto activities. This study provides the first description and economic analysis of the crypto tax landscape. In particular, we examine how recent increases in tax scrutiny lead to changes in trading behavior by crypto traders. Such changes include engaging in more tax-loss harvesting using wash sales—a tax-planning strategy that is evidence of tax compliance—and changes in crypto traders' preferences for U.S. and non-U.S exchanges.

Based on the economic theory of crime developed by Becker (1968), and later applied to tax evasion by Allingham and Sandmo (1972) and others (Sandmo, 2005; Slemrod, 2007), the increases in tax authority scrutiny implemented in the past several years are likely to be associated with increases in tax compliance. This framework predicts that crypto traders weigh the benefits of not reporting their crypto income to the tax authority against the costs of being detected and

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

punished by the tax authority. Of particular relevance to our study is how compliant investors endogenously adjust their (legal) tax planning strategies in response—where tax planning is both a spillover effect of tax scrutiny and an indication of compliance. To this end, we examine a tax planning strategy that has attracted the attention of investors and policymakers but has been largely missing from the emerging crypto literature: the widespread use of "tax-loss harvesting," in which investors sell cryptocurrency that has decreased in value to "harvest" the losses for tax purposes, often buying the same or a similar cryptocurrency shortly before or afterwards, which is referred to as "wash sale" or "wash trading."

What makes tax-loss harvesting in cryptocurrency particularly attractive to investors during the period of our study is the absence of the wash sale rule from crypto asset transactions. In securities markets (e.g., stock trading), the wash sale rule disallows losses for tax purposes from the sale of stocks and securities when the taxpayer has purchased the same asset within 30 days before or after the sale.[2] Because the most commonly traded crypto assets (e.g., Bitcoin) are generally not considered securities, they are free from the wash sale rule, which in crypto markets enables traders to recognize a tax loss and immediately repurchase the same crypto asset. However, a crypto investor's decision to make use of tax-loss harvesting as a tax planning strategy by necessity implies a degree of tax compliance, in that the investor must report his crypto trading to the tax authority to take advantage of the strategy. Our study not only highlights this linkage but also demonstrates the importance of considering regulatory policies holistically and coordinating tax with other regulatory policies.

To illustrate the usage of cryptocurrency in tax-loss harvesting, consider an investor facing a

[2]Internal Revenue Code Sec. 1091. Although there have been proposals to apply the wash sale rules to cryptocurrency, they have not made it into law by mid 2022.

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 Bitcoins 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 Bitcoins 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 Bitcoins for \$70,000, restoring the long position in the asset. Unlike securities markets, the absence of the wash sale rule for cryptocurrency enables traders to "have their cake and eat it too," thereby harvesting their tax losses while maintaining their exposure to the asset.

We extend the conceptual framework of Allingham and Sandmo (1972) incorporating similar tradeoffs as highlighted in Becker (1968). The model predicts that as crypto traders decrease their tax evasion following changes in tax authority scrutiny, they increase their crypto tax-loss harvesting. The effect is also more pronounced when investors' transactions or exchanges used are verifiable by tax authorities. We examine testable hypotheses guided by the model implications using two complementary data sets.

We first explore the detailed trading data from the proprietary dataset of 500 large retail traders ("trading account" dataset). We employ difference-in-differences regressions to compare the tax-loss harvesting of domestic traders (used interchangeably with "U.S. taxpayers") to their international peers in the period before and after increased tax scrutiny in 2018. The results of these difference-in-differences regressions indicate that domestic traders, relative to international peers, increased compliance and tax-loss harvesting by 8%, on average, following the increase in tax scrutiny. Moreover, we find that tax-loss harvesting (i.e., positions sold and bought within a month), rather than regular trading (i.e., positions sold and bought in more than a month), dominates domestic traders' activities around year-ends and during market downturns. For instance, domestic traders sell 47.7% more losing positions than international peers at the end of the year.

The trading account dataset, although granular, may be biased toward investors seeking to be tax-reporting compliant. We therefore complement our analyses by assessing billions of trades in the trading books of thirty-four major crypto exchanges ("exchange" dataset) from Kaiko, a digital assets data provider. The exchange data set is representative of, and potentially better describes, investor behaviors in aggregate. We focus our 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, see, e.g., Cong, Li, Tang, and Yang, 2020; Aloosh and Li, 2021; Amiram, Lyandres, and Rabetti, 2022) and underscore wash trading as an indication of tax-loss harvesting activity.[3] We find that exchanges with presence in, or regulated by, the United States exhibit an approximately 30% greater amount of wash trading than international peers following increases in tax scrutiny, and the effects are more pronounced during market downturns and year-ends.

Overall, domestic traders have become more compliant in response to tightened crypto tax scrutiny, but, at the same time, engaged in greater tax-loss harvesting, particularly through wash trades. We next consider the coordination between crypto tax policy and crypto regulation more generally, and its effects on investors' preferences for U.S. crypto exchanges and U.S. tax revenue. A holistic approach to regulating cryptocurrency, crypto exchanges, and emerging crypto assets is indeed a major focus of President Biden's Executive Order on regulating digital assets. To this end, we extend our analyses to document further patterns and derive several insights. First, focusing on specific shocks to tax scrutiny in 2018 and 2019, we find that broad-based increases in tax scrutiny

[3] See our detailed discussion on Appendix 3. Less liquid coins are more likely to be the subject of fake volume to attract demand (Amiram et al., 2022).

are associated with increases in crypto traders preference for U.S.-based exchanges. However, a campaign targeting solely U.S.-based crypto exchanges appears to have the opposite effect, driving traders away from U.S. exchanges to less transparent non-U.S. exchanges.

Second, applying a BTC price devaluation during 2018 and an assumed tax rate of 30%, we estimate the 2018 tax revenue loss of the U.S. Treasury in the absence of wash sale rules to be between $10.02 and $16.20 billion dollars. Although such estimates are only meant for illustrative purposes, they provide the order of magnitude of the economic effect of tax-loss harvesting through wash trading on tax revenues.

Third, although regulators are beginning to address crypto taxation and wash trading, the crypto sector is fast evolving, thereby creating new gray areas for tax regulation relating to new crypto assets such as Non-Fungible Tokens (NFTs) and Decentralized Finance (DeFi) protocols. We find that transactions in NFTs and the demand for and lending rate in DeFi lending peak toward year-ends, which is consistent with the seasonality of tax considerations.

Our contribution to the literature is threefold. First, 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 on financial reporting and auditing. Empirically, Bourveau, De George, Ellahie, and Macciocchi (2021) examines the role of analysts in mitigating information asymmetries in unregulated initial coin offering (ICO) markets. Lyandres, Palazzo, and Rabetti (2021) analyzes the role of disclosure on ICO-success and post-ICO operating performance. Amiram, Jørgensen, and Rabetti (2022) exploits a blockchain-enabled transparent accounting system to detect terrorist-associated transfers. Tang (2022) examines country-level regulation effects on crypto adoption. Chang and Cong (2022) documents 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, in particular to provide evidence that changes in tax scrutiny are affecting trading behavior in these markets.

Second, we add to the taxation literature by conducting the first empirical study on crypto taxation. Prior studies document important effects that taxes have on trading behavior, but they focus almost exclusively on trading in regulated securities markets, characterized by a high-degree of transparency and tax compliance; see, e.g., Landsman and Shackelford 1995; Graham 1996; Lang and Shackelford 2000; Dai, Maydew, Shackelford, and Zhang 2008; Blouin, Hail, and Yetman 2009; Sialm 2009; Hanlon and Heitzman 2010; Li, Lin, and Robinson 2016; Yost 2018; Hanlon, Verdi, and Yost 2021; He, Jacob, Vashishtha, and Venkatachalam 2022. 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 compliance has been low and key tax rules are, at least for the time being, absent. More broadly, our study lays out a basic description of the crypto tax landscape that provides a foundation for future research, including tax-motivated allocation of household wealth to alternative asset classes, for which we add to recent studies on foreign real estate (e.g., De Simone, Lester, and Markle, 2020; Alstadsæter, Zucman, Planterose, and Økland, 2022) a new digital asset dimension.

Third, 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., 2020; Fusaro and Hougan, 2019; Aloosh and Li, 2021) or to 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, and by showing that exchange regulation is also important for taxation.

The remainder of the study is organized as follows. Section 2 provides the institutional background and a simple conceptual framework to guide empirical analyses. Section 3 describes the data. Section 4 reports empirical findings on tax-loss harvesting with cryptocurrencies. Section 5 discusses policy coordination and quantifies the tax revenue loss due to wash trading before introducing other FinTech innovations pertinent to taxation. Section 6 concludes the study.

2 Institutional Background and Conceptual Framework

We start by providing the institutional background and introducing the conceptual framework that motivates and guides our empirical analyses.

2.1 Crypto Taxation and Scrutiny

Cryptocurrencies, such as Bitcoin and Ether, are treated as property under federal tax law in the United States.[4] The general tax principles applicable to property transactions also apply to cryptocurrencies, subjecting any gains from transactions to taxation. Moving beyond general principles, however, crypto taxation quickly becomes murky and uncertain. Because cryptocurrency and related digital assets are new types of assets and have only existed for a relatively short period (Cong and Xiao, 2021; Cong, Karolyi, Tang, and Zhao, 2022; Lyandres et al., 2021), there has been considerable uncertainty about how they are—and should be—treated for tax purposes. Meanwhile, tax regulators have become increasingly concerned with noncompliance, which in turn has led them to take actions to improve compliance, including issuing warnings to taxpayers,

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

providing guidance, and increasing direct enforcement actions.

The IRS first issued guidance in 2014 and clarified that (i) cryptocurrency is property for tax purposes, (ii) trading crypto for goods or services is a taxable event, (iii) receiving crypto for goods or services is a taxable event, and (iv) mining crypto is a taxable event. Despite this initial guidance, many gray areas remained.[5] For example, some traders believed that crypto-to-crypto transactions were "like-kind" exchanges, and thus gains from such transactions were not taxable.[6]

In 2016, the Treasury Department's Inspector General issued a report on virtual currencies recommending that the IRS issue additional guidance. The Inspector General's report also highlighted the need for the IRS to increase its efforts at enforcing compliance, noting that "none of the IRS operating divisions have developed any type of compliance initiatives or guidelines for conducting examinations or investigations specific to tax noncompliance related to virtual currencies."[7] A major impediment to compliance is the lack of information flowing to tax authorities regarding crypto traders gains and losses. In contrast to trading in securities in which brokerage firms report trading income to the IRS (e.g., Forms 1099), trading in crypto markets takes place largely outside this third-party reporting system. Prior research suggests that noncompliance and grey area tax planning tend to thrive in low-transparency environments (e.g., Hanlon, Maydew, and Thornock 2015; Balakrishnan, Blouin, and Guay 2019; De Simone et al. 2020).

In 2018, the IRS issued two releases indicating an increased level of tax scrutiny that crypto

[5] We discuss some of the gray areas in Section 5.3.

[6] Like-kind exchanges (also called "1031 exchanges" because they are governed by IRC Sec. 1031) allow for the exchange of property without creating a taxable event on the condition that the property exchange is "like kind." The Tax Cuts and Jobs Act of 2017 limited like-kind exchanges to real property after 2017. In 2021, the IRS issued guidance that, even prior to 2018, exchanges of Bitcoin, Ether, or Litecoin did not qualify for like-kind exchange treatment. See Office of Chief Counsel Internal Revenue Service Memorandum Number: 202124008.

[7] See https://www.treasury.gov/tigta/auditreports/2016reports/201630083fr.pdf. The lack of guidance on crypto taxation also prompted the American Institute of CPAs to request further clarification from the IRS (see http://docplayer.net/43122378-June-10-internal-revenue-service-attn-cc-pa-lpd-prnotice-room-5203-p-o-box-7604-ben-franklin-station-washington-dc-20044.html).

traders could expect in the future. In March 2018, the IRS initially issued a release cautioning taxpayers that if they fail to report income from virtual currencies they can be audited and liable for penalties and interest and may be subject to criminal prosecution.[8] Then, in July 2018, the IRS announced a compliance campaign targeting cryptocurrency.[9] The campaign focused on targeting U.S. taxpayers that fail to report income earned on foreign crypto exchanges. The increased IRS scrutiny resulted in an increase in demand for proper tax reporting, the rise of firms specialized in cryptocurrency tax services (such as the firm that provided one of the data sets used in this study), and the proliferation of online crypto tax software.

In July 2019, the IRS initiated a compliance campaign in which it sent letters to more than 10,000 crypto traders who the IRS had reason to believe had failed to report their income to the IRS or had filed their taxes improperly. The IRS reminded taxpayers that cryptocurrency is an ongoing focus of IRS criminal investigations.[10] The IRS has increased its tax scrutiny to the present. 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."[11]

As tax scrutiny of crypto traders increases, leading them to increase their tax compliance (i.e., report their crypto income to the tax authority), they will increasingly turn to legal forms of tax planning. An important form of tax planning for traders is known as tax-loss harvesting, a commonly used tax planning strategy in which traders selectively sell assets that have declined in value

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

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

[10] 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.

[11] See https://www.taxnotes.com/tax-notes-today-federal/cryptocurrency/irs-hunt-uncover-crypto-tax-fraud/2021/03/08/3k5l9.

so that the losses are recognized for tax purposes and can be used to reduce the tax on other income (Constantinides, 1983). When trading assets such as stocks, taxpayers attempting tax-loss harvesting face an important constraint known as the "wash sale" rule. U.S. tax law disallows losses if traders purchase the same security within a 61-day period starting 30 days before the sale of the security and ending 30 days after the sale of the security. However, clear wash sale rules for crypto assets were absent during our sample period, implying that traders could harvest losses for tax purposes by selling a cryptocurrency that has declined in value and then immediately repurchasing it.[12] Importantly, only traders who report their crypto trading to the IRS obtain the tax benefits from such tax-loss harvesting.

2.2 Conceptual Framework

To guide our empirical analyses, this section develops a stylized model based on the conceptual framework of Becker (1968) and Allingham and Sandmo (1972). Becker (1968) models potential criminals as rational economic actors who weigh the benefits of criminal behavior against the costs of such behavior. Allingham and Sandmo (1972) applies the framework to taxation, where taxpayers face a trade-off between the tax savings from evading taxes and the costs of being caught (which in turn depends on the probability of detection by the tax authorities and the taxes and penalties levied on the taxpayer if caught). Theoretically, only the taxpayer knows the actual income, W, and decides on X, the amount to declare or report, where $X \leq W$, which is subject to a constant tax rate θ. With probability p the taxpayer is subjected to investigation by the tax

[12] The IRC Section 1091 wash sale rules apply to sales of "stock or securities." During our sample period, there was little movement to apply the wash sale rules to cryptocurrency. However, the wash sale rules might be applied to crypto assets in the future, either by legislative or regulatory action. Congress has considered, but not passed, legislation that would apply the wash sale rules to crypto assets. As part of an insider trading case initiated in 2022, the SEC argued that some crypto assets meet the definition of a security (SEC v. Wahi, No. 2:22-cv-01009 (W.D.Wash. Jul. 21, 2022) at https://www.sec.gov/litigation/complaints/2022/comp-pr2022-127.pdf).

authorities, who then learn the true income. The investigated taxpayer has to pay the tax on the undeclared amount at a rate $\pi \in (\theta, 1]$. If taxpayers perceive a high likelihood that they can let their income go unreported to the tax authority, with little chance of being detected, the economic theory of crime would predict low levels of tax compliance (i.e., high levels of tax evasion), all else equal.[13]

2.2.1 The crypto taxation setting

Crypto traders face similar tax reporting decisions, with tax scrutiny affecting the probability of investigation or detection.[14] We thus adjust the Allingham and Sandmo (1972) model by introducing a variable I, the intensity of tax scrutiny, and assume that the probability of investigation and detection, $p(I)$, is differentiable and increasing in I.

Because of the digital and unregulated nature of the crypto markets and the lack of third-party reporting, crypto markets are characterized by low transparency to tax authorities. This low transparency environment provides fertile grounds for crytpo traders to evade taxes.[15] But heightened scrutiny in the U.S. makes U.S. taxpayers and domestic traders less able to evade taxes as easily as non-U.S. traders and therefore more likely to be affected by changes in tax scrutiny.[16] During our sample period, traders can wash trade cryptocurrencies to maintain portfolio composition while

[13]Empirical research on the effects of increased tax scrutiny at the corporate and executive level include Guedhami and Pittman (2008), Hanlon, Hoopes, and Shroff (2014), Shevlin, Thornock, and Williams (2017), Yost and Shu (2022), and Belnap, Hoopes, E., and Turk (2022).

[14]One can incorporate the accounting complexity of crypto taxation by introducing a cost of reporting $c(X, I)$. We leave it for future research. To the extent that the rising tax scrutiny also streamlines crypto tax reporting, our findings likely represent underestimates of the impact of rising tax scrutiny.

[15]Although Congress enacted third-party reporting for "digital assets," scheduled to begin in the 2023 tax-year (with the first reports issued in 2024), the Treasury and IRS are considering whether to defer its implementation. See `https://www.bloomberg.com/news/articles/2022-06-29/crypto-tax-cheats-likely-to-get-relief-as-us-crackdown-hits-snag`.

[16]To the extent that other countries are also increasing their tax scrutiny of cryptocurrency trading, it will make it more difficult for us to detect differences in behavior and U.S. and non-U.S. crypto investors in response to shocks to tax scrutiny by U.S. tax authorities.

offsetting their overall taxes, but only if their cryptocurrency transactions are reported to and recognized by tax authorities. Thus, the existence of tax-loss harvesting using cryptocurrencies is also an indication of tax compliance.

To capture these phenomena, we specify an additional tax-loss harvesting benefit entering the payoff, $\Phi(X, \phi) \in \mathbb{C}^2 : \mathbb{R}^2_{\geq 0} \longrightarrow \mathbb{R}_{\geq 0}$, which is increasing in the reported income, X, and in the efficacy of tax-planning strategies, ϕ. Reporting a greater X can reflect greater tax-compliance. Reporting more with tax authorities also means more transactions are recognized and the expected benefit of tax-loss harvesting increases. Because a tax-loss harvesting strategy works only when the trader reports the transactions, we also assume that $\frac{\partial^2 \Phi}{\partial X \partial \phi} \geq 0$. In general, we expect ϕ to be higher (i) when tax-loss harvesting is the most useful, e.g., toward the end of the year (e.g., Ritter 1988; Poterba and Weisbenner 2001; Grinblatt and Keloharju 2004), (ii) if the trader uses domestic exchanges with credentials that are more verifiable by the IRS, and (iii) following periods of large crypto price declines.

A domestic trader then reports X to maximize payoff Π:

$$\max_{X \in [0, W]} \Pi \equiv [1 - P(I)] \cdot U\Big(W - \theta X + \Phi(X, \phi)\Big) + P(I) \cdot U\Big(W - \theta X + \Phi(X, \phi) - \pi[W - X]\Big) \quad (1)$$

As in Allingham and Sandmo (1972), we assume the utility function U to be twice differentiable, increasing, and concave. The trader's optimal reporting X^* essentially reflects the compliance level in equilibrium, which is positively correlated with $\Phi(X^*, \phi)$, the amount of equilibrium tax-loss harvesting. To the extent that X^* is not observed, one may use tax-loss harvesting as an indirect indicator of tax compliance. Although one can further enrich the setup with multiple exchanges and agent heterogeneities, this simple model suffices for generating a number of plausible and robust predictions to motivate or rationalize our empirical exercises.

2.2.2 Model predictions

It is straightforward to verify that $\frac{\partial^2 \Pi}{\partial I \partial X} > 0$ and $\frac{\partial^2 \Pi}{\partial \phi \partial X} > 0$. An application of robust monotone comparative statics (e.g., Edlin and Shannon, 1998; Athey, Milgrom, and Roberts, 1996) directly yields that the optimal $X^*(I, \phi)$ is increasing in I and ϕ.[17] Because Φ is increasing in X and ϕ, and has no direct dependence on I, and $\frac{\partial^2 \Phi}{\partial X \partial \phi} \geq 0$, it follows that equilibrium tax-loss harvesting, Φ is also increasing in I and in ϕ by chain rules. Our first model prediction is therefore:

P1: Following increases in tax authority scrutiny, domestic crypto traders affected by tax authority scrutiny increase the extent of their tax-loss harvesting.

U.S. taxpayers tend to reside in the United States or have major business operations in the country, and thus use domestic exchanges—exchanges with presence in the United States, including those explicitly regulated by U.S. regulators. As a result, their engaging in more tax-loss harvesting should be reflected by a larger increase in tax-loss harvesting on U.S. exchanges. A corollary of the prediction is:

C1: Following increases in tax scrutiny, domestic exchanges experience greater tax-loss harvesting than international exchanges.

Because $\frac{\partial^2 \Pi}{\partial I \partial \phi} > 0$, and ϕ corresponds to periods when tax-harvesting becomes important, e.g., following market downturns and around year-ends, as crypto traders become more tax compliant in response to increases in tax authority scrutiny, domestic traders may seek to use the services of crypto exchanges whose credentials are verifiable to the tax authorities. This leads to our second prediction:

[17] We could also obtain this with reasonable explicit functional forms for U and Φ at the expense of generality.

P2: Following increases in tax authority scrutiny, domestic traders increase tax-loss harvesting following price declines or toward year-ends.

Finally, domestic exchanges have more domestic traders than international exchanges. In addition, domestic exchanges are more credible and more recognized by the U.S. tax authorities relative to international exchanges (offering a higher ϕ). Therefore, as tax scrutiny increases, a trader on a domestic exchange would report more transactions than someone using international exchanges, which in aggregate leads to a relatively larger tax-loss harvesting Φ. A corollary of the prediction is:

C2: Following increases in tax authority scrutiny, domestic exchanges experience greater tax-loss harvesting, especially following periods of price decline and toward year-ends.

In the remainder of the paper, we examine how these predictions are borne out in the data.

3 Data and Summary Statistics

We use two data sources in our analyses, each of which has detailed trade information. The first dataset comprises proprietary full-detailed account level trading reports for 500 large retail traders ("trading account" dataset). The second dataset is trade-by-trade information extracted from the trading books of thirty-four major crypto exchanges, comprising billions of trades ("exchange" dataset). The trading account dataset is granular, but the associated findings may not generalize beyond large retail traders because the traders are self-selected ones seeking assistance on compliance.[18] The trading book data in the exchange dataset do not allow identification of traders

[18] Accordingly, estimates based on these traders can be viewed as upper bounds of the compliance and wash trading response by crypto traders. We later utilize the crypto exchange dataset to complement current analysis and draw conclusions about trader responses in aggregate.

executing particular trades. However, they have the advantage of reflecting virtually all trading activities on major crypto exchanges, enabling us to draw market-wide conclusions.

3.1 Trading Account Dataset

We obtain proprietary data from a tax firm that has been operating in the cryptocurrency field since 2012.[19] The data include the trading activities in the form of trading reports for the tax firm's 500 largest retail traders.[20] Approximately one-third of the traders are U.S.-based taxpayers, and the remaining traders are internationally domiciled.[21] These traders became clients of the firm in early 2019, receiving specialized assistance in reporting their crypto taxable income. The data include 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.[22]

Table 1, Panel A, reports the summary statistics for 500 large retail traders obtained from the trading account database.[23] Appendix 1 provides definitions for variables in both datasets. Table 1 indicates that an average trader in the dataset engages in approximately $47 thousand worth of cryptocurrency trades daily (mean Volume = $46.94 thousand). On average, traders engage in 16 transactions per day (mean Trades = 16.21).[24] The standard deviation for daily volumes and transactions varies widely, with over $152 thousand in daily volumes and 41 in daily transactions

[19]This firm has retail and institutional clients all over the world. Besides tax reporting, the firm also provides auditing services. For the sample used in our empirical analysis, the firm did not disclose any direct or indirect information that could be used to reveal these individuals' identity.

[20]The largest traders are measured by activity (e.g., number of trades and volume) during 2017-2019.

[21]For international peers in which a local foreign exchange 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).

[22]Data limitations preclude us from testing IRS events in the post-mid-2019 period.

[23]We winsorize all continuous variables at one percent to mitigate the influence of outliers.

[24]Following standard practice, we set non-trading days to have zero transactions.

(SD Volume and Trades = $ 151.86 thousand and 41.05).

Traders often trade on multiple crypto exchanges (mean Exchange = 1.30), and are, on average, profitable (as indicated by mean and median daily average profits of 5.63% and 0.26%).[25] Tokens issued in Initial Coin Offerings (ICOs) dominate trading activities, where these trades occur 62 percent of the time (mean ICO = 0.62). The greatest portion of trading activity in the dataset, 40 percent, relates to the period after the increase in IRS scrutiny (mean IRS = 0.40).

Table 1, Panel B, presents summary statistics of trader characteristics for domestic and international traders based on a propensity score matched sample, in which each domestic trader is matched with an international trader based on observable trading characteristics.[26] Panel B indicates that both samples are virtually balanced in the 2017-2018 period.

3.2 Exchange Dataset

Table 1, Panel C, reports the summary statistics for the exchange dataset comprising data from the trading books of 34 crypto exchanges in the period from August 2011 to May 2021. The observations are at the exchange-pair-millisecond level and contain information on each trade executed during the pair life in a given exchange. Each transaction observation includes information on the direction (sell or buy), date, amount, and price at which each trade is executed.[27]

Exchanges in this sample have an average daily trading volume (TotalVolume) of USD $104 million, median of $7.83 million, and a standard deviation of $333.80 million. These figures

[25] We estimate returns from trading positions using 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. Although the method is beneficial in that it makes returns across traders comparable, it may not be the method used by traders when reporting their activity to tax authorities. 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.

[26] See Appendix 2 for the matching details.

[27] We obtain the exchange dataset from kaiko.com, a digital assets data provider used in several studies (e.g., Amiram et al., 2022; Makarov and Schoar, 2020).

suggest that, although the volume distribution is skewed toward 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. Finally, the Bitcoin (BTC) price (PriceClose) is quite volatile, as indicated by a minimum of \$10.30 and a maximum of \$76,245.

We turn to our variable of interest, wash trading, which we use as a proxy for tax-loss harvesting, and thus tax-compliance. Extant literature uses several techniques to detect wash trading. For instance, Bitwise's report to the SEC uses the densities of a few crypto exchanges' volume series to impute volume inflation Fusaro and Hougan (2019). Cong et al. (2020) introduces statistical measures for detecting fake or manipulated volume, and relate that to crypto exchang regulation. Amiram et al. (2022) combines statistical and machine learning measures. Because wash trading involves selling a losing position for tax purposes and buying it immediately back to retain the asset and portfolio position, one natural proxy for wash trading is based on matching a sell order with buy orders occurring within 60 seconds at the same price, pair, quantity, and exchange.[28] We use this measure to quantify the daily number of wash trades, their volume, and the percentage of wash trades to total trades, focusing on Bitcoin (BTC) to either U.S. dollars (USD) or Tether (USDT).[29]

Panel C indicates that based on the means of WashVolumePercTotal and $WashPercTotal$,

[28] Using a 60 second window to estimate wash trades is conservative and likely understates the extent of tax-loss harvesting using wash trades. Untabulated findings based on estimations in which we also use less conservative specifications for the timing cutoff (e.g., 2, 5, and 10 minutes) reveal the same inferences as those based on tabulated findings. Aloosh and Li (2021) employs a similar construct using internal data of Mt. Gox exchange leaked by hackers. Amiram et al. (2022) uses 10 minute buckets aggregated daily on several measures of volume inflation. See Appendix 3 for additional details regarding construction of the wash trading proxy for tax-loss harvesting.

[29] Wash trading can be used by exchanges to inflate trading volume (e.g., Cong et al., 2020; Amiram et al., 2022) to attract demand. Being the most liquid in the period, these trading pairs helps us develop a proxy for tax-loss harvesting that is less affected by crypto exchanges incentives to inflate volume.

8.75% of the daily volume and 18.12% of the daily number of trades in the sample are potentially wash trades. Consistent with Cong et al. (2020), wash trading as a percentage of total volume (WashVolumePercTotal) varies significantly across the exchanges and time. Mean wash trading volume (WashVolume) is $6.65 million per day, but its maximum value exceeds $2 billion. Finally, approximately 15% of the sample's trading activity occurs on U.S.-regulated exchanges (*Regulated*), and 23% on U.S.-present exchanges (*Presence*).[30]

4 Empirical Analyses and Discussion

As stated in our theoretical framework, we expect domestic traders to respond to increased tax scrutiny by increasing their tax-loss harvesting, which serves as a proxy for tax compliance because only traders who report crypto trading activities to the IRS can benefit from tax-loss harvesting using cryptocurrencies. We test the model predictions in a difference-in-difference framework first using the Trading Account Dataset and then using the Exchange Dataset.[31]

4.1 Test of Prediction 1 using Trading Account Dataset

Prediction 1 states that domestic taxpayers increase tax-loss harvesting when tax scrutiny increases. To test this, we estimate the following equation:

$$Harvest = \alpha + \beta(IRS \times Domestic) + \gamma IRS + \delta Domestic + \Theta + \Lambda + \epsilon, \tag{2}$$

[30]Following Cong et al. (2020), we classify exchanges as regulated if they have been licensed in the United States—including Coinbase, Gemini, and Kraken. We also allow exchanges with presence in the U.S. market (e.g., Binance) in the less restrictive specification "Presence."

[31]Appendix 4 examines the parallel trends assumption underlying the difference-in-differences model given by Eqs. (2) and (4).

where *Harvest* is the log of 1 plus the number of trades in which the crypto asset that is sold and is also bought back within 30 days.[32] The explanatory variables are: (i) *IRS*, an indicator that equals one during the period of increasing tax scrutiny (post-2017), and zero otherwise; (ii) *Domestic*, an indicator that equals one if a trader is U.S.-based, and zero otherwise; and (iii) the interaction of $IRS \times Domestic$. Θ is a vector of controls including *Trades*, which is the log of 1 plus the number of trades; *Volume*, which is the total volume (amount traded times price) reported in log; *Diversification*, which is the log of the number of unique cryptocurrencies traded; and, *Exchanges*, which is the log of the number of unique exchanges used. Λ is a trader fixed effect, and ϵ is the error term.[33] All variables are measured at the trader-daily level. β, the coefficient on the interaction of *IRS* and *Domestic*, reflects the difference in responses between U.S.-based and international traders during the period of increasing tax reporting scrutiny.

Table 2, Panel A, reports the regression summary statistics for Eq. (2). Columns 1, 2, and 3 present findings based on estimations that include all sample years and estimations for which we restrict observations to be within the window 2016-2019 and the 2017-2018 windows. These shorter time windows reduce the influence of events unrelated to changes in tax scrutiny, but they also reduce sample size. Column 4 presents findings based on the propensity score matched sample for domestic and international peers for the 2017-2018 window. The results across all four specifications support the prediction that increased IRS tax reporting scrutiny significantly increases tax-loss harvesting activities by domestic traders. In particular, relative to international peers, domestic traders respond by engaging more in tax-loss harvesting activities, as indicated by the significantly positive $IRS \times Domestic$ coefficient, which ranges from of 0.06 to 0.08.

[32] We use a 30-day cutoff to measure wash trades because that corresponds to the definition of wash trades.

[33] We report heteroskedastic robust standard errors clustered in time.

We also estimate versions of Eq. (2) using event windows surrounding two specific changes in tax scrutiny. The first (March 2018) corresponds to the "IRS Release" cautioning taxpayers that if they fail to report income from virtual currencies, they can be audited and liable for penalties and interest, and may be subject to criminal prosecution. The second (July 2018) corresponds to the IRS announcement of the compliance campaign ("IRS Campaign") targeting cryptocurrency, including both outreach and IRS examinations. For both IRS Release and IRS Campaign events, we present findings using observations for the six, four, and two months surrounding the event.

Columns 5, 6, and 7 present findings from estimation of Eq. (2) for the IRS Release event using the sample of observations six, four, and two months surrounding the event, while Columns 8, 9, and 10 contain findings from estimating the equation for the IRS Campaign. The findings for the two longer event windows reveal that for both events, the $IRS \times Domestic$ coefficient is significantly positive (coefficients = 0.05 and 0.07 for IRS Release and 0.03 and 0.04 for IRS Campaign). In the shorter event window, the coefficient is insignificantly different from zero for both events. Collectively, these findings support the prediction that increased IRS tax reporting scrutiny relating to the IRS Release and IRS Campaign significantly increases tax-loss harvesting activities by domestic traders relative to others.

4.2 Test of Prediction 2 using Trading Account Dataset

We next test Prediction 2 by assessing whether increased tax-scrutiny generates turn-of-the-year effects. Finding that domestic retail traders sell more losing positions around the turn of the year-the period than their international peers is evidence consistent with their trades reflecting the effects of increased tax reporting scrutiny. We thus estimate versions of the following equation using subsamples of observations relating to winning (losing) positions and whether the losing trades occur through regular or harvesting strategies:

$$\begin{aligned} Trades = \alpha + \beta_1(IRS \times Domestic \times Dec) + \beta_2(IRS \times Domestic \times Jan) \\ + \gamma IRS + \delta Domestic + \zeta Jan + \omega Dec + \Lambda + \epsilon, \end{aligned} \tag{3}$$

Winning (losing) positions are determined by the cumulative returns (estimated using FIFO method) being positive (negative) when the position is sold. Harvesting (regular) trades are defined by whether the asset sold is bought within (after) 30 days. In addition to the variables specified in Eq. (2), Eq. (3) includes the following indicator variables: Jan is an indicator variable that equals one for trades during 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. The variables of interest are the three-way interactions of IRS, $Domestic$, and Jan and of IRS, $Domestic$, and Dec. Their coefficients, β_1 and β_2, reflect the triple differences effects of domestic traders in the period of increased tax-scrutiny for moments of the year most and least sensitive for tax-motivated trading.

Based on Prediction 2, we expect U.S.traders to sell more (less) losing positions than international traders at the end of the year (beginning of the year), i.e., in December (January). Therefore, we expect that for losing positions, β_1 is positive and β_2 is negative. We have no predictions for winning positions. Columns 1 and 2 in Table 3 present findings for estimations of Eq. (3) relating to winning and losing positions. The findings are consistent with our predictions that domestic traders sell 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 scrutiny. In particular, the coefficients on $IRS \times Domestic \times Dec$ and $IRS \times Domestic \times Jan$ coefficients, 0.39 and -0.42, are significantly positive and negative.

We conduct an additional test to examine Prediction 2 by identifying winning and losing positions and their respective buybacks at the traders' portfolio level. This permits us to 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. Columns 3 and 4 present findings for estimations of Eq. (3) relating to winning and losing positions for trades we identify as tax-loss harvesting using wash sales, i.e., those involving repurchases within 30 days; Columns 5 and 6 present the analogous findings relating to regular trades, i.e., non-wash sales. The findings provide evidence that tax-loss harvesting dominates the end-of-the-year trading strategies for domestic traders in the period following increased tax scrutiny as evidenced by (i) the larger positive coefficient on $IRS \times Domestic \times Dec$ for the loss harvesting sub-sample relative to the regular trading sub-sample, 0.59 vs. 0.24, with the difference being significant at less than the 5% level, and (ii) a significantly negative coefficient on $IRS \times Domestic \times Jan$, -0.39, for only the loss harvesting sub-sample.[34]

4.3 Test of Corollary 1 using Exchange Dataset

To test Corollary 1 about tax-loss harvesting at the exchange level, we estimate:

$$WashTradesVolume = \alpha + \beta(IRS \times US\,Exchange) + \gamma IRS + \delta US\,Exchange + \Theta + \epsilon, \quad (4)$$

where *WashTradesVolume* is the log of 1 plus the wash trade volume. *IRS* is as defined above. Unlike the trading account dataset, the exchange dataset does not include information regarding the nationality of the traders. Therefore, we use characteristics of an exchange as a proxy for

[34] The difference in coefficients is 0.35 and it is significant at 5%.

whether trades are executed by U.S. traders. *U.S. Exchange* is an indicator variable that equals one if a crypto exchange is a U.S. exchange using two measures. The first (*Regulated*) is whether the exchange is regulated by the New York State Department of Financial Services or by FinCEN (a bureau of the U.S. Department of the Treasury), and includes three exchanges: Coinbase, Gemini, and Kraken. The second (*Presence*) is whether the exchange has presence in the United States, and includes eight exchanges, including the three regulated ones plus five others with offices in the country (and thus are likely to have a large base of U.S. traders).[35] Θ is a vector of controls including $BTCPrice$, the log of BTC close price in either USD or USDT; *PriceSD*, the log of 1 plus the standard deviation of the intraday prices; and $TotalVolume$, the product of traded amount and price in log. ϵ is the error term. All variables are measured at the exchange-daily level.

The key variable of interest is the interaction term, $IRS \times USExchange$. Its coefficient, β, reflects the difference in wash trades between exchanges with presence (or are regulated) in the United States and exchanges without a presence (or are not regulated) in the United States during the period of increased tax reporting scrutiny. Based on Corollary 1, we expect β to be positive. We report heteroskedastic robust standard errors clustered in time, to mitigate serial correlation in the error term.

Table 4, Panel A, reports the summary statistics for Eq. (4). Each pair of columns includes findings using *Regulated* and $Presence$. Columns 1 and 2 present findings based on estimations that include all sample years. Columns 3 and 4 report estimations for which we restrict observations to be within the 2016-2019 window, and Columns 5 and 6, within 2017-2018. As predicted, β_1 is significantly positive in all specifications, ranging from 0.73 to 1.67.

[35]The additional five exchanges included in the *Presence* specification are Binance, Bitfinex, Bitstamp, Bittrex, and Huobi.

As with the trading account dataset, we estimate Eq.(4) using event windows surrounding the March 2018 IRS Release and the July 2018 IRS Campaign. In addition, we also estimate Eq.(4) using event windows surrounding July 2019, which corresponds to the date the IRS issued letters ("IRS Letters") to thousands of cryptocurrency traders "that potentially failed to report income and pay the resulting tax from virtual currency transactions or did not report their transactions properly."[36] For each of the three events, we present findings using observations for the six, four, and two months surrounding the event.

Table 4, Panel B, presents findings from estimation of Eq.(4) for each event using the sample of observations three, two, and one months surrounding the event in Columns 1 and 2, Columns 3 and 4, and Columns 5 and 6. Findings for the two longer windows (Columns 1 through 4) reveal that for all three events, the $IRS \times US\,Exchange$ coefficient is significantly positive (coefficients range from 0.33 to 0.54 for the March 2018 IRS Release, from 0.22 to 0.37 for the July 2018 IRS Campaign, and from 0.13 to 0.29 for the July 2019 IRS Letters). Findings based on the shorter event window reveal mixed results, with only two significantly positive $IRS \times US\,Exchange$ coefficients. Collectively, the findings in Table 4 support Corollary 1 by showing that increased IRS tax reporting scrutiny increased tax-loss harvesting using wash trades on U.S. exchanges.

4.4 Test of Corollary 2 using Exchange Dataset

We next test Corollary 2 by assessing whether increased tax-scrutiny generates increased tax-loss harvesting using wash trades following large price declines on cryptocurrency markets. Bitcoin price achieved an all-time high in the 2017 end—about $20 thousand, and declined precip-

[36]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.

itously throughout 2018. In particular, Figure 1 shows that the BTC price dropped nearly 70% throughout 2018, potentially leaving many traders with unrealized losses. Therefore, the last months of 2018 are potentially beneficial for tax-loss harvesting.

To provide visual evidence of Corollary 2, we examine wash trades for four exchanges over time in Figure 2. The trading activity highlighted by the green circle indicates spikes in wash trading in the period beneficial for tax-loss harvesting. The visual evidence indicates increased wash trading toward the end of 2018 for two U.S.-based exchanges, Coinbase and Kraken, a large regulated international exchange, Binance, and an unregulated international exchange. Although there is an increase in wash trading over the same time period on the unregulated exchange, Okex, the increase appears smaller than that on the other three U.S.-based or regulated exchanges.[37]

To test Corollary 2 regarding tax-loss harvesting using wash trades following large price declines on cryptocurrency markets, we estimate the following equation:

$$WashPercTotal = \alpha + \beta(USExchange \times Harvest) + \gamma USExchange + \delta Harvest + \Theta + \epsilon, \quad (5)$$

where $WashPercTotal$, is the percentage of wash trades to total trades. $Harvest$ is an indicator variable that equals one for trades made from October to December 2018, a period of large BTC price declines, when tax-loss harvesting would be particularly beneficial. The indicator variable, $USExchange$, either reflects being an exchange with a presence in the United States (Presence = 1), a regulated exchange (Regulated = 1), or one of the following exchanges, each of which is regulated by U.S. authorities—Coinbase, Gemini and Kraken. The key variable of interest is the interaction term, $USExchange \times Harvest$. Its coefficient, β, reflects the difference in wash

[37] Note that wash trades increases after 2020 for Okex (red square), possibly generated endogenously as the result of increased market competition among unregulated exchanges (see Amiram et al. (2022)).

trades between exchanges with presence (or based) in the United States and exchanges without a presence or regulated in the United States during the period of increased tax reporting scrutiny. Based on Corollary 2, we expect β to be positive. Θ is a vector of controls including *BTCPrice*, *PriceSD*, and *TotalVolume*. ϵ is the error term. All variables are measured at the exchange-daily level. Following previous models, we cluster standard errors in time across all specifications.

Table 5, Panel A, presents regression summary statistics for various estimations of Eq.(5). In Column 1 (Column 2) *USExchange* is Presence (Regulated). In Column 3, *USExchange* is disaggregated into indicator variables for each of the three exchanges, Coinbase, Gemini and Kraken. Including the three indicators permits individual estimates of tax-loss harvesting activity for each of these exchanges. Overall, the results in Table 5 indicate that wash trades on U.S.exchanges increased more during the last three months of 2018, when cryptocurrencies sustained a large price decline. In particular, the Column 1 and 2 findings show that the $USExchange \times Harvest$ coefficients are significantly positive only for exchanges that have a presence or are regulated in the United States (coefficients = 1.01 and 5.12). Moreover, the Column 3 findings indicate that the increase in wash trades manifested in each of the regulated exchanges, with $USExchange \times Harvest$ coefficients ranging from 4.24 to 5.33.

Table 5, Panel B, presents regression summary statistics relating to estimations of versions of Eq. 5 in which we replace Harvest with the indicator variables, *Dec* and *Jan*, which relate to the last two weeks of December and the first two weeks of January. This permits us to focus on the end-of-year effects. Based on Corollary 2, we expect wash trading as a means to achieve tax-loss harvesting to increase in December, i.e., the coefficient on the interaction of *USExchange* and *Dec* is positive. Our results are consistent with this prediction. Turn-of-the-year effects are mostly accentuated for the immediate years following increased tax scrutiny (2018 and 2019).[38]

5 Extended Discussion and Policy Coordination

Our findings thus far suggest that increases in tax scrutiny lead to increases in tax-loss harvesting by crypto traders as they become more tax compliant and increase their tax planning. However, this finding does not rule out the possibility that traders also adopt strategies to reduce reported income by moving their trades to non-U.S. exchanges or to markets in new innovative virtual asset classes for which their tax treatment is to date uncertain. Moreover, the tax authorities are not working in isolation—other regulators such as the Securities and Exchange Commission (SEC) are introducing changes that interact with taxation. For example, in an insider trading case initiated in 2022, the SEC argues that some crypto assets meet the definition of a security (SEC v. Wahi, No. 2:22-cv-01009 (W.D.Wash. Jul. 21, 2022)).[39] If the SEC classifies some crypto assets as securities, then to the extent that determination carries over to the tax realm, then some crypto assets would become subject to the wash sale rules for securities.[40]

Predicting the effects on revenue collection from crypto currency traders of such a rule change is difficult, particularly in the absence of coordination among regulators. Other things equal, making crypto assets subject to wash sale rules makes tax-loss harvesting more difficult, which could decrease tax compliance and reduce the attractiveness of U.S. exchanges as venues for crypto

[38]This result is consistent with the literature that finds that tax-driven turn-of-the-year effects are primarily present in the years following changes in tax rules with incentives for investors to realize their losses before year-end (e.g., Poterba and Weisbenner (2001)).

[39]See https://www.sec.gov/litigation/complaints/2022/comp-pr2022-127.pdf. SEC Chair Gary Gensler has also repeatedly called on U.S. crypto exchanges to register with the SEC as securities exchanges (https://cryptobriefing.com/secs-gensler-says-no-difference-between-crypto-and-securities-exchanges/).

[40]Several crypto exchanges, including Binance, are currently under investigation by the SEC (See https://www.forbes.com/sites/michaeldelcastillo/2022/08/04/every-us-crypto-exchange-and-binance-is-being-investigated-by-the-sec-says-senator-lummis-staffer/.)

traders, thereby reducing revenue. However, if U.S. regulators coordinate with their international counterparts, then the reduction in attractiveness of U.S. exchanges would be mitigated and revenue losses would in turn be mitigated. Therefore, this subsection discusses the relevance of policy coordination and provides initial insights regarding traders' potential to avoid taxes or their incentives to move away from a segment of the crypto space that receives policy attention. Given that these markets are still in their infancy, our inferences are primarily descriptive, serving to facilitate future research and regulatory debate, as well as to provide initial insights on policy coordination.

To this end, we first examine the effects of tax reporting scrutiny on traders' exchange preferences, i.e., U.S.-regulated versus international exchanges. We then provide a rough estimate of the revenue loss attributable to tax-loss harvesting using wash trades in a partial equilibrium framework. Finally, we discuss how, while regulators are starting to recognize the importance of policy coordination, the space is fast evolving and new gray areas emerge (e.g., Non-Fungible Tokens and DeFi protocols for avoiding tax and regulation), requiring regulators to constantly catch up.[41]

5.1 Effects of Tax Reporting Scrutiny on Traders' Exchange Preferences

To assess the effects of increasing tax reporting scrutiny on exchanges preferences observed in the market, we adopt the specification in Eq. (4) but replace the response variable with *ExchangeActivity*, the log of the daily sum of the products of sell and buy orders and price. Table 6, Panel A, presents regression summary statistics for this estimation. The results provide evidence that during periods of increased tax scrutiny, net exchange activity is significantly larger for U.S. exchanges, i.e., those that have a presence or are regulated in the United States. In particular,

[41] For other examples, see Rev. Rul. 2019-24 regarding whether cryptocurrency received in airdrops and hard forks result in income for tax purposes. See Shapiro (2018) for a discussion uncertainty in the taxation of Bitcoin loans.

across all specifications, the coefficient on the interaction of $US\,Exchange$ and IRS is significantly positive (ranging from 0.37 to 1.88).

We extend the analyses to examine the effects of increased tax scrutiny surrounding the March 2018 IRS Release, the July 2018 IRS Campaign, and the July 2019 IRS Letters events. The findings, presented in Table 6, Panel B, illustrate the complexity of regulation by showing that increases in broad-based and targeted tax scrutiny do not necessarily have the same effects on crypto trading activity. Most notably, whereas traders increase their trading activity on U.S. exchanges consistently (all but one of the interaction coefficients are significantly positive) following the IRS Release and the IRS Campaign ($US\,Exchange \times IRS$ coefficients range from 0.51 to 0.78 for IRS Release and from 0.04 to 0.42 for IRS Campaign), they decrease their trading activity following the IRS Letters event (the four negative $US\,Exchange \times IRS$ coefficients are significantly negative and range from -0.25 to -0.43, and the other two are insignificant). The IRS Letters event differs from the earlier events in that it reportedly targeted traders on one U.S. exchange—Coinbase—rather than crypto traders or U.S. taxpayers in general.[42] Thus, the targeted IRS letter campaign could have driven traders away from the U.S.-based exchanges. Thus, a consequence (presumably unintended) of this form of tax scrutiny could be to reduce the attractiveness of U.S. exchanges.

5.2 Estimating the Size of Revenue Loss from Tax-Loss Harvesting

Recent crypto-tax proposals for raising additional tax revenue 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. Next, we provide

[42] See https://www.wsj.com/articles/irs-sending-warning-letters-to-more-than-10-000-cryptocurrency-holders-11564159523.

an order-of-magnitude estimate for the revenue loss attributable to tax-loss harvesting using wash trades, without considering traders' endogenous responses to a ban on crypto wash trading.

First, we calculate the median average wash trade as a percentage of total trades during the harvesting period (the last three months of 2018) and non-harvesting periods. We focus on the three regulated exchanges because these exchanges are less likely to be subject to endogenous volume inflation that can affect our estimates (see Appendix 3). Because the volume size across regulated exchanges varies widely, we calculate both volume-weighted and equally-weighted tax-loss harvesting estimates. Second, we estimate the dollar volume of wash sales as the difference between estimated wash trades in the harvesting and non-harvesting periods, multiplied by the total volume during the harvesting period. Third, we estimate the revenue loss to the government as the product of the estimate for the dollar volume of wash sales, the average BTC price devaluation in 2018 (70%), and then an assumed marginal tax rate (30%).

Table 7, Panel A, reveals that the volume-weighted (equal-weighted) estimate of wash trades is 21.56% (19.34%) for the harvesting period and 4.25% (5.24%) for the non-harvesting period. Panel B reports a range of estimates of wash volume and revenue loss to the government.[43] The first and second rows present estimates for all 34 exchanges, in the sample, and in the three regulated exchanges for Bitcoin to USD transactions; the third and fourth rows present analogous estimates for all Bitcoin transactions on the exchanges.

Table 7, Panel B, reports the estimates of the tax revenue loss for 2018. For each BTC-USD pair, we estimate a value-weighted (equal-weighted) wash volume of $25.52 ($20.80) billion and revenue loss of $5.36 ($4.37) billion across all exchanges. These estimates decline to a wash volume of $19.37 ($15.78) billion and revenue loss of $4.07 ($3.31) billion if only regulated ex-

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

changes are considered. Across all BTC pairs, we estimate a wash volume of $77.14 ($62.85) billion and revenue loss of $16.20 ($13.20) billion across all exchanges. These estimates decline to a wash volume of $58.53 ($47.69) billion and revenue loss 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.

These estimates are only meant for illustrating the order of magnitude of the impact of tax-loss harvesting through wash trading on tax revenues, in a particular episode. The actual impact of anti-tax-loss-harvesting proposals depend on the crypto market size and evolution, and importantly on investors' endogenous responses to the policy. For instance, because traders may lose a considerable incentive to trade on regulated exchanges if wash sale rules are extended to crypto assets, 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.[44] Consequently, the effects of a particular regulatory change on the overall tax revenue become more ambiguous in these rapidly changing markets.

5.3 FinTech Innovations and Gray Areas for Taxation

More broadly speaking, when enacting policy changes on one type of asset or market, policy makers need to consider potential spillover effects on other assets or markets. We discuss two emerging crypto markets involving Non-Fungible Tokens (NFTs) and Decentralized Finance (DeFi) and how they present challenges to regulators, underscoring the importance of policy coordination in the crypto sector.

[44] 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).

5.3.1 Trading of NFTs

NFTs representing blockchain-based digital ownership of collectibles and items (Cong and Xiao, 2021) are gaining popularity. CryptoKitties, an NFT for a unique digital cat collection launched in late 2017, sold 300 thousand crypto kitties in primary and secondary markets by the end of 2017. Several other NFT products have been launched subsequently, ranging from CryptoPunks to digital art, card games, metaverse assets, and even tweets. The IRS has not yet released specific tax guidance for NFT trading, making the NFT market a gray area for taxation.[45]

Because prior literature shows that year-end trading is often tax-motivated, we examine trading activity in NFTs around year-end. We do so by estimating the following fixed effect model:

$$Y = \alpha + \beta Jan + \delta Dec + \Lambda + \epsilon, \tag{6}$$

where Y is the log of one of five dependent 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 dependent variables are at the trader-daily level. *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. Λ is

[45] Some features of NFT transactions 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. Unlike other fungible crypto assets, trades from one NFT to another NFT cannot be interpreted as a "like-kind" exchange transaction to the extent that an NFT is considered unique. As with cryptocurrency, NFTs are not subject to the wash sale rules so long as they are not considered securities. Despite the 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. 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).

a year fixed effect and ϵ is the error term.

Table 8 reports the regression results for Eq. (6). The findings reveal that all trading variables are significantly larger in December than other months of the year, as indicated by significantly positive *Dec* coefficients across all five specifications. These findings are consistent with tax-motivated demand for NFTs at the year-end. Such activity may also reflect non-tax related wash trade activities intended to stimulate demand to pressure the price of these assets upwards. But *a priori*, it is unclear why such activities peak toward year-ends. Therefore, future research mapping (off-chain) online sales in marketplaces and on-chain transactions (i.e., among NFT blockchain addresses) can potentially advance understanding of the drivers behind the empirical patterns.

5.3.2 DeFi lending and long-term vs. short-term capital gains

DeFi uses smart contracts to create protocols that substitute and innovate upon centralized financial services, such as exchanges, liquidity pools, and lending platforms, in a decentralized manner.[46] DeFi protocols account for \$216 billion in total value locked as of March 2022, according to DeFiLama.com. Some DeFi services, such as decentralized lending, offer potential solutions for traders 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 run (i.e., interest), possibly converting short-term capital gains into long-term capital gains.[47] During our sample period, the IRS issued no specific guidance on decentralized financing platforms. Therefore, the strategy

[46] Ethereum pioneered the market for smart contracts. Despite the recent emergence of platforms such as Polygon and Avalanche, Ethereum is still the dominant infrastruture for DeFi, hosting over 90% of DeFi protocols Cong, Tang, Wang, and Zhao (2022).

[47] Crypto staking involves "locking up" a portion of your cryptocurrency for a period of time as a way of contributing to a blockchain network. In exchange, stakers can earn rewards, typically in the form of additional coins or tokens (see https://www.businessinsider.com/personal-finance/staking-crypto?).

of receiving synthetic tokens may provide an opportunity for investors in DeFi products to avoid taxes. Increased scrutiny on other cryptocurrencies may also incentivize traders to trade more DeFi tokens.

If the DeFi lending rates around year-end differs systemically from trading at other times of year, it could be an indication of tax-motivated lending that lock short-term positions into long-term synthetic tokens. To examine DeFi lending, we collect the information on interest rates in both lending and borrowing contracts for a composite index that is based on several lending platforms, and in the main lending platforms, Aave (the second largest lending platform) and Compound. To assess the demand of DeFi lending during the year we estimate the following regression:

$$Y = \alpha + \beta Jan + \delta Dec + \Lambda + \epsilon, \tag{7}$$

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 the Compound protocol; and (iii) Aave, the average rates for the 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 the last two weeks of December, and zero otherwise. 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 Eq. (7) for the most used Ethereum-based stablecoins (i.e., USDC and DAI) using monthly data beginning in October 2019 and ending in January 2022.

Table 9 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 unfulfilled market demand for synthetic products is greater than the supply.[48] 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, although only significantly so half the time. These findings suggest that the significant increase in demand for decentralized lending at year-end may be tax-motivated.

6 Conclusion

In this study, we describe the landscape of taxation in the crypto markets concerning U.S. taxpayers, and examine how recent increases in tax scrutiny have led to changes in trading behavior by crypto traders. Building on the conceptual framework of Becker (1968) and Allingham and Sandmo (1972), we predict and find that increased tax scrutiny leads crypto investors to utilize legal tax planning with tax-loss harvesting as an alternative to non-compliance. In particular, using a proprietary dataset for 500 traders, we find that domestic traders, relative to international peers, increased compliance and tax-loss harvesting following the increase in tax scrutiny, and that tax-loss harvesting dominates domestic traders' activities around year-ends and during market downturns.

In addition, using a dataset comprising detailed trading activity on 34 exchanges, we find that exchanges with presence in, or regulated by, the United States exhibit a significantly greater amount of wash trading than international peers following increases in tax scrutiny, and the effects are more pronounced during market downturns and year-ends. The greater use of tax-loss harvesting is not only a spillover effect of tax scrutiny, but also evidence of greater tax compliance because the tax

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

benefits of losses only accrue to investors that report their crypto income to tax authorities.

We also examine the effects of tax scrutiny on crypto investors' choice of exchange. Focusing on specific shocks to tax scrutiny in 2018 and 2019, we find that broad-based increases in tax scrutiny are associated with increases in crypto traders' preference for U.S.-based exchanges. However, a campaign targeting traders on U.S.-based crypto exchanges appears to have the opposite effect, driving traders away from U.S. exchanges to less transparent non-U.S. exchanges.

Finally, we discuss new gray areas for tax regulation relating to new crypto assets such as Non-Fungible Tokens (NFTs) and Decentralized Finance (DeFi) protocols. We find that transactions in NFTs as well as the lending rate in DeFi lending peak toward year-ends, which is consistent with the seasonality of tax considerations. These findings suggest that crypto investors are likely to make endogenous changes in tax planning strategies in response to changes in tax rules—including investing in new crypto assets—that create challenges for policy makers to predict the effects of tax policy changes. Collectively, our findings highlight the importance of coordinating tax policy and other regulations.

Accounting research on blockchain and cryptocurrencies is a nascent but vibrant field, offering valuable insights to market players and regulators. Understanding investors' responses to policy changes in crypto taxation, as well as describing patterns and trends are just the first steps. Using data from auditing firms or governmental agencies (e.g., IRS) to further understand how traders evade taxes constitute interesting future research. Equally promising are categorizing and valuing crypto assets, and developing disclosure or reporting strategies for firms holding digital assets. We look forward to future research in this economically large and understudied area.

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Table 1. Sample Descriptive Statistics. Panel A reports statistics for the Trading Account Dataset, comprising 47,666 trading reports of 500 retail traders in the period from 2011 to 2019. Panel B reports statistics for the propensity score-matched sample based on the Trading Account Dataset for the period from 2017 to 2018. Panel C reports statistics for the Exchange Dataset, comprising trading books of 34 crypto exchanges in the period of 2011 to 2021. All variables are aggregated daily. See Appendix 1 for variable definitions.

Panel A: Trading Account Dataset

	min	max	median	mean	sd	obs
Volume (thousand)	0.00	1158.98	4.52	46.94	151.86	47,666
Trades (thousand)	1.00	296.00	4.00	16.21	41.05	47,666
No. of Currencies traded	1.00	4.00	1.00	1.59	0.75	47,666
No. of Exchanges	1.00	4.00	1.00	1.30	0.63	47,666
Winning positions	0.00	150.35	2.00	7.79	20.22	47,666
Losing positions	0.00	129.35	0.00	5.37	17.19	47,666
Returns (%)	-11.47	59.21	0.26	5.63	16.97	47,666
Domestic	0.00	1.00	0.00	0.21	0.40	47,666
ICO Trades (%)	0.00	1.00	0.80	0.62	0.42	47,666
IRS Period (%)	0.00	1.00	0.00	0.40	0.49	47,666
$Harvest$	0.00	8.22	0.00	0.53	0.72	47,666
$Volume$	0.00	13.96	8.42	7.79	3.33	47,666
$Trades$	0.00	5.69	1.61	1.85	1.18	47,666
$Diversification$	0.69	2.20	0.69	0.92	0.27	47,666
$Exchanges$	0.69	2.20	0.69	0.81	0.23	47,666

Panel B: Trading Account Dataset—Propensity Score Matched Sample

	Unmatched		Matched	
	Domestic	Peers	Domestic	Peers
$Volume$	10.82	10.48	10.82	10.81
$Trades$	3.21	3.12	3.21	3.22
$Diversification$	1.24	1.15	1.24	1.23
$Exchanges$	1.12	1.04	1.12	1.14
Traders	86.00	405.00	86.00	86.00

Panel C: Exchange Dataset

	min	max	median	mean	sd	obs
TotalTrades (Million)	2.00	5.89	0.01	0.06	0.19	50,246
TotalVolume (Million)	0.00	13,400.00	7.83	104.00	333.80	50,246
PriceClose	10.30	76,245.10	8,205.00	11,990.80	14,623.61	50,246
WashTrades (Million)	0.00	3.36	0.00	0.01	0.05	50,246
WashVolume (Million)	0.00	2,180.00	0.36	6.65	28.15	50,246
WashVolumePercTotal	0.00	100.00	5.38	8.75	12.55	50,246
HarvestPeriod	0.00	1.00	0.00	0.03	0.18	50,246
Regulated	0.00	1.00	0.00	0.15	0.36	50,246
Presence	0.00	1.00	0.00	0.23	0.42	50,246
$WashTradesVolume$	0.00	21.50	12.79	11.95	4.25	50,246
$WashPercTotal$	0.00	100.00	13.14	18.12	17.33	50,246
$BTCPrice$	2.33	11.24	9.01	8.61	1.52	50,246
$PriceSD$	0.00	22.45	4.29	4.16	1.71	50,246
$TotalVolume$	0.00	23.32	15.87	15.49	3.45	50,246

Table 2. Tax-Loss Harvesting: Trading Account Dataset, Eq. (2) regression summary statistics. This table reports the effects of increased tax reporting scrutiny on tax-loss harvesting for the baseline specification (Panel A) and for major IRS events (Panel B) documented at the trader-day level. See Appendix 1 for variable definitions. Columns 1, 2, and 3 present findings based on estimations that include all sample years and estimations for which we restrict observations to be within the window 2016-2019 and the 2017-2018 windows. Column 4 presents findings for the propensity score-matched (PSM) sample. Columns 5, 6, and 7 (8, 9, and 10) present findings for the sample of observations three, two, and one month surrounding the March 2018 IRS Release (July 2018 IRS Campaign). All regressions include trader-fixed effects except for the PSM specification. Standard errors are heteroskedastic robust and clustered in time. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

(Dependent Variable = Harvest)

	Panel A: Baseline				**Panel B: Major IRS Events**					
	Post-2017 (Baseline)				**March 2018 (IRS Release)**			**July 2018 (IRS Campaign)**		
	1	**2**	**3**	**PSM**	**4**	**5**	**6**	**7**	**8**	**9**
Variable of Interest:										
IRS × Domestic	0.07 ***	0.07 ***	0.06 ***	0.08 ***	0.05 **	0.07 **	0.05	0.03 **	0.04 *	0.03
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)
Remainder:										
IRS	-0.06 ***	-0.05 ***	-0.05 ***	-0.11 ***	-0.05 ***	-0.03 *	-0.02	-0.01	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Domestic	-0.05	-0.05	-0.04	-0.37	-0.01	-0.02	-0.62	-0.07	-0.41	-0.40
	(0.24)	(0.25)	(0.25)	(0.37)	(0.49)	(0.53)	(0.63)	(0.22)	(0.36)	(0.38)
Trades	0.20 ***	0.20 ***	0.22 ***	-	0.26 ***	0.29 ***	0.27 ***	-0.06 ***	-0.06 ***	-0.06 ***
	(0.00)	(0.00)	(0.00)		(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Volume	0.02 ***	0.03 ***	0.02 ***	-	0.03 ***	0.02 ***	0.03 ***	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Diversification	0.56 ***	0.53 ***	0.50 ***	-	0.46 ***	0.41 ***	0.43 ***	0.09 ***	0.10 ***	0.11 ***
	(0.01)	(0.01)	(0.01)		(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)
Exchanges	-0.19 ***	-0.17 ***	-0.17 ***	-	-0.26 ***	-0.28 ***	-0.29 ***	-0.04 ***	-0.04 **	-0.04
	(0.01)	(0.01)	(0.01)		(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)
Trader FE	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	47,666	42,005	37,212	16,212	16,417	10,087	4,267	6,812	4,239	2,075
Adj.r^2	0.59	0.59	0.60	0.35	0.59	0.62	0.66	0.21	0.24	0.23

Table 3. Trading Activity at the End of the Year: Trading Account Data, Eq. (3) regression summary statistics. This table reports the effects on the year-end trading activity of U.S.-based traders and international traders during a period of increased tax scrutiny. See Appendix 1 for variable definitions. Columns 1 and 2 in present findings for estimations relating to winning and losing positions. Columns 3 and 4 (5 and 6) present findings for estimations relating to winning and losing positions for trades we identify as tax-loss harvesting using wash sales (regular sales), i.e., those involving repurchases within 30 days (greater than 30 days). All variables are reported at the trader-day level. All regressions include trader fixed effects. Standard errors are heteroskedastic robust and clustered in time. *** p < 0.01; ** p < 0.05; * p < 0.10.

(*Dependent Variable = Trades*)

	Selling positions (All)		**Harvesting Sales (<30 days)**		**Regular Sales (>30 days)**	
	1	**2**	**3**	**4**	**5**	**6**
	Winning	**Losing**	**Winning**	**Losing**	**Winning**	**Losing**
Variables of interest:						
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)
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)
Remainder:						
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)
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)
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)
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)
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)
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)
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)
Domestic × Jan	0.11 *	0.13 **	0.19 **	0.13 *	0.08	0.02
	(0.06)	(0.05)	(0.08)	(0.08)	(0.07)	(0.06)
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 4. Wash Trades: Exchange Dataset, Eq. (4) regression summary statistics. This table reports the effects of tax scrutiny on wash trades made on exchanges with a U.S. presence or regulated in the U.S. (Panel A) and for major IRS events (Panel B). See Appendix 1 for variable definitions. In Panel A, Columns 1 and 2 present findings based on estimations that include all sample years. Columns 3 and 4 report estimations for which we restrict observations to be within the 2016-2019 window, and Columns 5 and 6, within 2017-2018. In Panel B, columns 1 and 2 present findings for each IRS event using the sample of observations three, two, and one months surrounding each event in Columns 1 and 2, Columns 3 and 4, and Columns 5 and 6. Standard errors are heteroskedastic robust and clustered in time. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

(*Dependent Variable = WashTradesVolume*)

Panel A: Baseline (Post-2017)						
	1	**2**	**3**	**4**	**5**	**6**
U.S.Exchange =	**Presence**	**Regulated**	**Presence**	**Regulated**	**Presence**	**Regulated**
Variable of Interest:						
US Exchange × *IRS*	1.18 ***	0.63 ***	1.67 ***	0.79 ***	1.10 ***	0.73 ***
	(0.14)	(0.09)	(0.15)	(0.11)	(0.14)	(0.14)
Remainder:						
US Exchange	0.02	0.25 ***	-0.57 ***	0.10	-0.49 ***	-0.20 **
	(0.14)	(0.07)	(0.13)	(0.07)	(0.15)	(0.09)
IRS	-1.11 ***	-0.66 ***	-1.06 ***	-0.27	-0.72 ***	-0.23 *
	(0.19)	(0.20)	(0.22)	(0.23)	(0.15)	(0.12)
BTCPrice	-0.06	-0.13 **	-0.21 *	-0.30 ***	0.07	0.05
	(0.05)	(0.05)	(0.11)	(0.12)	(0.14)	(0.14)
PriceSD	0.00	0.00	-0.03	-0.01	-0.17 *	-0.19 *
	(0.04)	(0.04)	(0.07)	(0.07)	(0.10)	(0.10)
TotalVolume	1.04 ***	1.07 ***	1.03 ***	1.06 ***	1.11 ***	1.13 ***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)	(0.03)
Obs.	50,246	50,246	24,050	24,050	9,376	9,376
Adj.r^2	0.75	0.74	0.74	0.73	0.72	0.72

Table 4. Wash Trades: Crypto Exchanges (continuation).

(*Dependent Variable = WashTradesVolume*)

Panel B: Major IRS Events

	1	**2**	**3**	**4**	**5**	**6**
U.S.Exchange =	**Presence**	**Regulated**	**Presence**	**Regulated**	**Presence**	**Regulated**
March 2018 (IRS Release)						
US Exchange × IRS	0.54 ***	0.37 ***	0.36 ***	0.33 ***	0.18	0.23 ***
	(0.07)	(0.05)	(0.09)	(0.06)	(0.13)	(0.08)
US Exchange	0.00	-0.05	0.04	-0.08 *	-0.04	-0.08 **
	(0.05)	(0.03)	(0.06)	(0.04)	(0.07)	(0.04)
IRS	-0.50 ***	-0.27 ***	-0.32 ***	-0.19 **	-0.09	-0.03
	(0.10)	(0.08)	(0.11)	(0.08)	(0.14)	(0.09)
Obs.	2,509	2,509	1,685	1,685	864	864
Adj.r^2	0.77	0.77	0.85	0.85	0.90	0.90
July 2018 (IRS Campaign)						
US Exchange × IRS	0.22 ***	0.37 ***	0.23 **	0.26 ***	0.19	0.11
	(0.08)	(0.06)	(0.10)	(0.08)	(0.13)	(0.12)
US Exchange	0.86 ***	0.48 ***	0.94 ***	0.56 ***	0.78 ***	0.59 ***
	(0.06)	(0.04)	(0.07)	(0.05)	(0.09)	(0.08)
IRS	-0.27 ***	-0.19 ***	-0.22 *	-0.13	-0.17	-0.07
	(0.09)	(0.07)	(0.11)	(0.09)	(0.18)	(0.15)
Obs.	3,066	3,066	2,085	2,085	1,038	1,038
Adj.r^2	0.61	0.60	0.58	0.56	0.58	0.57
July 2019 (IRS Letters)						
US Exchange × IRS	0.21 ***	0.29 ***	0.13 **	0.25 ***	0.05	0.15 **
	(0.05)	(0.04)	(0.06)	(0.05)	(0.08)	(0.07)
US Exchange	1.03 ***	0.78 ***	1.15 ***	0.86 ***	1.38 ***	1.05 ***
	(0.04)	(0.03)	(0.05)	(0.04)	(0.07)	(0.05)
IRS	-0.37 ***	-0.34 ***	-0.32 ***	-0.31 ***	-0.27 ***	-0.26 ***
	(0.06)	(0.06)	(0.07)	(0.06)	(0.09)	(0.07)
Obs.	5,863	5,863	3,931	3,931	1,929	1,929
Adj.r^2	0.77	0.76	0.75	0.74	0.73	0.71

Table 5. Wash Trades During Harvesting Periods: Exchange Dataset, Exchange Dataset, Eq. (5) regression summary statistics. This table reports the effects of tax scrutiny on wash trades made on U.S. exchanges during tax-loss harvesting periods. See Appendix 1 for variable definitions. In Panel A, the harvest period is the final three months of 2018 (Panel B uses the last two weeks of December). In Column 1 of Panel A, US exchange includes those with a U.S. presence (Column 2 includes those regulated in the United States); Column 3 includes indicators for each of the three U.S. regulated exchanges (Coinbase, Kraken, and Gemini). In Columns 1, 3, and 5 (2, 4, and 6) of Panel B, US exchange includes those with a US presence (are regulated). All variables are reported at the exchange-day level. Standard errors are heteroskedastic robust and clustered in time. *** p < 0.01; ** p < 0.05; * p < 0.10.

(Dependent Variable = WashPercTotal)

Panel A: Harvesting Period			
	1	**2**	**3**
U.S. Exchange =	**Presence**	**Regulated**	**Exchanges**
Harvest	7.01 ***	5.56 ***	5.61 ***
	(0.62)	(0.55)	(0.55)
US Exchange	-1.96 ***		
	(0.16)		
US Exchange × *Harvest*	1.01 **		
	(0.40)		
US Exchange		-0.85 ***	
		(0.22)	
US Exchange × *Harvest*		5.12 ***	
		(0.55)	
Coinbase			1.95 ***
			(0.29)
Coinbase × *Harvest*			4.69 ***
			(0.79)
Gemini			0.02
			(0.48)
Gemini × *Harvest*			5.33 ***
			(0.98)
Kraken			-3.33 ***
			(0.29)
Kraken × *Harvest*			4.24 ***
			(0.52)
Obs	50,246	50,246	50,246
Adj.r^2	0.07	0.07	0.07

Table 5. Wash Trades During Harvesting Periods (continuation).

(Dependent Variable = WashPercTotal)

Panel B: Turn of the year

	2018		**2019**		**2020**	
	1	**2**	**3**	**4**	**5**	**6**
U.S. Exchange =	Presence	Regulated	Presence	Regulated	Presence	Regulated
$US Exchange \times Dec$	2.13 **	2.86 ***	3.03 ***	4.52 ***	0.39	-1.10
	(0.97)	(0.72)	(0.83)	(1.10)	(0.78)	(0.87)
$US Exchange \times Jan$	1.22	2.59 ***	2.16 ***	0.62	-0.39	-0.67
	(0.77)	(0.78)	(0.60)	(0.61)	(0.61)	(0.65)
$US Exchange$	-4.65 ***	-2.70 ***	-3.04 ***	-4.75 ***	-3.05 ***	-8.35 ***
	(0.27)	(0.34)	(0.25)	(0.24)	(0.21)	(0.26)
DEC	-9.62 ***	-9.75 ***	-4.23 ***	-3.80 ***	-1.24 **	-1.03 **
	(1.30)	(0.99)	(0.49)	(0.47)	(0.56)	(0.49)
JAN	-10.12 ***	-9.76 ***	-3.50 ***	-2.88 ***	-1.39 **	-1.39 **
	(0.89)	(0.82)	(0.50)	(0.45)	(0.70)	(0.65)
Obs.	6,046	6,046	11,205	11,205	14,671	14,671
Adj.r^2	0.09	0.07	0.04	0.04	0.02	0.04

Table 6. Trading Activities on Crypto Exchanges: Exchange Dataset, Eq. (4) regression summary statistics This table reports the effects of tax scrutiny on traders' preferences for exchanges with a U.S. presence or regulated in the U.S. (Panel A) and for major IRS events (Panel B). See Appendix 1 for variable definitions. In Panel A, Columns 1 and 2 present findings based on estimations that include all sample years. Columns 3 and 4 report estimations for which we restrict observations to be within the 2016-2019 window, and Columns 5 and 6, within 2017-2018. In Panel B, columns 1 and 2 present findings for each IRS event using the sample of observations three, two, and one months surrounding each event in Columns 1 and 2, Columns 3 and 4, and Columns 5 and 6. Standard errors are heteroskedastic robust and clustered in time. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

(*Dependent Variable = ExchangeActivity*)

Panel A: Baseline (Post-2017)

	1	**2**	**3**	**4**	**5**	**6**
U.S. Exchange =	**Presence**	**Regulated**	**Presence**	**Regulated**	**Presence**	**Regulated**
Variable of Interest:						
$US\,Exchange \times IRS$	1.88 ***	1.06 ***	1.46 ***	0.37 *	0.63 ***	0.90 ***
	(0.19)	(0.30)	(0.24)	(0.19)	(0.07)	(0.03)
Remainder:						
$US\,Exchange$	0.72 ***	2.76 ***	0.82 ***	1.13 ***	1.42 ***	0.12 ***
	(0.16)	(0.32)	(0.21)	(0.22)	(0.06)	(0.04)
IRS	-0.85 ***	-0.86 **	-1.22 ***	-0.88 ***	-0.63 ***	-0.36 ***
	(0.31)	(0.37)	(0.27)	(0.31)	(0.07)	(0.06)
$BTCPrice$	0.73 ***	0.73 ***	0.77 ***	0.71 ***	0.62 ***	0.59 ***
	(0.10)	(0.12)	(0.15)	(0.17)	(0.05)	(0.05)
$PriceSD$	0.15 ***	0.09 *	0.39 ***	0.40 ***	0.64 ***	0.67 ***
	(0.04)	(0.05)	(0.06)	(0.07)	(0.03)	(0.03)
$WashTrades$	0.02 ***	0.02 ***	0.02 **	0.01 **	0.02 ***	0.02 ***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
Obs.	50,246	50,246	24,050	24,050	9,376	9,376
Adj.r^2	0.19	0.12	0.19	0.12	0.35	0.22

Table 6. Trading Activities on Crypto Exchanges (continuation).

(***Dependent Variable = ExchangeActivity***)

Panel B: Major IRS Events						
	1	**2**	**3**	**4**	**5**	**6**
U.S. Exchange =	**Presence**	**Regulated**	**Presence**	**Regulated**	**Presence**	**Regulated**
March 2018 (IRS Release)						
US Exchange × IRS	0.78 ***	0.72 ***	0.77 ***	0.70 ***	0.51 ***	0.52 ***
	(0.10)	(0.08)	(0.14)	(0.12)	(0.13)	(0.12)
US Exchange	1.91 ***	0.53 ***	2.10 ***	0.69 ***	2.66 ***	1.30 ***
	(0.10)	(0.08)	(0.13)	(0.14)	(0.11)	(0.12)
IRS	-0.95 ***	-0.92 ***	-0.99 ***	-0.97 ***	-1.10 ***	-1.17 ***
	(0.14)	(0.13)	(0.16)	(0.15)	(0.21)	(0.23)
Obs.	2,509	2,509	1,685	1,685	864	864
Adj.r^2	0.41	0.13	0.39	0.10	0.43	0.16
July 2018 (IRS Campaign)						
US Exchange × IRS	0.04	0.27 ***	0.19 **	0.37 ***	0.42 ***	0.25 ***
	(0.07)	(0.04)	(0.08)	(0.05)	(0.11)	(0.08)
US Exchange	2.10 ***	0.97 ***	1.89 ***	0.91 ***	1.53 ***	1.00 ***
	(0.05)	(0.03)	(0.06)	(0.04)	(0.05)	(0.05)
IRS	-0.34 ***	-0.38 ***	-0.32 ***	-0.30 ***	-0.42 ***	-0.23 ***
	(0.06)	(0.05)	(0.06)	(0.05)	(0.11)	(0.08)
Obs.	3,066	3,066	2,085	2,085	1,038	1,038
Adj.r^2	0.26	0.07	0.21	0.05	0.15	0.04
July 2019 (IRS Letters)						
US Exchange × IRS	-0.43 ***	-0.39 ***	-0.25 ***	-0.26 ***	0.09	0.03
	(0.08)	(0.07)	(0.09)	(0.08)	(0.11)	(0.10)
US Exchange	2.73 ***	2.19 ***	2.64 ***	2.08 ***	2.50 ***	1.88 ***
	(0.06)	(0.05)	(0.06)	(0.06)	(0.08)	(0.07)
IRS	0.21 ***	0.12	0.28 ***	0.23 **	-0.02	0.01
	(0.08)	(0.08)	(0.10)	(0.10)	(0.13)	(0.12)
Obs.	5,863	5,863	3,931	3,931	1,929	1,929
Adj.r^2	0.13	0.06	0.16	0.08	0.18	0.10

Table 7. Estimating the Size of Revenue Loss from Tax-Loss Harvesting. Estimating the Size of Revenue Loss from Tax-Loss Harvesting. This table reports estimates of tax revenue loss arising from tax-loss harvesting in 2018. Panel A reports volume-weighted and equally-weighted estimates of the percentage of trades that are wash trades during tax-harvesting regular periods. Panel B reports the estimated wash volume and revenue loss to the government (in billions). See section 5.2 for computational details.

Panel A - Percentage of Wash Trades

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	ALL	77.14	16.20	62.85	13.20
Regulated	ALL	58.53	12.29	47.69	10.02

Table 8. Trading in Non-fungible Tokens (NFTs). This table examines whether trading activity in NFTs is greater at year-end based on Eq. (6). The data in this table are obtained from the largest and oldest NFT trading data source (`https://nonfungible.com/`), and include daily trading volume from June 2017 to January 2022. There are five dependent variables reflecting trading activity, each of which is measured in logs: (i) $TotalSales$, the total number of sales made during the period; (ii) $Sales(USD)$, the total USD spent on completed sales; (iii) $PrimaryMkt$, the total number of primary-market sales made during the period; (iv) $SecondaryMkt$, 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 dependent variables are at the trader-daily level. Jan and Dec, the variables of interest, are indicator variables that equal one for trades made during the first two weeks of January or two last weeks of December, and zero otherwise. 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 9. Decentralized Finance (DeFi) Lending and Borrowing Rates. This table examines whether DeFi lending and borrowing rates are greater at year-end based on Eq. (7). 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. *Jan* and *Dec*, the variables of interest, are indicator variables that equal one for trades made during the first two weeks of January or two last weeks of December, and zero otherwise. 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. Tax-loss harvesting period. This figure plots Bitcoin price scaled by all-time high (20,000 USD) from 2017-end to mid-2020. The vertical axis reports BTC price devaluation in percent. As indicated by the graph, BTC price declined about 70 percent throughout 2018. The green rectangular area indicates the harvesting period.

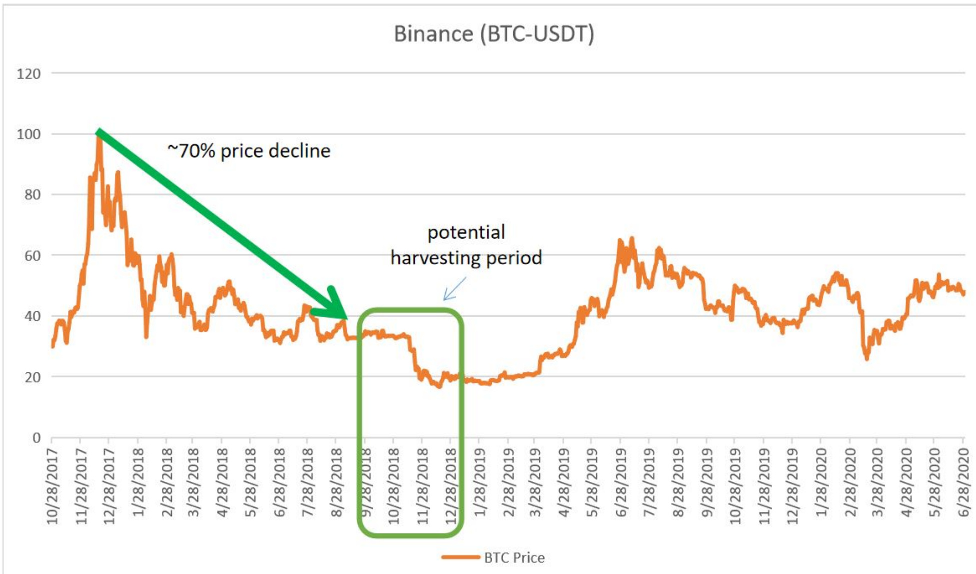
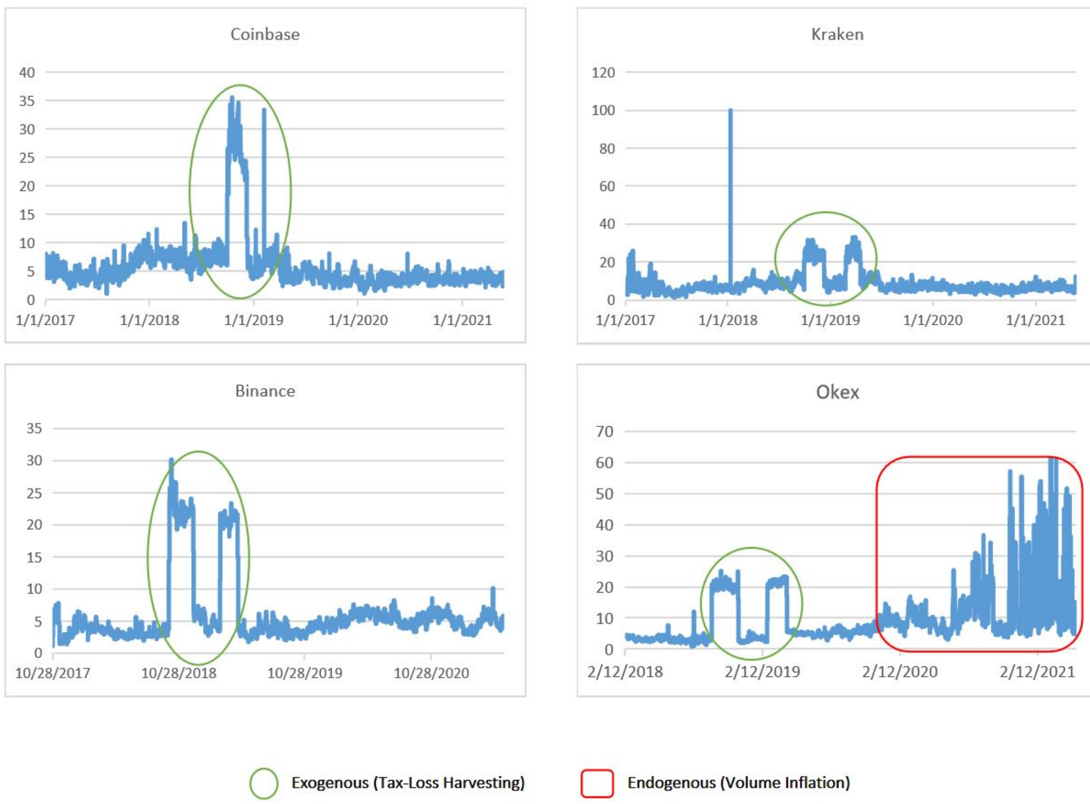


Figure 2. Tax-loss harvesting evidence. This figure shows the wash trade evolution for U.S.-based exchanges (Coinbase and Kraken), the largest international exchange (Binance), and an unregulated exchange (Okex). A wash trade is measured as a buy-sell order occurring in the same pair, price and quantity, 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).



Appendix 1. Variable Definition. This table describes all variables used in the summary statistics reported in Table 1. Panel A describes variables used with the trading account data. We report all variables in this panel at the daily trader level. Panel B describes variables used with the exchange data. We report all variables in this panel at the daily exchange-pair level.

Panel A: Trading Account Dataset

variable	**quantity**	**description**
Volume	Continuous	The product of traded amount and price
Trades	Integer	The number of trades
No. of Currencies traded	Integer	The number of unique pairs traded
No. of Exchanges	Integer	The number of unique exchanges used
Winning positions	Integer	Number of winning positions, determined by the cumulative returns (estimated using FIFO method) being positive when the position is sold
Losing positions	Integer	Number of losing positions, determined by the cumulative returns (estimated using FIFO method) being negative when the position is sold
Returns	Percent	The return on a trading position using FIFO method
Domestic	Indicator	Equals to one if a trader is located in the United States
ICO	Indicator	Equals to one if a coin is issued in an initial coin offering
IRS	Indicator	Equals one for the period of IRS scrutiny. In the baseline specification, the period of IRS scrutity is after 2017. For specific IRS events in 2018 and 2019, IRS equals one for the period after the event
Jan	Indicator	Equals to one for trades falling in the first two weeks of January
Dec	Indicator	Equals to one for trades falling in the last two weeks of December
HarvestingSales	Indicator	Trades in which the asset sold is bought within 30 days
RegularSales	Indicator	Trades in which the asset sold is bought in more than 30 days
Trader	Integer	The number of traders in the sample
$Trades$	Log	Log of 1 plus the number of trades
$Harvest$	Log	Log of 1 plus the number of harvesting trades
$Volume$	Log	Log of 1 plus the product of traded amount and price
$Diversification$	Log	Log of the number of unique cryptocurrencies traded
$Exchanges$	Log	Log of the number of unique exchanges used

Panel B: Exchange Dataset

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
WashVolume	Continuous	The total amount of wash trades
WashVolumePercTotal	Percent	Total amount ($) of wash trades to total amount ($) of trades
HarvestPeriod	Indicator	Equals to one for trades executed in the last quarter of 2018
US Exchange	Indicator	Equals to one if an exchange has a presence or is regulated in the U.S.
Regulated	Indicator	Includes: Coinbase, Gemini and Kraken
Presence	Indicator	Includes: Regulated, and Binance, Bitfinex, Bitstamp, Bittrex, and Huobi
Jan	Indicator	Equals to one for trades falling in the first two weeks of January
Dec	Indicator	Equals to one for trades falling in the last two weeks of December
$WashTradesVolume$	Log	Log of 1 plus the daily wash trade volume
$WashPercTotal$	Percent	The percentage of wash trades to total trades
$BTCPrice$	Log	Log of the daily close BTC price in either USD or USDT
$PriceSD$	Log	Log of 1 plus the standard deviation of the intraday prices
$TotalVolume$	Log	Log of the product of traded amount and price
$ExchangeActivity$	Log	Log of the daily sum of the products of sell and buy orders and price

Appendix 2. Matching results. This table reports the matching results between treated (domestic traders) and control (international traders) for the full sample. 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 log of the price times traded amount reported plus one. *Trades* is the log of the number of trades reported plus one. *Diversity* is the number of unique cryptocurrencies traded reported in log. *Exchanges* is the number of unique exchanges used reported in log.

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 (full sample)

	Unmatched		**Matched**	
	Treated	**Control**	**Treated**	**Control**
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 3: Wash Trade Proxy

Because the analysis of crypto exchange data requires developing a proxy for tax-loss harvesting, we start by describing the usage of wash sales in this setting and how our measure differs from that used in studies that focus on crypto exchanges volume inflation. A recent presentation to the SEC suggests that "the vast majority of reported bitcoin trading volume is either fake volume or represents non-economic wash trading" (Fusaro and Hougan, 2019). Following the episode, several academic studies examined the issue more scientifically.

Cong et al. (2020) is the first to introduce statistical measures to document systematic 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. For example, Michalski and Stoltz (2013) and Amiram, Bozanic, and Rouen (2015) use the measure to detect errors in financial statements.[49]

Tax-loss harvesting proxy

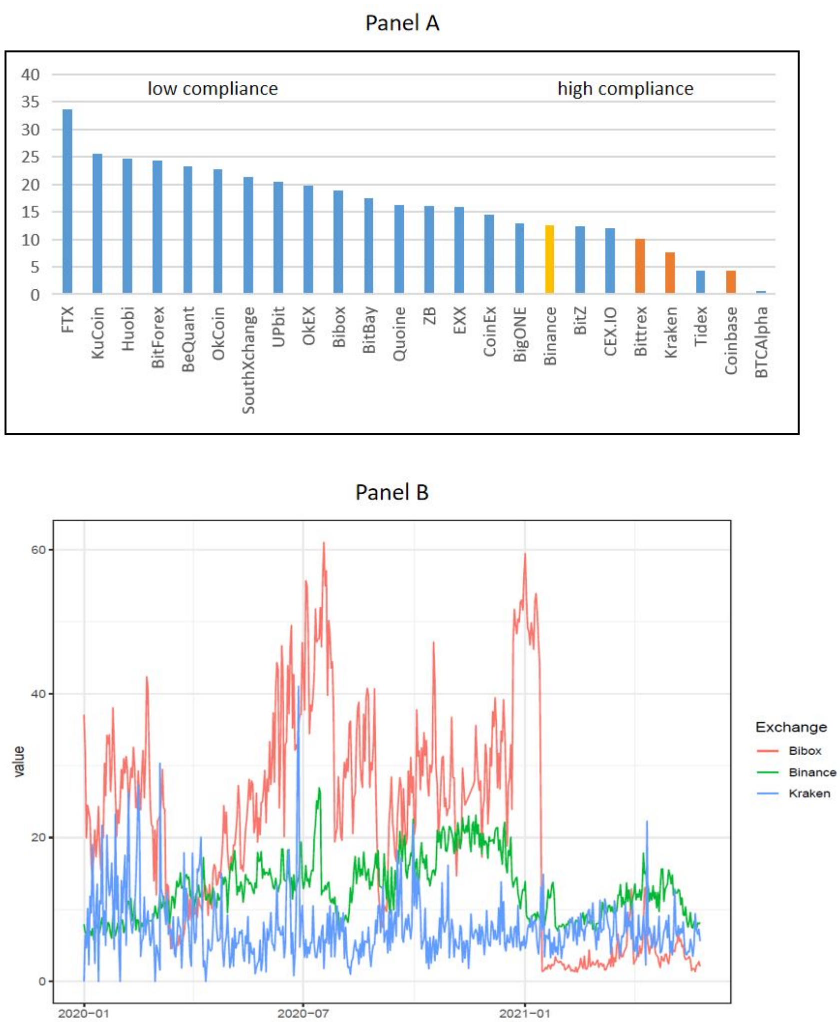
This study uses wash trades as a proxy for tax-loss harvesting because wash trades involve selling a losing position and buying it immediately back. The loss can be used for tax purposes, but the trader still retains the asset. The execution of such a trade is nothing but a wash, where prices are unlikely to be affected, but the process generates large volumes. Unlike prior studies examining wash trades by crypto exchanges to create fake volume (e.g., Aloosh and Li, 2021; Amiram et al., 2022; Cong et al., 2020), we use wash trades as a measure of tax-loss harvesting. This distinction is essential because the statistical measures used in prior studies are unlikely to serve our purposes because the data-generating process from tax-loss harvesting is not the outcome of manipulation.

[49] See also Nigrini (1999) and Pimbley (2014).

Therefore, our proxy for wash trades using the exchange dataset is based on matching a sell with buy orders occurring within 60 seconds at the same price, pair, quantity, and exchange.[50] 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 good proxy under the following circumstances: (i) During periods where tax-loss harvesting is more likely to be accentuated. (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) When wash trades take place on regulated exchanges because regulatory oversight makes these exchanges less likely to engage in volume inflation. For instance, Figure A1, Panel A, shows that wash trades are lower on exchanges with higher levels of regulatory compliance, where high (low) regulatory 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.

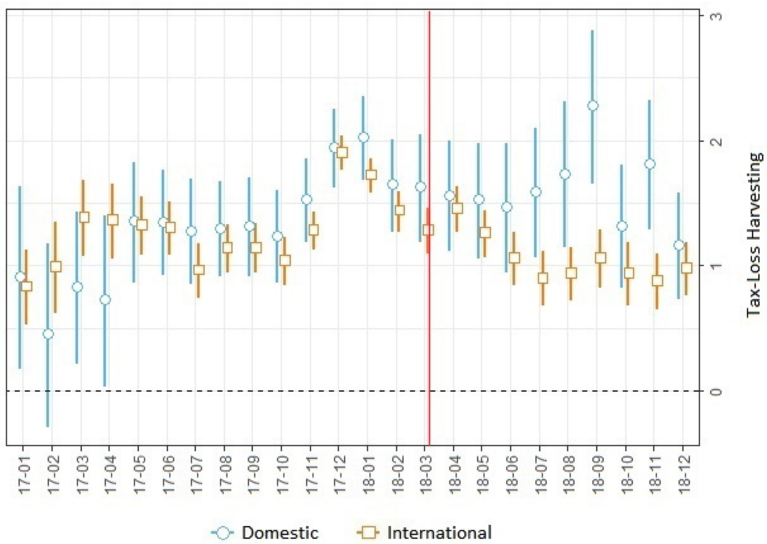
[50]We use 60 seconds because the mean average wash trade occurs near a minute across the exchanges in our dataset. The results of our empirical analysis are qualitatively unchanged for different specifications in wash sales timing.

Appendix 3. Figure A1. Wash trading and regulation. This figure shows the percentage of wash trading volume on exchanges with different levels of regulatory compliance (Panel A) and for three different exchanges with different levels of regulation (Panel B). A wash trade is measured as a sell-buy order occurring in the same pair, price and quantity, and within 60 seconds. In each panel, the vertical 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 horizontal axis is composed of 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 (a large regulated international exchange that has a presence in the US market) and Kraken (regulated in the United States).



Appendix 4. Parallel Trends. This figure shows the parallel trends underlying estimation of Eq. (2) and Eq. (4). The plots are generated with month fixed effects estimates in the period of January 2017 to December 2019 for the dependent variables: $Harvest$ in the Trading Dataset (Panel A) and $WashTradesPerc$ in the Exchange Dataset (Panel B). $Harvest$ and $WashTradesPerc$ are defined in Appendix 1. International refers to non-U.S. traders (non-U.S. crypto exchanges) in Panel A (Panel B). The red vertical line indicates the beginning of IRS tax reporting scrutiny. Plotted coefficients are reported at the trader-month level in Panel A and exchange-month level in Panel B for illustration purposes.

Panel A: Retail Traders



Panel B: Crypto Exchanges