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CRYPTO TAX EVASION

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ABSTRACT

We quantify and explain the extent of crypto tax noncompliance and evasion, and assess the efficacy of alternative tax enforcement interventions. The context of the study is Norway. This context allows us to address key measurement challenges by combining de-anonymized crypto trading data with individual tax returns, survey data, and information from tax enforcement interventions. We find that crypto tax noncompliance is pervasive, even among investors trading on exchanges that share identifiable trading data with tax authorities. However, since most crypto investors owe little in crypto-related taxes, enforcement strategies need to be well-targeted or cheap for benefits to outweigh costs.

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I. Introduction

Taxing cryptocurrency is a priority for governments across the world. In many countries, tax authorities are no longer turning a blind eye to crypto's potential for tax noncompliance and evasion. In the U.S., for example, the IRS is increasingly gathering information on individuals' crypto transactions from exchanges (DOJ, 2021; IRS, 2025). The IRS has also started sending reminder letters to taxpayers with crypto transactions who potentially failed to report their crypto income (IRS, 2019), and to actively target crypto investors in investigations and audits (IRS, 2024b; CNBC, 2024).

Advocates of such interventions claim the quasi-anonymity of crypto facilitates widespread tax noncompliance and evasion; thus, they argue, there is a large revenue potential from stricter crypto-related tax enforcement policy. For instance, in a recent letter to the U.S. Treasury, Senators Warren et al. (2023, p. 3) argue that crypto tax evaders "*[...] siphon off billions of dollars a year from the U.S. government.*" Others argue the revenue potential from stricter tax enforcement policy may be more limited, at least in the absence of a coordinated and automated exchange of information on crypto holdings and capital gains across countries (Thiemann, 2021, p. 12).

The challenge in assessing these arguments is that the evidence base is scarce. Within the burgeoning literature on crypto, tax aspects have received relatively little attention. Baer et al. (2023, p. 489), in their recent review article on taxation of crypto, summarize the state of the literature well: "[...] *so great is the ignorance in this area that even the crudest back-of-envelope calculations may be helpful.*"

This paper helps to close this knowledge gap by quantifying and explaining the extent of crypto tax noncompliance and evasion, and assessing the efficacy of alternative tax enforcement interventions. Our context is Norway in the period 2018–2024. In Section II, we describe relevant institutional information, including a comparison of crypto ownership in Norway and other developed countries. The Norwegian tax system treats cryptos as property, like any other financial asset.[1] Because Norway has a wealth tax, crypto investors are taxed on both their crypto holdings and any realized capital gains.

As described in Section III, our analyses are made possible by three strengths of the Norwegian data environment. The first is the ability to link individuals' crypto transactions on the domestic crypto exchanges to their tax returns and demographic characteristics. The data from the domestic exchanges were collected by the Norwegian Tax Administration through subpoenas, and later shared with us, and cover all individuals trading on the domestic exchanges, regardless of whether they declare cryptos in their tax return. The second is the access to a nationally representative survey with information on crypto ownership. The third is the ability to access and link data from several enforcement interventions carried out by the Norwegian Tax Administration.

We show, in Section IV, how the combination of these data sets can be used to point-identify the prevalence of crypto tax noncompliance, both in the broader population and for different subgroups. The results of this analysis are presented in Section V. In 2021, we find that 6% of the broader Norwegian population are crypto tax noncompliers in the sense that they hold undeclared cryptos. Conditional on holding cryptos, 88% fail to declare them. This tax noncompliance rate is fairly stable over time, exceeding 80% in each tax year 2018–2024. Crypto tax noncompliance is concentrated among young, male, and urban individuals. However, this concentration is driven by differences in crypto adoption across individual characteristics, not by differences in tax noncompliance conditional on holding crypto. This is arguably good news for tax authorities: They could use aggregated survey data on crypto adoption to target crypto tax noncompliers.

Another finding is that in 2021, 79% of the investors trading on the domestic crypto exchanges fail to declare their cryptos, even though these exchanges share identifiable

[1]Most other developed countries also treat cryptos as (intangible) property. See OECD (2020) and Baer et al. (2023) for an overview of the tax treatment of crypto across countries.

trading data with the Norwegian Tax Administration. Yet, the majority of Norwegian crypto tax noncompliers do not trade on the domestic exchanges. This is in part a composition effect, as many Norwegian crypto investors exclusively trade outside the domestic exchanges. However, behavior also plays a role, as those who trade outside the domestic exchanges have an even higher rate of noncompliance. Taken together, these results suggest that gathering identifiable trading data from domestic exchanges, by itself, is not going to solve the problem of tax noncompliance in the context of crypto.

A possible concern with the results in Section V is that our estimates of the population rate of crypto tax noncompliance rely on survey estimates of crypto ownership in the broader population, including among individuals who exclusively trade outside domestic exchanges. We conduct several robustness checks related to the coverage and reliability of the survey estimates of crypto ownership in the broader population. For example, we assess sensitivity to artificially increasing or decreasing the survey estimates of crypto ownership by as much as 50%, to reweighting the survey estimates of crypto ownership with respect to observable characteristics, and to using data from alternative surveys. We also present worst-case bounds on the population rate of crypto tax noncompliance that do not rely on survey estimates of crypto ownership. It is reassuring to find that our broad conclusions about crypto tax noncompliance remain unchanged.

While failing to declare crypto is unlawful in Norway regardless of the size of the tax liability, not all tax noncompliers owe taxes. For example, crypto investors may not owe taxes if they are insufficiently wealthy to be liable for wealth taxes and if they do not realize any capital gains. In Section VI, we shift attention from tax noncompliance to tax evasion. Taking a partial identification approach, we construct lower and upper bounds of \$81 and \$1,062 on the average value of tax evasion among all crypto tax noncompliers in 2021. Our upper bound estimates are even lower in later years, largely driven by a fall in crypto prices. In other words, while a large number of crypto investors fail to declare their cryptos, on average, each owes a modest amount of taxes.

In Section VII, we examine the mechanisms behind these findings. We first present a model of tax compliance in which taxpayers with different crypto tax liabilities face heterogeneous costs of compliance and form subjective beliefs about the probability of detection. Next, we show how to recover the model parameters from data on the tax liabilities and tax compliance decisions of individual crypto investors trading on the domestic exchanges.

The estimated model suggests that investors with larger tax liabilities perceive a higher expected cost of detection and are therefore more likely to declare crypto. By contrast, the majority of investors (who have small tax liabilities) are reluctant to declare because their compliance costs tend to exceed a relatively low expected cost of detection. These findings help explain why the average value of tax evasion among crypto tax noncompliers is quite modest. We conclude the analysis of mechanisms by applying the model to the results from two quasi-experiments that shifted the costs and benefits of tax noncompliance.

The combination of a high rate of tax noncompliance and a low average value of tax evasion may present a challenge for designing cost-effective tax enforcement interventions. In Section VIII, we examine how tax enforcement could be designed for the benefits to outweigh the costs. To do so, we examine the efficacy of two low-cost interventions. For each intervention, we compare the direct benefits in terms of increased crypto tax revenue against the cost of the intervention.

The first intervention involves indiscriminately sending letters to anyone who previously declared crypto in their tax returns but then stopped, reminding them that cryptos are taxable. A reminder letter is distinct from an audit as it does not require the recipient to respond, thereby eliminating the need for document review and thus reducing costs for the authorities. Using data from an actual intervention carried out in 2020, we find that such reminder letters increase the probability of crypto tax compliance by 17.1

percentage points, and, on average, raise (just) enough tax revenue to cover the cost of the intervention. Interventions carried out in later years produce comparable effects on compliance, but smaller effects on tax revenue due to lower crypto prices.

The second intervention, a correspondence audit, involves sending a letter to a taxpayer requesting documentation (e.g., bank statements) to support the claims in the filed tax return.[2] Unlike a reminder letter, the taxpayer must respond to a correspondence audit, which raises the cost of the intervention due to document review. Although correspondence audits in Norway have not (yet) been targeted at crypto investors, we can use our estimates of crypto tax noncompliance (Section V) and the value of crypto tax evasion (Section VI) to quantify the expected effects of such audits.

A key objective of our analysis of correspondence audits is to inform policy decisions that determine the allocation of such interventions to individuals with different observable characteristics. As explained in Section VIII.C, the method of Kitagawa and Tetenov (2018) is attractive for this purpose, both in terms of statistical performance and practical implementation in realistic settings of policy design. Our findings suggest that correspondence audits may well be profitable if one could directly target crypto tax noncompliers. However, if tax authorities cannot directly identify tax noncompliers and must draw audit subjects from the broader population, we find that audits would be profitable only if they are targeted at a very narrow part of the population (in terms of age and income). Still, the revenue gains from well-targeted audits would be economically modest, and need to be weighed against the burden (e.g., time cost and lawyer fees) imposed on audited taxpayers.

In Section IX, we offer concluding remarks and discuss the limitations of our study and implications for researchers. We argue that our paper provides a blueprint for empirically

[2]Correspondence audits are the most common audit type conducted by the IRS, accounting for approximately 75% of all audits (IRS 2024a, pp. 34, 46). These audits also appear to be the primary tax enforcement tool used in the context of crypto (Forbes, 2022).

analyzing tax noncompliance and evasion. We show how the combination of different data sets can be used to point-identify tax noncompliance and to construct informative bounds on the average value of tax evasion. The assumptions and resulting bounds can be tailored to the tax setting and data at hand. We also show how policymakers can design tax enforcement to increase tax compliance and revenue. Our findings suggest that a combination of soft audits and data collection from domestic exchanges yields only modest improvements in crypto tax compliance. At the same time, we find that crypto tax compliance increases sharply with the size of tax liabilities, suggesting that tax compliance may improve as households' crypto portfolios grow larger.

Our paper contributes to a large empirical literature on tax noncompliance and evasion across various sources of income and assets, surveyed by Slemrod (2007, 2019). Our key contributions are to quantify and explain the extent of crypto tax noncompliance and evasion, and to assess the efficacy of alternative tax enforcement interventions targeted at individual crypto investors. Hackethal et al. (2022), Weber et al. (2023), and Kogan et al. (2024) show that crypto investors are different from other investors in terms of risk taking, belief formation, and trading strategies, respectively, pointing to the possibility that they could also differ in terms of their tax noncompliance, evasion, and responsiveness to tax enforcement strategies. We find that, conditional on holding cryptos, 88% fail to declare them. This rate of tax noncompliance is broadly comparable to other assets that similarly lack third-party reporting, such as offshore real estate and offshore financial holdings (see, e.g., Alstadsæter et al., 2019 and Alstadsæter et al., 2025).[3]

Baer et al. (2023) review existing work on the taxation of crypto. They argue that although crypto protocols publicly record both the individual transactions and the unique identifiers (wallets) of the transacting parties, tying these transactions to individuals and

[3]Tax noncompliance rates for income sources that lack third-party reporting are somewhat lower. For example, Kleven et al. (2011) and Bott et al. (2020) both estimate tax noncompliance rates of about 45% for self-employment income and foreign earned income in Denmark and Norway, respectively.

their demographic characteristics and tax payments has proven difficult. As a result, the research to date has been limited in its ability to quantify the extent of crypto tax noncompliance and evasion, and we are not aware of any scientific studies of the efficacy of alternative enforcement interventions in the context of crypto.[4] There is some scientific evidence, however, on the converse of tax evasion: taxes paid. For the U.S., the results of Hoopes et al. (2022) imply that only one percent of all returns in 2020 reported some sales of crypto. This is well below the share of American adults that self-report to hold crypto, which points to the possibility of widespread tax evasion or that many crypto investors have not yet realized capital gains or losses from crypto. Using tax return data from Norway, Barake et al. (2025) study the portfolios and characteristics of crypto investors, including their position in the wealth distribution. The authors also consider the implications of crypto ownership for wealth inequality.

Our paper also connects to a broader literature on crypto, reviewed by Kogan et al. (2024). While much of this literature is centered around the question of who holds cryptos and why, our focus is on the extent of tax noncompliance and evasion by individual crypto investors.[5] Consistent with previous findings from the U.S. (e.g., Weber et al., 2023; Federal Reserve, 2023) and Europe (e.g., Steinmetz et al., 2021; Levkov et al., 2022), we

[4]Recent evidence from other countries corroborates our estimates. Using data from Danish crypto exchanges, Fejerskov Boas and Barake (2025) estimate a tax noncompliance rate of 90%, while the Swedish Tax Agency (2024) reports a similar estimate for Sweden. Based on data subpoenaed from select exchanges, the U.S. Internal Revenue Service (2023) reports a crypto tax noncompliance rate of 75% for the 2021 tax year. The corresponding estimate for Norway is 79%. Cong et al. (2023a) examine how increases in tax scrutiny impact the trading behavior of American crypto investors. They find that investors increasingly engage in tax-loss harvesting, a legal tax avoidance strategy which involves selling investments at a loss to offset capital gains, following increased tax scrutiny.

[5]Whereas existing literature (e.g., Hanlon et al., 2015; Alstadsæter et al., 2019; De Simone et al., 2020) documents that tax evasion is concentrated among the wealthy individuals, who may have access to more opaque financial arrangements, we find that crypto tax noncompliance is pervasive across the wealth distribution and for a wide range of investor types; see Panel B of Figure 2 and Internet Appendix

find that males, young, and urban individuals are more likely to hold crypto.[6]

Finally, we connect to the econometrics literature on statistical decision making, as surveyed by Manski (2021). The objective of this literature is to inform policy decisions that determine the allocation of treatments to individuals with different observable covariates. Kitagawa and Tetenov (2018) propose a framework for determining optimal rules for targeted interventions, which they use to study the optimal assignment of individuals to a job training program. We apply their framework to study tax enforcement interventions in the context of cryptos, and find there may be scope for profitable audits targeted based on individual characteristics available to tax authorities.[7]

II. Institutional Background and Setting

Context of the study. Norway has a population of 5.4 million. It consistently ranks among the richest countries in the world — GDP per capita is about 8% higher than in the U.S. (World Bank, 2023). The Norwegian economy is typically described as a small open economy with a large public sector. The population is well-educated with a large middle class and is comparable to other European countries in terms of demographics.

Figures IA.14–IA.15. One interpretation is that crypto democratizes tax evasion.

[6]Our paper relates to a broader literature on the use of crypto for economic crime and illicit finance. Meiklejohn et al. (2016), Sokolov (2021), and Amiram et al. (2022) study the role of Bitcoin in the Silk Road (2011–2013), ransomware, and terrorism financing. Other illicit uses of crypto include price manipulation (Gandal et al., 2018; Griffin and Shams, 2020), scams (Griffin and Mei, 2025; Phua et al., 2025), insider trading (Félez-Viñas et al., 2025), and wash trading (Pennec et al., 2021; Cong et al., 2023b); see Cong et al. (2023a) and Griffin and Kruger (2024) for surveys.

[7]Harju et al. (2025) estimate the compliance and revenue effects of non-random (risk-based) audits among Finnish firms. Applying the framework of Kitagawa and Tetenov (2018), we show that the revenue effects of risk-based audits can be substantially improved using simple targeting rules. Other papers analyze the effects of field experiments or random audits on the tax compliance decisions of households or firms (Kleven et al., 2011; Boning et al., 2020; Eerola et al., 2026).

While not a member of the European Union (EU), Norway is a part of the European Economic Area (EEA), which means that central components of Norwegian tax law and tax enforcement are harmonized with those of other European countries.[8]

Norwegians are taxed on their worldwide labor income, capital income, and wealth. Labor income is taxed progressively, with a top marginal tax rate of 55.8%. By contrast, capital income, which encompasses realized capital gains and other investment income, such as interest income, is taxed at a flat rate of 22%. Finally, the wealth tax is 0.85% as of 2021 and applies to taxpayers' net wealth in excess of NOK 1.5 million ($\approx$ USD 150,000) for single taxpayers and NOK 3 million ($\approx$ USD 300,000) for married ones. In other words, only sufficiently wealthy taxpayers are liable for wealth taxes.[9]

Between 2018 and 2022, the share of Norwegians holding crypto increased from 5% to 9.8%, as indicated by survey data in Internet Appendix Table IA.I. For comparison, Weber et al. (2023) find that the share of Americans holding crypto increased from 2% in 2018 to 11% in 2022. International surveys conducted by Statista (2024) indicate similar levels and trends in crypto adoption across other developed countries. Consistent with survey evidence from the U.S. (e.g., Weber et al., 2023; Federal Reserve, 2023) and Europe (e.g., Steinmetz et al., 2021; Levkov et al., 2022), crypto adoption in Norway is considerably higher among males than females and among younger than older individuals.[10]

[8] For example, Norway exchanges financial account information with EU countries and has adopted EU know-your-customer and anti–money laundering standards for crypto, including the so-called travel rule. Norway will also implement the Crypto-Asset Reporting Framework (CARF) on the same timeline as the EU, with implementation starting in 2026 (Norwegian Tax Administration, 2025a).

[9] See Mogstad et al. (2025) for more details on taxes and transfers in Norway, and Ring (2025) for a comprehensive overview of wealth taxation in Norway since the early 2000s. Eika et al. (2020), Fagereng et al. (2020), and Hvide et al. (2024) describe household investment behavior in Norway.

[10] In Internet Appendix Figure IA.13, we show that the distribution of crypto holdings among Norwegian investors mirrors that presented in Figure 2 of Weber et al. (2023) for American crypto investors.

Crypto taxation. In Norway, cryptos are taxed in the same way as any other financial asset. Let $V \equiv V^D + V^F$ denote an individual's end-of-year crypto holdings, accumulated either on domestic crypto exchanges (V^D) or on foreign crypto exchanges and blockchains (V^F). Similarly, let $G \equiv G^D + G^F$ denote their crypto income, also accumulated either on (G^D) or outside the domestic exchanges (G^F).[11] Since Norwegians pay taxes on their worldwide wealth and income, the total tax liability due to crypto is given by:

$$T = \overbrace{\mathbf{1}^W(\tau^W V)}^{\text{Wealth tax liability}} + \overbrace{\tau^G G}^{\text{Capital income tax liability}} \tag{1}$$

where τ^W and τ^G are the tax rates on wealth and capital income. In 2021, the tax rates are $\tau^W = 0.85\%$ and $\tau^G = 22\%$. Only individuals with a net wealth exceeding NOK 1.5 million if single and NOK 3 million if married are liable to pay wealth taxes on their crypto. This threshold is captured by the $\mathbf{1}^W$ indicator.[12] Note that T can be positive, zero, or negative, the latter occurring if the individual realizes crypto losses. There is no cap on the amount of crypto losses that can be deducted in a given tax year.[13]

Declaring cryptos. Both crypto income and wealth are supposed to be declared in the regular tax return. Every year in April, the Norwegian Tax Administration sends a prepopulated tax return for the previous fiscal year to all Norwegian tax residents. The

[11]Realized capital gains on crypto, income from staking and mining, and bonuses from exchange rewards programs are all considered capital income, and taxed at the same rate.

[12]In Internet Appendix Figure IA.7, we find that only 7% of crypto investors are liable for the wealth tax, as most have insufficient wealth. Using a regression discontinuity design around the liability threshold, in Internet Appendix Figure IA.8, we find that the wealth tax does not have a causal effect on tax reporting behavior. See Internet Appendix Section H for additional details on these tests.

[13]By contrast, American taxpayers can deduct only up to \$3,000 in capital losses. While most Norwegian crypto investors have less than \$3,000 in losses (see Figure 4), this institutional difference would, in isolation, predict higher tax compliance in Norway than in the U.S. due to more favorable treatment of tax losses. Similar to the U.S., Norway has no formal wash-sale rule for crypto.

vast majority of domestic incomes and assets are included in the prepopulated tax return based on extensive third-party reporting from both employers and domestic financial institutions. The taxpayer is required to add any missing incomes or assets. This is done via a (free) online tax preparation platform provided by the Tax Administration. Crypto holdings (V) and crypto income (G) are not prepopulated and must be self-reported through this online platform. The taxpayer has to declare the value of crypto holdings as of December 31 of the tax year and the total amount of crypto income and losses that have been realized that year. These values must be declared regardless of whether or not the taxpayer owes any taxes.

Penalties for misreporting. If caught misreporting crypto holdings V or income G, the taxpayer must pay their full crypto tax liability, T, plus a penalty. The penalty is a 20% surtax. While failing to declare V and G is unlawful even when there is no tax liability, there is typically little if any penalty for such noncompliance.

Detection. The Norwegian Tax Administration's ability to detect tax noncompliance depends on where the cryptos have been accumulated. Norwegians can accumulate crypto wealth and income on domestic exchanges, foreign exchanges, or directly on blockchains. The domestic exchanges are regulated by the Financial Supervisory Authority of Norway and require government-issued identification for account creation. Since 2019, the Tax Administration has subpoenaed complete and identifiable trading records from the domestic exchanges.[14] Accordingly, the Tax Administration directly observes domestic

[14]The first regulated exchange was formed in 2019, and by 2021, the number had grown to nine. Trading was modest in 2019, but increased sharply in 2020 and 2021, as shown in Appendix Table IA.VI. In 2021, about 26% of all Norwegian crypto investors traded on the domestic exchanges, as shown in Section V. Investors trading on the domestic exchanges are meaningfully younger (Internet Appendix Table IA.XVIII) and, on average, have lower tax liabilities (Table VI) than those trading outside the domestic exchanges. Internet Appendix Section C provides more detail on the domestic exchanges.

crypto trading. By contrast, the Tax Administration has less precise information about crypto trading outside the domestic exchanges. Due to third-party reporting from domestic financial institutions, the Tax Administration observes international wire transfers to foreign entities, including foreign crypto exchanges, and they may receive some information about Norwegians' crypto trading from partnering countries' tax authorities through data-sharing agreements (Baer et al., 2023). However, they do not directly observe Norwegians' trading activity on foreign crypto exchanges or blockchains.

Information about crypto tax rules. Every year during tax season, the Tax Administration announces on its website (Norwegian Tax Administration, 2018, 2020, 2021, 2022, 2023, 2024, 2025c) and in major newspapers (Pengenytt, 2018; Dagens Næringsliv, 2021; Bergens Tidende, 2022; Finansavisen, 2024) that cryptos are taxed and explains how to declare them. These announcements often emphasize that crypto trading is not anonymous and that the Tax Administration receives crypto transaction data from both domestic and international sources. In addition, major domestic exchanges send annual email reminders about crypto tax rules and provide free tax tools (see, e.g., Firi, 2020, 2021b, 2022, 2023).[15] These announcements emphasize that cryptos are not prepopulated in the tax return and must be self-reported, and explain how to do so.

III. Description of Our Data Sources

Our analyses are based on five data sources.

[15] The largest domestic exchange introduced a free tax tool in 2021, in time for the 2020 tax return filing; see Firi (2021a) and Section VII.C for more details. By 2024, the largest domestic and foreign exchanges typically support API-based tax reporting, allowing investors to transfer transaction records directly to external tax software (e.g., Kryptosekken.no and Koinly.com).

Table I. Notation

Notation	Definition	Explanation
V, V^*, V^D		True, declared, and domestically-accrued crypto holdings, respectively
G, G^*, G^D		True, declared, and domestically-accrued capital income, respectively
τ^W, τ^G		Tax rate on wealth and capital income, respectively
$\mathbf{1}^W$		Indicator for being liable for wealth taxation
X		Individual characteristics
T	$\mathbf{1}^W \tau^W V + \tau^G G$	True crypto tax liability
T^*	$\mathbf{1}^W \tau^W V^* + \tau^G G^*$	Declared crypto tax liability
T^D	$\mathbf{1}^W \tau^W V^D + \tau^G G^D$	Crypto tax liability accumulated on the domestic crypto exchanges
T^F	$T - T^D$	Crypto tax liability accumulated outside the domestic crypto exchanges
Set Definitions		
U		Norwegian population aged 15 and above
$B \subset U$	$\{V > 0\}$	... who hold cryptos
$A \subset B$	$\{V^* > 0\}$	... who hold and declare cryptos in their tax return
$D \subset B$	$\{V^D > 0\}$	... who hold cryptos accumulated on domestic exchanges
$A^C \subset B$	$B \setminus A$	... who hold but do not declare cryptos in their tax return
$D^C \subset B$	$B \setminus D$	... who hold cryptos accumulated exclusively outside the domestic exchanges

Tax data. Crypto tax return data come from the Norwegian Tax Administration. We observe declared crypto holdings and crypto income, which we denote V^* and G^*, in the 2018–2023 tax returns for the entire population. We also observe all other tax return items, such as taxable income and wealth, which allows us to translate V^* and G^* into the declared tax liability T^* according to the tax function in Equation (1).[16] The data set includes personal identification numbers and can be linked with other administrative databases.

Exchange data. Transaction-level data from the domestic crypto exchanges also come from the Norwegian Tax Administration. The data cover the years 2019–2021. Internet Appendix Section C describes the exchange coverage.[17] Based on the full history of buys

[16]Following existing literature (e.g., Carrillo et al., 2021; Kotsadam et al., 2022; Advani et al., 2023), we trim the tax liability distribution at the top and bottom 1% before calculating sample means.

[17]As explained in Internet Appendix Section C, the data cover seven of the nine regulated Norwegian exchanges in 2019–2020. For 2021, the data cover the three largest exchanges. The three largest ex-

and sells, we calculate, for each individual and year, the crypto holdings V^D and capital income G^D accrued on the domestic exchanges; see Internet Appendix Section D for details on how these are calculated. As the domestic exchanges require identification for account creation, the data include personal identification numbers and can be linked with other administrative databases. Linking the Exchange and Tax data, we translate V^D and G^D into the domestically-accrued tax liability T^D according to Equation (1).

Population data. Individual characteristics such as age, gender, and place of residence come from Statistics Norway. The data cover the entire population over the period 2018–2023. The data include personal identification numbers and can be linked with other administrative databases.

Survey data. Annual survey data on crypto ownership by Norwegians aged 15 and older come from Norstat, a leading European statistical agency. The surveys are nationally representative with respect to age, gender, and place of residence, which we verify in Internet Appendix A using our population data, and cover the years 2018, 2019, and 2021–2023.[18] The annual surveys provide estimates of the share of Norwegians (overall and by age, gender, and place of residence) who hold crypto, but we do not observe these investors' crypto holdings or their realized capital gains. Individual survey responses can-

changes accounted for 98.1 percent of all trades and 93.0 percent of all investors on the exchanges covered in 2020. In other words, our data capture the vast majority of trading on regulated crypto exchanges over the full 2019–2021 period during which such exchanges have existed in Norway.

[18]Internet Appendix Section A describes the survey sampling methods and data in more detail. For the 2021-2023 survey waves, the response rates are 25%, 19%, and 23%, which is comparable to the response rate in other surveys used for finance research, e.g., Weber et al. (2023). In the earlier years 2018 and 2019, the response rate is 14%. The surveys were commissioned by Arcane Research, later renamed K33 Research, a European research agency focusing on crypto-related topics. The survey estimates are presented in Arcane's annual "Norwegian Crypto Adoption Survey" publication.

not be linked with other databases, a fact disclosed to survey respondents.[19] In Section V, we conduct several robustness checks related to the coverage and reliability of the survey estimates.

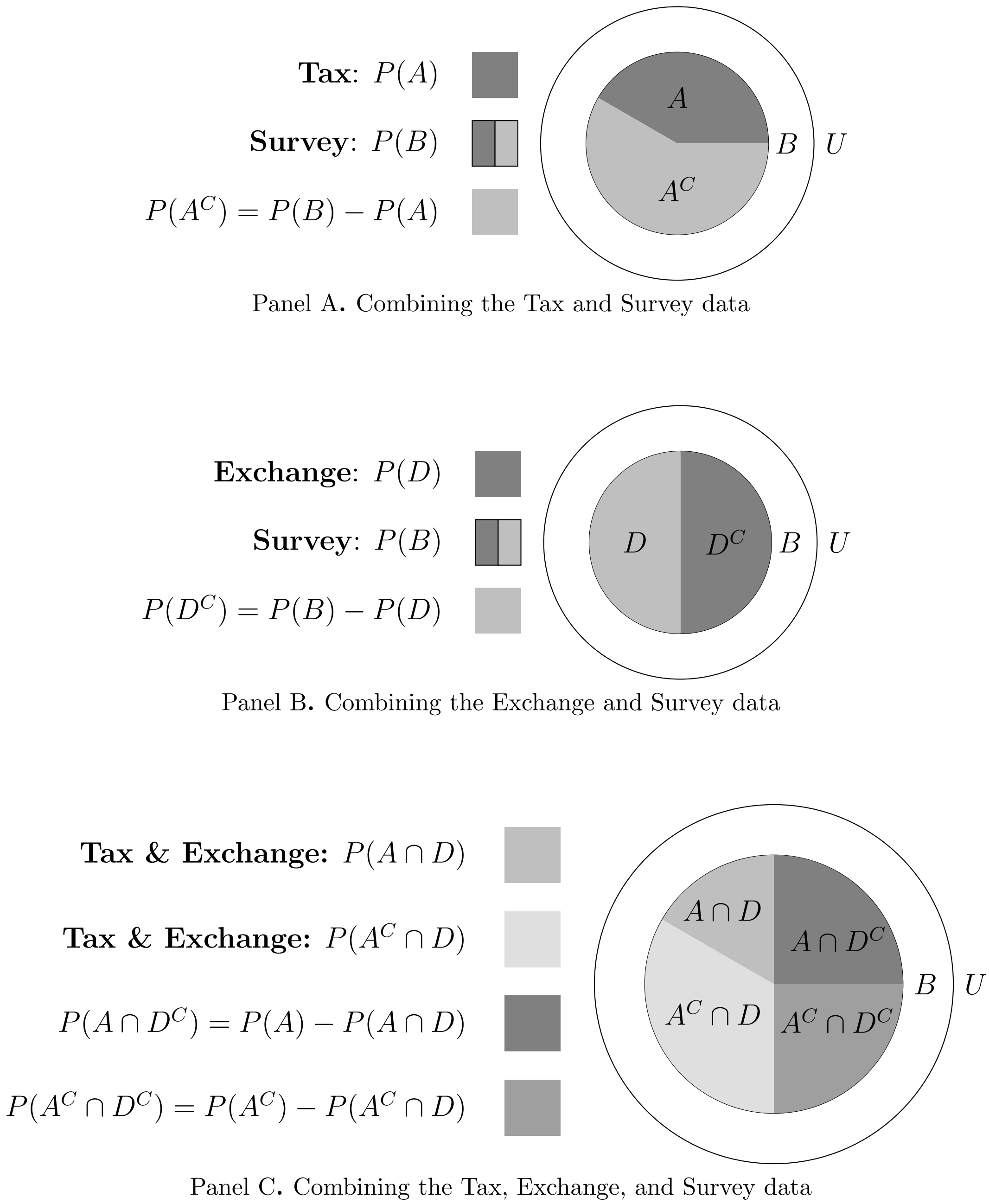
Tax enforcement data. Data on 1,398 reminder letters come from the Norwegian Tax Administration. The letters were sent in November 2020 by the Tax Administration to anyone who declared crypto in their 2018 tax return but stopped doing so in 2019. The full letter text can be found in Internet Appendix Section E. The data include personal identification numbers and can be linked with other administrative databases. Data on 2,668 analogous reminder letters sent in August 2022 also come from the Tax Administration; the letter text is described in Internet Appendix Section E.[20]

IV. What Can We Learn by Combining the Data?

In this section, we show how it is possible to draw inferences about crypto tax noncompliance by combining the data sources discussed in Section III. We explain this below, while summarizing the arguments in Figure 1.

[19] A key advantage of the Norstat survey is that it is conducted annually over multiple years using a consistent methodology. Other surveys corroborate Norstat's estimates in intermittent years. The Office of the Auditor General of Norway (2023), which is responsible for auditing state economic activities, reports that 6.3% of Norwegians held crypto in 2021, while the Central Bank of Norway (2024) reports that 11% did so in 2024. The corresponding Norstat estimates are 6.9% and 9.2%.

[20] In ancillary analyses, we use data on the international wire transfers of all Norwegians to identify individuals who trade on foreign crypto exchanges. The data, described in Internet Appendix Section G, include personal identification numbers and can be linked with other administrative databases.



Panel A. Combining the Tax and Survey data

Panel B. Combining the Exchange and Survey data

Panel C. Combining the Tax, Exchange, and Survey data

Figure 1. Identifying the prevalence of crypto tax noncompliance. This figure illustrates how we combine the available data sources to identify and estimate the prevalence of tax noncompliance among different groups of Norwegian crypto investors. Table I summarizes the notation.

A. Information available by combining the data

Combining Tax and Survey data. Let U denote the Norwegian population aged 15 and above. Let $B \subset U$ denote the subset of Norwegians who hold cryptos. Let $A \subset B$ denote the subset of crypto investors who declare crypto holdings in their tax return. Finally, let $A^C \equiv B \setminus A$.

The Tax data give us $P(A)$, the share of the Norwegian population who declare crypto holdings in their tax return, and the Survey data give us $P(B)$, the share of Norwegians who hold crypto. Using the law of total probability, as shown in Panel A of Figure 1, we can solve for $P(A^C)$, the share of Norwegians who hold cryptos but do not declare crypto holdings in their tax return — crypto tax noncompliers.

Combining Exchange and Survey data. Let $D \subset B$ denote the subset of Norwegians who hold cryptos that have been accumulated on the domestic exchanges. Let $D^C \equiv B \setminus D$.

Using the Exchange data, we can calculate $P(D)$, the share of Norwegians who hold cryptos that have been accumulated on the domestic exchanges. Combined with $P(B)$ from the Survey data, as shown in Panel B of Figure 1, we can solve for $P(D^C)$, the share of Norwegians who hold cryptos that exclusively have been accumulated outside the domestic exchanges, again using the law of total probability for identification.

Combining Tax, Exchange, and Survey data. Let $A \cap D$ denote the subset of Norwegians who hold cryptos that have been accumulated on the domestic exchanges and declare cryptos in their tax return, and let $A^C \cap D$ denote those who do *not* declare cryptos in their tax return.

Because we can link the Tax and Exchange data using personal identifiers, we can directly identify these subsets and calculate $P(A \cap D)$ and $P(A^C \cap D)$, the shares of Norwegians who are in both the Exchange and Tax data or only in the Exchange data.

Combined with $P(B)$ from the Survey data, as shown in Panel C of Figure 1, we can solve for $P(A \cap D^C)$ and $P(A^C \cap D^C)$, the prevalence of tax compliance and tax noncompliance among the investors exclusively trading outside the domestic exchanges, again using the law of total probability for identification.

Population data. Because we can link the Tax and Exchange data with our Population data, we can repeat the analyses above by individual characteristics, denoted by X. However, these analyses are restricted to characteristics that are observed both in the Survey and Population data — age (in bins), gender, and place of residence.

B. Key moments of the (combined) data

Table II presents key moments of our data, which we use in Section V to describe the prevalence of crypto tax noncompliance overall and by subgroups. We focus on 2021, the most recent year for which we observe both Tax, Survey, Exchange, and Population data. For completeness, we also present estimates for each year of data. We do not find meaningful changes in the prevalence of crypto tax noncompliance over time.

Tax data. Column (1) of Panel A, Table II shows that $P(A) = 0.008$, which means that 0.8% of Norwegians declare crypto in their tax return.[21]

Survey data. Column (2) of Panel A shows that $P(B) = 0.069$, which means that 6.9% of Norwegians hold crypto.

[21] We note that in the Tax data a total of 2,191 individuals declare $V^* = 0, G^* \neq 0$, i.e., that they have exited crypto during the tax year. These individuals are not included in the $A \subset B$ subset, as our analysis focuses on the tax compliance of individuals who *currently hold* cryptos. One may be concerned that these investors are "partially tax compliant", i.e., that they properly declare their crypto income but choose not to declare their crypto holdings. Reassuringly, including this small number of individuals in the A subset has no meaningful impact on any of our estimates (see Internet Appendix Table IA.XVII).

Table II. Data Moments

Panel A presents aggregate data moments from the Tax, Survey, and Exchange data. Panel B presents data moments broken down by individual characteristics. All moments are measured in 2021. The implied observation counts are presented in parentheses. Table I summarizes the notation.

	Panel A: Aggregate Moments				
	$P(A)$	$P(B)$	$P(D)$	$P(A \cap D)$	$P(A^C \cap D)$
$N = 4,447,123$	0.008 $(N = 36,574)$	0.069 $(N = 307,322)$	0.018 $(N = 79,525)$	0.004 $(N = 16,318)$	0.014 $(N = 63,207)$
	Panel B: Moments By Individual Characteristics				
	$P(A)$	$P(B)$	$P(D)$	$P(A \cap D)$	$P(A^C \cap D)$
Male $(N = 2,232,496)$	0.014 $(N = 31,421)$	0.109 $(N = 242,746)$	0.030 $(N = 65,975)$	0.006 $(N = 13,811)$	0.023 $(N = 52,164)$
Female $(N = 2,214,627)$	0.002 $(N = 5,153)$	0.029 $(N = 64,576)$	0.006 $(N = 13,550)$	0.001 $(N = 2,507)$	0.005 $(N = 11,043)$
Oslo $(N = 574,985)$	0.015 $(N = 8,590)$	0.106 $(N = 60,907)$	0.023 $(N = 13,393)$	0.006 $(N = 3,521)$	0.017 $(N = 9,872)$
Non-Oslo $(N = 3,872,138)$	0.007 $(N = 27,984)$	0.064 $(N = 246,415)$	0.017 $(N = 66,132)$	0.003 $(N = 12,797)$	0.014 $(N = 53,335)$
Age: 15–29 $(N = 995,341)$	0.010 $(N = 9,889)$	0.121 $(N = 119,980)$	0.038 $(N = 37,562)$	0.005 $(N = 4,693)$	0.033 $(N = 32,869)$
Age: 30–39 $(N = 729,700)$	0.018 $(N = 13,457)$	0.114 $(N = 83,298)$	0.029 $(N = 21,035)$	0.008 $(N = 5,489)$	0.021 $(N = 15,546)$
Age: 40–49 $(N = 704,057)$	0.011 $(N = 7,538)$	0.049 $(N = 34,273)$	0.016 $(N = 11,368)$	0.005 $(N = 3,389)$	0.011 $(N = 7,979)$
Age: 50+ $(N = 2,018,025)$	0.003 $(N = 5,690)$	0.035 $(N = 69,771)$	0.005 $(N = 9,560)$	0.001 $(N = 2,747)$	0.003 $(N = 6,813)$

Exchange data. Column (3) of Panel A shows that $P(D) = 0.018$, which means that 1.8% of Norwegians hold crypto accumulated on the domestic exchanges.

Linked Tax and Exchange data. Column (4) of Panel A shows that $P(A \cap D) = 0.004$, which means that 0.4% of Norwegians both hold crypto accumulated on the domestic exchanges and declare crypto in their tax return. Column (5) shows that $P(A^C \cap D) = 0.014$, which means that 1.4% of Norwegians hold crypto accumulated on the domestic exchanges but do not declare crypto in their tax return.

Panel B of Table II presents estimates by individual characteristic. We find that larger shares of male than female, young than old, and urban than rural Norwegians hold cryptos, as shown by the $P(B \mid X)$ column in Panel B of Table II.

V. Tax Noncompliance

In this section, we will use the data moments in Table II to identify and estimate the prevalence of tax noncompliance among Norwegian crypto investors, and to study how the prevalence varies across individual characteristics and trading venues that do and do not share identifiable trading data with the Norwegian Tax Administration. The identification arguments given our data are summarized in Table III and derived in the text. In Internet Appendix Section I, we show how our identification arguments can be adjusted depending on the tax setting or data at hand.

Prevalence of crypto tax noncompliance. We begin by showing that 6.1% of the Norwegian population are crypto tax noncompliers in the sense that they hold undeclared cryptos. Conditional on holding cryptos, 88% fail to declare them. This rate of tax noncompliance is broadly comparable to other assets that similarly lack third-party reporting, such as offshore financial assets and offshore real estate (see, e.g., Alstadsæter et al., 2019 and Alstadsæter et al., 2025).

To arrive at these conclusions, we first combine our Tax and Survey data to estimate $P(A^C)$, the share of the Norwegian population who hold undeclared cryptos. As illustrated in Panel A of Figure 1, those who hold crypto (B) either declare crypto holdings in their tax return ($A \subset B$) or do not ($A^C \subset B$). Accordingly, by the law of total probability, the prevalence of crypto tax noncompliance can be expressed as follows:

$$P(A^C) = \underbrace{P(B)}_{\text{Survey data}} - \underbrace{P(A)}_{\text{Tax data}} \tag{2}$$

which we can solve because $P(B)$ and $P(A)$ are both directly observed in Table II. As 6.9% of all Norwegians hold crypto, and 0.8% declare crypto, we find that $P(A^C) = 0.061$, which means that 6.1% of all Norwegians hold undeclared cryptos.

Second, we turn to $P(A^C \mid B)$, the share of Norwegian crypto investors who hold undeclared cryptos. By Bayes law, $P(A^C \mid B)$ can be expressed as:

$$P(A^C \mid B) = \frac{P(A^C \cap B)}{P(B)} = \frac{\overbrace{P(A^C)}^{\text{Equation (2)}}}{\underbrace{P(B)}_{\text{Survey data}}} \tag{3}$$

which we can solve because $P(B)$ is directly observed in Table II and $P(A^C)$ is given by Equation (2) above. We find that $P(A^C \mid B) = 0.88$, which means that 88% of all crypto investors in Norway fail to declare cryptos in their tax return.

One may be concerned that individuals under-report their tendency to hold cryptos in surveys, i.e., that $P(B)$ underestimates the true extent of aggregate crypto ownership. From Equations (2)–(3), it is clear that such under-reporting would imply that our estimates of $P(A^C)$ and $P(A^C \mid B)$ should be interpreted as lower bounds.

Characteristics of crypto tax noncompliers. Next, we characterize the population of crypto tax noncompliers. We find that the vast majority of crypto tax noncompliers are male, young, and reside in the capital. Indeed, crypto tax noncompliers are 1.6, 1.8, and 1.5 times more likely than the broader population to be male, aged 29 or below, and reside in the capital. This finding suggests that crypto tax noncompliers are quite different from the broader Norwegian population in terms of observable characteristics.

To arrive at these conclusions, we again combine the Tax and Survey data, but now leverage the fact that we observe gender, age in bins, and place of residence — X's — in both data sources. We first apply Bayes law to express $P(X \mid A^C)$, the characteristics

Table III. Parameters and Identifying Moments

Parameter	Identifying moments	Necessary data: Tax	Necessary data: Survey	Necessary data: Exchange	Estimate(s)
Prevalence of crypto tax noncompliance					
$P(A^C)$	$P(B) - P(A)$	✓	✓		0.061
$P(A^C \mid B)$	$P(A^C)/P(B)$	✓	✓		0.881
Characteristics of crypto tax noncompliers					
$P(X \mid B)$	$P(B \mid X) \cdot P(X)/P(B)$		✓		Table IV
$P(X \mid A)$	$P(A \mid X) \cdot P(X)/P(A)$	✓			Table IV
$P(X \mid A^C)$	$P(A^C \mid X) \cdot P(X)/P(A^C)$	✓	✓		Table IV
Prevalence of crypto tax noncompliance by individual characteristics					
$P(A^C \mid X)$	$P(B \mid X) - P(A \mid X)$	✓	✓		Figure 2
$P(A^C \mid B, X)$	$P(A^C \mid X)/P(B \mid X)$	✓	✓		Figure 2
Prevalence of crypto tax noncompliance by trading venue					
$P(D^C)$	$P(B) - P(D)$		✓	✓	0.051
$P(A^C \cap D^C)$	$P(A^C) - P(A^C \cap D)$	✓	✓	✓	0.047
$P(A^C \mid D^C)$	$P(A^C \cap D^C)/P(D^C)$	✓	✓	✓	0.911
$P(A^C \mid D)$	$P(A^C \cap D)/P(D)$	✓		✓	0.795
$P(D \mid A^C)$	$P(A^C \cap D)/P(A^C)$	✓	✓	✓	0.233
$P(D^C \mid A^C)$	$P(A^C \cap D^C)/P(A^C)$	✓	✓	✓	0.767
$P(A^C \mid D, X)$	$P(A^C \cap D \mid X)/P(D \mid X)$	✓		✓	Figure 2
$P(A^C \mid D^C, X)$	$P(A^C \cap D^C \mid X)/P(D^C \mid X)$	✓	✓	✓	Figure 2
Value of tax evasion					
$E[T \mid A^C]$:					
Lower	$E(T^D \mid A^C, D)$	✓		✓	\$81
Point	$E(T^* \mid A)$	✓			\$1,011
Upper	$1.05 \cdot E(T^* \mid A)$	✓			\$1,062
$E[T \mid A^C, X]$:					
Lower	$E(T^D \mid A^C, D, X)$	✓		✓	Figure 3
Point	$E(T^* \mid A, X)$	✓			Figure 3
Upper	$1.05 \cdot E(T^* \mid A, X)$	✓			Figure 3

distribution of the population of crypto tax noncompliers, as:

$$P(X \mid A^C) = \frac{P(A^C \cap X)}{P(A^C)} = \frac{\overbrace{P(A^C \mid X)}^{\substack{\text{Equation (2)} \\ \text{by } X}} \; \overbrace{P(X)}^{\substack{\text{Population} \\ \text{data}}}}{\underbrace{P(A^C)}_{\text{Equation (2)}}} \tag{4}$$

which we can solve because $P(X)$—the characteristics distribution of the broader Norwegian population—is observed in the Population data, $P(A^C)$ is given by Equation (2), and $P(A^C \mid X)$ is given by Equation (2) when repeated by characteristic X.

The estimates of $P(X \mid A^C)$ are presented in column (1) of Table IV. We find that 78% of tax noncompliers are male, 19% reside in Oslo, the capital, and 41% are aged 15–29. To explore over-representation compared to the broader Norwegian population, in column (2), we divide $P(X \mid A^C)$ by $P(X)$. Compared to the population, we find that tax noncompliers are about 1.6 times more likely to be male, 1.8 and 1.6 times more likely to be aged 15–29 and 30–39, and about 1.5 times more likely to reside in the capital.

Table IV. Investor Characteristics

This table summarizes the characteristics of different crypto investors. Table III summarizes the identification arguments. All moments are measured in 2021.

	$P(X \mid A^C)$	$\frac{P(X \mid A^C)}{P(X)}$	$P(X \mid B)$	$P(X \mid A)$
Male	0.781	1.555	0.790	0.859
Female	0.219	0.441	0.210	0.141
Oslo	0.193	1.495	0.198	0.235
Non-Oslo	0.807	0.927	0.802	0.765
Age: 15–29	0.407	1.817	0.390	0.270
Age: 30–39	0.258	1.572	0.271	0.368
Age: 40–49	0.099	0.624	0.112	0.206
Age: 50+	0.237	0.522	0.227	0.156

Prevalence by individual characteristics. What matters for tax authorities trying to target tax enforcement actions is not the characteristics distribution of crypto tax noncompliers, $P(X \mid A^C)$, but rather the likelihood of noncompliance among individuals with given characteristics, $P(A^C \mid X)$. We show that larger shares of male than female, young than old, and urban than rural Norwegians are crypto tax noncompliers. These group-level differences, however, are driven by differences in crypto adoption, not by differences in tax noncompliance conditional on holding crypto. This is arguably good news for tax authorities: They could use aggregated survey data on crypto adoption to effectively target crypto tax noncompliers.

To arrive at these conclusions, we first repeat Equation (2) by X to estimate how tax noncompliance varies across individual characteristics in the broader population:

$$P(A^C \mid X) = \underbrace{P(B \mid X)}_{\text{Survey data}} - \underbrace{P(A \mid X)}_{\text{Tax data}} \tag{5}$$

which we can solve because $P(B \mid X)$ and $P(A \mid X)$ are known from Table II. The estimates of $P(A^C \mid X)$ are presented in Panel A of Figure 2. We find that 9.5% of Norwegian males and 2.7% of females are crypto tax noncompliers. Around 11% of Norwegians aged 15–29 hold undeclared cryptos; among those aged 30-39, 40–49, and 50+, the numbers are 9.5%, 3.8%, and 3.2%, respectively. A larger share of those who reside in Oslo, the capital, are tax noncompliers compared to those who reside outside the capital.

Next, we repeat Equation (3) by X to estimate how the rate of tax noncompliance varies across individual characteristics within the population of crypto investors:

$$P(A^C \mid B, X) = \frac{\overbrace{P(A^C \mid X)}^{\text{Equation (5)}}}{\underbrace{P(B \mid X)}_{\text{Survey data}}} \tag{6}$$

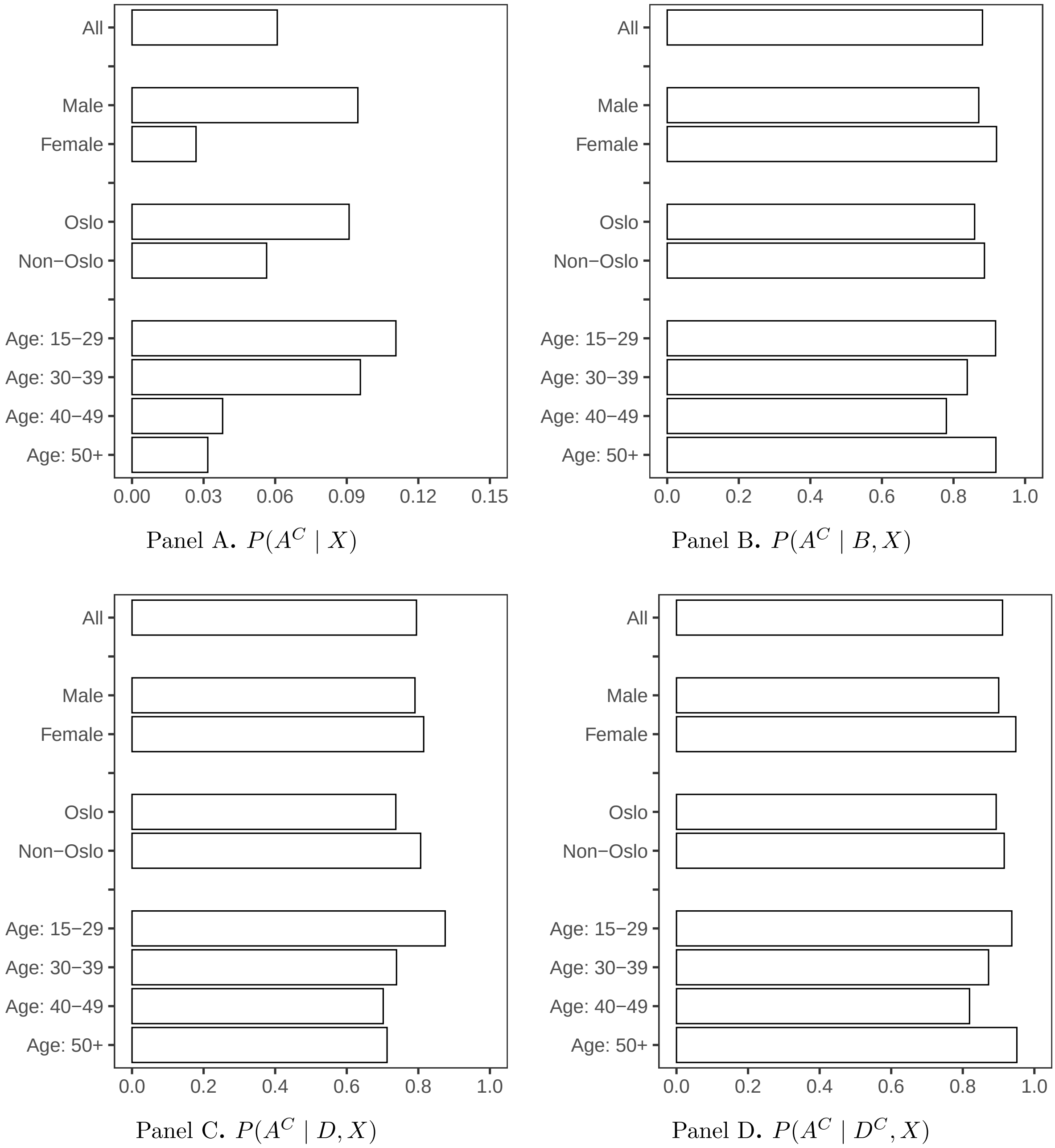


Figure 2. Crypto tax noncompliance by subgroup. This figure shows the prevalence of tax noncompliance for different subgroups of crypto investors. Table III summarizes the identification arguments. All estimates are based on data from 2021.

which we can solve because $P(B \mid X)$ is known from Table II and $P(A^C \mid X)$ is given by Equation (5). The estimates of $P(A^C \mid B, X)$ are presented in Panel B of Figure 2. We find that conditional on holding cryptos, the rate of tax noncompliance is remarkably stable across individual characteristics, with tax noncompliance rates exceeding 75% for male and female, young and old, urban and rural crypto investors alike.

Given the strong similarity in tax noncompliance rates across different crypto investors, it is natural to ask what is driving the observed variation in $P(A^C \mid X)$ in Panel A of Figure 2. To answer this question, we use a standard Oaxaca-Blinder approach to decompose the group-level differences in $P(A^C \mid X)$ into a composition effect (e.g., whether men are more likely to hold crypto) and a behavior effect (e.g., whether men are more tax noncompliant conditional on holding crypto). The results are presented in Internet Appendix Table IA.XVI. We find that the observed differences in $P(A^C \mid X)$ are almost entirely explained by differences across groups in crypto adoption, as opposed to differences in tax compliance conditional on holding crypto. In other words, survey data on crypto adoption ($P(B \mid X)$) are highly informative about population-wide crypto tax noncompliance ($P(A^C \mid X)$).

Prevalence by trading venue. Finally, we show that 79% of investors trading on the domestic exchanges fail to declare their cryptos, even though these exchanges share *identifiable* trading data with the Tax Administration. Still, the majority of Norwegian crypto tax noncompliers (76%) do *not* trade on the domestic exchanges. This is in part a composition effect, as many Norwegian crypto investors (74%) exclusively trade outside the domestic exchanges. However, behavior also plays a role, as those who trade outside the domestic exchanges have a higher (91%) rate of tax noncompliance. Combined, the results suggest that gathering identifiable trading data from domestic exchanges, by itself, is not going to solve the problem of tax noncompliance in crypto.

To arrive at these conclusions, we first combine the Exchange and Survey data to estimate how many Norwegians trade *outside* the domestic exchanges. As illustrated in Panel B of Figure 1, those who hold crypto (B) have accumulated some ($D \subset B$) or none ($D^C \subset B$) of their holdings on the domestic exchanges. By the law of total probability:

$$P(D^C) = \underbrace{P(B)}_{\text{Survey}} - \underbrace{P(D)}_{\text{Exchange}} \tag{7}$$

which we can solve because we observe both $P(B)$ and $P(D)$ in Table II. As 6.9% of Norwegians hold cryptos, and 1.8% have accumulated at least some holdings on the domestic exchanges, we find that $P(D^C) = 0.051$. This finding means that 5.1% of all Norwegians have accumulated crypto exclusively outside the domestic exchanges. The conditional probability, given by $P(D^C \mid B) = \frac{P(D^C)}{P(B)}$, is 0.74, implying that 74% of all Norwegian crypto investors exclusively trade outside the domestic crypto exchanges.

Next, we link our Exchange and Tax data to estimate how many of these are tax noncompliers. As illustrated in Panel C of Figure 1, the population of crypto tax noncompliers (A^C) have accumulated either some ($A^C \cap D$) or none ($A^C \cap D^C$) of their cryptos on the domestic exchanges. Accordingly, by the law of total probability:

$$P(A^C \cap D^C) = \underbrace{P(A^C)}_{\text{Equation (2)}} - \underbrace{P(A^C \cap D)}_{\text{Exchange} \times \text{Tax}} \tag{8}$$

where $P(A^C \cap D)$ is known from Table II and $P(A^C)$ is given by Equation (2). As 6.1% of all Norwegians are tax noncompliers and 1.4% are tax noncompliers and have accumulated at least some holdings on the domestic exchanges, we find that $P(A^C \cap D^C) = 0.047$. This finding means that 4.7% of all Norwegians are tax noncompliers and have not accumulated holdings on the domestic exchanges. The conditional probability, given by $P(D^C \mid A^C) = \frac{P(A^C \cap D^C)}{P(A^C)}$, is 0.77, implying that 77% of all Norwegian crypto tax noncompliers exclusively trade outside the domestic centralized exchanges.

The finding that individuals who trade outside the domestic exchanges account for 74% of all Norwegian crypto investors but 77% of all crypto tax noncompliers suggests a higher rate of tax noncompliance among those who trade outside the domestic exchanges. To examine this, we can use Equations (7)–(8) to solve for $P(A^C \mid D^C)$, the prevalence of tax noncompliance among those who only trade outside the domestic exchanges. By Bayes law:

$$P(A^C \mid D^C) = \frac{\overbrace{P(A^C \cap D^C)}^{\text{Equation (8)}}}{\underbrace{P(D^C)}_{\text{Equation (7)}}} \tag{9}$$

We find that $P(A^C \mid D^C) = 0.91$, which means that 91% of investors exclusively trading outside the domestic exchanges fail to declare crypto in their tax return.

We directly observe the prevalence of tax noncompliance among those who trade on the domestic crypto exchanges. Specifically, by Bayes law:

$$P(A^C \mid D) = \frac{\overbrace{P(A^C \cap D)}^{\text{Tax} \times \text{Exchange}}}{\underbrace{P(D)}_{\text{Exchange}}} \tag{10}$$

where $P(A^C \cap D)$ and $P(D)$ are both known from Table II. In Table III, we find that $P(A^C \mid D) = 0.79$. This finding means that 79% of investors trading on the domestic exchanges fail to declare crypto in their tax return, an 12 percentage point lower rate than among those who exclusively trade outside the domestic exchanges. As shown in Figure 2, Panels C and D, this difference persists and is comparable even when conditioning on X.

Robustness checks. While tax noncompliance on the domestic exchanges, $P(A^C \mid D)$, is directly observed in the data, tax noncompliance in the broader population, $P(A^C \mid B)$, and outside the domestic exchanges, $P(A^C \mid D^C)$, requires survey estimates of crypto adoption in the broader population for identification; see Table III.

We now conduct robustness checks related to the coverage and reliability of the survey estimates, which are nationally representative with respect to age, gender, and place of residence. Table V reports robustness checks for $P(A^C \mid B)$, while Internet Appendix Table IA.V reports the corresponding checks for the remaining parameters. Panel A in each figure or table reproduces the main results discussed above. Additional details on each specification check are provided in Internet Appendix Section B.

Panel B reports results using estimates of $P(B)$ that are reweighted based on additional characteristics observed in the survey data: Education (in bins), income (in bins), and employment. The results change little. The reason is that the survey sample, although slightly more educated, is already fairly comparable to the Norwegian population along these characteristics, as documented in Internet Appendix Section A.

Panel C replaces the annual estimates of $P(B)$ with rolling averages across survey waves. The idea is that averaging across years may smooth out year-specific errors in the survey estimates. The resulting estimates are very similar to the baseline estimates in Panel A. The reason is that the estimates of $P(B)$ are fairly stable over time.

Panel D artificially increases or decreases $P(B)$ by 10% to 50%. The idea is that survey estimates may be biased up or down — by small or large amounts — due, for example, to nonresponse bias or misreporting conditional on responding. We find that $P(B)$ would need to be about 45% lower for $P(A^C \mid B)$ to fall below 79%, the rate of noncompliance directly observed on domestic exchanges. The reason is that the prevalence of tax compliance, $P(A)$, is small even relative to conservative estimates of $P(B)$.

Panel E replaces Norstat's estimates of $P(B)$ with corresponding estimates from two alternative surveys commissioned in 2021 and 2024 by the Office of the Auditor General of Norway, which is responsible for auditing state economic activities, and the Central Bank of Norway. The resulting estimates are similar or slightly higher. The reason is

Table V. Robustness Checks: $P(A^C \mid B)$

This table reports estimates of $P(A^C \mid B)$ from Equation (3). All estimates are based on data from 2021. Specification details are provided in the main text and in Internet Appendix Section B.

	$P(B)$	$P(A^C)$	$P(A^C \mid B)$
Panel A. Baseline:			
	0.069	0.061	0.881
Panel B. Reweighting:			
Education	0.070	0.062	0.883
Education, employment	0.070	0.062	0.883
Education, employment, income	0.072	0.063	0.885
Panel C. Average across survey waves:			
Average: 2018–2021	0.054	0.046	0.847
Average: 2019–2022	0.070	0.062	0.883
Average: 2018–2024	0.070	0.061	0.882
Panel D. Arbitrarily scaling $P(B)$ up or down:			
$P(B^*) = (1 - 0.5)P(B)$	0.035	0.026	0.762
$P(B^*) = (1 - 0.4)P(B)$	0.041	0.033	0.802
$P(B^*) = (1 - 0.3)P(B)$	0.048	0.040	0.830
$P(B^*) = (1 - 0.2)P(B)$	0.055	0.047	0.851
$P(B^*) = (1 - 0.1)P(B)$	0.062	0.054	0.868
$P(B^*) = (1 + 0.1)P(B)$	0.076	0.068	0.892
$P(B^*) = (1 + 0.2)P(B)$	0.083	0.075	0.901
$P(B^*) = (1 + 0.3)P(B)$	0.090	0.082	0.908
$P(B^*) = (1 + 0.4)P(B)$	0.097	0.089	0.915
$P(B^*) = (1 + 0.5)P(B)$	0.104	0.095	0.921
Panel E. Alternative surveys:			
Office of the Auditor General of Norway (from 2021)	0.063	0.055	0.870
Central Bank of Norway (from 2024)	0.110	0.102	0.925

that the alternative estimates of $P(B)$ are similar to or slightly higher than Norstat's.[22]

Finally, it is useful to note that we can construct a worst-case lower bound on $P(A^C \mid$

[22] An alternative approach to estimating $P(B)$ is to combine information on observed crypto ownership on domestic exchanges, $P(D)$, with assumptions about the share of Norwegian investors who trade on those exchanges, $P(D \mid B)$. Barake et al. (2025) use this approach. Combining estimates of $P(D)$ from our Table II with survey-based estimates of $P(D \mid B)$, they conclude that 5% of Norwegians held crypto in 2021. Setting $P(B) = 0.05$ in Equation (3), we obtain $P(A^C \mid B) = 84\%$.

B) that does not rely on survey estimates for identification. To see this, let $P(B^*)$ denote the true crypto adoption rate. By the law of total probability, we have that:

$$P(B^*) = \underbrace{P(A \cup D)}_{\text{Observed}} + \underbrace{P(A^C \cap D^C)}_{\text{Unobserved}}.$$

We directly observe $P(A \cup D) = 0.022$, the share of Norwegians who are in the Tax data, Exchange data, or both. By contrast, we do not observe $P(A^C \cap D^C)$, the share of Norwegians who hold crypto but are in neither of these data sets. However, since $P(A^C \cap D^C) \geq 0$, it follows that $P(B^*) \geq P(A \cup D)$. Setting $P(B) = 0.022$ in Equation (3), we obtain an estimate of $P(A^C \mid B) = 63\%$. In other words, in the extreme scenario where *all* Norwegian crypto investors are directly observed in either our Tax or Exchange data, aggregate tax noncompliance would remain economically meaningful.

VI. Value of Tax Evasion

Above, we showed that the vast majority of Norwegian crypto investors fail to declare their cryptos. While failing to declare crypto is unlawful in Norway regardless of the size of the tax liability, not all tax noncompliers owe taxes. As shown in Equation (1), crypto investors may not owe taxes if i) they are insufficiently wealthy to be liable for wealth taxes and ii) they do not realize any capital income.

We now shift attention from tax noncompliance to tax evasion. Taking a partial identification approach, we construct lower and upper bounds of \$81 and \$1,062 on the average value of tax evasion among all crypto tax noncompliers. In other words, while a large number of crypto investors fail to declare their cryptos, each owes a modest amount of taxes. This finding suggests that tax enforcement strategies in the context of cryptos need to be well-targeted or cheap for the benefits to outweigh the costs, an insight we further develop in Section VIII.

To arrive at these conclusions, we cannot use the same identification arguments as in Section V. The reason is that our survey data provide information about the share of Norwegians who hold any crypto, but not about these investors' crypto holdings or capital income. This creates a key missing data problem: We do not observe investors' true tax liability, T. We do, however, observe the declared tax liability, T^*, for all those who declare crypto in their tax return, and we observe the true tax liability accrued on the domestic exchanges, T^D, for all those who trade on the domestic exchanges.

We now explain how we can combine our data on tax liabilities with various assumptions to construct bounds on the value of tax evasion by crypto tax noncompliers.

A. Data

Table VI summarizes our data on tax liabilities.

Declared tax liabilities. In Panel A, we first estimate the sample mean of declared tax liabilities among those who declare crypto, which we denote $E(T^* \mid A)$. We find that these tax compliers on average pay $E(T^* \mid A) = \$1,011$ in crypto taxes. Decomposing this estimate, we find that about 54% declare a positive tax liability, as given by $P(T^* > 0 \mid A)$, while the remainder declare zero (34%) or negative (12%) tax liabilities.

Undeclared tax liabilities. Since we are able to link the Tax and Exchange data, we can estimate mean tax liabilities also for those who trade on the domestic exchanges but do *not* declare their cryptos. We find that these tax noncompliers on average owe \$81 in taxes due to their domestic trading, as given by $E(T^D \mid A^C, D)$. Decomposing this estimate, we find that about 75% of the domestic tax noncompliers have positive tax liabilities, while the remainder have zero (20%) or negative (5%) tax liabilities. In Panel B of Table VI, we report tax liability estimates by individual characteristics.

B. *Identification approach*

We now show how to use the moments in Table VI to construct bounds on $E(T \mid A^C)$, the mean tax liability among all crypto tax noncompliers, which we do not observe.

Lower bound based on undeclared tax liabilities. We begin by using data on $E(T^D \mid A^C, D)$, the mean tax liability accrued by tax noncompliers on the domestic exchanges, to construct a lower bound on $E(T \mid A^C)$. There is a *direct link* between $E(T^D \mid A^C, D)$ and $E(T \mid A^C)$. In particular, by the law of total expectation:

$$E(T \mid A^C) = \overbrace{E(T \mid A^C, D)}^{\text{Unobserved}}\,\overbrace{P(D \mid A^C)}^{\text{Table III}} + \overbrace{E(T \mid A^C, D^C)}^{\text{Unobserved}}\,\overbrace{[1 - P(D \mid A^C)]}^{\text{Table III}} \tag{11}$$

where, by linearity of expectations:

$$E(T \mid A^C, D) = E(T^D + T^F \mid A^C, D) = \overbrace{E(T^D \mid A^C, D)}^{\$81} + \overbrace{E(T^F \mid A^C, D)}^{\text{Unobserved}} \tag{12}$$

where T^F is the tax liability accrued due to trading *outside* the domestic exchanges.

Since investors trading on the domestic exchanges can accumulate positive, negative, or zero tax liabilities outside the domestic exchanges, their *total* tax liability, $E(T \mid A^C, D)$, can be greater, smaller, or equal to $E(T^D \mid A^C, D) = \$81$. Even if we were to assume that these investors only trade on the domestic exchanges (which we do not) so that $E(T^F \mid A^C, D) = 0$, we cannot immediately ascertain the relationship between $E(T^D \mid A^C, D)$ and $E(T \mid A^C)$. This is because the tax liabilities of investors exclusively trading outside the domestic exchanges, $E(T \mid A^C, D^C)$, may be greater, smaller, or equal to those of investors trading on the domestic exchanges, $E(T \mid A^C, D)$.

Table VI. Tax Liabilities

This table shows average tax liabilities for different groups of individual crypto investors. All moments are measured in 2021.

Panel A. All Investors

All Tax Compliers		**Domestic Noncompliers**		**Domestic Compliers**		**Non-domestic Compliers**	
$P(T^* = 0 \mid A)$	0.343	$P(T^D = 0 \mid A^C, D)$	0.203	$P(T^* = 0 \mid A, D)$	0.227	$P(T^* = 0 \mid A, D^C)$	0.438
$P(T^* < 0 \mid A)$	0.115	$P(T^D < 0 \mid A^C, D)$	0.051	$P(T^* < 0 \mid A, D)$	0.135	$P(T^* < 0 \mid A, D^C)$	0.099
$P(T^* > 0 \mid A)$	0.542	$P(T^D > 0 \mid A^C, D)$	0.746	$P(T^* > 0 \mid A, D)$	0.638	$P(T^* > 0 \mid A, D^C)$	0.463
$E(T^* \mid T^* = 0, A)$	\$0	$E(T^D \mid T^D = 0, A^C, D)$	\$0	$E(T^* \mid T^* = 0, A, D)$	\$0	$E(T^* \mid T^* = 0, A, D^C)$	\$0
$E(T^* \mid T^* < 0, A)$	–\$434	$E(T^D \mid T^D < 0, A^C, D)$	–\$115	$E(T^* \mid T^* < 0, A, D)$	–\$366	$E(T^* \mid T^* < 0, A, D^C)$	–\$508
$E(T^* \mid T^* > 0, A)$	\$1,960	$E(T^D \mid T^D > 0, A^C, D)$	\$116	$E(T^* \mid T^* > 0, A, D)$	\$1,166	$E(T^* \mid T^* > 0, A, D^C)$	\$2,853
$E(T^* \mid A)$	\$1,011	$E(T^D \mid A^C, D)$	\$81	$E(T^* \mid A, D)$	\$695	$E(T^* \mid A, D^C)$	\$1,270
				$E(T^D \mid A, D)$	\$315		

Panel B. By Investor Characteristic

$E(T^* \mid A, X)$		$E(T^D \mid A^C, D, X)$		$E(T^* \mid A, D, X)$		$E(T^* \mid A, D^C, X)$	
Male	\$1,112	*Male*	\$88	*Male*	\$774	*Male*	\$1,380
Female	\$408	*Female*	\$45	*Female*	\$265	*Female*	\$545
Oslo	\$1,190	*Oslo*	\$106	*Oslo*	\$788	*Oslo*	\$1,472
Non-Oslo	\$957	*Non-Oslo*	\$76	*Non-Oslo*	\$669	*Non-Oslo*	\$1,202
Age: 15-29	\$815	*Age: 15-29*	\$49	*Age: 15-29*	\$607	*Age: 15-29*	\$1,005
Age: 30-39	\$1,149	*Age: 30-39*	\$96	*Age: 30-39*	\$722	*Age: 30-39*	\$1,447
Age: 40-49	\$1,092	*Age: 40-49*	\$129	*Age: 40-49*	\$793	*Age: 40-49*	\$1,340
Age: 50+	\$923	*Age: 50+*	\$139	*Age: 50+*	\$670	*Age: 50+*	\$1,163

To resolve this identification problem, we use the observed moments in Table VI to inform assumptions. First, we exploit that for tax compliers trading on the domestic exchanges, we observe both the total (declared) tax liability and the tax liability accrued on the domestic exchanges. In Table VI, we find that $E(T^* \mid A, D) = \$695 > E(T^D \mid A, D) = \$315$, which means that these tax compliers on average accumulate *positive* tax liabilities outside our data from the domestic exchanges. This finding motivates the following assumption concerning Equation (12):

Assumption 1: $E(T \mid A^C, D) \geq E(T^D \mid A^C, D)$. *That is, tax noncompliers who trade on the domestic exchanges do not on average accumulate negative tax liabilities based on their trading (if any) outside the domestic exchanges.*

Second, we exploit that for tax compliers, we observe the total (declared) tax liability not only for the investors trading on the domestic exchanges but also for those exclusively trading outside the domestic exchanges. In particular, these investors are present in the tax return data but not in the domestic exchange data. In Table VI, we find that $E(T^* \mid A, D^C) = \$1,270 > E(T^* \mid A, D) = \$695$, which means that tax compliers trading outside the domestic exchanges on average have considerably higher tax liabilities.[23] This finding motivates the following assumption concerning Equation (11):

Assumption 2: $E(T \mid A^C, D^C) > E(T \mid A^C, D)$. *That is, the total tax liability of those who trade exclusively outside the domestic exchanges is on average larger than the total tax liability of those who trade on the domestic exchanges.*

[23] In Internet Appendix Table IA.XVIII, we show that tax compliers trading on the domestic exchanges are more likely than tax compliers trading outside the domestic exchanges to be young and rural, groups that on average have lower tax liabilities. The same compositional differences exist between tax *non-compliers* trading on and outside the domestic exchanges, as also shown in Table IA.XVIII.

Under Assumptions 1 and 2, it is clear from Equations (11) and (12) that:

$$E(T \mid A^C) > E(T^D \mid A^C, D) = \$81. \tag{13}$$

which means that $E(T^D \mid A^C, D) = \$81$ forms a *lower bound* on $E(T \mid A^C)$.

Upper bound based on declared tax liabilities. Next, we use $E(T^* \mid A)$, the mean declared tax liability, to construct an upper bound on $E(T \mid A^C)$. To explain the identification argument, it is useful to first consider a special case where we can get point identification by imposing two strong assumptions. We then relax these assumptions to construct the upper bound. The two assumptions for point identification are:

Assumption 3: $E(T \mid A^C) = E(T \mid A)$. *That is, the expected tax liability is the same for crypto investors who do and do not declare crypto in their tax return.*

Assumption 4: $E(T \mid A) = E(T^* \mid A)$. *That is, there is no systematic misreporting of tax liabilities conditional on declaring crypto in the tax return.*

Under Assumptions 3 and 4, we have that:

$$E(T \mid A^C) \underbrace{=}_{\text{Assumption 3}} E(T \mid A) \underbrace{=}_{\text{Assumption 4}} E(T^* \mid A) = \$1,011. \tag{14}$$

which means $E(T \mid A^C)$ is *point-identified* from data on $E(T^* \mid A)$.

To assess Assumption 3, we exploit that for investors trading on the domestic exchanges, we observe an identical measure of tax liabilities for both tax compliers and noncompliers, namely, the tax liability T^D accrued on the domestic exchanges. In Table VI, we find that $E(T^D \mid A^C, D) = \$81 < E(T^D \mid A, D) = \$315$, which means that tax compliers trading on the domestic exchanges have higher tax liabilities than their noncomplier counterparts.[24] Motivated by this finding, we revise Assumption 3:

$$E(T \mid A^C) \underbrace{<}_{\substack{\text{Revised} \\ \text{Assumption 3}}} E(T \mid A) \underbrace{=}_{\text{Assumption 4}} E(T^* \mid A) = \$1,011. \tag{15}$$

which means that under weaker assumptions, \$1,011 forms an *upper bound* on $E(T \mid A^C)$.

To assess Assumption 4, we draw on existing literature. Using random audit data from Denmark, Kleven et al. (2011) find that individuals under-report their true tax liability from self-declared incomes (e.g., self-employment income) by about 5% conditional on declaring *any* such income — that is, $E(T \mid A) \approx 1.05 \times E(T^* \mid A)$.[25] Allowing for the same magnitude of under-reporting in our context, we can revise Assumption 4:

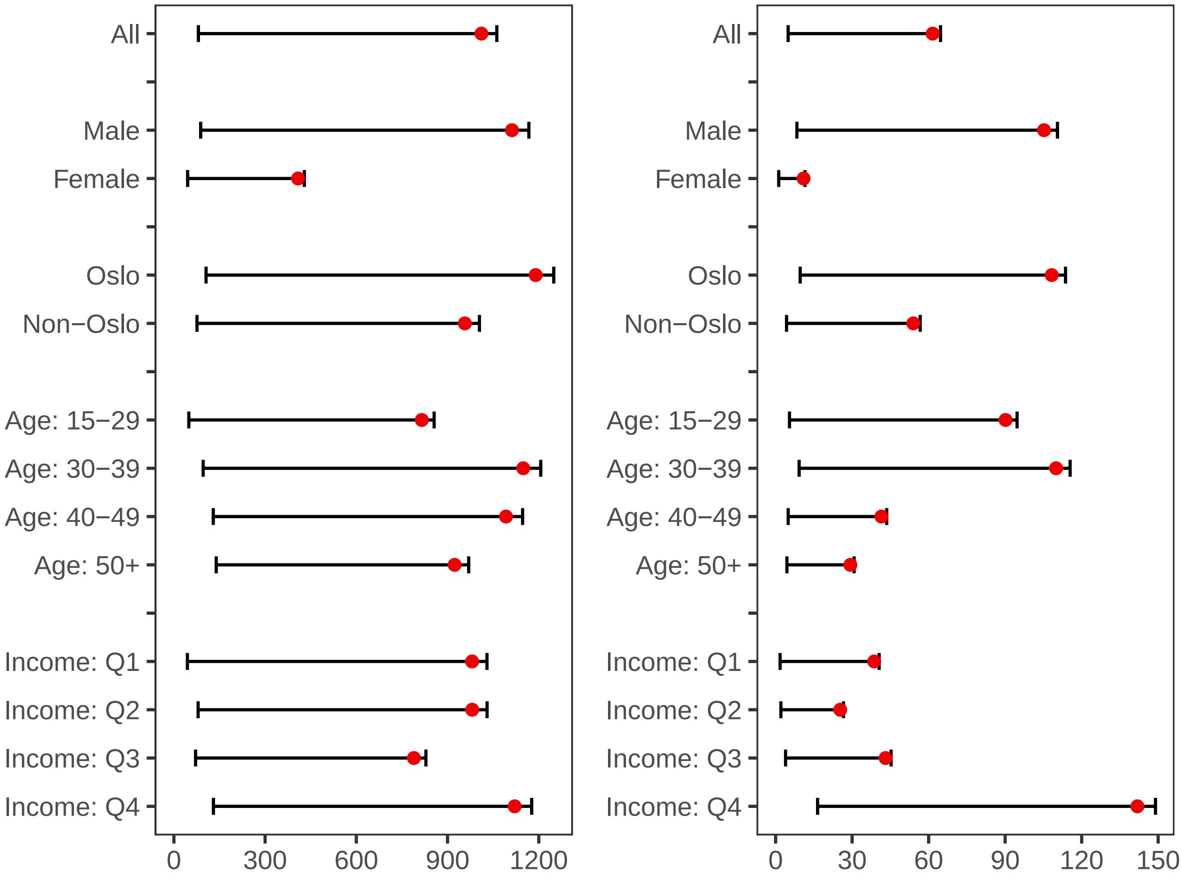
$$E(T \mid A^C) \underbrace{<}_{\substack{\text{Revised} \\ \text{Assumption 3}}} E(T \mid A) \underbrace{=}_{\substack{\text{Revised} \\ \text{Assumption 4}}} 1.05 \times \$1,011 = \$1,062 \tag{16}$$

which means that under an arguably weaker version of Assumption 4, the upper-bound estimate on $E(T \mid A^C)$ increases from \$1,011 to \$1,062. Naturally, allowing for a greater magnitude of under-reporting would increase the upper-bound estimate further.

In Panel A of Figure 3, we present bound estimates by individual characteristics. To do so, we apply Assumptions 1–4 conditional on individual characteristics. We find that upper and lower bounds are higher or similar for male than female tax noncompliers, for urban than rural tax noncompliers, for prime-aged tax noncompliers compared to other age groups, and for high-income compared to low-income tax noncompliers.

[24]This inequality arises primarily because tax compliance on domestic exchanges increases sharply with the tax liability; see Figure 4 in Section VII. In Internet Appendix Section G, we show that the same pattern holds for a subset of investors observed to trade outside domestic exchanges.

[25]This figure is derived from Panel A of Figure 3 in Kleven et al. (2011) and its legend.



Panel A. $E(T \mid A^C, X)$ Panel B. $P(A^C \mid X) \cdot E(T \mid A^C, X)$

Figure 3. Average tax liability, bound and point estimates. Panel A shows bound and point estimates of the average crypto tax liability among crypto tax noncompliers differentiated by individual characteristics, obtained by applying Assumptions 1–4 conditional on individual characteristics. Panel B shows point and bound estimates of the average crypto tax liability among the broader Norwegian population differentiated by individual characteristics, obtained by multiplying $P(A^C \mid X)$ from Panel A of Figure 2 with $E(T \mid A^C, X)$ from Panel A above. In both panels, vertical lines indicate the lower and upper bounds, while red dots indicate point estimates. All estimates are based on data from 2021.

VII. Mechanisms

Above, we showed that a large number of crypto investors fail to declare their cryptos (Section V) but that each investor, on average, owes a modest amount of taxes (Section VI). We now examine the mechanisms behind these findings.

We first present a model of tax compliance in the spirit of Allingham and Sandmo (1972) in which taxpayers with different crypto tax liabilities face heterogeneous compliance costs and form subjective beliefs about the probability of detection. Next, we show how to recover the model parameters from data on the tax liabilities and tax compliance decisions of individual crypto investors trading on the domestic exchanges.

The estimated model suggests that investors with larger tax liabilities perceive a higher expected cost of detection and are therefore more likely to declare crypto. By contrast, the majority of investors (who have small tax liabilities) are reluctant to declare because their compliance costs tend to exceed a relatively low expected cost of detection. We conclude the analysis of mechanisms by connecting these model-based findings to the results from two quasi-experiments that shifted the costs and benefits of crypto tax compliance.

A. Model of tax compliance

Preferences. There are two state variables of the individuals' utility functions. The first state variable is an indicator variable A that is equal to one if the investor chooses to comply by declaring her crypto tax liability. The monetary cost of tax compliance is given by the tax liability, T. We also allow for a fixed cost of tax compliance, denoted by μ^1, which may, for example, reflect the time and effort associated with tax filing. The indicator variable A is equal to zero if the investor chooses to be a tax noncomplier by failing to declare her crypto tax liability. Let μ^0 denote the fixed cost of tax noncompliance due, for example, to moral costs.

The other state variable of the utility function is an indicator variable C that is equal to one if the investor is detected for tax noncompliance, and zero otherwise. We allow for both fixed and variable costs of being detected for tax noncompliance. The fixed cost, denoted by κ, may reflect the effort cost of being audited. The variable cost is given by the tax liability T and a penalty surtax cT. In the Norwegian tax system, $c = 0.2$.

We consider a population of heterogeneous investors whose costs and benefits of tax compliance are allowed to differ both across and within observable types. The state-specific utility function of a given investor of observable type $X = x$ is given by:

$$u_x(A,C) = \begin{cases} \gamma(Y-T) - \xi^1 - \mu_x^1 & \text{if } A=1,\, C=0 \\ \gamma Y - (\kappa_x + \gamma(1+c)T) - \xi^0 - \mu_x^0 & \text{if } A=0,\, C=1 \\ \gamma Y - \xi^0 - \mu_x^0 & \text{if } A=0,\, C=0 \end{cases}$$

where γ is the marginal utility of income Y. The fixed cost of compliance or noncompliance of a given investor of observable type x is specified as the sum of a type-specific average cost and an idiosyncratic preference shock: $\mu^j = \mu_x^j + \xi^j$ for $j = 0, 1$. The fixed costs of compliance and noncompliance are therefore allowed to vary systematically across investor types and within a type. As is common in analysis of discrete choice, we assume that the idiosyncratic preference shocks, ξ^1 and ξ^0, are drawn i.i.d. from a standard Gumbel distribution.

Decision rule. An investor of type x forms beliefs over the probability of being detected, $p_x(T)$. We allow these beliefs to vary across investor types and within each investor type by tax liability. The dependence on tax liability reflects that investors may recognize that the probability of an audit increases in the tax liability. Maximizing expected utility, an investor declares crypto if their perceived expected cost of detection exceeds the costs of compliance:

$$A = \mathbb{1}\left[\underbrace{p_x(T)\,(\kappa_x + \gamma(1+c)T)}_{\substack{\text{Expected Cost}\\ \text{of Detection}}} > \underbrace{\gamma T}_{\substack{\text{Variable Cost}\\ \text{of Compliance}}} + \underbrace{\mu}_{\substack{\text{Fixed Cost}\\ \text{of Compliance}}}\right].$$

where $\mu \equiv \mu^1 - \mu^0$ is the fixed *net* cost of compliance, which may be positive (e.g., due to large hassle costs of filing) or negative (e.g., due to large moral costs of tax noncompliance). The probability of tax compliance among investors of type x with tax liability t can be expressed in terms of the model as:

$$P_x(t) \equiv \underbrace{P\left(A \mid X = x, T = t\right)}_{\text{Data}} = \underbrace{\frac{\exp\left(m_x(t)\right)}{1 + \exp\left(m_x(t)\right)}}_{\text{Logistic Transformation}} \equiv \underbrace{H\left(m_x(t)\right)}_{\text{Model}}, \tag{17}$$

where $m_x(t)$ captures the average net benefits of tax compliance for such investors:

$$m_x(t) \equiv \underbrace{p_x(t)(\kappa_x + \gamma(1+c)t)}_{\text{Expected Cost of Detection}} \mathbb{1}[t > 0] - \underbrace{(\gamma t + \mu_x)}_{\substack{\text{Costs of} \\ \text{Compliance}}}. \tag{18}$$

It is useful to observe that the expected cost of detection captures perceptions about the probability and costs of being detected for tax noncompliance in the *current* tax year. However, these may not be the only expected costs that matter for the compliance decision. For example, investors could also be reluctant to declare crypto in the current tax year if doing so constrains their ability to evade taxes in *future* tax years. In our static model, such strategic or anticipatory behavior will be loaded into the type-specific average fixed cost of compliance, μ_x. For this reason, this parameter should be interpreted as a broad measure of perceived compliance costs.

B. *Taking the model to the data*

We now use the model to analyze the compliance decisions of investors trading on the domestic exchanges. For them, we observe a (possibly imperfect) measure of tax liability, T^D. For simplicity, we assume in this section that $T = T^D$, however, in Internet Appendix Section K, we present results under alternative assumptions regarding measurement error. Suppose that the investor type x can be represented by the following observed characteristics: Age, gender, place of residence, income, wealth, education, employment status, marital status, and past tax compliance. We can then compute $P_x(t)$ from Equation (17).

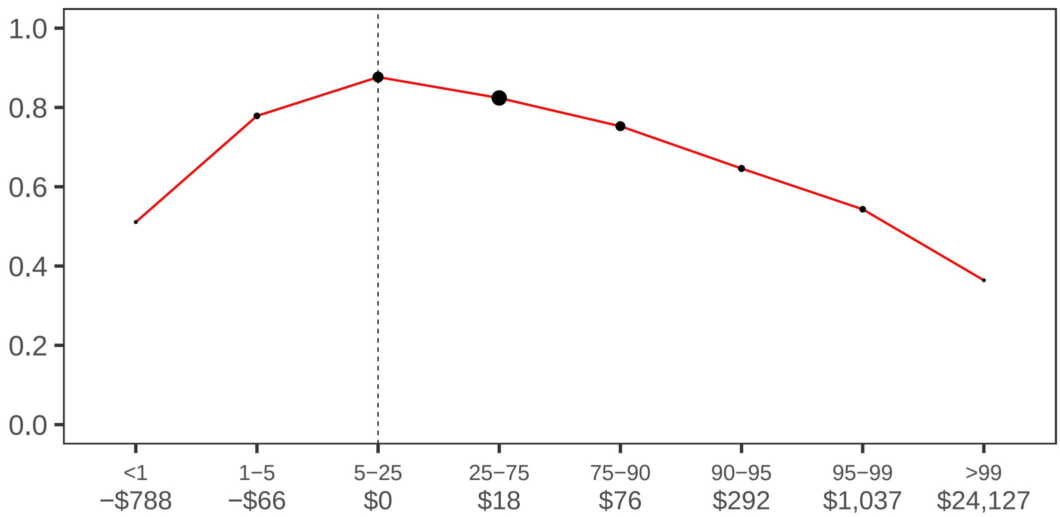


Figure 4. Data on tax noncompliance by tax liability. This figure plots $1 - P_x(t)$, the observed rate of tax noncompliance among investors trading on the domestic exchanges by percentile bins of crypto tax liability, averaged across investor types. The black circles indicate the average level of tax noncompliance within each tax liability bin, with dot size proportional to the number of investors in the bin. The red line connects the black circles. All estimates are based on data from 2021.

Figure 4 plots the average of $1 - P_x(t)$ across observed investor types, and illustrates the variation we will use to identify the model parameters. The figure shows a strong inverted-U relationship between tax noncompliance and tax liabilities: Tax compliance is low for small tax liabilities and higher for negative and large positive tax liabilities. In Internet Appendix Figure IA.14, we document a similar inverted-U relationship within each observable investor type. This finding suggests that the inverted-U relationship is not due to differences in the observed characteristics of investors across the tax liability distribution. Under the model, this pattern is consistent with fixed compliance costs that deter compliance even for small or negative tax liabilities, and with expected costs of detection that increase with the tax liability. Below, we quantify these forces by recovering the model parameters. The identification arguments and estimates are summarized in Table VII.

Table VII. Identification and Estimation of Model Parameters.

This table summarizes the identification and estimation of the model parameters. Columns (1) and (2) list the parameters and their associated symbols. Column (3) describes how each parameter is identified from the data. Column (4) reports the parameter estimates. All estimates are based on data from 2021.

Name	Symbol	Link between parameters and data	Estimate
Average fixed compliance cost	μ_x	$-H^{-1}(P_x(t_\ell)) - \gamma t_\ell$	\$1917
SD of fixed compliance cost	σ	$\frac{\pi}{\sqrt{3}}\frac{1}{\gamma}$, $\gamma = \frac{H^{-1}(P_x(t_\ell)) - H^{-1}(P_x(t_h))}{t_h - t_\ell}$	\$1873
Perceived probability of detection	$p_x(t)$	$\frac{t'_\ell\, L_h - t'_h\, L_\ell}{t'_\ell\, t'_h\, (t'_h - t'_\ell)\, \gamma(1+c)} \cdot t$	0.38
Fixed cost of detection	κ_x	$\frac{\left[t'^2_h\, L_\ell - t'^2_\ell\, L_h\right]\gamma(1+c)}{t'_\ell\, L_h - t'_h\, L_\ell}$	\$958
Expected fixed cost of detection	$p_x(t) \cdot \kappa_x$		\$270
Expected variable cost of detection	$p_x(t) \cdot 1.2t$		\$334

Step I: Fixed costs of compliance, μ_x, γ. We begin by identifying and estimating the average net fixed cost of compliance, μ_x. The marginal utility of money, γ, scales utility into dollars and therefore pins down the fixed cost in dollar terms.

The parameters γ and μ_x can be identified by considering the compliance behavior of investors with weakly negative tax liabilities in Figure 4. To see this, note that when $T \leq 0$, Equation (18) becomes:

$$m_x(t) = -\gamma t - \mu_x. \tag{19}$$

Consider two levels of negative tax liabilities: A small negative value $T = t_\ell$ and a large negative value $T = t_h < t_\ell$. For $k = \ell, h$, we can rewrite Equation (19):

$$\underbrace{m_x(t_\ell)}_{H^{-1}(P_x(t_\ell))} = -\gamma t_\ell - \mu_x \qquad \text{and} \qquad \underbrace{m_x(t_\ell)}_{H^{-1}(P_x(t_\ell))} - \underbrace{m_x(t_h)}_{H^{-1}(P_x(t_h))} = \gamma(t_h - t_\ell). \tag{20}$$

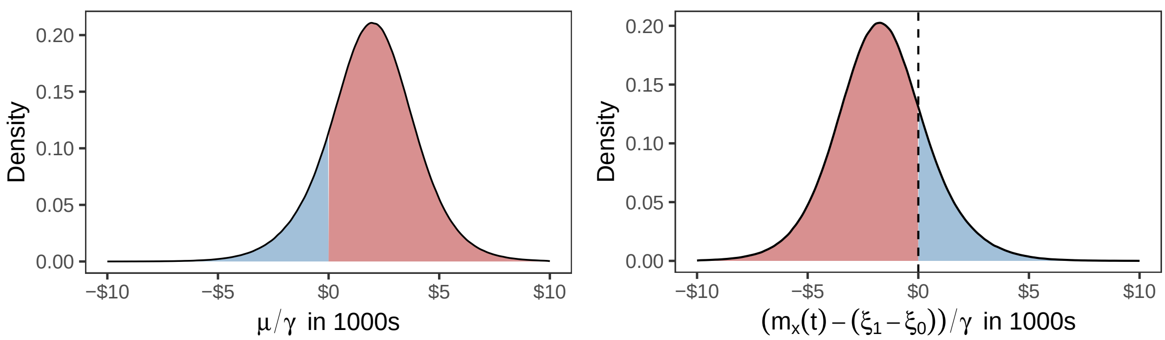
Equation (20) defines a system of two independent linear equations with two unknowns.

Solving these, we jointly identify:

$$\mu_x = -(H^{-1}(P_x(t_\ell)) + \gamma t_\ell), \qquad \text{and} \qquad \gamma = \frac{H^{-1}(P_x(t_\ell)) - H^{-1}(P_x(t_h))}{t_h - t_\ell},$$

where the tax compliance rates $P_x(t_\ell)$ and $P_x(t_h)$ are observed in the data.

The estimates are presented in Table VII. Fixed costs of compliance rationalize the relatively high level of tax noncompliance for small and negative tax liabilities in Figure 4. We estimate an average net fixed cost of compliance, μ_x/γ, of \$1,917. However, there is considerable variation in the net fixed cost of compliance across investors. The standard deviation of μ/γ is \$1,873. As is clear from Panel A of Figure 5, a large majority of investors (84%) have positive μ/γ, suggesting that the fixed costs of compliance μ^1 (e.g., hassle costs) outweigh the fixed costs of noncompliance μ^0 (e.g., moral costs).



Panel A. Distribution of μ/γ Panel B. Distribution of $(m_x(t) - (\xi^1 - \xi^0))/\gamma$

Figure 5. Distribution of fixed net compliance costs and net benefits. Panel A shows the distribution of fixed net compliance costs, μ/γ, while Panel B shows the distribution of net benefits of tax compliance, $m_x(t)/\gamma - (\xi^1 - \xi^0)/\gamma$.

Step II: Variable and fixed costs of detection, $p_x(t)$, κ_x. Next, we identify and estimate the variable and fixed costs of detection. The parameters $p_x(t)$ and κ_x can be identified by considering the compliance behavior of investors with positive tax liabilities in Figure 4. To see this, note that when $T > 0$, Equation (18) becomes:

$$m_x(t) = \underbrace{(\overbrace{p_x(t)\kappa_x}^{\substack{\text{Fixed Cost}\\\text{of Detection}}} + \overbrace{\gamma p_x(t)(1+c)t}^{\substack{\text{Variable Cost}\\\text{of Detection}}})}_{\text{Unique to } T>0} - \underbrace{\gamma t - \mu_x}_{\text{Identified}}. \tag{21}$$

where the latter two terms are identified from the left-hand side of Figure 4. Consider two levels of positive tax liabilities: A small value $T = t'_\ell$ and a large value $T = t'_h > t'_\ell$, and assume that $p_x(t)$ is linear in t: $p_x(t) \equiv \beta_x t$. For $k = \ell, h$, we can rewrite Equation (21):

$$\overbrace{\underbrace{m_x(t'_k)}_{H^{-1}(P_x(t'_k))} + \underbrace{\gamma t'_k + \mu_x}_{=\text{Identified}}}^{\equiv L_k} = \kappa_x \beta_x t'_k + \gamma(1+c)\beta_x t'^2_k, \tag{22}$$

where the left-hand side is observed or identified. Equation (22) defines a system of two independent linear equations with two unknowns. Solving these, we jointly identify:

$$p_x(t) = \underbrace{\frac{t'_\ell\, L_h - t'_h\, L_\ell}{t'_\ell\, t'_h\, (t'_h - t'_\ell)\, \gamma(1+c)}}_{\beta_x} \cdot t \qquad \text{and} \qquad \kappa_x = \frac{\left[t'^2_h\, L_\ell - t'^2_\ell\, L_h\right] \gamma(1+c)}{t'_\ell\, L_h - t'_h\, L_\ell}$$

The above argument assumes (for simplicity) that the perceived probability of detection is linear in t. This is not necessary. We have as many independent linear equations as we have positive values of t. This means that we can specify a flexible function of t and still identify κ_x. In our estimation, we specify $p_x(t)$ flexibly as the logit transformation of a monotonic spline anchored at $t = 0$. We specify μ_x, κ_x, and the coefficients of this spline as linear functions of observed characteristics, and estimate all parameters jointly via maximum likelihood estimation.

Table VII presents our estimates of $p_x(t)$ and κ_x. We estimate an average $p_x(t)$ of 0.38. Figure 6 plots $p_x(t)$ as a function of the tax liability T, averaging over types x. We find that $p_x(t)$ increases substantially with T. As a result, investors with larger tax liabilities have a higher expected variable cost of detection, contributing to their higher rate of tax compliance in Figure 4. The average fixed cost of detection, κ_x/γ, is \$958, indicating that investors also perceive a meaningful fixed cost of being detected. Multiplying by $p_x(t)$, the expected fixed cost of detection is \$270. Adding this to the expected variable cost of detection, $p_x(t) \cdot 1.2t$, we get an average expected cost of detection of \$604.

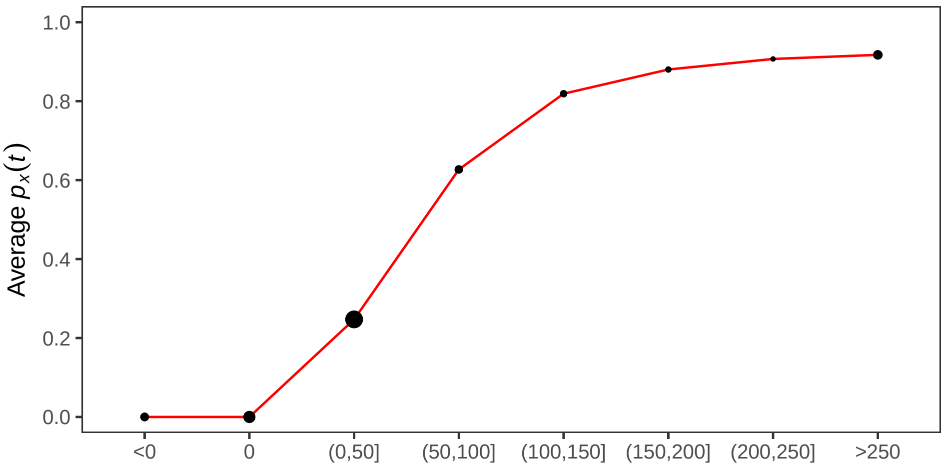


Figure 6. Perceived probability of detection by tax liability. The figure plots the estimated perceived probability of detection, $p_x(t)$, by bins of crypto tax liability. The black circles indicate the average perceived probability of detection across observed types within each bin, with dot size proportional to the number of investors in the bin. The red line connects the black circles.

C. Model-based insights

We now use the estimated model parameters to derive four sets of model-based insights.

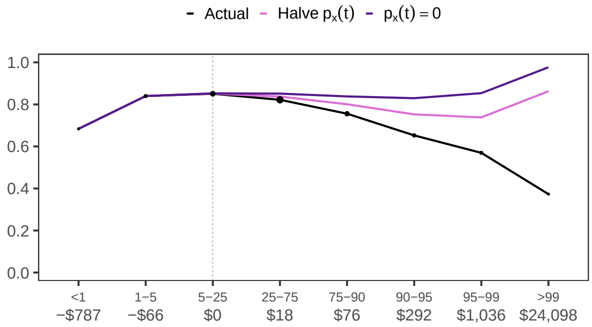
Distribution of net benefits of tax compliance. The first set of results is about how the net benefits of tax compliance, $m_x(t)-(\xi_1-\xi_0)$, vary in the population. In Panel B of Figure 5, we plot the distribution of net benefits relative to the marginal utility of money, γ, that is, in dollar terms. We find that most investors have negative net benefits of tax compliance and therefore choose not to report. At the same time, the compliance threshold is close to the mode of the distribution, implying that a large share of investors are close to the margin of compliance. As a result, even modest policy interventions have the potential to shift a substantial number of crypto investors into compliance. However, we also find considerable variability in the net benefits of compliance across investors, implying that a meaningful share of investors are inframarginal: They are reluctant to comply due to high fixed compliance costs, or low expected detection costs, or both.

Determinants of tax compliance. The second set of results concerns the drivers of tax compliance. In Figure 7, we plot the actual and counterfactual level of tax compliance as a function of tax liability. The counterfactual is computed by fixing the value of certain model parameters and then recomputing the probability of compliance.

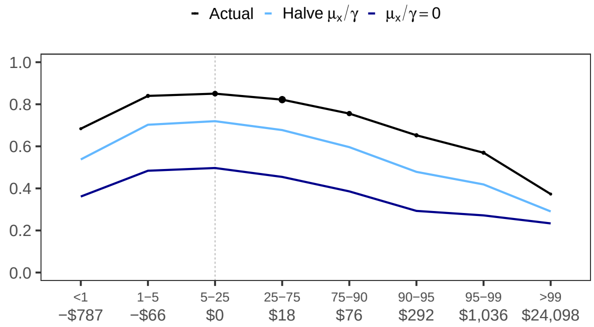
Panel A shows the effects of decreasing $p_x(t)$ by half or setting it to zero. If $p_x(t) = 0$, tax compliance would be decreasing, not increasing, in the tax liability. The reason is that when $p_x(t) = 0$, the variable cost of detection is zero and necessarily lower than the (positive) variable cost of compliance. For the investors with the largest tax liabilities, setting $p_x(t) = 0$ would reduce compliance by as much as 60 percentage points.

Panel B shows the effects of decreasing μ_x by half or setting it to zero. If $\mu_x = 0$, tax compliance would be about 40 percentage points higher across the tax liability distribution. The reason is that many investors are not too inframarginal with respect to their compliance decision. As a result, a substantial reduction in average net fixed compliance costs would induce a substantial increase in tax compliance.

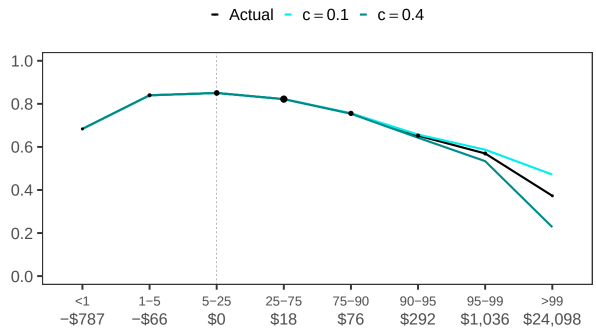
Panel C shows the effects of decreasing the penalty for tax noncompliance, c, by half or doubling it. On average, changing the penalty rate would have only a modest impact on tax compliance. However, the impact of changing the penalty depends strongly on the tax liability. If c were doubled, tax compliance would be about 15 percentage points higher at the top of the tax liability distribution. By contrast, the effect would be small among investors with smaller tax liabilities. The reason is that these investors perceive



Panel A. Halving $p_x(t)$ or setting it to zero



Panel B. Halving μ_x or setting it to zero



Panel C. Doubling or halving c

Figure 7. Determinants of tax compliance. In each panel, the black line shows the actual (model-implied) level of tax noncompliance by percentile bins of crypto tax liability, averaged across investor types. The other lines show counterfactual levels of tax noncompliance. The counterfactuals are computed by fixing the value of certain model parameters and then recomputing the probability of noncompliance. Panel A shows the effects of decreasing the perceived probability of detection, $p_x(t)$, by half or setting it to zero. Panel B shows the effects of decreasing the average fixed compliance cost, μ_x, by half or setting it to zero. Panel C shows the effects of decreasing the penalty surtax, c, by half or doubling it.

a low probability of detection and thus of incurring the penalty at all.

Decomposing group-level differences. The third set of insights concerns differences in compliance across investor types. Under the model, differences in tax compliance across types x and x' can arise due to differences in the net benefits of tax compliance:

$$P_x(t) - P_{x'}(t) = H^{-1}(m_x(t)) - H^{-1}(m_{x'}(t)), \tag{23}$$

where the components of m_x are defined in Equation (18). Panel B of Figure 2 showed no meaningful variation in tax compliance across investor types based on broad demographic groups — age, gender, and place of residence. This suggests that the net benefits of tax compliance do not vary much between these types of investors.

This contrasts sharply with the findings in Figure 8, where we compare tax compliance among investors who were tax compliers and tax noncompliers in the previous year. For past compliers, the current rate of tax noncompliance is 19% (left blue bar in Figure 8), while for past noncompliers it is 82% (right blue bar). In other words, current compliance differs by 63 percentage points based on past compliance behavior.

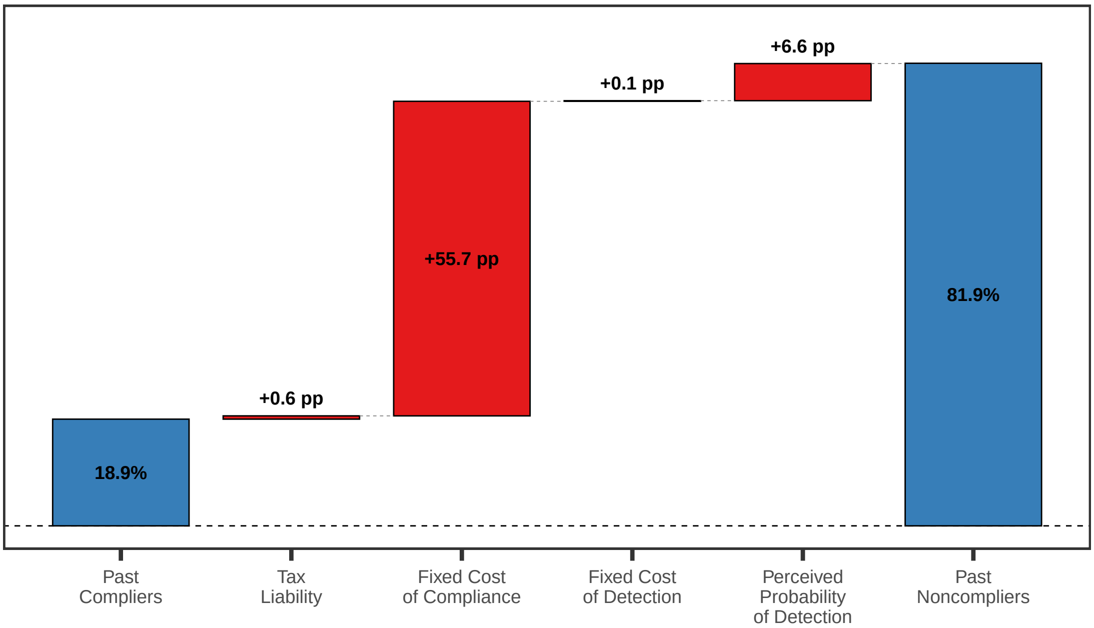


Figure 8. Decomposing group-level differences. The blue bars show tax noncompliance rates for past tax compliers (left) and past tax noncompliers (right). The red bars decompose the compliance gap into parts driven by differences in tax liability, fixed compliance costs, fixed detection costs, and the perceived probability of detection. To avoid the problem of path dependence in these calculations, we follow Shorrocks (2013) in computing the marginal impact of each of the factors as they are eliminated in succession, and then average these marginal effects over all the possible elimination sequences.

This difference in compliance may reflect variation in μ_x, $p_x(t)$, κ_x, or T, or some combination. To isolate the contribution of each component, we construct counterfactual estimates of P_x and $P_{x'}$ in Equation (23) in which the contribution of a given component is set to zero by equalizing it across investor types. This counterfactual shows how compliance would differ across types if they were identical with respect to that component. The portion of the compliance gap attributable to each component is shown as red bars in Figure 8. We find that past compliers perceive a higher probability of detection, $p_x(t)$, and, in particular, a lower fixed cost of compliance, μ_x, than past noncompliers.

Quasi-experiments. A natural question is why past tax compliers perceive lower costs of compliance. One possibility is that they have already paid a large fixed cost associated with learning how to file crypto taxes. For example, calculating capital gains may be difficult the first time an investor files. Another possibility is that μ_x reflects the option value of future tax evasion. Investors may be reluctant to declare crypto in the current year because doing so would complicate tax evasion in future years. Distinguishing between these sources of compliance costs is of interest to policymakers seeking to understand which interventions are most effective at increasing tax compliance.

To make progress on this question, we connect the estimated model to two quasi-experiments that shifted the costs and benefits of crypto tax compliance. The *first quasi-experiment* reduces the hassle cost of filing and provides information about crypto tax rules. In April 2021, the largest domestic exchange introduced a free crypto tax preparation tool for its customers. Before the intervention, customers had to compile their own trading records and calculate their tax liabilities, T. After the intervention, the exchange provided a downloadable tax statement detailing T, which customers could copy into their tax returns. The rollout of the tax tool was accompanied by information about crypto tax rules and how to report crypto in the tax return.[26]

[26] The tax tool only covers trades executed on the largest domestic exchange. Accordingly, it produces incorrect measures of T for investors who also trade outside the exchange. It is useful to note that our analysis focuses on whether investors declare *any* crypto in their tax return, not whether they make

We start by quantifying the change in tax compliance associated with access to the new tax tool and accompanying information. Because the intervention took place in early April 2021, the treated group could begin using the tax tool as of the 2020 tax return, filed at the end of April 2021. As shown in row (1) of Table VIII, 28% of the treated group declare crypto in their 2020 return, up from 19.8% in 2019. Column (3) shows that this 8.2 percentage point increase is significantly different from zero.

Of course, investors may have increased their compliance over time even absent the intervention, suggesting that the 8.2 percentage point increase in tax compliance represents an upper bound on the effect of the intervention. To mitigate this concern, we compare the reporting behavior of treated investors to that of a control group of unaffected investors. Other domestic exchanges did not introduce tax tools in 2021. For this reason, the control group consists of investors trading on the other domestic exchanges. Even absent the intervention, tax compliance in the control group increases by 2.3 percentage points between the 2019 and 2020 tax returns, as shown in row (2) of Table VIII. This implies a difference-in-differences estimate of 5.9 percentage points. Row (3) of Table VIII shows that this estimate is not significantly different from zero.

As an alternative control group, we use the broader population of crypto investors. The blue line in Figure 9 plots aggregate tax noncompliance, $1 - P(A \mid B)$, over time, excluding treated investors on the largest domestic exchange. We find that tax compliance outside the largest domestic exchange increases by 2.4 percentage points from 2019 to 2020, implying a difference-in-differences estimate of the effect of the tax tool intervention of 5.8 percentage points, nearly identical to the estimate in Table VIII. Under the model, this effect can be rationalized by a reduction in μ_x of \$434, as shown in the bottom row of Table VIII. In other words, a lack of free tax tools and knowledge about tax rules are unlikely to be primary drivers of μ_x and crypto tax noncompliance.[27]

mistakes conditional on declaring. See Firi (2021a) for more details on the intervention.

[27] These results are supported by our analyses in Internet Appendix Figure IA.14. There, we find that

Table VIII. Quasi-Experiments: Effects on Tax Compliance

Panel A reports estimates of the effect on tax compliance of providing access to a free crypto tax preparation tool and information about crypto tax rules, while Panel B reports estimates of the effect on tax compliance of sending reminder letters to anyone who declared crypto in their 2018 tax return but not in 2019. Specification details are provided in the main text. Control variables include age, gender, an indicator for residing in Oslo, an indicator for being married, education (in bins), employment status, gross wealth, total income, and total tax liability, all measured in 2019. Standard errors are reported in parentheses. Stars indicate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

	Panel A. Tax Tool			Panel B. Letter		
	2019	2020	Δ	2019	2020	Δ
$P(A)$: Treated group	0.198	0.280	0.082**	0.000	0.450	0.450***
			(0.037)			(0.013)
$P(A)$: Control group	0.112	0.135	0.023	0.000	0.196	0.196***
			(0.034)			(0.005)
Difference in differences			0.059			0.254***
			(0.050)			(0.014)
Difference in differences with controls			0.062			0.171***
			(0.049)			(0.015)
Model-implied $\Delta\mu_x$			–\$434			–\$558
N	210	6,918	7,128	7,948	7,948	7,948

It is useful to note that access to tax tools and information about the tax status of crypto has continued to expand after 2021. To assess how crypto tax noncompliance has evolved over time, the black line in Figure 9 plots aggregate tax noncompliance, $1 - P(A \mid B)$, over 2018–2023, the latter tax return filed in April 2024, while Internet Appendix Table IA.XIX presents the corresponding estimates broken down by individual characteristics. We find that aggregate tax noncompliance has decreased modestly over time, consistent with the modest effects of tax tools and information provision reported in Table VIII. However, crypto tax noncompliance rates exceed 80% in every year from 2018 to 2023, inconsistent with an argument that a lack of free tax tools and knowledge about tax rules are important drivers of crypto tax noncompliance.[28] Preliminary figures

tax noncompliance is high across all observed investor types, including accountants who presumably understand the tax system; see Panel D of Internet Appendix Figure IA.14.

[28]In Internet Appendix Section J, we report separate time-series estimates for domestic and foreign

(marked with an asterisk in Figure 9) indicate that aggregate tax noncompliance exceeds 80% also for the 2024 tax return, which was filed in April 2025.

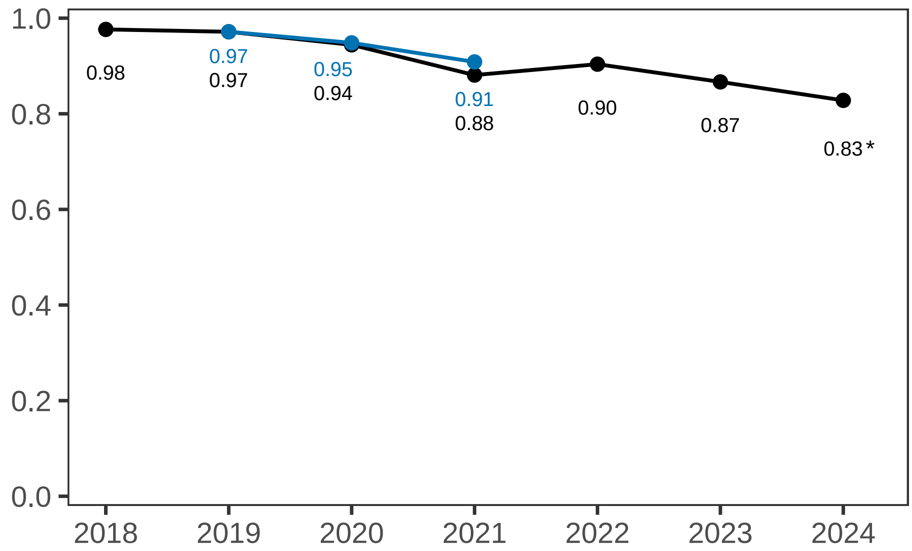


Figure 9. Aggregate crypto tax noncompliance, 2018–2024. The black line shows annual estimates of $1 - P(A \mid B)$, aggregate crypto tax noncompliance. Table III summarizes the identification arguments. The blue line shows annual estimates of $1 - P(A \mid B)$ after excluding investors on the largest domestic exchange from both A and B. The 2024 estimate is constructed by combining preliminary estimates of $P(A)$ from the Norwegian Tax Administration (2025b) with survey estimates of $P(B)$ for 2024. The survey estimates for 2024 are presented in Internet Appendix Section A. Survey estimates of $P(B)$ for 2020 are interpolated as the average of the 2019 and 2021 estimates.

The *second quasi-experiment* plausibly shifts the probability of detection while holding fixed the hassle costs of filing and knowledge about the tax status of crypto. We use data on 1,398 reminder letters sent in 2020 by the Tax Administration to investors who reported crypto in their 2018 tax return but not in 2019. Since all recipients filed in 2018, they necessarily know that crypto is taxable and how to report it. The letter states that the agency knows the recipient owned crypto in 2018 and warns that tax noncompliance is unlawful, effectively signaling that past compliance is being used in tax enforcement. Interpreted through the lens of our static model, the letter raises the perceived probability of *current* detection, $p_x(t)$, and possibly also the perceived cost of compliance, μ_x, to the extent that this parameter also captures concerns about *future* detection.

exchanges and similarly find that tax noncompliance decreases only modestly over time.

We start by quantifying the increase in compliance associated with receiving a letter. As the letters were issued in November 2020, the treated group of letter recipients could start declaring crypto as of the 2020 return, filed in April 2021. As shown in row (1) of Table VIII, 45.0% of the recipients declare crypto in their 2020 return, up from 0% in 2019. Column (3) shows that this estimate is significantly different from zero.

Of course, letter recipients may have declared their crypto even absent the letters, suggesting that 45% is an upper bound on the effect of the intervention. To mitigate this concern, it is useful to compare the behavior of letter recipients to that of a control group of non-recipients. The control group consists of all investors who hold crypto on the domestic crypto exchanges in 2019 or 2020 and, like the treated group, do not declare crypto in their 2019 tax return. Even absent letters, 19.6% of the control group declare crypto in 2020, up from 0% in 2019. This gives an estimate of the difference in tax compliance between the treated and control group of 25.4 percentage points. Row (3) of Table VIII shows that this difference is significant at the 1% level.

Next, we turn to regressions to adjust for observable differences between the treated and control group. In row (4) of Table VIII, we control for a wide range of social, socioeconomic, and tax return factors known to impact compliance (see Kleven et al., 2011), all measured before the intervention. Adding controls impacts the estimated effect, decreasing it from 25.4 to 17.1 percentage points. However, the difference in compliance between the treated and control group remains significant at the 1% level.[29]

To interpret the estimated effect, we calculate how much the letter must shift $p_x(t)$, or both $p_x(t)$ and μ_x, to rationalize a 17.1 percentage point increase in tax compliance. We find that this effect cannot be explained by changes in $p_x(t)$ alone. Thus, the model implies that the letters raise the perceived probability of both current and future detection. To

[29]Consistent with the limited variation in tax compliance across broad demographic groups documented in Panel B of Figure 2, we find no meaningful heterogeneity across demographic groups in the compliance response to the letter intervention; see Internet Appendix Figure IA.16.

quantify the increase in μ_x required to rationalize the estimated effect, we assume that the letters raise $p_x(t)$ to 1 and compute the *minimum change* in μ_x needed to rationalize a 17.1 percentage point increase in compliance. Even under this assumption, μ_x must decrease by as much as \$558, suggesting that perceptions about future detection are an important driver of compliance costs.

VIII. Tax Enforcement

The combination of a high rate of tax noncompliance (Section V) and a relatively low average value of tax evasion (Section VI) may make it difficult to design cost-effective tax enforcement interventions in the context of crypto. Below, we examine how crypto tax enforcement could be designed for the benefits to outweigh the costs.

We first assess the revenue effect of an indiscriminate tax enforcement strategy: Sending reminder letters to anyone who previously declared crypto in their tax return but then stopped. Next, we use estimates of tax noncompliance and tax evasion from Sections V–VI to predict the impact of a counterfactual tax enforcement strategy — correspondence audits. Using the Empirical Welfare Maximization method proposed by Kitagawa and Tetenov (2018), we estimate the impact of targeted implementations of this counterfactual audit intervention. For each alternative enforcement strategy, we compare the benefits in terms of increased crypto tax revenue to the cost of the intervention. We primarily focus on the additional crypto tax revenue collected as the direct result of the interventions. However, we also report estimates under alternative assumptions about the magnitude of indirect effects (e.g., deterrence effects) of interventions on non-targeted individuals.

A. Actual letter intervention

Intervention and data. We use data on 1,398 reminder letters sent in November 2020 by the Norwegian Tax Administration to anyone who declared crypto in their 2018 tax return but stopped doing so in 2019.[30] As explained in Section VII.C, the letter states that the agency knows the recipient owned crypto in 2018 and reminds that tax noncompliance is unlawful. We note that reminder letters are distinct from audits in that they do not require the recipient to respond, eliminating the need for document review and thus reducing costs for the authorities; the cost of such interventions is estimated by the Tax Administration to be \$30 per letter.[31] For each letter, we observe the recipient's personal identifier, which allows us to link the letters to our tax return data.[32]

Estimates. To estimate the impact of the letters on tax revenue, we repeat the specifications in Panel B of Table VIII using the declared crypto tax liability, T^*, as the outcome variable. The estimates are presented in Panel A of Table IX. We find that letter recipients declare an average tax liability of \$147 in 2020, compared to \$23 among letter non-recipients. This implies a difference in tax revenue between the treated and control groups of \$124. Controlling for observable characteristics reduces the estimated effect to \$109. However, the difference in tax revenue between the treated and control groups remains statistically significant at the 1% level. Taken together, the estimates in Table IX suggest that sending reminder letters to individuals who previously filed crypto

[30] In the U.S., Slemrod et al. (2001) find that recipients of letters warning about increased audit risks subsequently increase their tax payments. In Norway, Bott et al. (2020) find that individuals report more foreign income after receiving a reminder letter from the Tax Administration. Their estimated compliance effect is comparable to that obtained in other countries in response to similar reminder letters; see, e.g., Castro and Scartascini (2015), Dwenger et al. (2016), Del Carpio (2014), De Neve et al. (2021), Eerola et al. (2026) for evidence from Argentina, Germany, Peru, Belgium, and Finland, respectively. However, the effect of reminder letter interventions in the context of crypto remains unknown.

[31] According to U.S. Government Accountability Office (2012), the cost of comparable letter interventions by the U.S. IRS was \$52–\$72 in 2011, corresponding to \$64–\$89 in 2021 dollars, while the cost of a correspondence audit was \$274 in 2007, corresponding to \$364 in 2021 dollars.

[32] Internet Appendix Table IA.XX shows that letter recipients are somewhat more likely to reside in Oslo, be male, and be prime-aged compared to the broader population of crypto investors.

taxes but then stopped can be a profitable strategy, given a cost of $30 per letter.

In Panel B of Table IX, we report estimates of the revenue effects of the same letter intervention carried out in August 2022, targeting anyone who declared crypto in their 2020 tax return but not in 2021. The control group consists of all investors who hold crypto on the domestic crypto exchanges in 2020 or 2021 and, like the treated group, do not declare crypto in their 2021 tax return. We find that the 2022 intervention leads to an average tax revenue *loss* of $11 per letter for the Norwegian Tax Administration. The reason is that crypto prices fell in 2022, leading many investors to realize negative capital gains.[33] In Internet Appendix Section F, we reach the same conclusion about average direct tax losses for a different letter intervention carried out in 2023.

Table IX. Effect of 2020 and 2022 Reminder Letters on Tax Revenue

This table reports estimates of the effects on tax revenue of the 2020 and 2022 reminder letter interventions. Specification details are provided in the main text. Control variables include age, gender, an indicator for residing in Oslo, an indicator for being married, education (in bins), employment status, gross wealth, total income, and total tax liability. Standard errors are presented in parentheses. Stars indicate statistical significance at the 10% (*), 5% (**), and 1% (***) level.

	Panel A. 2020 Letter			Panel B. 2022 Letter		
	2019	2020	Δ	2021	2022	Δ
$E[T^*]$: Treated group	$0	$147	$147***	$0	–$40	–$40***
			($23)			($12)
$E[T^*]$: Control group	$0	$23	$23***	$0	–$16	–$16***
			($3)			($1)
Difference in differences			$124***			–$24**
			($23)			($12)
Difference in differences with controls			$109***			–$11
			($23)			($12)
N	7,948	7,948	7,948	64,934	64,934	64,934

[33]Internet Appendix Table IA.XIX presents annual estimates of the average value of tax evasion. Our point estimates are -$272 and $74 in 2022 and 2023, compared to $458 and $1,011 in 2020 and 2021. Internet Appendix Table IA.XXI shows that the 2022 letter intervention increases tax compliance among letter recipients by an economically and statistically significant 32.4 percentage points.

B. Counterfactual audit intervention

Next, we estimate the effect on tax revenue of another widely-used tax enforcement strategy: correspondence audits. A correspondence audit involves sending a letter to a taxpayer requesting documentation — e.g., bank statements — to support the claims in the filed tax return. Unlike the reminder letters studied above, which do not require a response, the taxpayer must respond to a correspondence audit. The Tax Administration estimates that a correspondence audit costs \$180 per tax return, higher than the \$30 cost of a reminder letter, reflecting the extra cost of reviewing documentation.

We are unaware of any systematic data on correspondence audits in the context of crypto. Yet, we can use our estimates of tax noncompliance and tax evasion from Sections V–VI to bound the effect of counterfactual correspondence audits on tax revenue. We consider two target populations for these audits: the broader Norwegian population, U, and the population of crypto tax noncompliers, A^C. Although A^C may be difficult to observe in practice, this group is interesting because it represents an ideal starting point for audits. For each of these populations, we first estimate the average effect on gross tax revenue of auditing a random person from the target population. Next, we estimate the effect of audits targeted by the marginal distribution of individual characteristics.

Random audits. We begin with the effect of auditing a random crypto tax noncomplier, A^C. Let $T^*(1)$ and $T^*(0)$ denote the crypto tax liability a person would declare with and without an audit. By definition, crypto tax noncompliers declare no crypto taxes absent an audit, so that $T^*(0) = 0$. We assume that correspondence audits recover the audit subject's true tax liability, so that $T^*(1) = T$. If this assumption is violated, our upper bound estimates are still valid.

Drawing audit subjects at random from A^C, the average effect of audits on gross tax revenue is then given by:

$$\Delta_1 = E(T^*(1) - T^*(0) \mid A^C) = \underbrace{E(T \mid A^C)}_{\text{Table III}}$$

where we have derived bounds and a point estimate of $E(T \mid A^C)$ in Table III. The lower bound estimate, at \$81, falls slightly below the audit cost of \$180. By contrast, the upper bound and point estimates, at \$1,062 and \$1,011, are well above the audit cost. Thus, our results suggest that the benefits of such an audit may well exceed the costs.[34]

Next, we consider the arguably more realistic scenario where authorities must draw audit subjects from the broader Norwegian population, U, where only a fraction $P(A^C)$ are tax noncompliers. The average tax revenue raised from tax noncompliers is then:

$$\Delta_2 = E(T^*(1) - T^*(0) \mid U) = \underbrace{P(A^C)}_{\text{Table III}} \cdot \underbrace{E(T \mid A^C)}_{\text{Table III}} \tag{24}$$

where $P(A^C)$ is known from Table III.[35] In Panel B of Figure 3, we find that even the upper bound estimate of Δ_2, at \$65, falls below the audit cost of \$180. Thus, we can confidently conclude that the benefits of such an audit fall below the costs.

Targeted audits. There are two reasons why our upper bound and point estimates of Δ_1 may exceed the audit cost. One is that crypto tax liabilities are consistently high

[34] As explained in Section II, the Tax Administration can impose a 20% penalty surtax on the amount of taxes evaded by tax noncompliers. This penalty is not included in our calculations of Δ_1 or Δ_2 below. Naturally, incorporating such a penalty would increase the estimated effect of audits on tax revenue.

[35] Drawing audit subjects from the broader population means there is a probability $P(A)$ that the subject is a tax *complier*, who may also owe taxes. Assuming tax compliers initially under-report their true tax liability by 5% (Revised Assumption 4), and that audits recover the full tax liability, this source of revenue can be captured by adding $0.05 \cdot P(A) \cdot E(T^* \mid A)$ to Equation (24). This adjustment would increase our lower and upper bound estimates of Δ_2 by an economically insignificant \$0.42.

across tax noncompliers, while the other is that a select few tax noncompliers have very high crypto tax liabilities. To distinguish between these alternatives, we allow Δ_1 to vary across sub-populations of tax noncompliers:

$$\Delta_1(X) = E(T^*(1) - T^*(0) \mid A^C, X) = \underbrace{E(T \mid A^C, X)}_{\text{Panel A, Figure 3}} \tag{25}$$

where we have derived bounds and point estimates of $E(T \mid A^C, X)$ in Panel A of Figure 3 according to the marginal distributions of age, gender, location, and income. Across all these individual characteristics, we find that the upper bound and point estimates of $\Delta_1(X)$ consistently exceed the audit cost of \$180. This suggests that the benefits of auditing tax noncompliers may well exceed the costs.

To explore heterogeneity in the effect of audits in the broader population, we similarly allow Δ_2 to vary across sub-populations by individual characteristics:

$$\Delta_2(X) = E(T^*(1) - T^*(0) \mid U, X) = \underbrace{P(A^C \mid X)}_{\text{Panel A, Figure 2}} \cdot \underbrace{E(T \mid A^C, X)}_{\text{Panel A, Figure 3}} \tag{26}$$

where we have estimated $P(A^C \mid X)$ in Panel A of Figure 2 according to the marginal distributions of age, gender, and location; individual characteristics observed in our survey data. To estimate $P(A^C \mid X)$ for characteristics that are not observed in our survey data, such as income, we assume that $P(A^C \mid B, X) = P(A^C \mid B)$. By combining and rearranging Equations (5)–(6), we then have that $P(A^C \mid X) = \frac{P(A^C|B,X) \cdot P(A|X)}{1-P(A^C|B,X)} = \frac{P(A^C|B) \cdot P(A|X)}{1-P(A^C|B)}$, where $P(A^C \mid B)$ is known from Table III and $P(A \mid X)$ can be estimated for any characteristic observed in our register data. Supporting this assumption, Panel B of Figure 2 shows that $P(A^C \mid B, X) \approx P(A^C \mid B)$ for the individual characteristics observed in the survey data.

Our bound and point estimates of $\Delta_2(X)$ are presented in Panel B of Figure 3. Across all the individual characteristics, we find that even the upper bound estimates of $\Delta_2(X)$ fall below the audit cost. Thus, we can confidently conclude that the benefits of such targeted audits within the broader population consistently fall below the costs.

C. Optimal targeted audits

The results above suggest that audits are costly relative to their benefits when drawing audit subjects from the broader Norwegian population, whereas the benefits of exclusively auditing crypto tax noncompliers, if feasible, may well exceed the costs. These conclusions hold true even when audits are targeted based on the marginal distributions of age, gender, location, or income. A natural question is whether there exist better ways to target audits that could increase the benefit or reduce the cost of audits.

Kitagawa and Tetenov (2018) propose a framework for determining optimal rules for targeted interventions. As explained below, Kitagawa and Tetenov (2018) restrict attention to targeting rules that are simple enough to feasibly be adopted by policymakers, given the various budgetary, ethical, or legislative constraints policymakers face. Nevertheless, these rules allow for targeting based on the joint distribution of individual characteristics, as opposed to only the marginal distributions considered in Section VIII.B. We now apply their framework to our context of targeted crypto audits.

Objective function. We focus on audits within the broader population, but for completeness, we also report results for audits within the population of crypto tax noncompliers. Let $\Delta_2(X)$ be defined as in Section VIII.B, with $X \equiv [X_1, X_2]$ now denoting age and income.[36] Let $c = \$180$ denote the cost of a correspondence audit and let $G : \mathcal{X}_1 \times \mathcal{X}_2 \to \{0, 1\}$ denote the Tax Administration's choice of whom to target for audits based on their age and income.

[36]Internet Appendix Table IA.XXII considers alternative combinations of individual characteristics.

Optimal targeting involves choosing the targeting rule, G, that maximizes the sum of crypto tax revenue net of audit costs:

$$\max_{G(\cdot)} \sum_{i=1}^{N} \overbrace{(\Delta_2(X_i) - c)}^{\substack{\text{Net Audit}\\ \text{Revenue}}} \overbrace{G(X_i)}^{\substack{\text{Policy}\\ \text{function}}} \tag{27}$$

We follow Kitagawa and Tetenov (2018) and consider a targeting rule of the form:

$$G(x_1, x_2) = \overbrace{1[s_1\ (x_1 - \beta_1) \geq 0]}^{\substack{\text{Above or below the}\\ \text{threshold for } X_1}} \cdot \overbrace{1[s_2\ (x_2 - \beta_2) \geq 0]}^{\substack{\text{Above or below the}\\ \text{threshold for } X_2}}$$

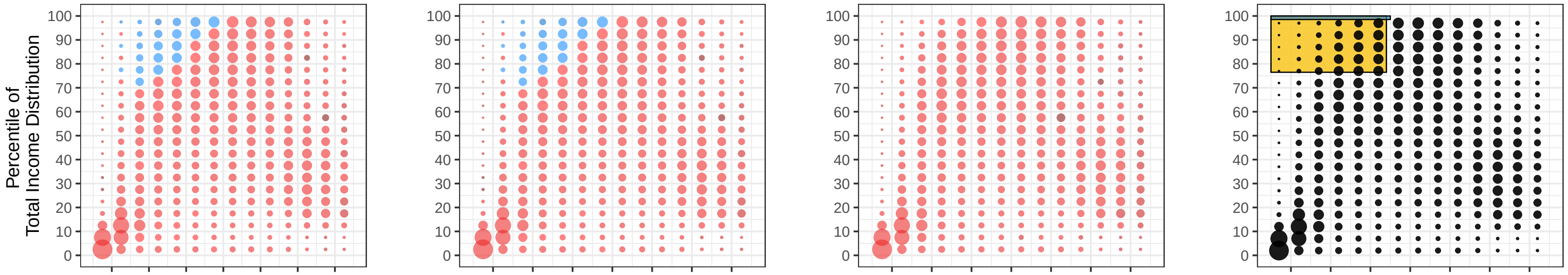
where $\beta_1, \beta_2 \in \mathbb{R}$ and $s_1, s_2 \in \{-1, 1\}$. This targeting rule is easy to implement and often used in practice. For an individual to be selected for an audit under this rule, their age and income must either be above or below some specific thresholds. The thresholds for characteristics x_1 and x_2 are set by β_1 and β_2, while s_1 and s_2 specify whether the audit should be conducted above or below the thresholds. We solve the program by conducting a grid search across all possible combinations of β_1, β_2, s_1, and s_2. We present our results in two steps.

Estimates of $\Delta_2(X)$. First, in Panels A–C of Figure 10, we present our bound and point estimates of $\Delta_2(X)$, which are obtained by repeating the identification steps in Section VIII.B for each combination of age and income. The color of the dots in Figure 10 indicates the value of the audit effect for a given covariate combination: Blue colors indicate audit effects exceeding the audit cost of \$180, while red colors indicate audit effects below \$180. The darker the color, the further the estimate is above or below the audit cost. The size of the dots represents the number of individuals within each cell.

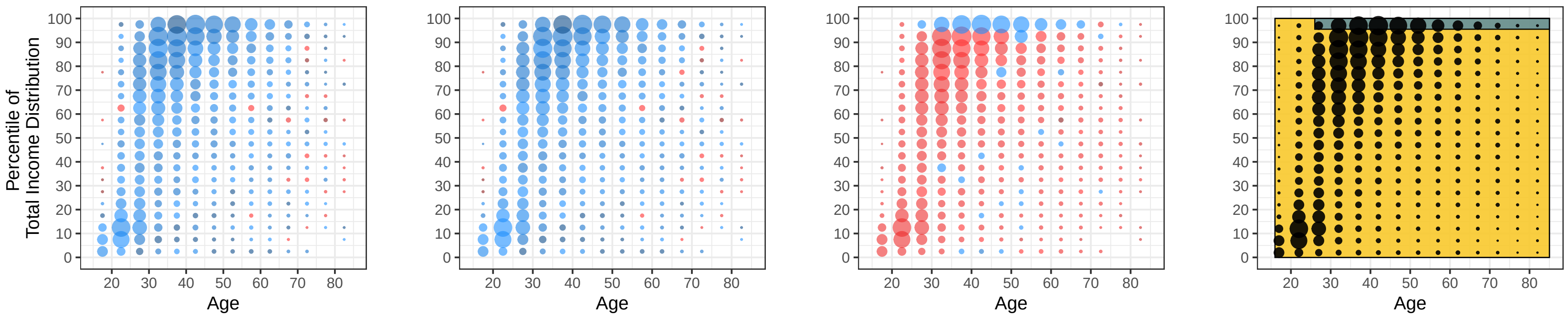
The figure shows that both our upper bound and point estimates of $\Delta_2(X)$ exceed the audit cost for a meaningful segment of young, high-income Norwegians. The figure also shows that our lower bound estimates generally do not exceed the audit cost, with the exception of a small subgroup of young Norwegians with very high incomes.

Optimal audit strategy. Next, in Table X and Panel D of Figure 10, we present the optimal audit strategy given $\Delta_2(X)$. We are primarily interested in determining whether there is any scope for profitable audits without using information on A^C. For this reason, we first solve Program (27) using our point estimates of $\Delta_2(X)$, which are close to the upper bound estimates. We find that the optimal strategy is to audit any Norwegian aged below 44, with income above the 76$^{\text{th}}$ percentile. This group represents about 7.3% of the Norwegian population. Within this group, the average effect of audits on gross tax revenue is \$360, which is considerably higher than the effect of random audits in Section VIII.B. Auditing everyone in the target group would raise a total of \$58.5 million in net crypto tax revenue, as shown in column (5) of Table X.

When considering the point estimates of $\Delta_2(X)$, it is therefore possible to target audits in such a way that their benefits meaningfully exceed the costs. A natural next question is whether profitable targeting can be ensured using our lower bound estimates of $\Delta_2(X)$. Solving Program (27) using our lower bound, we find that there are still benefits from targeting. However, the optimal audit strategy becomes highly selective, targeting only individuals aged below 45, with income above the 98$^{\text{th}}$ percentile. This group represents about 0.17% of the Norwegian population. Within this group, the average effect of audits on gross tax revenue is \$345. Still, auditing everyone in this group would raise only about \$1.2 million in net tax revenue, due to the small size of the targeted group.



Panel A. $\Delta_2(X)$: Upper Panel B. $\Delta_2(X)$: Point Panel C. $\Delta_2(X)$: Lower Panel D. $\Delta_2(X)$: Optimal targeting



Panel E. $\Delta_1(X)$: Upper Panel F. $\Delta_1(X)$: Point Panel G. $\Delta_1(X)$: Lower Panel H. $\Delta_1(X)$: Optimal targeting

Figure 10. Effect of correspondence audits by age and taxable income. Panels A–C show upper, point, and lower bound estimates of $\Delta_2(X)$, with $X \equiv [X_1, X_2]$ denoting age and income. Panels E–G show upper, point, and lower bound estimates of $\Delta_1(X)$. The color of the dots indicates their value: Blue colors indicate audit effects exceeding the audit cost of $c = \$180$, while red colors indicate audit effects below \$180. The darker the color, the further the estimate is above or below the audit cost. The size of the dots represents the number of individuals with different covariate values. Panels D and H show the optimal audit targeting rules based on $\Delta_2(X)$ and $\Delta_1(X)$, respectively. The areas shaded in red, yellow, and green represent the individuals recommended for auditing based on solving Program (27) with the upper bound, point, and lower bound estimates of $\Delta_2(X)$ and $\Delta_1(X)$, respectively. All estimates are based on data from 2021.

Table X. Optimal Targeted Audits

This table presents optimal audit strategies as determined by Program (27). In Panel A, the program is solved using our point and bound estimates of $\Delta_2(X)$ from Figure 10, while in Panel B, the program is solved using our point and bound estimates of $\Delta_1(X)$ from the same figure. In each panel, Column (1) specifies the optimal targeting rule; Column (2) reports the average effect of audits on gross tax revenue among the optimally chosen target group of individuals, denoted by G; Column (3) reports the average effect on net tax revenue; Column (4) reports the share of the underlying population optimally chosen for audits; and Column (5) reports the total net tax revenue raised if all the individuals in G were audited, calculated as the product of the net audit effect and the number of individuals targeted by the rule in Column (1).

Panel A. Targeting In The Broader Population

	Treatment Rule	$E[\Delta_2(X) \mid G, U]$	$E[\Delta_2(X) - c \mid G, U]$	$P(G \mid U)$	Total Net Revenue ($M)
	(1)	(2)	(3)	(4)	(5)
Using Point Estimate of $\Delta_2(X)$	Age $<$ 44 and Income $\geq 76^{th}$ pctile	$360	$180	7.3%	$58.5
Using Upper Bound of $\Delta_2(X)$	Age $<$ 44 and Income $\geq 76^{th}$ pctile	$378	$198	7.3%	$64.3
Using Lower Bound of $\Delta_2(X)$	Age $<$ 45 and Income $\geq 98^{th}$ pctile	$345	$165	0.17%	$1.2

Panel B. Targeting Crypto Tax Noncompliers

	Treatment Rule	$E[\Delta_1(X) \mid G, A^C]$	$E[\Delta_1(X) - c \mid G, A^C]$	$P(G \mid A^C)$	Total Net Revenue ($M)
	(1)	(2)	(3)	(4)	(5)
Using Point Estimate of $\Delta_1(X)$	All Treated	$1011	$831	100%	$224.9
Using Upper Bound of $\Delta_1(X)$	All Treated	$1061	$881	100%	$238.6
Using Lower Bound of $\Delta_1(X)$	Age $\geq$ 26 and Income $\geq 96^{th}$ pctile	$294	$114	5.0%	$1.5

A natural question is how sensitive our estimates of optimal audit strategies are to potential spillover effects of interventions on non-targeted individuals or to persistence in tax compliance over time. In Internet Appendix Figure IA.17, we examine this by re-calculating optimal audit strategies assuming that our upper bounds on $\Delta_2(X)$ are as much as 200% larger than our estimates suggest. Our broad conclusions remain unchanged: The optimal targeting rule for correspondence audits in the broader population remains highly selective even if audit revenue effects were substantially higher.

IX. Conclusion

Combining several detailed data sets from Norway, we provide the first comprehensive analysis of tax noncompliance, tax evasion, and tax enforcement in the context of crypto. We show that a large number of crypto investors fail to declare their cryptos but that each investor, on average, owes a modest amount of taxes. As a result, tax enforcement strategies need to be well-targeted or cheap for benefits to outweigh costs.

One limitation of our study is that it analyzes tax compliance taking individuals' decisions to invest in crypto as given. An interesting question is how perceptions of tax enforcement affect the decision to invest in crypto and, conditional on investing, where to trade. Another is that our analysis focuses on a specific setting, Norway; crypto tax noncompliance and evasion may of course differ in other settings. However, the methods used in our paper could easily be applied to a wide range of settings: We offer a blueprint for empirically analyzing tax noncompliance and evasion, showing how the combination of different data sets can be used to point-identify tax noncompliance and to construct informative bounds on the average value of tax evasion. We also show how the underlying assumptions and resulting bounds can be tailored to the tax setting and data at hand.

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Internet Appendix

A. About the Survey Data

The surveys are conducted by Norstat, a leading European statistical agency. Norstat maintains a panel of about 120,000 active survey subjects. Subjects are continually recruited to maintain a panel that is representative of the Norwegian population in terms of age, gender, and place of residence. From this broader panel, each year since 2018 — except for 2020, due to the COVID-19 pandemic — a random sample has been drawn to answer questions about their crypto ownership.[1] Each survey wave includes about 1,000 interviews. In 2019 and 2021–2024, the interviews were conducted in end of February or early March, while in 2018, the interviews were conducted in October.

In all survey waves, respondents are asked: "Do you own bitcoin or other cryptocurrency?" ("Eier du bitcoin eller annen kryptovaluta?"). Survey responses are then weighted by Norstat to adjust for differences in age, gender, and place of residence between the realized survey sample and the broader Norwegian population. In the main text, $P(B)$ is given by the weighted share of survey subjects that respond "Yes" to this question, while $P(B \mid X)$ denotes the corresponding shares by age, gender, and place of residence. Internet Appendix Table IA.I reports survey response rates, the number of interviews, and estimates of $P(B)$ and $P(B \mid X)$ for each survey wave 2018–2024.

Representativeness. As explained above, the crypto survey sample is drawn randomly from a subject pool that is supposed to be representative of the Norwegian population in terms of age, gender, and place of residence. Survey responses are then weighted by Norstat to adjust for any remaining differences in age, gender, and place of residence between the realized survey sample and the Norwegian population. As a result, the weighted survey sample should mechanically be representative of the Norwegian population in terms

[1]This yearly crypto survey is commissioned by Arcane Research (now K33 Research) and forms the basis of their annual "Norwegian Crypto Adoption Survey" publication; see k33.com.

of age, gender, and place of residence. Using population data from Statistics Norway, in rows (1)–(8) of Internet Appendix Table IA.II, we verify that the weighted survey sample is nearly identical to the broader population in terms of age, gender, and place of residence.

We can also examine how representative the weighted survey sample is in terms of characteristics *other* than age, gender, and place of residence. This is possible because the survey contains information on a limited set of additional characteristics: Education in bins, an employment indicator, and income in bins. In rows (9)–(18) of Internet Appendix Table IA.II, we compare the weighted survey sample to the Norwegian population along these dimensions. We find that the weighted survey sample is comparable to the population across coarse income bins but is somewhat more educated. For example, in 2021, the share reporting a college education is 34.7% in the survey, compared to 23.4% in our population data. These differences are similar across survey waves.

In Internet Appendix Table IA.III, we examine how the annual estimates of $P(B)$ change when we adjust for differences between the weighted survey sample and the broader population. In particular, we successively reweight the survey responses to match the broader population in terms of education in bins, employment, and income in bins, in addition to age, gender, and place of residence. Across survey waves, reweighting on these additional characteristics has a relatively modest impact on $P(B)$. For example, $P(B)$ decreases from 0.098 to 0.096 in 2022 and increases from 0.069 to 0.072 in 2021. The largest impact is in 2018, when $P(B)$ increases from 0.048 to 0.061 due to reweighting. Internet Appendix Table IA.IV reports annual estimates of $P(B \mid X)$, crypto adoption by individual characteristics, under the different weighting schemes.

One may also be interested in how representative the survey sample would be in the *absence* of Norstat's reweighting with respect to age, gender, and place of residence. In Internet Appendix Table IA.II, we compare the unweighted survey sample to the Norwegian population. Across survey waves, the unweighted survey sample is already comparable to the population in terms of age, gender, and place of residence, although men are slightly underrepresented. Norstat's reweighting on age, gender, and place of residence brings the survey sample closer to the population in terms of education, employment, and income, as shown in rows (9)–(18). In Internet Appendix Table IA.III, we report estimates of $P(B)$ with and without Norstat's reweighting. We find that Norstat's reweighting on age, gender, and place of residence increases $P(B)$; in 2021, $P(B)$ increases from 0.057 to 0.069 after reweighting. A key reason is that men are more likely to hold crypto.

Table IA.I. Overview: Norstat Survey

	2018	2019	2021	2022	2023	2024
$P(B)$	4.8%	4.3%	6.9%	9.8%	8.1%	9.2%
$P(B \mid \text{Male})$	8.0%	5.9%	10.9%	13.5%	12.8%	13.7%
$P(B \mid \text{Female})$	1.5%	2.7%	2.9%	6.2%	3.5%	4.5%
$P(B \mid \text{Oslo})$	5.3%	7.2%	10.6%	11.3%	9.2%	12.4%
$P(B \mid \text{Non-Oslo})$	4.7%	3.8%	6.4%	9.6%	8.0%	8.7%
$P(B \mid \text{Age: 15–29})$	14.5%	8.4%	11.9%	18.2%	12.9%	19.7%
$P(B \mid \text{Age: 30–39})$	5.6%	8.4%	11.3%	19.8%	18.2%	15.9%
$P(B \mid \text{Age: 40–49})$	2.9%	2.7%	4.8%	7.9%	6.6%	7.2%
$P(B \mid \text{Age: 50+})$	0.9%	1.4%	3.4%	2.6%	2.6%	2.1%
Other Survey Statistics						
Implied # crypto investors	208,190	187,114	307,322	440,822	370,365	422,358
Response rate	14%	14%	25%	19%	23%	18%
Number of interviews	1,020	1,016	1,020	1,017	1,051	1,052

Table IA.II. Characteristics of the Survey Sample and Norwegian Population

Panel A reports respondent characteristics in Norstat's weighted survey sample, by survey wave. Panel B reports the corresponding characteristics of the broader Norwegian population. Panel C reports respondent characteristics in Norstat's unweighted survey sample, by survey wave. Because we do not observe population data in 2024, we focus on the survey waves 2018–2023 for which we observe both survey and population data.

	Panel A: Survey (Baseline)					Panel B: Population					Panel C: Survey (Unweighted)				
	2018	2019	2021	2022	2023	2018	2019	2021	2022	2023	2018	2019	2021	2022	2023
P(Male)	0.501	0.501	0.502	0.503	0.503	0.502	0.502	0.502	0.502	0.502	0.494	0.494	0.443	0.488	0.500
P(Female)	0.499	0.499	0.498	0.497	0.497	0.498	0.498	0.498	0.498	0.498	0.506	0.506	0.557	0.512	0.500
P(Oslo)	0.130	0.130	0.131	0.131	0.130	0.127	0.128	0.129	0.129	0.129	0.156	0.169	0.149	0.158	0.158
P(Non-Oslo)	0.870	0.870	0.869	0.869	0.870	0.873	0.872	0.871	0.871	0.871	0.844	0.831	0.851	0.842	0.842
P(Age: 15–29)	0.203	0.203	0.232	0.229	0.226	0.232	0.230	0.224	0.222	0.221	0.191	0.199	0.263	0.181	0.179
P(Age: 30–39)	0.170	0.170	0.165	0.165	0.166	0.162	0.163	0.164	0.165	0.165	0.187	0.136	0.159	0.138	0.135
P(Age: 40–49)	0.176	0.176	0.163	0.161	0.158	0.166	0.163	0.158	0.156	0.155	0.164	0.159	0.139	0.179	0.163
P(Age: 50+)	0.450	0.450	0.440	0.445	0.449	0.440	0.444	0.453	0.457	0.459	0.458	0.506	0.439	0.502	0.523
P(No College)	0.381	0.427	0.457	0.504	0.502	0.681	0.676	0.666	0.662	0.658	0.375	0.412	0.453	0.482	0.479
P(College)	0.484	0.408	0.347	0.256	0.259	0.227	0.229	0.234	0.236	0.236	0.485	0.419	0.347	0.269	0.265
P(Master's+)	0.135	0.165	0.196	0.240	0.239	0.092	0.095	0.100	0.103	0.106	0.139	0.168	0.200	0.249	0.257
P(Working)	0.586	0.560	0.548	0.534	0.545	0.694	0.701	0.690	0.696	0.695	0.589	0.541	0.537	0.550	0.547
P(Not Working)	0.414	0.440	0.452	0.466	0.455	0.306	0.299	0.310	0.304	0.305	0.411	0.459	0.463	0.450	0.453
P(Income: Unknown / <\$40k)	0.362	0.347	0.321	0.339	0.317	0.358	0.343	0.318	0.299	0.277	0.345	0.342	0.331	0.312	0.294
P(Income: \$40k–\$70k)	0.258	0.281	0.209	0.218	0.221	0.285	0.286	0.284	0.279	0.266	0.264	0.284	0.210	0.229	0.227
P(Income: \$70k–\$100k)	0.195	0.186	0.216	0.175	0.189	0.148	0.150	0.154	0.163	0.175	0.202	0.192	0.215	0.185	0.196
P(Income: \$100k+)	0.185	0.186	0.255	0.268	0.273	0.209	0.221	0.244	0.259	0.283	0.189	0.182	0.244	0.274	0.283

Table IA.III. Estimates of $P(B)$ Under Different Reweighting Procedures

The table reports annual estimates of $P(B)$ based on different reweighting procedures. Row (1) reports Norstat's baseline estimates, which are nationally representative with respect to age, gender, and place of residence. Rows (2)–(4) successively reweight the survey responses to match the broader population in terms of education in bins, employment, and income in bins, in addition to age, gender, and place of residence. Row (5) reports estimates of $P(B)$ from Norstat's unweighted survey sample.

	$P(B)$				
	2018	2019	2021	2022	2023
Baseline	0.048	0.043	0.069	0.098	0.081
Reweight on additional characteristics:					
Education	0.066	0.052	0.070	0.088	0.085
Education, employment	0.061	0.044	0.070	0.097	0.089
Education, employment, income	0.061	0.045	0.072	0.096	0.090
Unweighted survey sample	0.038	0.036	0.057	0.081	0.070

Table IA.IV. Estimates of $P(B|X)$ Under Different Reweighting Procedures

The table reports annual estimates of $P(B|X)$ based on different reweighting procedures. Panel A reports Norstat's baseline estimates. Panels B–D successively reweight the survey responses to match the broader population in terms of education in bins, employment, and income in bins, in addition to age, gender, and place of residence. Panel E reports estimates of $P(B|X)$ from Norstat's unweighted survey sample.

	Panel A: Baseline					Panel B: Weights I				
	2018	2019	2021	2022	2023	2018	2019	2021	2022	2023
$P(B \mid \text{Male})$	8.0%	5.9%	10.9%	13.5%	12.8%	11.6%	7.2%	11.1%	12.4%	13.4%
$P(B \mid \text{Female})$	1.5%	2.7%	2.9%	6.2%	3.5%	1.6%	3.1%	2.9%	5.1%	3.5%
$P(B \mid \text{Oslo})$	5.3%	7.2%	10.6%	11.3%	9.2%	3.1%	7.2%	9.0%	10.1%	11.3%
$P(B \mid \text{Non-Oslo})$	4.7%	3.8%	6.4%	9.6%	8.0%	7.1%	4.9%	6.7%	8.6%	8.1%
$P(B \mid \text{Age: 15–29})$	14.5%	8.4%	11.9%	18.2%	12.9%	19.0%	9.9%	11.9%	15.6%	13.9%
$P(B \mid \text{Age: 30–39})$	5.6%	8.4%	11.3%	19.8%	18.2%	8.6%	9.2%	13.9%	17.5%	20.4%
$P(B \mid \text{Age: 40–49})$	2.9%	2.7%	4.8%	7.9%	6.6%	2.8%	4.1%	4.6%	9.2%	7.2%
$P(B \mid \text{Age: 50+})$	0.9%	1.4%	3.4%	2.6%	2.6%	0.8%	1.6%	3.0%	2.1%	2.0%
$P(B \mid \text{No College})$	6.3%	5.5%	8.3%	10.5%	10.1%	8.0%	6.2%	8.0%	8.5%	9.7%
$P(B \mid \text{College})$	4.2%	3.2%	6.1%	9.5%	6.2%	4.3%	2.9%	5.4%	9.6%	6.7%
$P(B \mid \text{Master's+})$	2.8%	3.9%	5.1%	8.9%	6.1%	2.5%	3.1%	4.4%	8.3%	5.3%
$P(B \mid \text{Working})$	4.6%	4.3%	7.5%	11.4%	10.2%	4.9%	3.6%	7.2%	11.1%	11.3%
$P(B \mid \text{Not Working})$	5.1%	4.2%	6.2%	8.0%	5.7%	8.5%	6.9%	6.8%	6.3%	5.5%
$P(B \mid \text{Income: Unknown / <\$40k})$	6.8%	4.3%	7.8%	9.5%	6.5%	10.7%	7.1%	7.8%	7.2%	6.9%
$P(B \mid \text{Income: \$40k–\$70k})$	4.4%	3.0%	6.8%	9.5%	7.7%	6.5%	3.0%	7.6%	8.6%	8.7%
$P(B \mid \text{Income: \$70k–\$100k})$	2.5%	3.2%	5.8%	10.0%	6.1%	2.3%	3.1%	5.8%	11.4%	5.5%
$P(B \mid \text{Income: \$100k+})$	3.7%	7.1%	6.8%	10.5%	11.8%	1.9%	6.2%	6.5%	9.2%	12.8%

	Panel C: Weights II					Panel D: Weights III					Panel E: Unweighted				
	2018	2019	2021	2022	2023	2018	2019	2021	2022	2023	2018	2019	2021	2022	2023
$P(B \mid \text{Male})$	10.6%	5.9%	11.0%	12.5%	14.1%	10.7%	6.0%	11.2%	12.4%	14.2%	6.0%	4.4%	9.1%	10.9%	10.3%
$P(B \mid \text{Female})$	1.5%	2.9%	3.0%	6.9%	3.6%	1.5%	3.1%	3.1%	6.9%	3.7%	1.7%	2.9%	3.0%	5.4%	3.8%
$P(B \mid \text{Oslo})$	3.1%	6.5%	9.6%	9.9%	11.0%	3.2%	7.0%	8.5%	10.7%	11.0%	4.4%	5.2%	7.2%	9.3%	7.8%
$P(B \mid \text{Non-Oslo})$	6.5%	4.1%	6.6%	9.7%	8.6%	6.5%	4.2%	7.0%	9.5%	8.7%	3.7%	3.3%	5.4%	7.8%	6.9%
$P(B \mid \text{Age: 15–29})$	17.6%	8.6%	13.1%	18.6%	15.6%	17.6%	8.4%	13.6%	18.7%	15.4%	10.3%	6.9%	9.0%	16.3%	12.8%
$P(B \mid \text{Age: 30–39})$	7.2%	7.0%	12.7%	17.0%	21.6%	7.8%	7.9%	13.2%	16.9%	22.1%	4.7%	8.0%	8.6%	17.9%	14.8%
$P(B \mid \text{Age: 40–49})$	2.3%	2.4%	5.0%	11.0%	6.8%	2.5%	2.3%	4.7%	10.6%	6.9%	3.0%	2.5%	3.5%	7.1%	7.6%
$P(B \mid \text{Age: 50+})$	0.9%	2.0%	2.6%	2.3%	1.8%	0.8%	2.1%	2.6%	2.3%	1.8%	1.1%	1.6%	3.3%	2.7%	2.9%
$P(B \mid \text{No College})$	7.3%	5.1%	7.7%	10.1%	10.1%	7.4%	5.3%	7.8%	9.9%	10.0%	4.7%	4.8%	6.3%	8.2%	8.3%
$P(B \mid \text{College})$	3.5%	3.1%	5.9%	8.9%	7.4%	3.4%	3.0%	6.2%	8.6%	7.8%	3.4%	2.6%	5.4%	8.0%	6.1%
$P(B \mid \text{Master's+})$	3.0%	2.5%	4.9%	9.3%	5.0%	3.0%	3.0%	5.0%	10.2%	5.0%	2.8%	3.5%	4.9%	7.9%	5.6%
$P(B \mid \text{Working})$	4.9%	3.6%	7.3%	11.3%	10.6%	4.9%	3.6%	7.5%	11.2%	10.6%	3.8%	3.8%	5.8%	9.3%	8.2%
$P(B \mid \text{Not Working})$	8.6%	6.2%	6.3%	6.1%	5.1%	8.9%	6.8%	6.4%	6.0%	5.1%	3.8%	3.4%	5.5%	6.6%	5.7%
$P(B \mid \text{Income: Unknown / <\$40k})$	9.6%	5.4%	7.6%	6.6%	7.4%	9.6%	5.8%	7.7%	6.6%	7.3%	5.4%	3.7%	6.2%	7.9%	5.8%
$P(B \mid \text{Income: \$40k–\$70k})$	7.2%	4.0%	7.5%	11.3%	8.5%	6.9%	3.9%	7.4%	11.4%	8.4%	3.3%	2.8%	5.1%	7.3%	7.5%
$P(B \mid \text{Income: \$70k–\$100k})$	2.9%	3.1%	5.6%	13.2%	6.2%	2.8%	2.9%	5.5%	13.1%	6.2%	1.9%	2.1%	5.0%	8.5%	4.9%
$P(B \mid \text{Income: \$100k+})$	1.3%	4.5%	7.1%	9.1%	12.8%	1.3%	4.7%	7.3%	9.1%	12.9%	3.6%	6.5%	6.0%	8.6%	9.4%

B. Robustness to Alternative Survey Estimates

In Section V of the main text, we combine survey estimates of $P(B)$ and $P(B \mid X)$ with moments from tax returns and domestic exchange data to estimate the prevalence of crypto tax noncompliance overall and by trading venue. We now examine the sensitivity of these estimates to alternative specifications of the survey moments.

The results are summarized in Internet Appendix Table IA.V. Panel A reproduces the baseline estimates from the main text, which pertain to the year 2021; Internet Appendix Figure IA.1 summarizes the robustness checks by calendar year. Panel B of Internet Appendix Table IA.V reports results in which we use estimates of $P(B)$ and $P(B \mid X)$ from Internet Appendix Table IA.IV that are reweighted based on additional characteristics observed in the survey data: Education, income, and employment. The results change little. The reason is that reweighting has a relatively modest impact on $P(B)$ and $P(B \mid X)$, as documented in Internet Appendix Section A.

Panel C replaces the annual estimates of $P(B)$ and $P(B \mid X)$ from Internet Appendix Table IA.I with averages of these moments across survey waves. The idea is that averaging across years may smooth out year-specific errors in the survey estimates. We consider three alternatives: Averaging over all years up to the present, a three-year rolling average, and an average over the full period 2018–2024. The resulting estimates are very similar to the baseline estimates. The reason is that crypto ownership, $P(B)$, and its variation across individual characteristics, $P(B \mid X)$, are fairly stable over time.

Panel D artificially increases and decreases the survey estimates by 10% to 50%. Specifically, we replace $P(B)$ with $(1 \pm \alpha)P(B)$, where $\alpha \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$. The idea is that survey estimates may be biased up or down — by small or large amounts — due, for example, to underreporting or selection into the survey based on correlates of crypto ownership. Increasing $P(B)$ naturally leads to higher estimated tax noncompliance, while decreasing $P(B)$ leads to lower tax noncompliance. Importantly, we find that

$P(B)$ would need to be about 45% lower for $P(A^C \mid B)$ to fall below $P(A^C \mid D) = 79\%$, the rate of tax noncompliance directly observed on domestic exchanges.

Panel E replaces Norstat's estimates of $P(B)$ and $P(B \mid X)$ with corresponding estimates from *other* surveys. The first is a survey conducted by the provider Opinion on behalf of the Office of the Auditor General of Norway, which reports estimates of both $P(B)$ and $P(B \mid X)$ in 2021 (see OAGN (2023) for details). Since Opinion's estimates of $P(B)$ and $P(B \mid X)$ are very similar to those from Norstat, the resulting estimates of tax noncompliance are very similar. The second survey is conducted by Ipsos on behalf of the Central Bank of Norway in 2024 and provides an estimate of $P(B)$ for that year. Since we do not observe tax return data for 2024, we recompute our estimates of tax noncompliance for 2018–2023 using the Central Bank's 2024 estimate. Since $P(B)$ has increased over time, using the 2024 adoption rate implies a higher estimated tax noncompliance.

One may also be interested in how our estimates of aggregate tax noncompliance, $P(A^C \mid B)$, would change if Norwegian crypto investors had the same observed characteristics as crypto investors in other countries. Panels A and B of Internet Appendix Figure IA.2 plot country-specific estimates of $P(X \mid B)$, the characteristics distribution of crypto investors, obtained from the Finder Cryptocurrency Adoption Index. Norwegian investors are broadly comparable in terms of gender and age to those in other relevant countries, such as the U.S. Panels C and D then report estimates of $P(A^C \mid B)$ reweighted to adjust for differences in investor characteristics between Norway and each comparison country. The estimates change little. The reason is that crypto tax noncompliance varies relatively little across broad demographic groups, as shown in Panel B of Figure 2.

Table IA.V. Robustness to Alternative Survey Estimates

Panel A reports our baseline estimates from Section V, which pertain to the year 2021. Table III summarizes the identification arguments. Panel B uses estimates of $P(B)$ and $P(B \mid X)$ from Internet Appendix Table IA.IV that are reweighted successively based on additional observed characteristics: Education (I), income (II), and employment (III). Panel C replaces the annual estimates of $P(B)$ and $P(B \mid X)$ from Internet Appendix Table IA.I with rolling averages of these moments across survey waves. Panel D increases and decreases the survey estimates by 10% to 50%. Specifically, we replace $P(B)$ with $(1 \pm \alpha)P(B)$, where $\alpha \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$. Panel E replaces Norstat's estimates of $P(B)$ and $P(B \mid X)$ with corresponding estimates from two other surveys: OAGN (2023) and the Central Bank of Norway (2024).

	A: Baseline	B: Weights			C: Survey timing			D: Scaling $P(B)$ by...										E: Alt. estimates		F: Unweighted
		I	II	III	2018–21	2019–22	2018–24	−50%	−40%	−30%	−20%	−10%	+10%	+20%	+30%	+40%	+50%	OAGN	Central bank	
Prevalence:																				
$P(B)$	0.069	0.070	0.070	0.072	0.054	0.070	0.070	0.035	0.041	0.048	0.055	0.062	0.076	0.083	0.090	0.097	0.104	0.063	0.110	0.057
$P(A^C)$	0.061	0.062	0.062	0.063	0.046	0.062	0.061	0.026	0.033	0.040	0.047	0.054	0.068	0.075	0.082	0.089	0.095	0.055	0.102	0.049
$P(A^C \mid B)$	0.881	0.883	0.883	0.885	0.847	0.883	0.882	0.762	0.802	0.830	0.851	0.868	0.892	0.901	0.908	0.915	0.921	0.870	0.925	0.855
Characteristics:																				
$P(\text{Male} \mid A^C)$	0.781	0.789	0.780	0.776	0.756	0.703	0.740	0.768	0.773	0.776	0.778	0.779	0.781	0.782	0.783	0.783	0.784	0.812		0.736
$P(\text{Female} \mid A^C)$	0.219	0.211	0.220	0.224	0.244	0.297	0.260	0.232	0.227	0.224	0.222	0.221	0.219	0.218	0.217	0.217	0.216	0.188		0.264
$P(\text{Oslo} \mid A^C)$	0.193	0.157	0.170	0.143	0.185	0.172	0.164	0.187	0.189	0.191	0.192	0.193	0.194	0.194	0.194	0.195	0.195	0.200		0.154
$P(\text{Non-Oslo} \mid A^C)$	0.807	0.843	0.830	0.857	0.815	0.828	0.836	0.813	0.811	0.809	0.808	0.807	0.806	0.806	0.806	0.805	0.805	0.800		0.846
$P(\text{Age: 15–29} \mid A^C)$	0.407	0.394	0.439	0.447	0.497	0.431	0.463	0.428	0.420	0.415	0.411	0.409	0.405	0.404	0.402	0.402	0.401	0.500		0.380
$P(\text{Age: 30–39} \mid A^C)$	0.258	0.320	0.287	0.293	0.246	0.303	0.291	0.241	0.247	0.251	0.254	0.256	0.259	0.260	0.261	0.262	0.263	0.272		0.239
$P(\text{Age: 40–49} \mid A^C)$	0.099	0.089	0.100	0.092	0.085	0.105	0.105	0.082	0.088	0.092	0.095	0.097	0.100	0.101	0.102	0.103	0.103	0.112		0.084
$P(\text{Age: 50+} \mid A^C)$	0.237	0.197	0.174	0.169	0.172	0.161	0.142	0.249	0.245	0.242	0.240	0.238	0.236	0.235	0.234	0.234	0.233	0.117		0.297
Prevalence by X:																				
$P(A^C \mid B, \text{Male})$	0.871	0.874	0.872	0.874	0.830	0.860	0.865	0.741	0.784	0.815	0.838	0.856	0.882	0.892	0.900	0.908	0.914	0.864		0.835
$P(A^C \mid B, \text{Female})$	0.920	0.919	0.921	0.925	0.906	0.941	0.932	0.840	0.867	0.886	0.900	0.911	0.927	0.934	0.939	0.943	0.947	0.899		0.917
$P(A^C \mid B, \text{Oslo})$	0.859	0.835	0.845	0.824	0.814	0.846	0.839	0.718	0.765	0.799	0.824	0.843	0.872	0.882	0.892	0.899	0.906	0.851		0.795
$P(A^C \mid B, \text{Non-Oslo})$	0.886	0.892	0.891	0.896	0.855	0.891	0.891	0.773	0.811	0.838	0.858	0.874	0.897	0.905	0.913	0.919	0.924	0.875		0.867
$P(A^C \mid B, \text{Age: 15–29})$	0.918	0.917	0.924	0.927	0.911	0.923	0.927	0.835	0.863	0.882	0.897	0.908	0.925	0.931	0.937	0.941	0.945	0.925		0.893
$P(A^C \mid B, \text{Age: 30–39})$	0.838	0.867	0.854	0.860	0.788	0.861	0.855	0.677	0.731	0.769	0.798	0.820	0.853	0.865	0.876	0.885	0.892	0.832		0.794
$P(A^C \mid B, \text{Age: 40–49})$	0.780	0.765	0.785	0.775	0.695	0.793	0.791	0.560	0.633	0.686	0.725	0.756	0.800	0.817	0.831	0.843	0.853	0.784		0.706
$P(A^C \mid B, \text{Age: 50+})$	0.918	0.905	0.894	0.893	0.860	0.886	0.872	0.837	0.864	0.883	0.898	0.909	0.926	0.932	0.937	0.942	0.946	0.834		0.919
Prevalence by trading venue:																				
$P(A^C \mid D)$	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795	0.795
$P(A^C \mid D^C)$	0.911	0.913	0.913	0.915	0.874	0.913	0.912	0.727	0.807	0.851	0.878	0.897	0.922	0.930	0.937	0.942	0.947	0.900	0.951	0.883

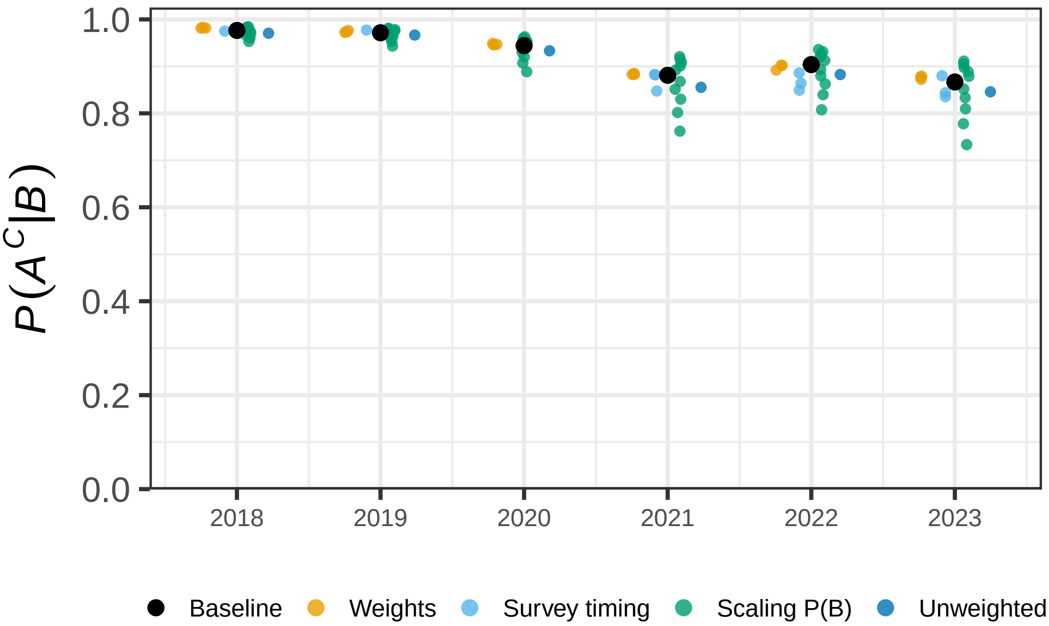
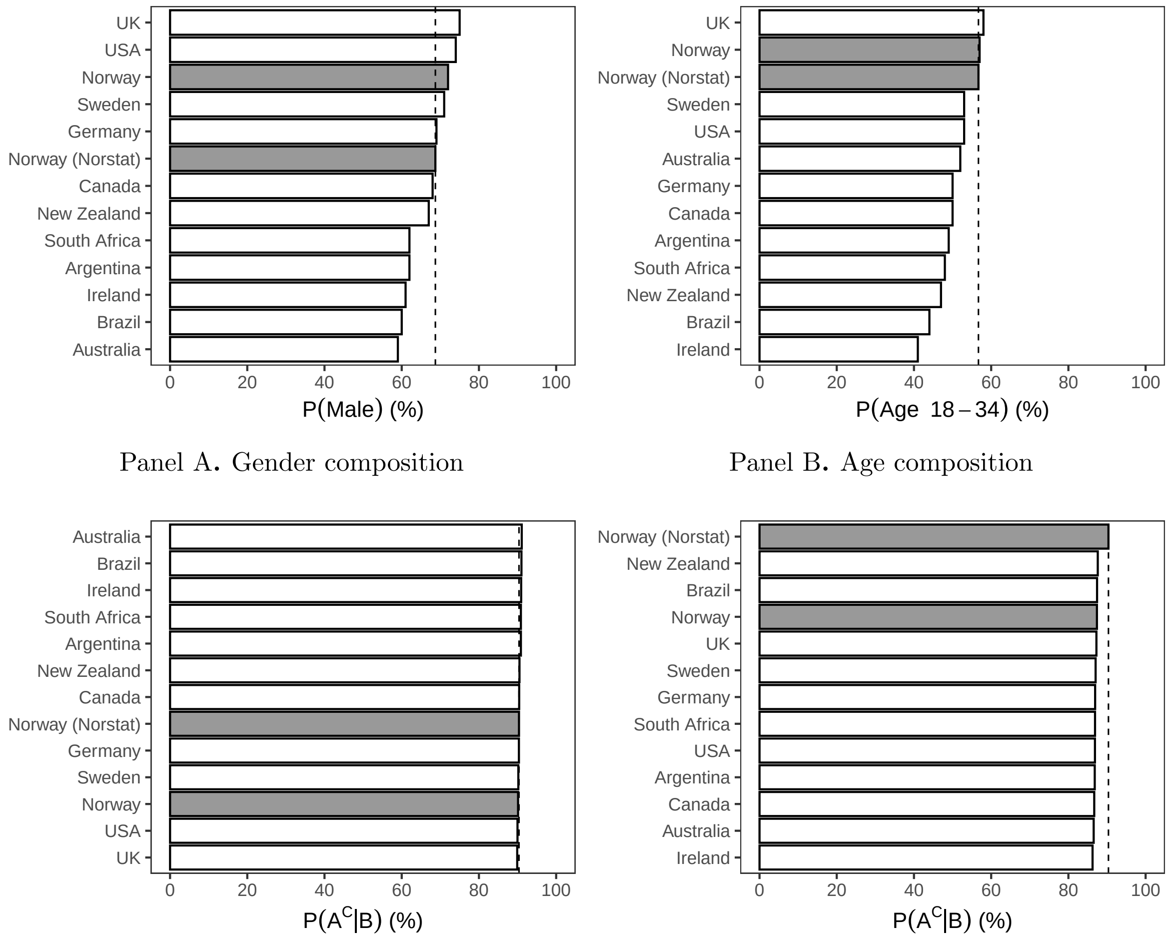


Figure IA.1. Robustness to alternative survey estimates, by year. This figure plots annual estimates of $P(A^C \mid B)$. The black dot indicates the baseline estimate. The other dots show estimates from robustness checks, which are grouped by type and scattered for clarity. The robustness specifications are described in the main text and in Internet Appendix Table IA.V. Survey moments for 2020 are interpolated as the average of the 2019 and 2021 survey moments.



Panel A. Gender composition

Panel B. Age composition

Panel C. Reweighted $P(A^C \mid B)$: Gender

Panel D. Reweighted $P(A^C \mid B)$: Age

Figure IA.2. Adjusting for cross-country differences in investor characteristics. The top row reports country-specific estimates of $P(X \mid B)$, the distribution of characteristics among crypto investors, obtained from the Finder Cryptocurrency Adoption Index. Panel A shows the share of crypto investors who are male, while Panel B shows the share aged 18–34. Panels C and D report estimates of $P(A^C \mid B)$ that have been reweighted to adjust for differences in investor characteristics between Norway and each comparison country. Since the country-specific estimates of $P(X \mid B)$ are measured in 2022, we report estimates of $P(A^C \mid B)$ for 2022. In all panels, estimates are sorted from highest to lowest.

C. About the Exchange Data

The regulatory context is useful for understanding our data access. Before 2019, Norway had no clear legal framework for crypto exchanges or their regulation, allowing any business to facilitate crypto transactions for Norwegians. In 2019, new regulations required any business involved in crypto trading — whether registered in, operating from, or targeting the Norwegian market — to register with the Financial Supervisory Authority of Norway, akin to the SEC in the U.S. Registered exchanges must comply with anti-money laundering and counter-terrorism regulations by verifying user identities before account creation, similar to U.S. know-your-customer rules, and reporting suspicious transactions to authorities. The first regulated exchange was formed in 2019, and by 2021, there were nine. However, virtually all regulated crypto trading takes place on a handful of major exchanges (see, e.g., EY and K33 (previously Arcane) Research 2023).

Exchange coverage I. Our data cover trading on the regulated exchanges. The data were subpoenaed in 2021 and 2022 by the Norwegian Tax Administration and later shared with us.[2] For the years 2019–2020, our data cover seven of the nine regulated exchanges. The two remaining exchanges are minor operations organized as sole proprietorships without employees. For 2021, the data cover the three biggest exchanges.

To assess how our coverage of regulated crypto trading changes from 2020 to 2021, in Internet Appendix Table IA.VI, we calculate each exchange's market share of trading in 2020. We find that the three major exchanges account for 98.1% of all trades and 93.0% of all investors in 2020. Thus, our data cover the vast majority of trading on regulated exchanges over the full 2019–2021 period for which such exchanges have existed in Norway.

[2]The Tax Administration's data collection efforts have been detailed in several public sources, e.g., Finansavisen (2024), Bare Bitcoin (2024), and Office of the Auditor General of Norway (2023). For confidentiality reasons, we cannot disclose how the Tax Administration selects exchanges for data collection.

Exchange coverage II. While unlawful, an estimated 10–20 *unregulated* crypto trading platforms continued to operate in Norway after 2019 (National Authority for Investigation and Prosecution of Economic and Environmental Crime, 2021). To assess our coverage of overall domestic trading, we draw on survey evidence. Using the same survey methods described in Internet Appendix Section A, EY and K33 (previously Arcane) Research 2023 asked Norwegian crypto investors about their choice of trading platform. Among those trading domestically, around 90% report trading on one of the three biggest regulated exchanges. The remaining survey subjects report trading on "Other domestic platforms", which includes the remaining regulated exchanges, which are covered by our data, as well as unregulated domestic exchanges, which are not covered by our data. This suggests that our data cover the vast majority of not only regulated domestic trading, but also overall domestic trading.

Summary. In the main text, we use data from all the available exchange-years in Internet Appendix Table IA.VI to calculate V^D and G^D; the value of crypto holdings and capital income accrued on the regulated domestic crypto exchanges between 2019 and 2021. (See Internet Appendix Section D for details on how these variables are calculated). Accordingly, these measures do not include any crypto holdings or capital income accrued on *unregulated* domestic exchanges, where trading activity appears minimal, nor do they include crypto holdings or income accrued outside the regulated or unregulated domestic exchanges, for example, on foreign exchanges. The measures also do not account for investors' trading, if any, that takes place before 2019 on any trading platform, domestic or foreign. All such values are captured by the T^F term in Equation (12).

Table IA.VI. Exchange Coverage

This table summarizes our coverage of regulated domestic crypto exchanges over the period 2019–2021. The leftmost panel indicates the years for which we observe data from a given exchange. We note that exchange coverage increases from 2019 to 2020 as new exchanges are formed; exchange coverage decreases from 2020 to 2021 as data was collected from fewer exchanges. The middle panel indicates a given exchange's annual market share of total trading, as measured by the number of transactions. The rightmost panel indicates a given exchange's annual market share of total trading, as measured by the number of active (at least one trade) investors. The footer of the table provides annual totals for the number of trades, trading volume, and number of active investors across all exchanges in our data.

	Observed			**Share of trades**			**Share of investors**		
	2019	2020	2021	2019	2020	2021	2019	2020	2021
Exchange A	×	×	×	92.2%	91.3%	97.2%	62.8%	81.9%	91.3%
Exchange B		×	×		6.1%	2.5%		7.4%	5.5%
Exchange C		×	×		0.7%	0.3%		3.7%	3.2%
Exchange D	×	×		7.8%	1.5%		37.2%	5.9%	
Exchange E		×			0.2%			0.5%	
Exchange F		×			0.1%			0.2%	
Exchange G		×			0.0%			0.5%	
Total # of trades	3,812	94,865	2,661,099						
Trading volume (1000s)	42,332	569,268	16,503,032						
Number of investors	258	5,760	84,438						

D. Calculating V^D and G^D

In Section V, we use V^D, the value of crypto holdings accumulated on the domestic exchanges, combined with survey moments to estimate the prevalence of crypto tax noncompliance among investors trading on and outside the domestic exchanges. In Sections VI–VIII, we use both V^D and G^D, the capital income accrued on the domestic exchanges, to construct a lower bound on the tax liabilities owed by tax noncompliers.

Here, we explain how V^D and G^D are calculated.

Both V^D and G^D are calculated using the full history of buys and sells from all the domestic crypto exchanges and years tabulated in Internet Appendix Table IA.VI.

Calculating V^D. To calculate V^D, for each investor, we use the full history of buys and sells from the domestic exchanges to calculate net positions of each coin, for example, bitcoin, by the end of each year. Bonuses from exchange rewards programs are added to the end-of-year coin holding. Then, we use coin exchange rates as of December 31 each year to calculate V^D as the end-of-year crypto holdings measured in USD.

Calculating G^D. We calculate G^D in two steps. First, we account for capital income derived from realized gains. For each investor, we use the full transaction history observed on the domestic exchanges to calculate realized gains for each sale using the first-in-first-out (FIFO) method, consistent with standard practice for other taxable assets.

Internet Appendix Table IA.VII illustrates the FIFO method for a hypothetical investor who makes two purchases and two sales. The investor buys 100 coins in January at \$10 per coin and another 50 coins in February at \$15 per coin. In March, the investor sells 80 coins at \$20 per coin. Under FIFO, the realized gains on this transaction are evaluated against the earliest purchase (January) at \$10 per coin, resulting in a gain of

$80 \times (\$20 - \$10) = \$800$. In April, the investor sells another 70 coins at \$25 per coin. The first 20 coins are evaluated against the remaining 20 coins from the January purchase at \$10, and the next 50 coins are evaluated against the February purchase at \$15, resulting in an additional gain of $20 \times (\$25 - \$10) + 50 \times (\$25 - \$15) = \$800$.

Using the FIFO method, we assign realized gains to 84% of the sales observed in our data. For the remaining 16%, the quantity sold exceeds the investor's previously accumulated coin balance, which means that we lack a purchase price against which to evaluate the sale price. This can occur when investors transfer coins from external wallets to domestic exchanges and sell from these balances. In these cases, the sale price is evaluated against the average cost basis of the investor's prior purchases.

In the second step, we account for capital income *not* derived from realized capital gains. In Norway, staking, mining, and bonuses from exchange rewards programs are all classified as capital income from crypto, and taxed as the same rate as realized capital gains. One cannot mine crypto on centralized crypto exchanges. In addition, the regulated crypto exchanges in Norway did not introduce staking services until 2022, after our data ends. However, the biggest domestic exchange did offer rewards programs, such as referral and welcome bonuses, which we observe in the data. We therefore add these bonus payments to the yearly domestic capital income for each investor.

Finally, for each year, we add up all realized gains and bonuses received by December 31 that year to arrive at G^D, the end-of-year capital income measured in USD.

Table IA.VII. Illustration: First-in-First-Out Method

Type	Date	Quantity	Price	Realized Capital Gains
Buy	Jan 1, 2020	100	\$10	-
Buy	Feb 1, 2020	50	\$15	-
Sell	Mar 1, 2020	80	\$20	\$800
Sell	Apr 1, 2020	70	\$25	\$800

E. About the 2020 and 2022 Reminder Letters

In Sections VII–VIII, we assess the impact of two reminder letter interventions carried out in November 2020 and August 2022 by the Norwegian Tax Administration. Below, we describe the content of the letters, starting with the 2020 intervention.

2020 letter content. Internet Appendix Figure IA.3 presents a copy of the letter.[3] The letter is in Norwegian. We therefore provide a translation of the key points of the letter.

The letter is organized into five parts:

The first part clarifies the purpose of the letter: "*The Norwegian Tax Administration aims for everyone to accurately report on their tax returns. For 2019, we have noticed an increase in errors and omissions in the reporting of cryptocurrency.*"

The second part identifies two reasons the recipient may have received the letter:

- "*You declared crypto holdings or gains/losses in the tax returns for 2018 or 2019.*"
- "*You are in a group that has been indicated by our analysis tools or transaction records to be part of transactions involving cryptocurrencies.*"

The third part of the letter urges recipients to identify and amend any discrepancies in past tax returns and explains the process for making these amendments. However, the letter does not point out specific discrepancies in the recipient's tax returns.

The fourth part addresses how to ensure tax compliance moving forward. It notes that crypto holdings and income are taxable but not pre-populated in tax returns, requiring self-reporting by the taxpayer. It also explains how to report these items.

[3] The letter content is also described in publicly available sources, e.g., Kryptosekken (2020).

The letter concludes by emphasizing the penalties for tax noncompliance.

2022 letter content. The content of the 2022 letter is very similar to that of the 2020 letter. Internet Appendix Figure IA.4 presents a copy of the letter. The letter is again in Norwegian. We therefore provide a translation of the key points of the letter.

The letter is organized into four parts:

The first part explains why the recipient received the letter: "*You declared crypto holdings or gains/losses in the tax returns for 2020 but not in 2021.*"

The second part clarifies the purpose of the letter: "*The Norwegian Tax Administration aims for everyone to accurately report on their tax returns. For 2019, we have noticed an increase in errors and omissions in the reporting of cryptocurrency.*"

The third part of the letter urges recipients to identify and amend any discrepancies in past tax returns and explains the process for making these amendments. However, the letter does not point out specific discrepancies in the recipient's tax returns.

The letter concludes by emphasizing the penalties for tax noncompliance.

Skatteetaten

Vår dato
27. november 2020

Vår referanse
[redacted]

800 80 000
skatteetaten.no

Org. nr
974 761 076

[redacted]

INFORMASJON TIL SKATTEMELDINGEN 2019 – VIRTUELL VALUTA

Skatteetaten har et mål om at alle skal rapportere riktig på skattemeldingen.

For 2019 har vi sett tegn på at det er en stor økning i feil og manglende rapportering innenfor virtuell valuta (kryptovaluta).

Hvorfor mottar jeg dette brevet?

Du mottar dette brevet enten fordi

> du har rapportert gevinst/tap eller beholdning av kryptovaluta på skattemeldingen for 2018 eller 2019 eller
>
> du er i en gruppe som våre analyseverktøy eller transaksjonsoversikter har indikert at er part i transaksjoner med kryptovaluta.

Hva bør jeg gjøre?

Hvis du er du usikker på om du har rapportert formue eller gevinst/tap i kryptovaluta riktig, da oppfordrer vi deg til å kontrollere tidligere skattemeldinger.

Finner du feil i skattemeldingene kan du selv endre din egen skattemelding inntil 3 år tilbake i tid.

> Skattemeldingen for 2019 endrer du ved å logge inn i skattemeldingen, endre og levere på nytt.
>
> For skattemeldingen 2017 og 2018 må du levere endringsmelding som du kan lese mer om her.

Kryptovaluta forhåndsutfylles ikke

Det er ingen forhåndsutfylling av informasjon om kryptovaluta i skattemeldingen per i dag og du må derfor selv fylle ut denne informasjonen. Eide du kryptovaluta ved årsskiftet må du oppgi formue for kryptovaluta. Solgte eller realiserte du på annen måte kryptovaluta i løpet av året må gevinst/tap føres. Utvinning av kryptovaluta (som mining) og andre inntekter skal du også føre opp for det året de er utvunnet/opptjent.

I den nye skattemeldingen for 2019 fyller du enkelt ut kortet *Virtuell valuta/kryptovaluta* som ligger under temaet *Finans*. Det er hjelpetekster til alle postene og du får vite mer om hvordan du fastsetter verdiene her.

Aktuelle regler og lover

Det følger av skatteforvaltningsloven § 8-1 at alle skal gi riktige og fullstendige opplysninger i skattemeldingen. Dersom det blir oppgitt uriktige eller ufullstendige opplysninger kan det ilegges tilleggsskatt etter skatteforvaltningsloven § 14-3 første ledd og skjerpet tilleggsskatt etter § 14-6. Dersom den skattepliktige frivillig retter sin egen skattemelding, vil unntaket fra tilleggsskatt i skatteforvaltningsloven § 14-4 d) komme til anvendelse.

Dette brevet er kun til informasjon, og du trenger ikke å svare på det. Du må levere skattemelding eller endringsmelding om du oppdager feil eller manglende opplysninger i tidligere leverte skattemeldinger.

Med hilsen

Skatteetaten

Figure IA.3. Reminder letter sent in November 2020

Skatteetaten

Vår dato
15. august 2022

Vår referanse
[redacted]

800 80 000
skatteetaten.no

Org. nr
974 761 076

[redacted]

Informasjon om kryptovaluta i skattemeldingen 2021

I skattemeldingen din for 2020 førte du opp at du eide kryptovaluta, men du har ikke ført opp at du eier kryptovaluta i skattemeldingen for 2021. Du har heller ikke ført opp at du har et tap eller en gevinst ved salg av kryptovaluta i 2021.

Skatteetaten har et mål om at alle skal rapportere riktig på skattemeldingen og vi vil derfor gi deg veiledning slik at du vet hvordan du legger inn opplysninger om kryptovaluta i skattemeldingen for 2021.

Hva bør du gjøre?

Siden informasjon om kryptovaluta ikke blir forhåndsutfylt, oppfordrer vi deg til å sjekke skattemeldingen din for 2021.

Hvis du eide kryptovaluta ved årsskiftet, legger du inn opplysninger om formue i skattemeldingen.
Hvis du solgte eller på annen måte realiserte kryptovaluta i løpet av året, legger du inn opplysninger om gevinst eller tap.

Hvis du mener at du har fylt ut skattemeldingen for 2021 riktig, kan du se bort fra dette brevet.

Slik kan du endre

Skattemeldingen for 2021 endrer du ved å logge inn i skattemeldingen, endre og levere på nytt. I skattemeldingen for 2021 fyller du enkelt ut kortet *Virtuell valuta/kryptovaluta* som ligger under temaet *Finans*. Det er hjelpetekster til feltene i selve skattemeldingen og du får vite mer om kryptovaluta på skatteetaten.no/kryptovaluta.

Finner du feil i skattemeldingen din for i år eller for tidligere år, kan du selv gjøre endringer inntil 3 år tilbake i tid. For skattemeldingen 2019 og 2020 leverer du en endringsmelding som du kan lese mer om her.

Aktuelt regelverk

Følgende lovhjemler er aktuelle for informasjon i dette brevet:

Skatteplikt for inntekter, se skatteloven § 5-1.
Fradragsrett for kostnader og tap, se skatteloven § 6-1 og § 6-2.
Fastsetting av formue, se skatteloven § 4-1.
Egenfastsetting og egenretting ved levering av skattemeldingen, se skatteforvaltningsloven § 9-1 og § 9-4.

Side 1 / 2

Dette brevet er kun til informasjon, og du trenger ikke å svare på det.

Har du spørsmål?

Du kan ta kontakt med oss på skatteetaten.no/kontakt, eller på telefonnummer 800 80 000 hvis du har spørsmål. Hvis du ringer fra utlandet, er telefonnummeret +47 22 07 70 00.

Med hilsen

Skatteetaten

Figure IA.4. Reminder letter sent in August 2022.

F. About the 2023 Letter Intervention

As explained in Internet Appendix Section E, the Norwegian Tax Administration carried out reminder letter interventions in 2020 and 2022. These letters targeted individuals who had declared crypto in the past but subsequently stopped. The Tax Administration also implemented a letter intervention in January 2023. This intervention targeted individuals who, on the Tax Administration's online filing platform, opened and attached the tax form associated with crypto holdings and income to their 2021 tax return, but ultimately did not report any information on that form. Below, we first describe the content of the letters and then estimate their effects on tax compliance and tax revenue.

2023 letter content. Internet Appendix Figure IA.5 presents a copy of the letter. The letter is in Norwegian. We therefore provide a translation of the key points of the letter.

The letter is organized into four parts:

The first part explains why the recipient received the letter: "*For the 2021 tax return, you attached a tax form related to cryptocurrency but did not report any information on that form.*"

The second part of the letter urges recipients to identify and amend any discrepancies in past tax returns and explains the process for making these amendments. However, the letter does not point out specific discrepancies in the recipient's tax returns.

The third part addresses how to ensure tax compliance moving forward. It notes that crypto holdings and income are taxable but not pre-populated in tax returns, requiring self-reporting by the taxpayer. It also explains how to report these items.

The letter concludes by emphasizing the penalties for tax noncompliance.

Summary statistics. The letters were sent to 561 individuals. In Internet Appendix Table IA.IX, we start by describing the characteristics of the letter recipients. Column (1) shows that about 80% of recipients are male, 18.5% reside in Oslo, and the majority are under age 40. Compared to the broader population of crypto investors (column (2)), letter recipients are more likely to be male, reside in Oslo, and are older.

Estimates. Next, we quantify the increase in compliance associated with receiving a letter. As the letters were issued in January 2023, the treated group of letter recipients could start declaring crypto as of the 2022 return, filed in April 2023. As shown in column (1) of Internet Appendix Table IA.IX, 53.9% of recipients declare crypto in their 2022 return, up from 0% in 2021. The estimate is significantly different from zero.

Of course, letter recipients may have declared their crypto even absent the letters, suggesting that 53.9% is an upper bound on the effect of the intervention. To mitigate this concern, it is useful to compare the behavior of letter recipients to that of a control group of non-recipients. The control group consists of all investors who hold crypto on the domestic crypto exchanges in 2020 or 2021 and, like the treated group, did not declare crypto in their 2021 tax return. Even absent letters, Internet Appendix Table IA.IX shows, 6.0% of the control group declare crypto in their 2022 tax return, up from 0% in 2021. This gives an estimate of the difference in tax compliance between the treated and control group of 47.9 percentage points, statistically significant at the 1% level.

Next, we turn to regressions to adjust for observable differences between the treated and control groups. In row (4) of Internet Appendix Table IA.IX, we control for a wide range of demographic, socioeconomic, and tax return characteristics known to affect compliance. Adding these controls has little impact on the estimated effect, reducing it from 47.9 to 47.0 percentage points, and the difference in compliance between the treated and control groups remains statistically significant at the 1% level.

Lastly, we examine the effect of the letters on tax revenue. To do so, we repeat the analyses above using the declared tax liability as the outcome variable. Column (2) of Internet Appendix Table IA.IX shows that letter recipients report an average tax loss of $-$224 in 2022, compared to $0 in 2021. The control group reports an average tax loss of $-$17. This implies an average tax revenue effect of $-$207 per letter, which is statistically significant at the 1% level. Controlling for observable characteristics increases the magnitude slightly, to $-$209, and the estimate remains significant at the 1% level.

Skatteetaten

Returadresse:
Postboks 9200 Grønland, N-0134 OSLO

Vår dato	Vår referanse
20.januar 2023	[redacted]
800 80 000	Orgnr
Skatteetaten.no	974 761 076

[redacted]

Veiledning til utfylling av virtuelle eiendeler / kryptovaluta og andre finansprodukter i skattemeldingen 2021

I skattemeldingen for 2021 la du ved et vedlegg om virtuell valuta / kryptovaluta, men du la ikke inn noen beløp i skattemeldingen din. Vi vil derfor gi deg veiledning om hvordan du fortsatt kan legge inn opplysninger i skattemeldingen.

Slik kan du endre
Du kan fortsatt endre skattemeldingen din for 2021. Dette gjør du ved å logge inn i på skatteetaten.no/skattemelding. Velg «Åpne skattemeldingen».

I skattemeldingen for 2021 fyller du ut kortet «Andre finansprodukter og virtuell valuta/kryptovaluta», som ligger under temaet «Finans». Hvis du eide virtuell valuta / kryptovaluta ved årsskiftet, legger du inn opplysninger om formue. Solgte du, eller på annen måte realiserte virtuell valuta/ kryptovaluta i løpet av året, legger du inn opplysninger om gevinst eller tap.

Hvis ikke handelsplattform/børs eller lignende beregner formuesverdi og gevinst/tap for deg, så må du gjøre denne beregningen selv. Er du usikker på beløpenes størrelse, legger du inn det du mener er riktig.

Det er hjelpetekster til feltene i selve skattemeldingen, og du får vite mer om kryptovaluta på skatteetaten.no/virtuellvaluta.

Hvis du mener at du har fylt ut skattemeldingen for 2021 riktig, kan du se bort fra dette brevet.

Du kan endre lengre tilbake i tid
Hvis du finner feil i tidligere skattemeldinger kan du selv gjøre endringer inntil 3 år tilbake i tid. Da kan du enten sende inn skattemeldingen for det aktuelle året eller bruke endringsskjema som du finner på skatteetaten.no/RF1366.

Husk skattemeldingen din for 2022
Hvis du har solgt, minet eller hadde verdier i virtuell valuta / kryptovaluta i løpet av 2022, minner vi om at du må legge inn beløpene i riktig kort i skattemeldingen din.

Aktuelt regelverk i dette brevet
På lovdata.no kan du lese mer om

- skatteplikt for inntekter, se skatteloven § 5-1
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Figure IA.5. Reminder letter sent in January 2023

Table IA.VIII. Characteristics of 2023 Letter Recipients

This table compares the demographic characteristics of recipients of the 2023 Tax Administration reminder letters ($Z = 1$) to those of the broader population of crypto investors in 2022.

	$P(X \mid Z = 1)$	$P(X \mid B)$	$\frac{P(X \mid Z=1)}{P(X \mid B)}$
Male	0.807	0.687	1.176
Female	0.193	0.313	0.615
Oslo	0.185	0.148	1.254
Non-Oslo	0.815	0.852	0.956
Age: 15–29	0.321	0.416	0.770
Age: 30–39	0.258	0.336	0.769
Age: 40–49	0.166	0.127	1.307
Age: 50+	0.255	0.120	2.116

Table IA.IX. Effect of 2023 Letters on Tax Compliance and Tax Revenue

This table reports estimates of the effect on tax compliance (Panel A) and tax revenue (Panel B) of the 2023 Tax Administration letter intervention. Control variables include age, gender, an indicator for residing in Oslo, an indicator for being married, education (in bins), employment status, gross wealth, total income, and total tax liability. Standard errors are presented in parentheses. Stars indicate statistical significance at the 10% (*), 5% (**), and 1% (***) level.

	Panel A. $P(A)$			Panel B. $E[T^*]$		
	2021	2022	Δ	2021	2022	Δ
Treated group	0.000	0.539	0.539***	$0	–$224	–$224***
			(0.021)			($56)
Control group	0.000	0.060	0.060***	$0	–$17	–$17***
			(0.001)			($1)
Difference in differences			0.479***			–$207***
			(0.021)			($56)
Difference in differences with controls			0.470***			–$209***
			(0.021)			($57)
N	63,283	63,283	63,283	63,283	63,283	63,283

G. About the International Wire Transfer Data

We use data on international wire transfers by all Norwegians to identify individuals who transfer funds to or from foreign crypto exchanges. These data allow us to describe the tax compliance of a subset of investors trading outside domestic exchanges. We find high levels of tax noncompliance among investors who transfer funds to or from foreign crypto exchanges. Similar to Figure 4, we find that tax compliance increases sharply with a crude measure of the size of the crypto portfolio held on foreign exchanges.

About the data. The Norwegian Tax Administration collects data on cross-border financial settlements to and from Norway. These data are recorded in the Registry of Cross-Border Transactions and Currency Exchange (in Norwegian: *Valutaregisteret*) and include information on all wire transfers from Norwegian bank accounts to foreign individuals or corporations. The data also cover Norwegians' credit card payments abroad and purchases or sales of foreign currency; see Valutaregisterloven (2021) for details. For each transaction, we observe the transferred amount in Norwegian kroner, the transaction date, and which foreign entity is the counterparty to the transaction. The domestic party is identified by a unique tax identifier and can be linked to other administrative data sources. The foreign counterparty is identified by name through a textual description of the recipient individual or corporation. The data cover the period 2010–2023.

Identifying transfers to known crypto exchanges. We proceed in three steps to identify transfers to known crypto exchanges. First, we restrict attention to transfers where the foreign counterparty is a corporation, excluding transfers to individuals. Second, following Kroft et al. (2025), we clean the foreign corporation name by removing common firm designators such as "gmbh," "llc," and "corp," as well as any punctuation. Third, using the cleaned names, we classify transfers to or from known crypto exchanges.

We focus on transfers to and from Coinbase, Binance, and Kraken, which are the main foreign crypto exchanges used by Norwegian investors (see EY and K33 Research, 2023). We classify transfers as crypto-related if the cleaned counterparty name contains an exact match to "coinbase" or "binance." Because "kraken" is a more common term, we classify transfers as crypto-related only if the text field contains an exact match to "kraken" *and* either a known bank or intermediary used for transfers to Kraken (fidor, fick, clear junction, signature, one london, london wall) or keywords plausibly associated with crypto (sepa, wallet, bitcoin). We also classify transfers as crypto-related if the text field contains an exact match to "payward," Kraken's (less common) legal name.

It is useful to note that this procedure does not capture all transfers to or from foreign crypto exchanges. For example, individuals may transfer funds to or from payment intermediaries such as PayPal rather than directly to exchanges. While such transfers are observed in the data, we do not classify them as crypto-related since these intermediaries also serve many other purposes. Similarly, we do not classify transfers to or from foreign exchanges other than Kraken, Coinbase, and Binance, and we may fail to capture some transactions even for these exchanges. (For example, the exchange name may be misspelled, abbreviated, or otherwise inaccurately recorded in the text field). For these reasons, our sample represents a selected subset of investors trading on foreign exchanges that are easy to identify, both for us and for the Norwegian Tax Administration.[4]

Calculating a measure of crypto holdings. While we observe transfers to and from foreign exchanges, we do not observe the actual crypto transactions that take place on those exchanges. This starting point is similar to Aiello et al. (2025), who observe wire transfers by U.S. individuals to known crypto exchanges. We follow their approach to construct a measure of crypto holdings accumulated on foreign exchanges.

[4] For example, more sophisticated crypto investors may opt for greater opacity by transferring funds through channels that are less easily detected by the Norwegian Tax Administration.

Specifically, we assume that when Norwegians transfer fiat currency to a foreign exchange, they immediately invest 95% of the transferred amount in a market-capitalization-weighted basket of bitcoin and ethereum, and keep the remaining 5% in U.S. dollars or invest it in a U.S.-dollar-pegged stablecoin. We further assume that transfers *from* exchanges occur immediately after crypto has been converted into fiat, and that sales are proportional to the investor's current portfolio composition.

Let $\Delta_{i,t}$ denote the net transfer of fiat currency to the foreign exchanges by investor i on day t. Let $p_{i,t}$ and $p_{i,t-1}$ denote an investor-specific price index based on the composition of Bitcoin, Ethereum, and dollars in the investor's portfolio on day $t-1$. We compute the foreign-accumulated crypto holdings of investor i on day t as:

$$V_{i,t}^{F} = V_{i,t-1}^{F} \cdot \frac{p_{i,t}}{p_{i,t-1}} + \Delta_{i,t}. \tag{IA.1}$$

By iterating over periods $s \leq t$, we compute the investor's portfolio value on day t using identified transfers to and from the exchanges over the full period 2010–2023. We then define the portfolio value on December 31 as the portfolio value for that year.

Summary statistics. Internet Appendix Table IA.X reports the count of investors with $V^F > 0$ in each year 2018–2023. The investor count increases from 17,541 in 2018 to 27,595 in 2023, with 25,901 investors observed on foreign exchanges in 2021.

Column (1) of Internet Appendix Table IA.XI describes investors trading on foreign exchanges in 2021. Most are male and below age 40; average income is \$71,924 and average net wealth is \$102,521. To put these figures in perspective, we compare these investors to all investors observed on domestic exchanges (column (2)) and to the broader population of crypto investors (column (3)). Relative to both groups, investors on foreign exchanges are more likely to be male and are older. They also, on average, have higher income and wealth than investors trading on domestic exchanges. Conditional on declaring crypto, investors on foreign exchanges report substantially larger tax liabilities.

We also compare tax noncompliance rates across these groups. As shown in the bottom row of Internet Appendix Table IA.XI, tax noncompliance among the subset of investors observed on foreign exchanges is comparable to that of investors on domestic exchanges and slightly lower than that of crypto investors overall. To interpret this finding, it is useful to note that the Tax Administration can directly identify investors transferring funds to and from foreign exchanges as well as those trading on domestic exchanges, although it observes actual crypto transactions only for the latter. It is also useful to consider how tax compliance correlates with observable characteristics. As shown in Figure 4, tax noncompliance among domestic investors decreases sharply with tax liability. In Internet Appendix Figure IA.6 below, we show that the same pattern holds for the subset of investors observed trading on foreign exchanges when tax noncompliance is plotted against our measure of foreign-accumulated crypto holdings, V^F.

We turn to regressions to adjust for differences in observable characteristics. In Internet Appendix Table IA.XII, we pool investors observed on domestic and foreign exchanges, excluding a small set of investors present on both. Column (1) shows that, absent controls, tax noncompliance is 1.3 percentage points lower among investors trading on foreign exchanges than among those trading on domestic exchanges. As we successively add controls for demographic and socio-economic characteristics and the value of crypto holdings in columns (2)–(4), this difference becomes positive and both economically and statistically significant. In other words, conditional on observable characteristics, tax noncompliance is higher among investors trading on foreign exchanges.

Table IA.X. Investor Count: Investors Identified From Wire Transfers Data

	Investor Count
2018	17,541
2019	18,024
2020	18,996
2021	25,903
2022	26,562
2023	27,595

Table IA.XI. Individual Characteristics: Investors Identified From Wire Transfers Data

Column (1) summarizes the characteristics of investors observed on foreign exchanges (VR) in 2021. Columns (2) and (3) summarize the characteristics of investors observed on domestic exchanges (D) and of the broader population of crypto investors in 2021.

	VR	D	B
Male	91%	83%	79%
Female	9%	17%	21%
Oslo	27%	17%	20%
Non-Oslo	73%	83%	80%
Age: 15-29	26%	47%	39%
Age: 30-39	39%	26%	27%
Age: 40-49	21%	14%	11%
Age: 50+	13%	12%	23%
Income: Q1	15%	25%	
Income: Q2	11%	16%	
Income: Q3	20%	24%	
Income: Q4	53%	35%	
Mean Income	\$71,460	\$54,600	
Net Wealth	\$101,862	\$81,690	
$E[T^* \mid A]$	\$2,265	\$700	
$P(A)$	24%	21%	12%
N	25,903	79,525	

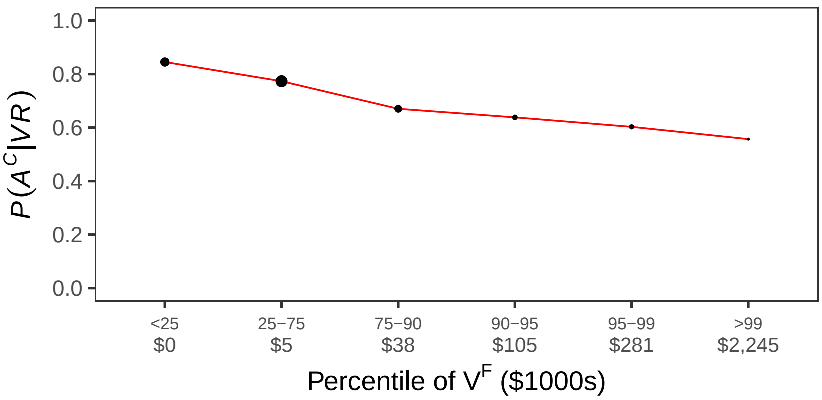


Figure IA.6. Tax noncompliance among investors observed on foreign exchanges, by V^F. This figure plots tax noncompliance by percentile bins of V^F. The black circles indicate the average level of tax noncompliance within each percentile bin, with dot size proportional to the number of investors in the bin. The red line connects the black circles. All estimates are based on data from 2021.

Table IA.XII. Regressions: Investors Identified From Wire Transfers Data

Column (1) regresses an indicator for crypto tax noncompliance, A^C, on an indicator for whether the investor is observed to transfer funds to or from foreign exchanges. The sample is comprised of investors observed only on foreign exchanges ($VR = 1$) or only on domestic exchanges ($VR = 0$). Columns (2)–(4) successively control for age, gender, and an indicator for residing in Oslo (column (2)); crypto holdings (column (3)); and marital status, education (in bins), employment status, gross wealth, total income (column (4)). Standard errors are presented in parentheses. Stars indicate statistical significance at the 10% (*), 5% (**), and 1% (***) level. All estimates are based on data from 2021.

	$P(A^C)$	$P(A^C)$	$P(A^C)$	$P(A^C)$
$\mathbf{1}[VR]$	-0.013***	0.024***	0.035***	0.067***
	(0.003)	(0.003)	(0.003)	(0.003)
N	99,344	99,344	99,344	99,111

H. Role of the Wealth Tax

Here, we describe the role of the wealth tax in our setting. Internet Appendix Figure IA.7 reports the share of crypto investors on domestic exchanges who are liable for the wealth tax. Only 7% of investors are liable, reflecting the fact that most crypto investors are relatively young and have insufficient net wealth ($150,000 for singles, $300,000 for married) to trigger the wealth tax. Conditional on being liable, the wealth tax amounts to 0.85% of crypto wealth. In Internet Appendix Table IA.XIII, we decompose total tax liabilities from Table VI into capital gains taxes and wealth taxes. Across all investor groups, the wealth tax accounts for less than 15% of the total crypto tax bill.

The presence of a wealth tax may still affect tax reporting behavior. To assess this possibility, in Internet Appendix Figure IA.8, we compare crypto tax noncompliance marginally above and below the wealth tax threshold. Graphically, we find no significant evidence of a discontinuity or kink at the threshold. Implementing a regression discontinuity design around the wealth tax threshold following Calonico et al. (2017), we obtain an economically and statistically insignificant estimate of 0.001, suggesting that the wealth tax does not causally affect crypto tax reporting behavior.

Above, we find that the wealth tax liability is economically small and does not meaningfully affect reporting behavior. This suggests that our results should be similar when restricting attention to capital gains taxes only. Consistent with this, Panel A of Internet Appendix Figure IA.9 shows that the relationship between crypto tax noncompliance and tax liability is nearly identical when we exclude the wealth tax from our measure of crypto tax liabilities. Panel B of Internet Appendix Figure IA.9 further shows that the same pattern holds when restricting the sample to individuals who sell crypto in the current tax year and therefore necessarily realize non-zero capital gains.

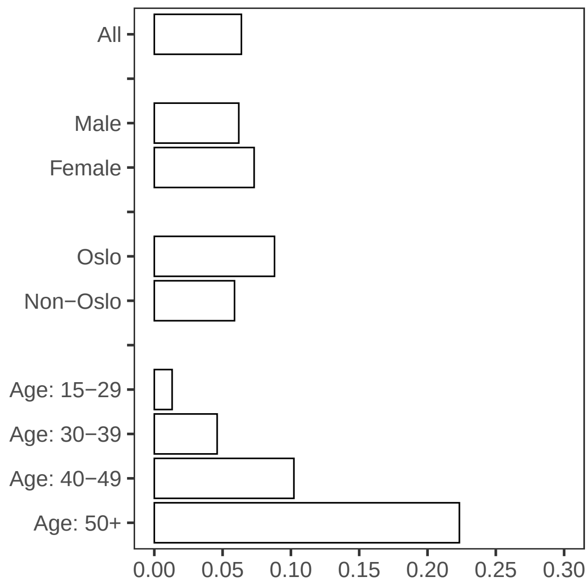
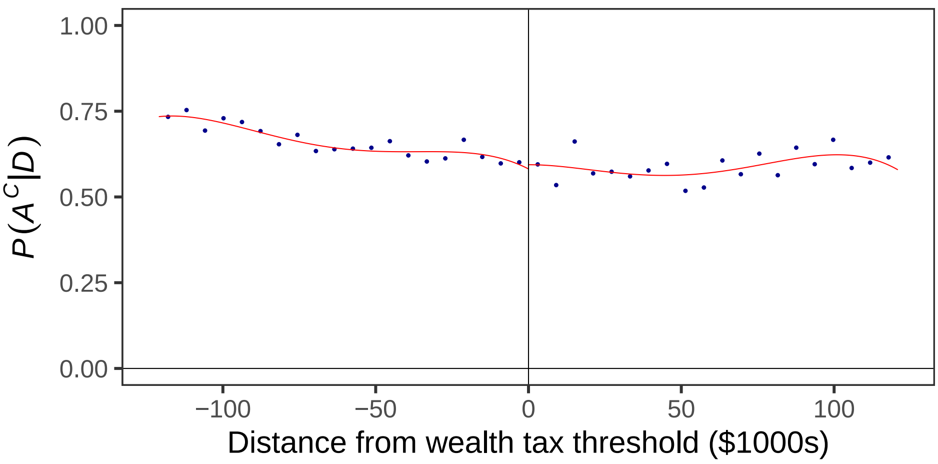


Figure IA.7. Share of investors subject to the wealth tax. This figure shows the share of investors on domestic exchanges who are subject to the wealth tax, by individual characteristics. All estimates are based on data from 2021. Individuals with net taxable wealth above $150,000 for singles and $300,000 for married couples are subject to the wealth tax.

Table IA.XIII. Wealth and Capital Gains Tax

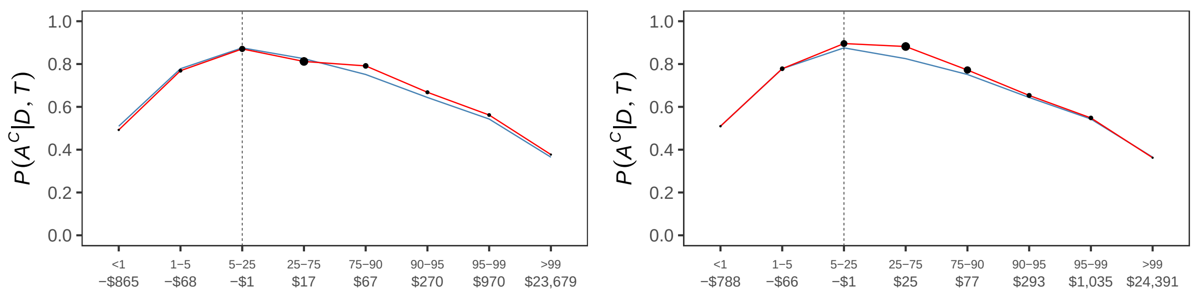
This table decomposes total crypto tax liabilities from Table VI into capital gains taxes (T_G) and wealth taxes (T_V). Capital gains taxes are defined as $T_G = \tau^G G$, and wealth taxes are defined as $T_V = \mathbf{1}^W \tau^W V$. Column (1) reports the tax liability measure being decomposed, column (2) reports the investor group, columns (3)–(5) report the average total tax liability, the wealth tax component, and the capital gains tax component, respectively, and column (6) reports the share of capital gains taxes in total tax liabilities.

T	Group (Z)	$E[T \mid Z]$	$E[T_V \mid Z]$	$E[T_G \mid Z]$	Share $E[T_G \mid Z]$
T^*	A	\$1,011	\$127	\$884	87%
T^D	A^C, D	\$81	\$3	\$77	96%
T^*	A, D	\$695	\$75	\$619	89%
T^D	A, D	\$315	\$24	\$291	92%
T^*	A, D^C	\$1,270	\$169	\$1,100	87%



RD Estimate	0.001
	(0.045)

Figure IA.8. Impact of wealth tax on crypto tax noncompliance. This figure plots $P(A^C \mid D)$ by investors' net taxable wealth. Net taxable wealth is centered at the wealth tax threshold. The table at the bottom reports estimates from a regression discontinuity design (RDD) comparing observations marginally above and below the wealth tax threshold. The RDD is implemented using an optimal bandwidth following Calonico et al. (2017). All estimates are based on data from 2021.



Panel A. Exclude wealth tax from T^D Panel B. Restrict sample to investors with sales

Figure IA.9. Role of wealth tax: Exclude wealth tax, alternative sample. This figure plots $P(A^C \mid D)$ by percentile bins of crypto tax liability. Panel A excludes wealth taxes from T^D. Panel B restricts the sample to investors observed selling crypto and therefore necessarily realizing capital gains. In both panels, the blue line indicates $P(A^C \mid D)$ without these restrictions, reproduced from Figure 4. The black circles indicate the average level of tax noncompliance within each tax liability bin, with circle size proportional to the number of investors in the bin. All estimates are based on data from 2021.

I. Blueprint for Other Tax Settings and Data

In the main text, we show how combining different data sets can be used to point-identify tax noncompliance and to construct informative bounds on the value of tax evasion. Our analysis focuses on a specific setting — the prevalence of crypto tax noncompliance and the value of crypto tax evasion in Norway. However, the methods used in our paper can be easily adapted to a wide range of other tax settings and data.

As most countries do not have a wealth tax, we focus in this appendix on a setting in which a researcher is interested in whether taxpayers declare a relevant income, rather than their asset holdings. Let U denote the broader population of interest. Let $B \subset U$ denote the subset of the population that receives the relevant income, for example, crypto gains or self-employment income. Let $A \subset B$ denote the subset that declares this income in their tax return.

Internet Appendix Table IA.XIV summarizes what a researcher can learn about tax noncompliance and the average value of tax evasion depending on the data at hand. We consider a wide range of parameters of interest and three types of data. The first data set collects information on how many in the broader population receive the relevant income and their characteristics (survey data). The second collects information on how many declare the income in their tax return, their characteristics, and the amounts declared (tax return data). The third collects information on actual incomes, whether declared or not, for example from crypto platforms or payment apps (transaction data).

The first seven rows show what the researcher can learn from survey and tax return data on the shares of the population that receive and declare the relevant income. Even without transaction data, the table shows that it is possible to identify the prevalence of tax noncompliance, both overall and broken down by observed individual characteristics, and to infer the distribution of characteristics among tax noncompliers.

The next eight rows show what a researcher can learn about tax noncompliance when transaction data on actual incomes are available. Given access to transaction and tax return data, the researcher can directly identify tax noncompliance among investors observed in the transaction data, for example, on crypto platforms or payment apps. When combined with survey data, the researcher can also infer tax noncompliance *outside* these platforms. If only survey and transaction data are available, the researcher can still draw inferences about where individuals accumulate the relevant incomes.

The last six rows show what a researcher can learn about the average value of tax evasion given access to tax return data, or to tax return data combined with Transaction data. The table shows that it is possible to construct bounds on the average value of tax evasion even without survey data. The conclusions depend not only on the data at hand but also on the assumptions one is willing to impose. In some settings, it may be reasonable to adopt strong assumptions that deliver point identification. For example, one may assume that declared incomes, on average, exactly equal undeclared ones, in which case the average value of tax evasion is point-identified from tax return data alone. In other settings, such as ours, these assumptions may seem too strong, in which case weaker assumptions can be imposed to obtain informative bounds instead.

Table IA.XIV. Blueprint: Identification Arguments

Let $B \equiv \{G > 0\}$, $A \equiv \{G^* > 0\}$, $A^C \equiv B \setminus A$, $D \equiv \{G^D > 0\}$ and $D^C \equiv B \setminus D$.

		Necessary data		
Parameter	**Identifying moments**	**Tax**	**Survey**	**Transactions**
Prevalence of tax noncompliance				
$P(A^C)$	$P(B) - P(A)$	$\checkmark$	$\checkmark$	
$P(A^C \mid B)$	$P(A^C)/P(B)$	$\checkmark$	$\checkmark$	
Characteristics of tax noncompliers				
$P(X \mid B)$	$P(B \mid X) \cdot P(X)/P(B)$		$\checkmark$	
$P(X \mid A)$	$P(A \mid X) \cdot P(X)/P(A)$	$\checkmark$		
$P(X \mid A^C)$	$P(A^C \mid X) \cdot P(X)/P(A^C)$	$\checkmark$	$\checkmark$	
Prevalence of tax noncompliance by individual characteristics				
$P(A^C \mid X)$	$P(B \mid X) - P(A \mid X)$	$\checkmark$	$\checkmark$	
$P(A^C \mid B, X)$	$P(A^C \mid X)/P(B \mid X)$	$\checkmark$	$\checkmark$	
Prevalence of tax noncompliance by venue				
$P(D^C)$	$P(B) - P(D)$		$\checkmark$	$\checkmark$
$P(A^C \cap D^C)$	$P(A^C) - P(A^C \cap D)$	$\checkmark$	$\checkmark$	$\checkmark$
$P(A^C \mid D^C)$	$P(A^C \cap D^C)/P(D^C)$	$\checkmark$	$\checkmark$	$\checkmark$
$P(A^C \mid D)$	$P(A^C \cap D)/P(D)$	$\checkmark$		$\checkmark$
$P(D \mid A^C)$	$P(A^C \cap D)/P(A^C)$	$\checkmark$	$\checkmark$	$\checkmark$
$P(D^C \mid A^C)$	$P(A^C \cap D^C)/P(A^C)$	$\checkmark$	$\checkmark$	$\checkmark$
$P(A^C \mid D, X)$	$P(A^C \cap D \mid X)/P(D \mid X)$	$\checkmark$		$\checkmark$
$P(A^C \mid D^C, X)$	$P(A^C \cap D^C \mid X)/P(D^C \mid X)$	$\checkmark$	$\checkmark$	$\checkmark$
Value of tax evasion				
$E[T \mid A^C]$:				
Lower	$E(T^D \mid A^C, D)$	$\checkmark$		$\checkmark$
Point	$E(T^* \mid A)$	$\checkmark$		
Upper	$1.05 \cdot E(T^* \mid A)$	$\checkmark$		
$E[T \mid A^C, X]$:				
Lower	$E(T^D \mid A^C, D, X)$	$\checkmark$		$\checkmark$
Point	$E(T^* \mid A, X)$	$\checkmark$		
Upper	$1.05 \cdot E(T^* \mid A, X)$	$\checkmark$		

J. Time Trends in Crypto Tax Noncompliance

In the main text, we report estimates of aggregate crypto tax noncompliance, $P(A^C \mid B)$, over the period 2018–2024. We find no evidence that $P(A^C \mid B)$ declines meaningfully over time. Under the model in Section VII, this implies that the net benefits of crypto tax compliance are relatively stable over time. In the following, we consider two alternative approaches to assessing time trends in crypto tax noncompliance.

The first approach uses data on individuals observed making wire transfers to foreign crypto exchanges, described in Internet Appendix Section G. Internet Appendix Figure IA.10 plots tax compliance for this group over the period 2018–2023. We find that tax noncompliance exceeds 70% throughout the period. Thus, the evidence again indicates that crypto tax noncompliance does not decline meaningfully over time.

The second approach uses data from domestic exchanges. For 2019–2021, we directly observe the number of investors present on the domestic exchanges, $P(D)$, and how many of them are also present in the tax return data, $P(A \cap D)$. We can therefore directly compute the rate of tax noncompliance on domestic exchanges, $P(A^C \mid D)$, each year 2019–2021. For later years, however, these moments are no longer observed.

To clarify the identification challenge, let Δ denote the change in a given data moment relative to 2021. For a given year t, $P(A_t^C \mid D_t)$ can be expressed as:

$$P(A_t^C \mid D_t) = 1 - P(A_t \mid D_t) = 1 - \frac{P(A_t \cap D_t)}{P(D_t)} = 1 - \frac{\overbrace{P(A_{21} \cap D_{21})}^{\text{Observed}} + \overbrace{\Delta(A \cap D)}^{\text{Unobserved}}}{\underbrace{P(D_{21})}_{\text{Observed}} + \underbrace{\Delta(D)}_{\text{Unobserved}}}.$$

Since we do not observe $P(A \cap D)$ or $P(D)$ after 2021, we cannot ascertain how many investors on the domestic exchanges subsequently enter or exit tax compliance, $\Delta(A \cap D)$, nor how many individuals enter or exit the domestic exchanges, $\Delta(D)$.

From the tax return data, however, we observe $\Delta(A)$, the change in the total number of individuals declaring crypto each year 2018–2023, and from the survey data we observe $\Delta(B)$, the change in the total number of crypto investors. Using this information, we can construct bounds and a point estimate for $P(A_t^C \mid D_t)$ after 2021.

To construct our lower bound, we assume that *all* new tax compliers after 2021 come from the domestic exchanges and that there is no growth in the number of investors on those exchanges: $\Delta(A \cap D) = \Delta(A)$ and $\Delta(D) = 0$. This yields a lower bound on $P(A_t^C \mid D_t)$ by maximizing the possible increase in compliance among domestic exchange investors. The estimates are shown in Internet Appendix Figure IA.11. Even under these extreme assumptions, noncompliance exceeds 65% in both 2022 and 2023.

To construct our upper bound, we assume that all new tax compliers after 2021 come from *outside* the domestic exchanges and that all changes in crypto adoption occur on domestic exchanges: $\Delta(A \cap D) = 0$ and $\Delta(D) = \Delta(B)$. This yields an upper bound on $P(A_t^C \mid D_t)$ by minimizing the possible increase in compliance among domestic exchange investors. The estimates are shown in Internet Appendix Figure IA.11. Under these assumptions, the noncompliance rate is around 90% in both 2022 and 2023.

To construct our point estimate, we assume that changes in both tax compliance and crypto adoption are split proportionally between domestic and other exchanges: $\Delta(A \cap D) = P(D_{21} \mid B_{21}) \cdot \Delta(A)$ and $\Delta(D) = P(D_{21} \mid B_{21}) \cdot \Delta(B)$, where $P(D_{21} \mid B_{21})$ denotes the share of Norwegian crypto investors trading on domestic exchanges in 2021, reported in Table III. The estimates are shown in red in Internet Appendix Figure IA.11. Under these assumptions, the noncompliance rate is around 80% in both 2022 and 2023, indicating that tax noncompliance does not decline meaningfully over time.

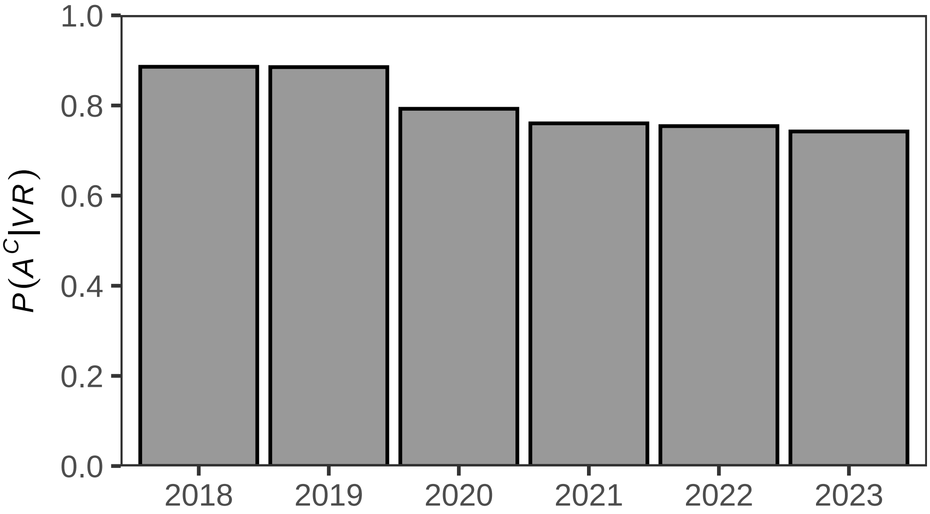


Figure IA.10. Trends in crypto tax noncompliance: International wire transfer data. The figure shows annual estimates of tax noncompliance among investors observed making wire transfers to foreign crypto exchanges (VR), described in Internet Appendix Section G.

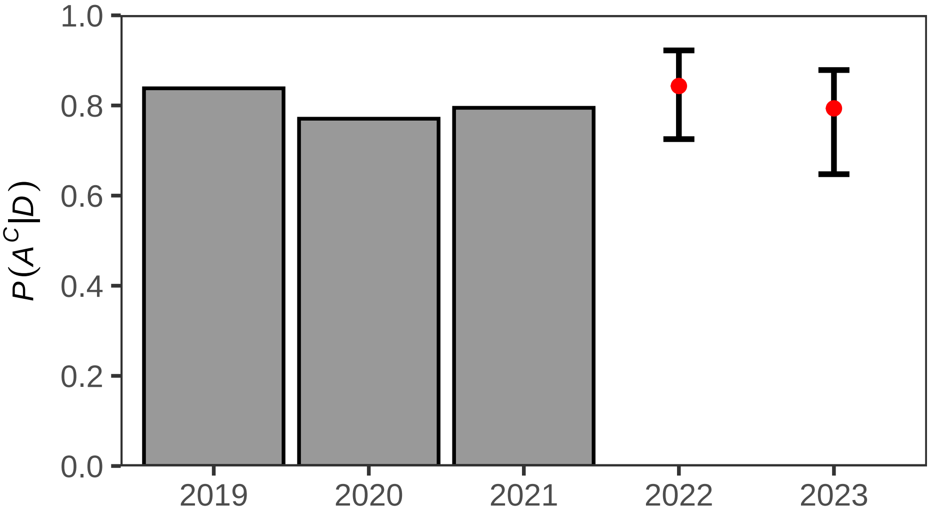


Figure IA.11. Trends in crypto tax noncompliance: Domestic exchange data. The figure shows annual estimates of tax noncompliance among investors on domestic exchanges (D). Brackets indicate lower and upper bounds and the red circles indicate point estimates.

K. Measurement Error in Model Estimation

In Section VII, we present a model of tax compliance and show how to recover the model parameters from data on individual investors' tax liabilities and tax compliance decisions. We focus on investors trading on domestic exchanges because, for these investors, we observe both tax liabilities and compliance decisions. Still, it could be that the tax liability observed on domestic exchanges, T^D, is measured with error.

We now assess the sensitivity of our parameter estimates to measurement error in tax liabilities. Assume the following relationship between the true tax liability, T, and the tax liability observed on domestic exchanges, T^D: $T = \alpha \cdot T^D$, where α captures the extent of measurement error. In Internet Appendix Table IA.XV, we re-estimate the model in Section VII for values of α ranging from 1 (no measurement error) to 2 (true tax liability twice the observed). Reassuringly, our key conclusions remain unchanged. We continue to find that fixed compliance costs are relatively high and vary considerably in the population, while Internet Appendix Figure IA.12 shows that the perceived probability of detection is increasing and concave in the crypto tax liability.

Table IA.XV. Sensitivity to Measurement Error in Model Estimation

			Sensitivity, $\alpha =$		
Name	**Symbol**	**1**	**1.3**	**1.5**	**2**
Average fixed compliance cost	μ_x	\$1917	\$1802	\$1659	\$1662
SD of fixed compliance cost	σ	\$1873	\$1781	\$1814	\$1794
Perceived probability of detection	$p_x(t)$	0.38	0.33	0.42	0.48
Fixed cost of detection	κ_x	\$958	\$998	\$266	\$238
Expected fixed cost of detection	$p_x(t) \cdot \kappa_x$	\$270	\$238	\$90	\$91
Expected variable cost of detection	$p_x(t) \cdot 1.2t$	\$334	\$502	\$610	\$810

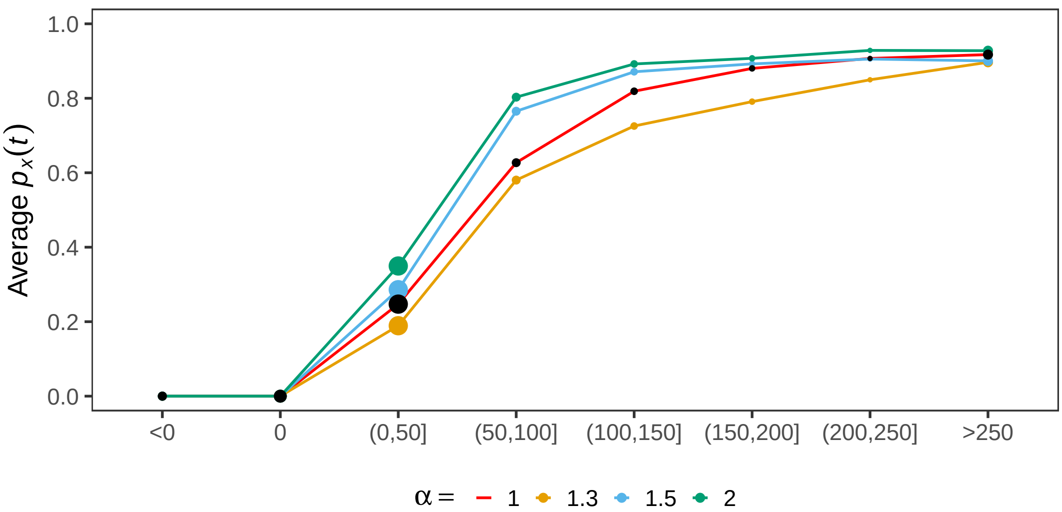
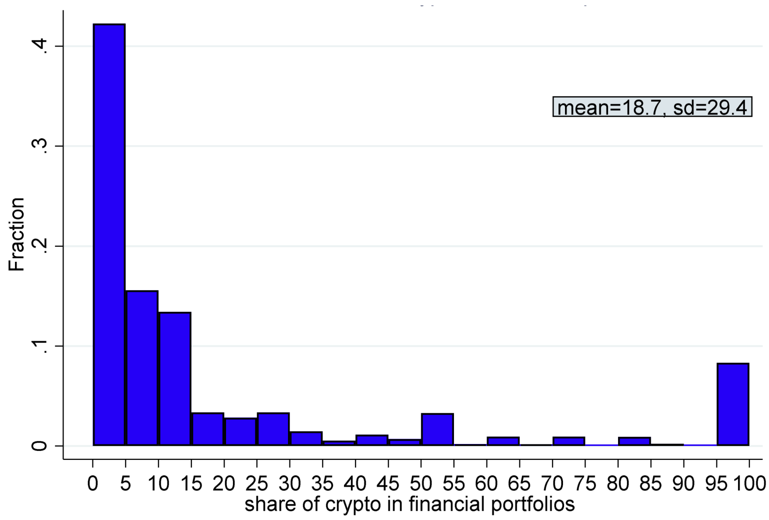
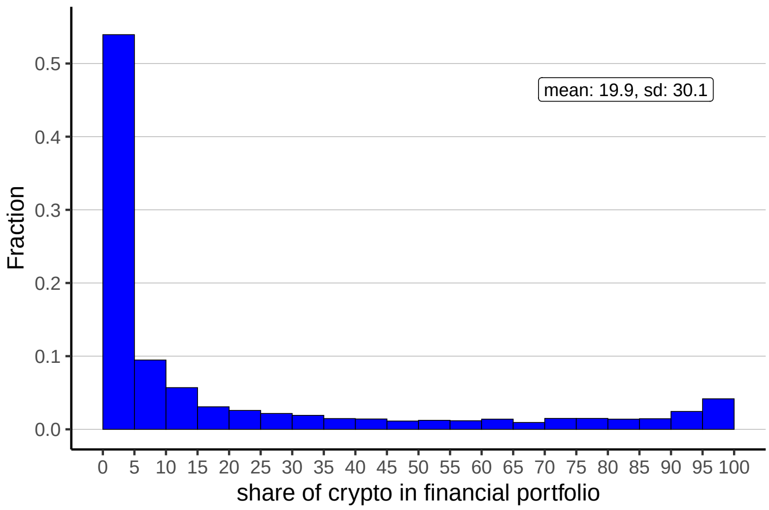


Figure IA.12. Sensitivity: Perceived probability of detection. This figure plots the average perceived probability of detection, $p_x(t)$, by bins of crypto tax liability, for different values of the measurement error parameter, α. The circles indicate the average $p_x(t)$ within each tax liability bin, with circle size proportional to the number of investors in the bin. All estimates are based on data from 2021.

L. Additional Tables and Figures



Panel A. American crypto investors' crypto holdings



Panel B. Norwegian crypto investors' crypto holdings

Figure IA.13. Crypto holdings: American and Norwegian investors. Panel A is a screenshot of Figure 2, Panel A from Weber et al. (2023), which is based on American survey data from the 2021 wave of the Nielsen Homescan Panel. The survey asked respondents, "*What percent of your financial wealth (excluding housing) do you invest in the following categories? Put '0' if you do not invest in a given category.*" The figure shows the distribution of wealth share responses for the category "*Bitcoin and other cryptocurrencies*" among respondents who report owning crypto. Panel B shows the corresponding distribution for Norwegian crypto investors calculated based on tax return data from 2021. Analogous to Weber et al. (2023), we calculate individuals' crypto wealth shares by dividing the value of their declared crypto holdings from their tax returns by their total financial wealth as reported in the tax returns.

Table IA.XVI. Oaxaca-Blinder Decomposition

This table decomposes the group-level differences in $P(A^C \mid X)$ in Panel A of Figure 2 into group-level differences in $P(B \mid X)$ and $P(A^C \mid B, X)$ using an Oaxaca-Blinder approach (Fortin et al., 2011).

		Gap Due To...	
Group Comparisons	$P(A^C \mid X_1) - P(A^C \mid X_2)$	$P(B \mid X)$	$P(A^C \mid B, X)$
X_1 = Male, X_2 = Female	0.068	0.073	-0.005
X_1 = Oslo, X_2 = Non-Oslo	0.035	0.037	-0.003
X_1 = Age: 15–29, X_2 = Age: 30–39	0.015	0.005	0.010
X_1 = Age: 15–29, X_2 = Age: 40–49	0.073	0.056	0.017
X_1 = Age: 15–29, X_2 = Age: 50+	0.079	0.079	0.000

Table IA.XVII. Alternative Definition of A

Column (1) presents our baseline estimates of the prevalence of crypto tax noncompliance, the characteristics of crypto tax noncompliers, and the average value of tax evasion. Table III summarizes the identification arguments. All moments are measured in 2021. In the main text, the set A includes those who declare positive crypto holdings ($V^* > 0$) and potentially crypto income ($G^* \in R$) in their tax return. Column (2) presents alternative estimates where we re-define A to include also those who declare $\{V^* = 0, G^* \neq 0\}$ in their tax return, that is, that they have exited crypto during the year.

	Baseline estimates	Include $\{V^* = 0, G^* \neq 0\}$ in A
Prevalence:		
$P(A^C)$	0.061	0.060
$P(A^C \mid B)$	0.881	0.874
Characteristics:		
$P(\text{Male} \mid A^C)$	0.781	0.780
$P(\text{Female} \mid A^C)$	0.219	0.220
$P(\text{Oslo} \mid A^C)$	0.193	0.193
$P(\text{Non-Oslo} \mid A^C)$	0.807	0.807
$P(\text{Age: 15–29} \mid A^C)$	0.407	0.407
$P(\text{Age: 30–39} \mid A^C)$	0.258	0.257
$P(\text{Age: 40–49} \mid A^C)$	0.099	0.098
$P(\text{Age: 50+} \mid A^C)$	0.237	0.237
Prevalence by X:		
$P(A^C \mid B, \text{Male})$	0.871	0.863
$P(A^C \mid B, \text{Female})$	0.920	0.917
$P(A^C \mid B, \text{Oslo})$	0.859	0.851
$P(A^C \mid B, \text{Non-Oslo})$	0.886	0.880
$P(A^C \mid B, \text{Age: 15–29})$	0.918	0.912
$P(A^C \mid B, \text{Age: 30–39})$	0.838	0.830
$P(A^C \mid B, \text{Age: 40–49})$	0.780	0.768
$P(A^C \mid B, \text{Age: 50+})$	0.918	0.913
Prevalence by trading venue:		
$P(A^C \mid D)$	0.795	0.790
$P(A^C \mid D^C)$	0.911	0.903
Value of Tax Evasion:		
$E[T \mid A^C]$: Lower	\$81	\$84
$E[T \mid A^C]$: Point	\$1,011	\$1,032
$E[T \mid A^C]$: Upper	\$1,062	\$1,084

Table IA.XVIII. Characteristics By Trading Venue

This table summarizes the characteristics of crypto investors by trading venue. All moments are measured in 2021. For any W_1, W_2, for example, A and D, we have that $P(X \mid W_1, W_2) = \frac{P(W_1 \cap W_2 | X) P(X)}{P(W_1 \cap W_2)}$.

	$P(X \mid D)$	$P(X \mid D^C)$	$P(X \mid A^C, D)$	$P(X \mid A^C, D^C)$	$P(X \mid A, D)$	$P(X \mid A, D^C)$
Male	0.830	0.776	0.825	0.767	0.846	0.869
Female	0.170	0.224	0.175	0.233	0.154	0.131
Oslo	0.168	0.209	0.156	0.205	0.216	0.250
Non-Oslo	0.832	0.791	0.844	0.795	0.784	0.750
Age: 15–29	0.472	0.362	0.520	0.372	0.288	0.257
Age: 30–39	0.265	0.273	0.246	0.262	0.336	0.393
Age: 40–49	0.143	0.101	0.126	0.090	0.208	0.205
Age: 50+	0.120	0.264	0.108	0.276	0.168	0.145

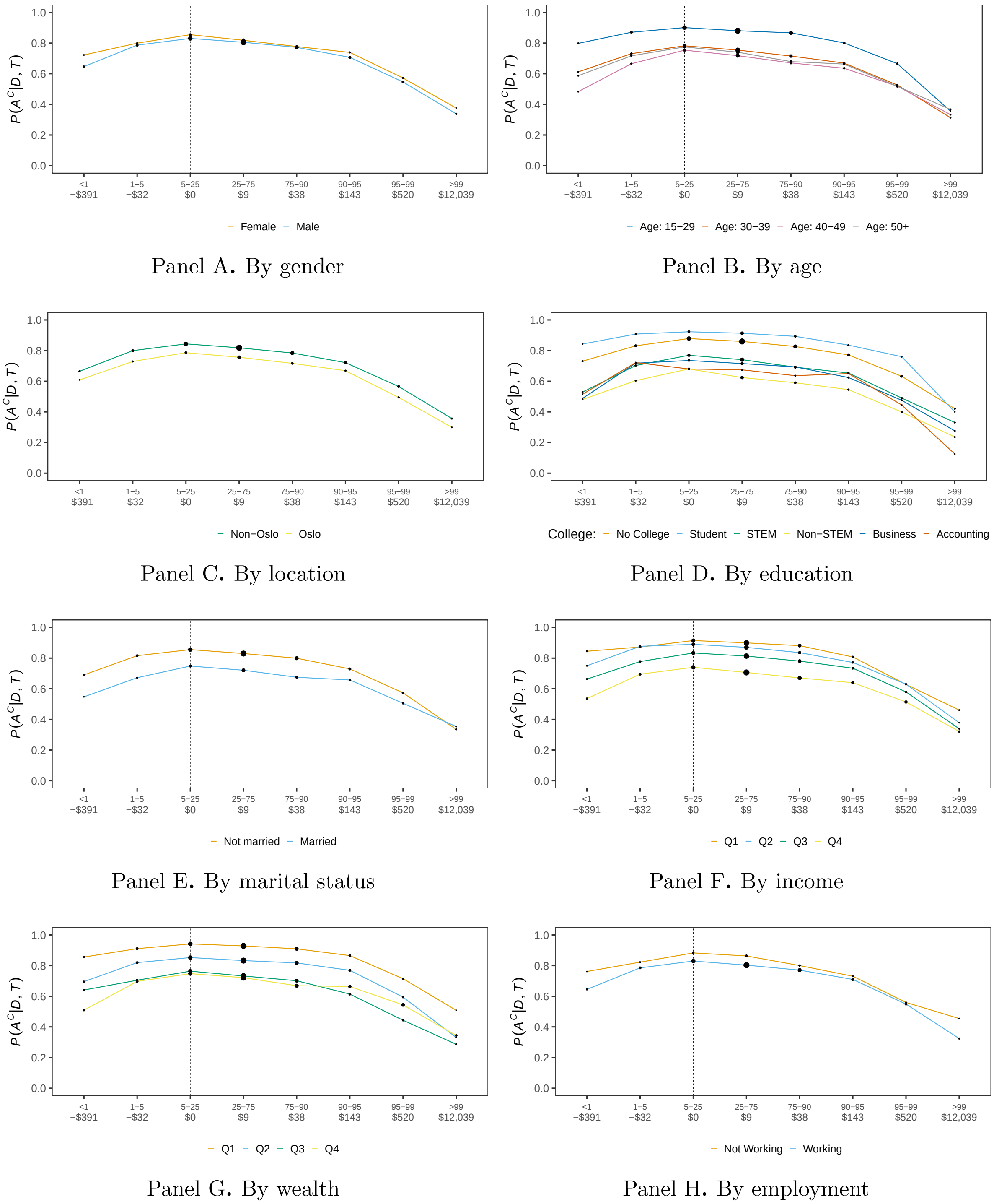
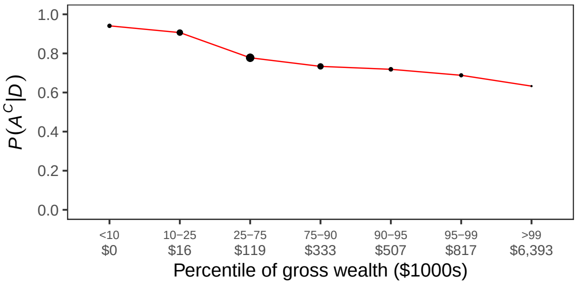
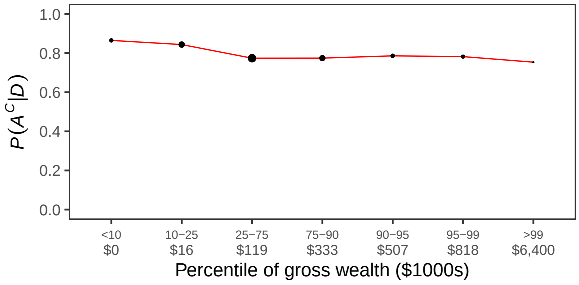


Figure IA.14. Data on tax noncompliance by tax liability and investor type. The figure plots $P(A^C \mid D)$, the observed rate of tax noncompliance among investors on domestic exchanges, by percentile bins of crypto tax liability and investor type. The black circles indicate the tax noncompliance within each tax liability bin, with circle size proportional to the number of investors in the bin. The lines connect the black circles. All moments are measured in 2021.

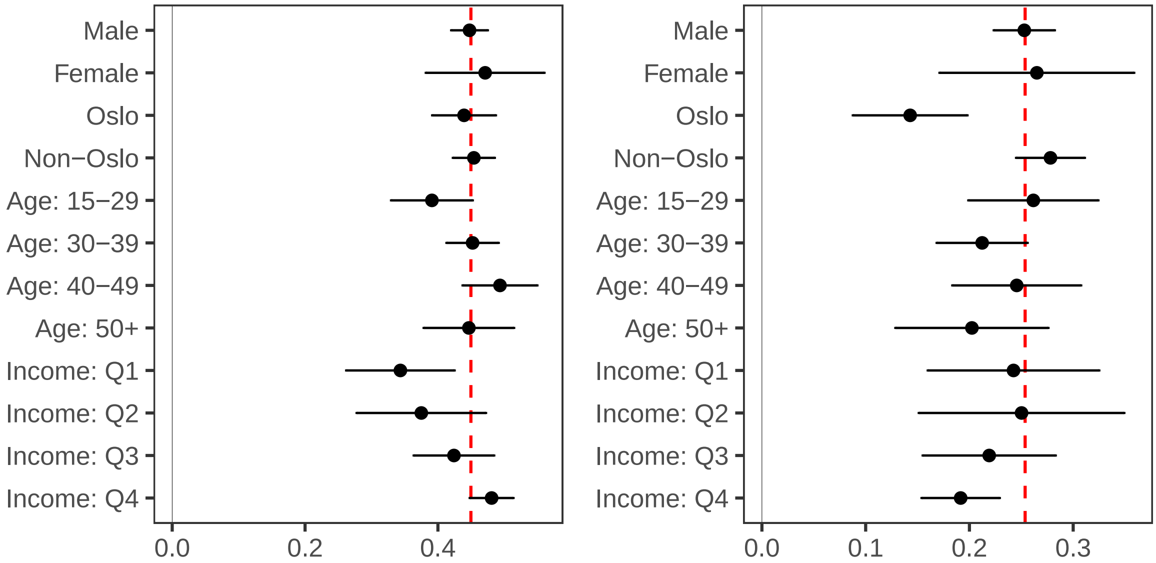


Panel A. No controls



Panel B. Controls

Figure IA.15. Tax noncompliance across the wealth distribution. The figure plots $P(A^C \mid D)$, the observed rate of tax noncompliance among investors on domestic exchanges, by percentile bins of investors' gross wealth. Panel A plots the raw data. Panel B plots the data after residualizing with respect to demographic characteristics, marital status, education, employment, income, and the domestic tax liability (T^D). The black circles indicate the average level of tax noncompliance within each percentile bin, with circle size proportional to the number of investors in the bin. The red line connects the black circles. All moments are measured in 2021.



Panel A. First-difference Panel B. Difference-in-differences

Figure IA.16. Effect of 2020 reminder letters by individual characteristics. The figure reports estimates of the effect on tax compliance of the 2020 reminder letter intervention. Panel A reports the raw change in tax compliance between 2019 and 2020 for letter recipients, estimated separately by individual characteristics. Panel B reports difference-in-differences estimates comparing the change in compliance between 2019 and 2020 for letter recipients and a control group of non-recipients, estimated separately by individual characteristics. The horizontal black lines indicate 95% confidence intervals. The vertical red lines indicate the (unconditional) mean effects across all letter recipients from Table VIII.

Table IA.XIX. Estimates By Year

This table presents estimates of the prevalence of crypto tax noncompliance, the characteristics of crypto tax noncompliers, and the value of tax evasion, by calendar year. Table III summarizes the identification arguments. We observe survey moments only in the years 2018–2019 and 2021-2023; survey moments for 2020 are interpolated as the average of the 2019 and 2021 survey moments.

	2018	2019	2020	2021	2022	2023
Prevalence:						
$P(A^C)$	0.047	0.041	0.053	0.061	0.089	0.071
$P(A^C \mid B)$	0.976	0.972	0.944	0.881	0.904	0.867
Characteristics:						
$P(\text{Male} \mid A^C)$	0.838	0.683	0.743	0.781	0.669	0.781
$P(\text{Female} \mid A^C)$	0.162	0.317	0.257	0.219	0.331	0.219
$P(\text{Oslo} \mid A^C)$	0.138	0.215	0.202	0.193	0.139	0.136
$P(\text{Non-Oslo} \mid A^C)$	0.862	0.785	0.798	0.807	0.861	0.864
$P(\text{Age: 15–29} \mid A^C)$	0.667	0.445	0.420	0.407	0.436	0.375
$P(\text{Age: 30–39} \mid A^C)$	0.169	0.309	0.281	0.258	0.333	0.376
$P(\text{Age: 40–49} \mid A^C)$	0.090	0.099	0.102	0.099	0.117	0.110
$P(\text{Age: 50+} \mid A^C)$	0.074	0.146	0.197	0.237	0.114	0.140
Prevalence by X:						
$P(A^C \mid B, \text{Male})$	0.974	0.962	0.933	0.871	0.881	0.858
$P(A^C \mid B, \text{Female})$	0.989	0.993	0.978	0.920	0.954	0.898
$P(A^C \mid B, \text{Oslo})$	0.950	0.962	0.926	0.859	0.853	0.802
$P(A^C \mid B, \text{Non-Oslo})$	0.981	0.974	0.949	0.886	0.913	0.878
$P(A^C \mid B, \text{Age: 15–29})$	0.991	0.984	0.967	0.918	0.947	0.921
$P(A^C \mid B, \text{Age: 30–39})$	0.941	0.959	0.921	0.838	0.896	0.872
$P(A^C \mid B, \text{Age: 40–49})$	0.949	0.945	0.893	0.780	0.831	0.757
$P(A^C \mid B, \text{Age: 50+})$	0.963	0.978	0.959	0.918	0.854	0.817
Value of Tax Evasion:						
$E[T \mid A^C]$: Point	\$282	\$9	\$458	\$1,011	–\$272	\$74
$E[T \mid A^C]$: Upper	\$296	\$10	\$481	\$1,062	–	\$78

Table IA.XX. Characteristics of Letter Recipients

This table compares the characteristics of recipients of the 2020 and 2022 Tax Administration reminder letters to those of the broader population of crypto investors in 2020 and 2022, respectively. Survey moments for 2020 are interpolated as the average of the 2019 and 2021 survey moments.

	Panel A. 2020 letters			Panel B. 2022 letters		
	$P(X \mid Z=1)$	$P(X \mid B)$	$\frac{P(X \mid Z=1)}{P(X \mid B)}$	$P(X \mid Z=1)$	$P(X \mid B)$	$\frac{P(X \mid Z=1)}{P(X \mid B)}$
Male	0.912	0.752	1.213	0.884	0.687	1.287
Female	0.088	0.248	0.354	0.116	0.313	0.370
Oslo	0.300	0.206	1.457	0.248	0.148	1.676
Non-Oslo	0.700	0.794	0.881	0.752	0.852	0.883
Age: 15–29	0.177	0.410	0.431	0.208	0.416	0.499
Age: 30–39	0.451	0.288	1.567	0.397	0.336	1.181
Age: 40–49	0.222	0.108	2.048	0.222	0.127	1.746
Age: 50+	0.150	0.194	0.775	0.174	0.120	1.443

Table IA.XXI. Effect of 2022 Reminder Letter on Tax Compliance

This table reports estimates of the effect on tax compliance of the 2022 Tax Administration letter intervention. The control group consists of all investors who hold crypto on the domestic exchanges in 2020 or 2021 and, like the treated group, do not declare crypto in their 2021 tax return. Control variables include age, gender, an indicator for residing in Oslo, an indicator for being married, education (in bins), employment status, gross wealth, total income, and total tax liability. Standard errors are reported in parentheses. Stars indicate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

	Tax return		
	2021	2022	Δ
$P(A)$: Treated group	0.000	0.413	0.413***
			(0.010)
$P(A)$: Control group	0.000	0.058	0.058***
			(0.001)
Difference in differences			0.355***
			(0.010)
Difference in differences with controls			0.324***
			(0.010)
N	64,934	64,934	64,934

Table IA.XXII. Optimal Targeting: Other Covariates

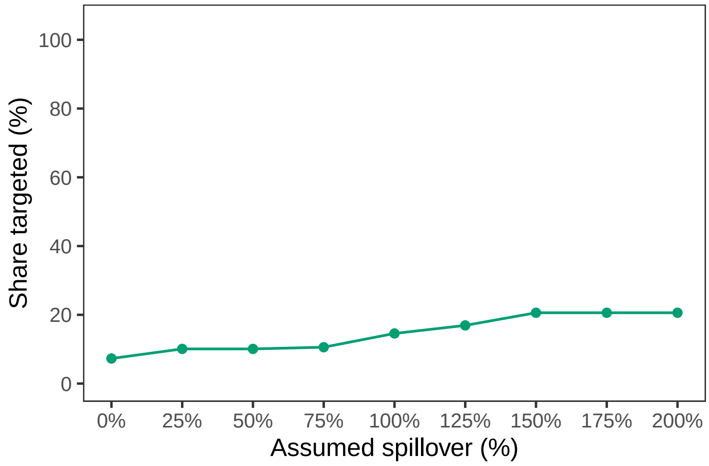
This table presents optimal audit strategies as determined by Program (27). In Panel A, Program (27) is solved using our point and bound estimates in Figure 10 of $\Delta_2(X)$, while in Panel B, the program is solved using our point and bound estimates of $\Delta_1(X)$. We solve the program using as our targeting variables (X) different combinations of age, taxable income, total declared capital income, and gross wealth. In each panel, Column (1) specifies the optimal targeting rule; Column (2) reports the average effect of audits on gross tax revenue among the optimally chosen target group of individuals, denoted by G; Column (3) reports the average effect on net tax revenue; Column (4) reports the share of the underlying population optimally targeted for audits; and Column (5) reports the total net tax revenue raised if all the individuals in G were audited, calculated as the product of the net audit effect and the number of individuals targeted by the rule in Column (1). All estimates are based on data from 2021.

Panel A. Targeting In The Broader Population

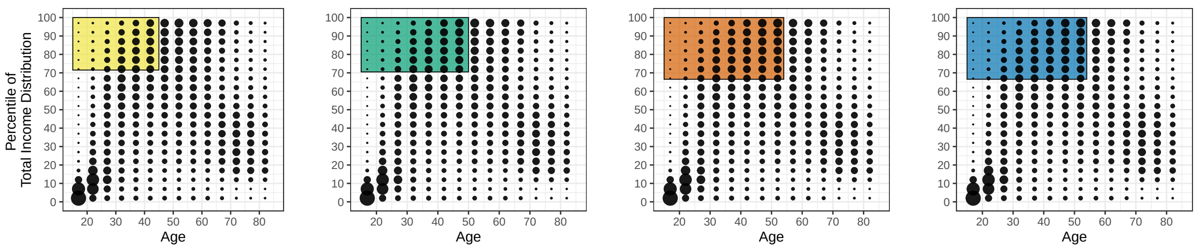
	Rule	$E[\Delta_2(X) \mid G, U]$	$E[\Delta_2(X) - c \mid G, U]$	$P(G \mid U)$	Total Net Revenue ($M)
Using Point Estimate of $\Delta_2(X)$					
Age (X_1) and Income (X_2)	$X_1 < 44$ and $X_2 \geq 76^{th}\%$	$360	$180	7.3%	$58.5
Age (X_1) and Capital Income (X_2)	$X_1 < 42$ and $X_2 \geq 56^{th}\%$	$225	$45	11.8%	$23.6
Age (X_1) and Wealth (X_2)	$X_1 < 52$ and $X_2 \geq 35^{th}\%$	$709	$529	3.7%	$87.4
Income (X_1) and Capital Income (X_2)	$X_1 \geq 4^{th}\%$ and $X_2 \geq 62^{nd}\%$	$499	$319	5.0%	$71.6
Using Upper Bound of $\Delta_2(X)$					
Age (X_1) and Income (X_2)	$X_1 < 44$ and $X_2 \geq 76^{th}\%$	$378	$198	7.3%	$64.3
Age (X_1) and Capital Income (X_2)	$X_1 < 42$ and $X_2 \geq 56^{th}\%$	$236	$56	11.8%	$29.5
Age (X_1) and Wealth (X_2)	$X_1 < 52$ and $X_2 \geq 35^{th}\%$	$744	$564	3.7%	$93.2
Income (X_1) and Capital Income (X_2)	$X_1 \geq 4^{th}\%$ and $X_2 \geq 54^{th}\%$	$462	$282	6.2%	$77.6
Using Lower Bound of $\Delta_2(X)$					
Age (X_1) and Income (X_2)	$X_1 < 45$ and $X_2 \geq 98^{th}\%$	$345	$165	0.17%	$1.2
Age (X_1) and Capital Income (X_2)	None Treated	$297	$117	0.05%	$0.2
Age (X_1) and Wealth (X_2)	$X_1 < 46$ and $X_2 \geq 94^{th}\%$	$269	$89	0.16%	$0.6
Income (X_1) and Capital Income (X_2)	$X_1 \geq 98^{th}\%$ and $X_2 \geq 98^{th}\%$	$284	$104	0.14%	$0.6

Panel B. Targeting Crypto Tax Noncompliers

	Rule	$E[\Delta_1(X) \mid G, A^C]$	$E[\Delta_1(X) - c \mid G, A^C]$	$P(G \mid A^C)$	Total Net Revenue ($M)
Using Point Estimate of $\Delta_1(X)$					
Age (X_1) and Income (X_2)	All Treated	$1011	$831	100%	$224.9
Age (X_1) and Capital Income (X_2)	All Treated	$1011	$831	100%	$224.9
Age (X_1) and Wealth (X_2)	All Treated	$1025	$845	100%	$225.1
Income (X_1) and Capital Income (X_2)	All Treated	$1011	$831	100%	$224.9
Using Upper Bound of $\Delta_1(X)$					
Age (X_1) and Income (X_2)	All Treated	$1061	$881	100%	$238.6
Age (X_1) and Capital Income (X_2)	All Treated	$1061	$881	100%	$238.6
Age (X_1) and Wealth (X_2)	All Treated	$1076	$896	100%	$238.8
Income (X_1) and Capital Income (X_2)	All Treated	$1061	$881	100%	$238.6
Using Lower Bound of $\Delta_1(X)$					
Age (X_1) and Income (X_2)	$X_1 \geq 26$ and $X_2 \geq 96^{th}\%$	$294	$114	5.0%	$1.5
Age (X_1) and Capital Income (X_2)	$X_1 \geq 27$ and $X_2 \geq 96^{th}\%$	$326	$146	4.7%	$1.9
Age (X_1) and Wealth (X_2)	$X_1 \geq 30$ and $X_2 \geq 66^{th}\%$	$400	$220	3.4%	$2.0
Income (X_1) and Capital Income (X_2)	$X_1 \geq 34^{th}\%$ and $X_2 \geq 78^{th}\%$	$464	$284	2.5%	$2.0



Panel A. Share of population targeted



Panel B. Targeting rules

Figure IA.17. Optimal targeting: Robustness to spillover effects of tax enforcement. This figure examines the sensitivity of our optimal audit targeting rule to increasing the upper bound on $\Delta_2(X)$ by 0% (baseline) to 200% (i.e., an expected audit effect three times larger than our estimates suggest). Panel A shows the share targeted by audits under different assumptions about the magnitude of spillover effects. Panels B–E show the corresponding optimal targeting rules for spillover effects of 50%, 100%, 150%, and 200%, respectively. All estimates are based on data from 2021.

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