Tax-Loss Harvesting with Cryptocurrencies*

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First Draft: October 2021; Current Draft: September 2022

Abstract

We describe the landscape of taxation in the crypto markets, especially that concerning U.S. tax-payers, and examine how recent increases in tax scrutiny have led to changes in trading behavior by crypto traders. We predict under a simple conceptual framework and then empirically document 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 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 also discuss new gray areas for tax regulation relating to new crypto assets such as Non-Fungible Tokens and Decentralized Finance protocols that further highlight the importance of coordinating tax policy and other regulations.

JEL classification: G15, G18, G29, K29, K42, O16.
Keywords: Bitcoin, Cryptocurrencies, DeFi, IRS, NFT, Regulation, Taxation, Trading Behavior.

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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

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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."

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 clear wash sale rules for crypto assets were absent during our sample period, traders could harvest losses for tax purposes by selling a cryptocurrency that has declined in value and then immediately repurchasing it. 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 crypto trading to the tax authority to take advantage of the strategy. Engaging in tax-loss harvesting implies a commitment to reporting gains and losses to the tax authority which likely identifies the investor as a cryptocurrency trader. In that sense, engaging in tax-loss harvesting reflects a form of voluntary commitment to transparency with the tax authority. 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

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[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.

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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. In the absence of the wash sale rule for cryptocurrency, traders can "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 indicate that domestic traders, relative to international peers, increased tax-loss harvesting by approximately 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 dur-

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ing market downturns. For instance, domestic traders sell 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 are regulated by, the United States exhibit a 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.[4]

Overall, domestic traders have become more compliant in response to tightened crypto tax scrutiny as indicated by 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

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[3]See our detailed discussion on Appendix 4. Less liquid coins are more likely to be the subject of fake volume to attract demand (Amiram et al., 2022).

[4]See Appendix 2, Panel B: Exchange Dataset, for the list of regulated exchanges (i.e., licensed by US authorities) and exchanges with presence in the US (i.e., not licensed but with operations in the US).

are associated with increases in crypto traders preference for U.S.-based exchanges. However, a campaign targeting regulating 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, absent coordinated policies on taxation and wash sales.

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. Not taking a holistic approach to tax regulation may simply push from tax-loss harvesting from one market to another.

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) and Lyandres, Palazzo, and Rabetti (2021) examine the roles of analysts and disclosure in unregulated initial coin offering (ICO) markets and post-ICO operating performance. Amiram, Jørgensen, and Rabetti (2022) exploits a blockchain-enabled transparent accounting system to detect terrorist-associated transfers. Tang and Zhang (2022) examines country-level regulation effects on crypto adoption. Cong, Harvey, Rabetti, and Wu (2022) assem-

bles a diverse set of public, proprietary, and hand-collected data, and using accounting forensics assess the economics of crypto-enabled cybercrimes. Luo and Yu (2022) compares and contrasts U.S. and international accounting and nancial reporting practices for cryptocurrency. Our study is, to our knowledge, the rst study of crypto markets from a tax perspective, in particular to provide evidence that changes in tax scrutiny are ecting trading behavior in these markets.

Second, we add to the taxation literature by conducting the rst empirical study on crypto taxation. Prior studies document important ects 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, fsuch as foreign real estate (e.g., De Simone, Lester, and Markle, 2020; Alstadsæter, Zucman, Planterose, and Økland, 2022).

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 in ate 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.[5]

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 ndings on tax-loss harvesting with cryptocurrencies. Section 5 discusses policy coordination and quanti es 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

2.1   Crypto Taxation and Scrutiny

Cryptocurrencies, such as Bitcoin and Ether, are treated as property under federal tax law in the United States.[6] 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, providing guidance, and increasing direct enforcement actions.

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[5]Appendix 4 provides an extended discussion on how our proxy is constructed and how it di ers from other proxies used in the literature.

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

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.[7] For example, some traders believed that crypto-to-crypto transactions were "like-kind" exchanges, and thus gains from such transactions were not taxable.[8]

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."[9] 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 gray 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 traders could be expected going forward. In March 2018, the IRS initially issued a release cau-

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[7]See Avi-Yonah and Salaimi (2022) for a discussion.

[8]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.

[9]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).

tioning 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.[10] Then, in July 2018, the IRS announced a compliance campaign targeting cryptocurrency.[11] 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 rms specialized in cryptocurrency tax services (such as the rm 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 led their taxes improperly. The IRS reminded taxpayers that cryptocurrency is an ongoing focus of IRS criminal investigations.[12] 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, nd, and work to seize crypto in both a civil and criminal setting."[13]

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 so that the losses are recognized for tax purposes and can be used to reduce the tax on other income

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

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

[12]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 .

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

(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.[14] Importantly, only traders who report their crypto trading to the IRS obtain the tax bene ts from such tax-loss harvesting.

As Kollmann, Qichao, and Fangbei (2021) notes, the US has generally been at the forefront in issuing crypto tax guidance. However, not surprisingly, as the IRS issued guidance, their counterparts in non-US countries were also doing the same. During our sample period, there is a lot of heterogeneity in the extent to which countries provide guidance and even in the extent to which they permit trading of cryptocurrencies. For example, several countries, including Algeria, Bangladesh, Bolivia, China, Colombia, Ecuador, Egypt, Iran, Macedonia, Morocco, Nepal, Venezuela, and Vietnam, simply banned crypto currencies. At the other end of the spectrum, one country, El Salvador, approved Bitcoin as legal tender.[15] Some countries, including Australia, require cryptocurrency service providers to report transactional data as part of a data matching program to ensure tax compliance. Other countries, such as Germany and India, provided no national

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[14]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 de nition 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) .

[15]See https://www.wsj.com/articles/el-salvador-becomes-first-country-to-approve-bitcoin-as-legal-tender-11623234476 .

guidance on the tax treatment of crypto currencies.[16]

Because of the uncertainty caused by wide variation in tax guidance for crypto currency trans-actions worldwide, the Organization for Economic Cooperation and Development (OECD (2022)) recently called for development of a framework for harmonizing the taxation of crypto curren-cies. Appendix 1 provides a brief summary of crypto currency tax guidance policies for several countries during our sample period. To the extent that other countries are also increasing their tax scrutiny of cryptocurrency trading, tests comparing changes in behavior of US traders to non-US traders will be biased against our ability to detect differences, and cause our estimated βs to be conservative.

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 (taxable) 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 authorities, who then learn the true W. The investigated taxpayer has to pay the tax on the

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[16]Although Germany provided no national guidance, the German tax system has general rules that apply to crypto assets. As PwC notes in a recent tax report (PwC, 2021), the German tax system is complex system of principles and exceptions, leaving much room for gray areas for crypto investors to assess appropriate tax treatment for their trading activities.

undeclared amount at a rate $2 \in (\beta; 1]$. 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.[17] Note that in this simple static setup, switching back and forth between tax reporting and evasion is not allowed, which is realistic. For example, moving back and forth across countries to get different tax treatment is not easy; once someone reports the holdings of certain amounts of ETH and BTC, they also cannot suddenly stop reporting the trading activities on them, which raises a red flag with tax authorities.

2.2.1 The crypto taxation setting

Crypto traders face similar tax reporting decisions, with tax scrutiny I affecting the probability of investigation or detection.[18] 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. Obviously, when income X is reported, the transactions and activities associated with this income are also reported. Following Allingham and Sandmo (1972), we require $X \leq W$, i.e., there is no net under-reporting of losses in activities not associated with tax-loss harvesting activities.[19]

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 trans-

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[17]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, Maydew, and Turk (2022).

[18]One can incorporate the accounting complexity of crypto taxation by introducing a cost of reporting X, $c(X)$. 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.

[19]The monotone comparative statics and thus our results are not dependent on $X \leq W$, but because X excludes the losses that one can realize through tax-loss harvesting, for X to be larger than W the taxpayer would have to under-report losses (but not gains) from non-tax-loss-harvesting activities overall.

parency environment provides fertile grounds for crypto traders to evade taxes.[20] 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 acted by changes in tax scrutiny. During our sample period, traders can wash trade cryptocurrencies to maintain portfolio composition while o setting 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 stipulate that W and X can include regular trading and investment involving cryptocurrencies, but excludes tax-loss harvesting activities. Instead, we specify an additional net tax-loss-harvesting bene t entering the payo in the reduced-form of $(X, \cdot) \in C^2$: $R^2_0 \geq R_0$, which is increasing in the reported income, X, and in the e cacy of tax-planning strategies, . Reporting a greater X can re ect greater tax-compliance. Reporting more with tax authorities also means more transactions are recognized and the expected bene t of tax-loss harvesting increases. Because a tax-loss harvesting strategy works only when the trader reports the transactions, we also assume that $\frac{\partial}{\partial X \partial} \geq 0$. In general, we expect to be higher (i) when tax-loss harvesting is the most useful and salient to the taxpayers, 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 veri able by the IRS, and (iii) following periods of large crypto price declines.[21]

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[20]Although Congress enacted third-party reporting for "digital assets," scheduled to begin in the 2023 tax-year (with the rst 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.

[21]We thank the reviewer for pointing out that correlation between crypto prices and prices of other assets may a ect the net bene t of tax-loss harvesting. However, in our setting (if factual income overall, including non-crypto asset holdings) is negatively correlated crypto price declines, we can simply reinterpret a bigger as greater crypto price declines relative to price declines in other assets that the tax-payer holds for generating income.

A domestic trader then reports X to maximize payoff:

$$\max_{X\in[0;W]} \quad [1-P(I)] \cdot U\left(W-X+\phi(X;\cdot)\right) + P(I) \cdot U\left(W-X+\phi(X;\cdot)-\theta[W-X]\right) : \quad (1)$$

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 $\phi(X;\cdot)$, 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 $\frac{\partial^2 \phi}{\partial I \partial X} > 0$ and $\frac{\partial^2 \phi}{\partial \theta \partial X} > 0$. An application of robust monotone comparative statics (e.g., Edlin and Shannon, 1998; Athey, Milgrom, and Roberts, 1996) directly yields that the optimal $X^*(I;\theta)$ is increasing in I and θ.[22] Because ϕ is increasing in X and θ, and has no direct dependence on I, and $\frac{\partial^2 \phi}{\partial X \partial \theta} \geq 0$, it follows that equilibrium tax-loss harvesting, ϕ, is also increasing in I and in θ 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

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

harvesting should be re ected 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 $\frac{@}{@@}$ > 0, and 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 veri able to the tax authorities. This leads to our second prediction:

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 (ering a higher). 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 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.[23] The trading book data in the exchange dataset do not allow identification of traders 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.[24] The data include the trading activities in the form of trading reports for the tax firm's 500 largest retail traders.[25] Approximately one-fourth of the traders are U.S.-based taxpayers, and the remaining traders are internationally domiciled.[26] These traders became clients of the firm in early 2019, receiving specialized assistance in reporting their crypto taxable income. The data

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[23]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.

[24]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.

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

[26]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).

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 trans-action between April 2011 to September 2019.[27]

Table 1, Panel A, reports the summary statistics for 500 large retail traders obtained from the trading account database.[28] Appendix 2 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). The standard deviation for daily volume and transactions varies widely, with $152 thousand in daily volume and 41 in daily 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%).[29] 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 Period = 0.40).[30]

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

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

[29]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.

[30]IRS equals one for the period of IRS scrutiny. In the baseline specification reported in Table 1, the period of IRS scrutiny is after 2017.

3.2 Exchange Dataset

Table 1, Panel B, 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.[31]

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 gures 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 in ation 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

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[31]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).

with buy orders occurring within 60 seconds at the same price, pair, quantity, and exchange.[32] 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).[33]

Panel B also indicates that, on average, 8.75% of the daily volume ($WashVolumePercTotal$)

are potentially wash trades. Consistent with Cong et al. (2020), wash trading as a percentage of

total volume, i.e., 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).[34]

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

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[32]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 4 for additional details regarding construction of the wash trading proxy for tax-loss harvesting.

[33]USDT and USD can be used interchangeably in our analysis because USDT (Tether) is pegged to USD (US Dollar). 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.

[34]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."

using the Trading Account Dataset and then using the Exchange Dataset.[35]

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:

$$\text{Harvest}_{t,i} = \alpha + \beta(\text{IRS} \times \text{Domestic}) + \gamma\,\text{IRS} + \delta\,\text{Domestic} + \theta X + \mu + \epsilon; \tag{2}$$

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.[36] 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 × Domestic. We define the period of increased scrutiny beginning in 2018 to correspond to the IRS's issuing two releases 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.[37] The key variable of interest is the interaction IRS and Domestic. Its coefficient, β, reflects the difference in responses between U.S.-based and international traders during the specific period of increasing tax reporting scrutiny affecting U.S. taxpayers. We have no predictions for the coefficients on IRS and Domestic because the crypto sector is in fast transition with time trends that can cause them to take either sign. X is a vector of controls including Trades, which is the

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[35] Appendix 5 examines the parallel trends assumption underlying the difference-in-differences model given by Eqs. (2) and (4).

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

[37] Although it is never possible entirely to rule out the effects of time trends, several features of our research design help to mitigate such effects. First, Eq. (2) and subsequent equations essentially use foreign investors as the control sample. As a result, any worldwide trends would be reflected in actions taken by the control and treated sample investors. Second, in later tests we focus on shorter window tests around the March and July 2018 event dates. By design, such short-window tests reduce the influence of trends. Third, we conduct parallel trends analysis. Fourth, tests below focusing on year-end effects are unlikely to be affected by time trends.

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; is a trader fixed

effect, and is the error term.[38] All variables are measured at the trader (i) and day (j) level.[39]

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 speci-

fications 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 × Domestic* coefficient, which ranges from of 0.06 to 0.08.

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.

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

[39] For simplicity, hereafter we suppress subscripts when referring to regression variables.

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:

$$Trades_{ij} = \alpha + \beta_1(IRS \times Domestic \times Dec) + \beta_2(IRS \times Domestic \times Jan)$$
$$+ \gamma IRS + \delta Domestic + \eta Jan + \iota Dec + \theta + \epsilon; \tag{3}$$

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

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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. All variables are measured at the trader (i) and day (j) level. 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 relat-

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ing to regular trades, i.e., non-wash sales.[40] The findings provide evidence that tax-loss harvesting

dominates the end-of-the-year trading strategies for domestic traders in the period following in-

creased 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.[41]

4.3 Test of Corollary 1 using Exchange Dataset

We now turn to test Corollary 1, which predicts that following increases in tax scrutiny, domes-

tic exchanges experience greater tax-loss harvesting than international exchanges. At the exchange

level, we estimate:

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

where $WashTradesVolume$ is the log of 1 plus the wash trade volume.[42] 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

whether trades are executed by U.S. traders. $US\ Exchange$ 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,

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[40]The vast majority of harvest trades are in the same day and quantity as the position sold. In contrast, regular trades mostly do not match the amount sold at a loss.

[41]The difference in coefficients is 0.35 and it is significant at the 5% level.

[42]Eq. (4) uses wash trade volume rather than the number of wash trades so as not to lose information on the magnitude of each trade. Nonetheless, we also estimated versions of Eq. (4) using the number of wash trades rather than their volumes. Untabulated findings yield the same inferences as those based on tabulated findings.

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 no in the country (and thus are likely to have a large base of U.S. traders).[43] 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. is the error term. All variables are measured at the exchange (k) and day (j) level.

The key variable of interest is the interaction term, $IRS \times USExchange$. Its coefficient, , 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 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, $_1$ is significantly positive in all specifications, ranging from 0.73 to 1.67.

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

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[43]The additional five *Presence* exchanges are Binance, Bitfinex, Bitstamp, Bittrex, and Huobi.

and pay the resulting tax from virtual currency transactions or did not report their transactions properly."[44] 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, which predicts that domestic exchanges experience greater tax-loss harvesting, especially following periods of price decline and toward year-ends, 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 precipitously 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

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[44]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.

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 bene cial 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.[45]

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

$$WashPercTotal_{i,j} = \ + \ (US\,Exchange \ Harvest) + \ US\,Exchange \ + \ HarvestPeriod \ + \ + \ ; \quad (5)$$

where $WashPercTotal_{i,j}$ is the percentage of wash trades to total trades.[46] $HarvestPeriod$ 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 bene cial. The indicator variable, $US\,Exchange$, either re ects 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 $US\,Exchange \ Harvest$. Its coe cient, , re ects the di erence in wash trades between exchanges with presence (or based) in the United States and exchanges

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[45]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)).

[46]We use the scaled version of the wash trade variable to mitigate e ects of potential di erences in year-end trading volume in the U.S. and non-U.S. exchanges. This approach also facilitates comparison of e ects, especially when breaking down the analysis among regulated exchanges. However, untabulated ndings from estimations using non-scaled wash trades or wash trades volume yield the same inferences as the tabulated ndings.

without a presence or regulated in the United States during the period of increased tax reporting scrutiny. Based on Corollary 2, we expect to be positive. is a vector of controls including BTC Price, PriceSD, and TotalVolume is the error term. All variables are measured at the exchange (k) and day (j) level. Following previous models, we cluster standard errors in time across all specications.

Table 5, Panel A, presents regression summary statistics for various estimations of Eq.(5). In Column 1 (Column 2), US Exchange is Presence (Regulated). In Column 3, US Exchange 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 ndings show that the US Exchange Harvest coefcients are signi cantly positive only for exchanges that have a presence or are regulated in the United States (coecients= 1.01 and 5.12). Moreover, the Column 3 ndings indicate that the increase in wash trades manifested in each of the regulated exchanges, with US Exchange Harvest coe cients 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 rst two weeks of January. This permits us to focus on the end-of-year eects. Based on Corollary 2, we expect wash trading as a means to achieve tax-loss harvesting to increase in December, i.e., the ocient on the interaction of US Exchange and Dec is positive. Our results are consistent with this prediction. Turn-of-the-year eects are mostly

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accentuated for the immediate years following increased tax scrutiny (2018 and 2019).[47]

5 Extended Discussion and Policy Coordination

Our ndings 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 nding 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 de nition of a security (SEC v. Wahi, No. 2:22-cv-01009 (W.D.Wash. Jul. 21, 2022)).[48] If the SEC classi es 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.[49]

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

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[47]This result is consistent with the literature that nds that tax-driven turn-of-the-year eects 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)).

[48]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/).

[49]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.[50]

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 Ex with changeActivity, 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,

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[50]For other examples, see Rev. Rul. 2019-24 regarding whether cryptocurrency received in airdrops and hard forks result in income for tax purposes, Avi-Yonah and Salaimi (2022) for a proposed framework, and Shapiro (2018) for a discussion uncertainty in the taxation of Bitcoin loans. Outside crypto, Rabetti (2022) highlights the importance of policy coordination in financial rescue programs.

across all speci cations, the coe cient on the interaction of US Exchange and IRS is signi cantly

positive (ranging from 0.37 to 1.88).

We extend the analyses to examine the e ts of increased tax scrutiny surrounding the March

2018 IRS Release, the July 2018 IRS Campaign, and the July 2019 IRS Letters events. The nd-

ings, presented in Table 6, Panel B, illustrate the complexity of regulation by showing that in-

creases in broad-based and targeted tax scrutiny do not necessarily have the same e on crypto

trading activity. Most notably, whereas traders increase their trading activity on U.S. exchanges

consistently (all but one of the interaction coe cients are signi cantly positive) following the IRS

Release and the IRS Campaign (US Exchange IRS coe cients 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 IRS coe cients are signi cantly negative and

range from -0.25 to -0.43, and the other two are insigni cant). The IRS Letters event di ers 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.[51] Thus, the targeted IRS letter campaign could

have driven traders away from the U.S.-based exchanges. Thus, a consequence (presumably unin-

tended) of this form of tax scrutiny could be to reduce the attractiveness of U.S. exchanges. The

contrast between the IRS letter campaign and previous events, all of which are scrutiny increasing,

illustrate that general and targeted scrutiny can have di erent e ects on exchange preferences.

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

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

Recent crypto-tax proposals for raising additional tax revenue may have unintended e ects
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
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 in ation that can a ect our estimates (see Appendix 4). 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 di erence
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.[52] 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

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

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 exchanges 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.[53] Consequently, the effects of a particular regulatory change on the overall tax revenue become more ambiguous in these rapidly changing markets.

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[53]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 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.

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 specic tax guidance for NFT trading, making the NFT market a gray area for taxation.[54]

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 index model:

$$NFT_{ij} = + Jan + Dec + + ; \qquad\qquad (6)$$

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[54]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 denes 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).

where NFT 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 variables are measured at the trader (i) and day (j) 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. τ is 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.[55] DeFi protocols account for $57.6 billion in total value locked as of September 2022,

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[55]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).

according to DeFiLama.com. Some DeFi services, such as decentralized lending, offer potential

solutions for traders to defer taxes and perhaps convert what would otherwise be short-term capital

gains into (lower-taxed) long-term capital gains. Consider, for example, a trader considering selling

a crypto asset that has appreciated in value but has been held by the trader for less than twelve

months. Selling the crypto asset would generate short-term capital gains. The trader may instead

opt for a tax strategy that defers the taxable event (and thus defers the tax) and also results in long-

term capital gains treatment. The trader instead stakes the crypto asset for a period of time until

it qualifies for long-term capital gains treatment, and then sells the crypto asset.[56] By supplying

the lending pool or lending tokens to the platform, the trader receives synthetic tokens or shares

from the lending pool and additional tokens (sometimes called "rewards") in the long run, and

might convert what would otherwise be short-term capital gains into long-term capital gains, by

deferring the sale of the original crypto asset. This is not the only gray area involving DeFi taxation,

but illustrates the possibilities that DeFi raises for tax strategies.[57]

During our sample period, the IRS issued no specific guidance on decentralized financing plat-

forms. Therefore, the strategy of receiving synthetic tokens may provide an opportunity for in-

vestors 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-

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[56]Crypto staking has been described as an arrangement that "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?

[57]Another DeFi gray area is how and when the "rewards" from staking are taxed. For example, see https://news.bloombergtax.com/daily-tax-report/taxpayers-in-jarrett-case-still-seek-an-answer-on-crypto-staking?

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:

$$DeFi_{ij} = \ + \ Jan + \ Dec + \ + \ ; \qquad\qquad (7)$$

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 rst two weeks of January or the last two weeks of December, and zero otherwise. is a year xed e ect and 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. All variables are reported at the protocol (i)(month (j) level. 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 di erences 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 unful lled market demand for synthetic products is greater than the supply.[58] The coe cients for lending and borrowing rates across the two most relevant pairs (USDC and DAI) indicate that December and January rates are substantially larger

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

than other months, although only signi cantly so half the time.[59] These ndings suggest that the signi cant 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 asset investors. Building on Becker (1968) and Allingham and Sandmo (1972), we predict and nd 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 nd 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 nd that exchanges with presence in, or regulated by, the United States exhibit a signi cantly greater amount of wash trading than international peers following increases in tax scrutiny, and these are more pronounced during market downturns and year-ends. The greater use of tax-loss harvesting is not only a spillover e ect of tax scrutiny, but also evidence of greater tax compliance because the tax bene ts of losses only accrue to investors that report their crypto income to tax authorities.

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[59]The positive coe cient for January relates to the potential hysteresis e ect in which rates rise or fall with a delay. This delay occurs because some traders are locked into stacking positions (deposited tokens in exchange for interest) in which interest has not accrued yet (e.g., before a certain maturity). Therefore, a portion of these traders will exit a position just weeks after observing a decline in the market demand. For NFTs, this delay is not documented because our variables are straightforward proxies for demand (e.g., total sales), therefore, being more sensitive to changes in market conditions.

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, giving 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 StatisticsPanel 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 Exchange Dataset, comprising trading books of 34 crypto exchanges in the period of 2011 to 2021. Variables on Panel A (B) are reported at the trader-day (exchange-day) level. See Appendix 2 for variable de nitions. Variables used in the regression are italicized. The remaining variables are included for descriptive purposes.

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	0.26	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
Diversi f ication	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: 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 2 for variable definitions. In Panel A, Column 1 present findings based on estimations that include all sample years. Column 2 report estimations for which we restrict observations to be within the 2016-2019 window, and Column 3, within the 2017-2018 window. Column PSM 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 variables are reported at the trader-day level. All regressions include trader 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
	All	2 Years	1 Year	1 Year	3 Months	2 Months	1 Month	3 Months	2 Months	1 month
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 2 for variable definitions. Columns 1 and 2 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 2 for variable definitions. In Panel A, Columns 1 and 2 present findings based on estimations that include all sample years. Columns 3 and 4 (Columns 5 and 6) report findings for estimations for which we restrict observations to be within the 2016-2019 window (within the 2017-2018 window). Panel B present findings for each IRS event using the following sample period. Three months in columns 1 and 2. Two months in columns 3 and 4. One month in columns 5 and 6. 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 = WashTradesVolume)					
	Panel A: Baseline (Post-2017)					
	1	2	3	4	5	6
	All	All	2 Years	2 Years	1 Year	1 Year
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.r²	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
	3 Months	3 Months	2 Months	2 Months	1 Month	1 Month
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 2 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 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 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 2 for variable definitions. In Panel A, Columns 1 and 2 present findings based on estimations that include all sample years. Columns 3 and 4 (Columns 5 and 6) report findings for estimations for which we restrict observations to be within the 2016-2019 window (within the 2017-2018 window). Panel B presents findings for each IRS event using the following sample period. Three months in columns 1 and 2. Two months in columns 3 and 4. One month in columns 5 and 6. 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 = ExchangeActivity)					
	Panel A: Baseline (Post-2017)					
	1	2	3	4	5	6
	All	All	2 Years	2 Years	1 Year	1 Year
U.S. Exchange =	Presence	Regulated	Presence	Regulated	Presence	Regulated
Variable of Interest:						
US Exchange · 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
	3 Months	3 Months	2 Months	2 Months	1 Month	1 Month
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). All variables are reported at the regulated-exchanges level. 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. 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. All variables are reported at the trades-day level. 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 De -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 rst two weeks of January or two last weeks of December, and zero otherwise. All variables are reported at the monthly level. 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.
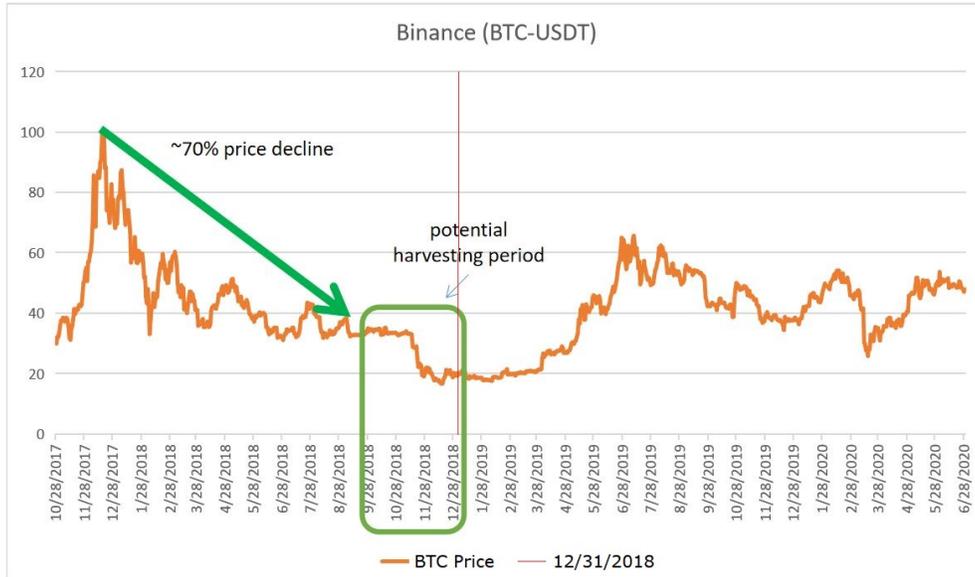
Figure 2. Tax-loss harvesting evidence. This figure shows the wash trade evolution for U.S.-based exchanges (Coinbase and Kraken), the largest international exchange (Binance), and an unregulated exchange (Okex). A wash trade is measured as a buy-sell order occurring in the same pair, price and quantity, 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).

Appendices for

Tax-Loss Harvesting with Cryptocurrencies

Lin William Cong, Wayne Landsman, Edward Maydew, and Daniel Rabetti

September 2022

Appendix 1: Crypto Tax Regulation Across the World

Although Bitcoin was launched in 2009, tax authorities only began to provide some initial tax guidance in 2014. Australia, Denmark, France, Netherlands, Sweden, the United Kingdom, and the United States were the first countries in the world to release tax guidance. Multiple countries followed suit beginning in 2017 (Argentina, Colombia, Japan, and Switzerland), and in 2018 (Germany, Ireland, Luxembourg, Malta, Poland, Portugal, South Africa, and Thailand). Figure 1 depicts the timeline of tax guidance releases according to PWC Annual Global Crypto Tax Report (PWC (2021)).[60]

Countries also differ on the tax treatment of cryptocurrencies. Whereas the United States treats crypto as a capital asset (e.g., property), other countries treat it as a commodity (e.g., Canada), digital asset (e.g., Australia), private asset (e.g., Germany), wealth asset (e.g., Switzerland), and legal tender (e.g., El Salvador), or have not yet to assign it to an asset class (e.g., United Kingdom).[61] Some countries, such as Malta, approximate the treatment of crypto to the accepted notion in the crypto community, considering it as a "unit of account, medium of exchange or a store of value." The heterogeneity in the tax treatment of cryptocurrencies worldwide is also present in its tax type. Although capital gains are a dominant type (e.g., the United States and Canada), cryptocurrency transactions also generates income tax (e.g., Germany, United Kingdom, and Australia), wealth tax (e.g., Netherlands), or are not taxable (e.g., Portugal, Singapore, Germany (if the asset holding period exceeds six months), Malta, Bermuda, Cayman Islands, Puerto Rico, Switzerland (for retail investors), Georgia, Uzbekistan, and Cyprus).[62]

Cryptocurrencies are also explicitly or implicitly banned in some countries. Notably, China banned the trading of cryptocurrencies in 2017, and more recently, businesses relating to crypto activities, such as exchanges and miners. Although China is the most significant player in the

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[60]A Japanese trader received a $200,000 fine and one year in prison for not reporting to the tax authorities (See https://news.bitcoin.com/japanese-court-convicts-bitcoin-tax-evader-trader-gets-a-year-in-prison-plus-fine-for-200k/).

[61]Since it became legal tender, more people have Bitcoin wallets than regular bank accounts in El Salvador (See https://www.forbes.com/sites/theapothecary/2021/10/07/in-el-salvador-more-people-have-bitcoin-wallets-than-traditional-bank-accounts/).

[62]Iceland has one of the most rigorous tax rates where gains up to (more than) $7,000 are taxed at 40% (46%).

crypto market to ban these activities within its borders, many other countries, mainly in Africa, South America, and Asia, explicitly banned (through law or rule) or implicitly (actions that prevent the acquisition of crypto).[63] Figure 2 depicts the ban of cryptocurrencies around the world according to the Law Library of Congress, "Regulation of Cryptocurrency Around the World: November 2021 Update" (The Law Library of Congress (2021)). According to the report, in the November 2021, 9 jurisdictions applied an absolute ban and 42 jurisdictions applied an implicit ban. In contrast, the previous report in 2018, only 8 jurisdictions explicitly imposed bans and 15 had implicit bans.

Finally, we also asses the regulatory framework surrounding cryptocurrencies according to The Law Library of Congress (2021) report. Figure 3 depicts the application of tax laws in cryptocurrencies across the world. The report states that the application of tax laws and compliance laws (e.g., anti-money laundering) have increased exponentially. In the November 2021 update, 103 jurisdictions are identified as applying these laws to cryptocurrencies. In contrast, the previous report in 2018, only 33 jurisdictions were found to regulate cryptocurrencies in these areas.

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[63]Not all bans are politically driven. For instance, Kosovo banned cryptocurrency mining after a series of electricity blackouts in 2021 (See https://www.bbc.com/news/world-europe-59879760).

Appendix 1. Figure 1. Guidance Issued Timeline. This figure shows the timeline of releases of tax guidance on digital assets across worldwide jurisdictions. The table below the figure tabulates the initial tax-guidance per country. Source: PWC (2021).
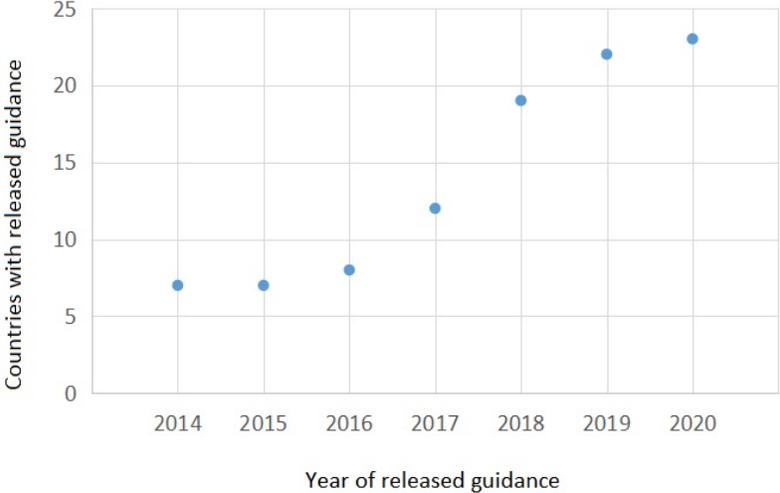
Country	Initial Tax-Guidance
Australia	2014
Denmark	2014
France	2014
Netherlands	2014
Sweden	2014
United Kingdom	2014
United States	2014
Italy	2016
Argentina	2017
Colombia	2017
Japan	2017
Switzerland	2017
Germany	2018
Ireland	2018
Luxembourg	2018
Malta	2018
Poland	2018
South Africa	2018
Thailand	2018
Canada	2019
Luechtenstein	2019
Singapore	2019
Hong Kong	2020

Appendix 1. Figure 2. Ban of Cryptocurrencies Around the World (November 2021). This figure depicts the ban of cryptocurrencies around the world. Dark blue indicates banned countries. Light blue indicates no banned countries. Light Gray indicates unclear ban policy. Source: The Law Library of Congress (2021).

Appendix 1. Figure 3. Tax Laws Around the World (November 2021). This figure depicts the application of tax laws on cryptocurrencies around the world. Dark blue indicates countries with applicable tax laws. Light blue indicates countries with no applicable tax laws. Light Gray indicates countries with unclear ban policy. Source: The Law Library of Congress (2021).

Appendix 2. 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. Variables used our estimating equations appear italics. The remaining variables are included for descriptive purposes.

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 one if a trader is located in the United States
ICO	Indicator	Equals one for coins generated in an Initial Coin Offerings (ICO) (e.g., Ethereum), and zero for coins not generated in an ICO (e.g., Bitcoin)
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 one for trades falling in the first two weeks of January
Dec	Indicator	Equals 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 number of wash trades times their amount in dollars
WashVolumePercTotal	Percent	Total amount ($) of wash trades to total amount ($) of trades
HarvestPeriod	Indicator	Equals one for trades executed in the last quarter of 2018
US Exchange	Indicator	Equals 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
HarvestPeriod	indicator	Equals one for trades falling from October to December 2018
Jan	Indicator	Equals one for trades falling in the first two weeks of January
Dec	Indicator	Equals 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 3. 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. Panel D reports statistics for the propensity score-matched sample based on the Trading Account Dataset for the period from 2017 to 2018. *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. *Diversification* 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
Diversification	0.41	0.36	0.41	0.42
Exchanges	0.20	0.18	0.20	0.21

Panel C: Percent balance improvement

	Std. Mean Di .	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
Diversification	81.70	88.30	58.20	62.20
Exchanges	76.90	-415.10	19.00	64.00

Panel D: Summary of balance (2017-2018)

	Unmatched		Matched	
	Treat	Control	Treat	Control
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

Appendix 4: 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.[64]

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.

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[64]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.[65] 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.

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[65]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 4. Figure 1. Wash trading and regulation. This figure shows the percentage of wash trading volume to total volume on exchanges with different levels of regulatory compliance (Panel A) and for three different exchanges with different levels of regulation (Panel B). In Panel A, 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). In both panels, the vertical axis is wash trade volume reported in percentage. The exchanges in Panel B are highlighted in Panel A with the following colors. Bibox is highlighted in salmon. Binance is highlighted in green. Kraken is highlighted in light blue.