Tax Sentiment and Compliance: Evidence from Social Media

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Abstract: Motivations for voluntary tax compliance that fall outside of a standard, rational model can be intrinsic or extrinsic. We use social media rhetoric about taxes to create a measure of tax sentiment that reflects taxpayers' extrinsic, behavioral motivations for voluntary compliance, and then examine the association between public tax sentiment and tax compliance. Our machine-learning based approach for measuring sentiment uses millions of tax-related tweets, which vary by time and geography. We find that tax sentiment is negatively associated with tax compliance. Our main findings and cross-sectional tests are consistent with the notion that paying one's taxes is a way to disassociate one's social identity from the tax evasion, inequity, and waste that are often the target of negative social ire. Overall, our study provides key insights on the evolution of tax-related discourse on social media and its association with tax compliance.

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1. Introduction

In this study, we examine the sentiment of tax-related discussions on social media and its relation with personal tax compliance. Tax policymakers, administrators, and researchers recognize that people pay taxes for a variety of reasons. In traditional tax compliance models, rational taxpayers make tax reporting decisions to maximize utility subject to a limited number of standard pecuniary factors (e.g., tax rates, detection risk, penalties; Allingham and Sandmo 1972). More recently, studies have introduced the notion that taxpayer compliance can be influenced by a variety of behavioral factors. The degree to which these factors collectively influence compliance is often referred to as tax morale. In a wide review of the literature, Luttmer and Singhal (2014) emphasize that tax morale is not a single concept, but an "umbrella term" capturing all behavioral motivations for voluntary tax compliance. Tax morale is difficult to observe because it includes such a wide array of compliance motivations—many of which are intrinsic and private. However, some determinants of tax morale are extrinsic, public facing, or inter-social. We label these as "tax sentiment," as they capture taxpayers' openly expressed feelings and attitudes towards major tax issues, authorities, and fellow taxpayers. We empirically capture these extrinsic determinants using social media, which has arguably become the primary location for public discourse on major events and social issues, including taxation.

We focus on two outward-facing, social motivations for voluntary compliance from the tax morale literature that are relevant to our research question: peer effects and reciprocity. Theory on peer effects of voluntary tax compliance suggests that one's utility from paying one's own taxes is influenced by perceptions of others' tax behavior. Relatedly, theory on reciprocity suggests that the utility a taxpayer experiences for paying their taxes varies with their observations of how the tax system operates, such as the provision of public goods or the overall equity of the tax system.

While these social motivations have been examined in prior literature, there is relatively little large sample evidence. Specifically, prior research has relied primarily on experiments (e.g., Blumenthal et al., 2001; Belnap et al., 2023) or survey data (Giaccobasso et al., 2022), which are usually smaller in scale and subject to inherent research limitations (e.g., self-reporting bias, demand effects) that limit the ability to measure social components of tax morale. We build on this literature by examining social motives for tax compliance in a venue built for social interactions, namely social media.[1]

We begin with a raw sample from Twitter of 186 million tax-related tweets in the United States spanning the period from 2014 to 2022.[2] We apply a machine learning model to capture the sentiment of users' views and attitudes towards tax issues and tax authorities. The model has been specifically trained on Twitter data by prior researchers (Liu et al., 2019; Barbieri et al., 2020) to extract sentiment from each tweet, while at the same time adjusting for emojis, sarcasm, and other language patterns that are inherent to Twitter. A portion of our sample of tweets also contains geographic tags, which allows us to capture localized variation in tax sentiment and aids in data validation and empirical identification. After sample requirements to ensure data validity and accurate geolocations, the primary sample contains over 3 million tax-related tweets that have been liked more than 100 million times.

Descriptively, our new measure of tax sentiment offers several unique insights. First, we find that the prevalence of tax-related discourse on social media has substantially increased over the past decade, as the fraction of total tweets that are tax-related has increased nearly 300% from the start to the end of the sample period. Moreover, relative to other major topics discussed on Twitter, tax-related tweets are surprisingly common.[3] Second, we find that tax sentiment on social media has

[1] We acknowledge that our conceptualization of tax sentiment is inherently tied to the venue in which it is measured, social media. Thus, all stated references to these constructs throughout the paper relate to tax sentiment on social media.
[2] The platform, Twitter, has been recently renamed, X. Because it was called Twitter throughout our sample period, and because it is still often referred to as Twitter, we maintain usage of this name throughout the paper. We discuss the strengths and limitations of using Twitter in Section 3. Although Twitter is not perfectly representative, it is used by nearly one fourth of Americans (Pew, 2021b) and arguably represents the social media venue most likely to host public discussion about tax-related issues. Because of Twitter's user base, the measure is largely U.S. centric, and appeals to the younger and more urban. Also, it varies on a daily basis and over geographies. Both of these features of the data stand in stark contrast with the aggregate, full-country measures used in prior literature (e.g., OECD 2019). While there are inherent tradeoffs made by focusing on a measure with these attributes, we believe these characteristics make the measure useful to researchers and policymakers.
[3] For example, from March 9-14, 2024, two of the most common are topics are Israel/Palestine and Russia/Ukraine, which have 10.1m and 4.6m tweets, respectively. Over the same period there are 2.2m tax-related tweets—roughly

become increasingly negative over the sample period, with the largest drop in tax sentiment occurring during 2016, during and after the election of President Trump. Third, we find that the sentiment with respect to several controversial tax issues – such as taxing the rich, tax inequity, wasting tax dollars, and the release of President Trump's tax returns – is significantly more negative than other tax issues; meanwhile, sentiment related to tax refunds is significantly more positive than other tax issues. Fourth, we find that approximately two-thirds of the 1,000 most-liked Tweets at the end of our sample are authored by politically motivated sources—and that number is a significant shift from the start of our sample when 65% of the 1,000 most-liked tax tweets came from journalists.

Overall, these descriptive features of tax sentiment demonstrate its potential to capture variation in the feelings and attitudes of taxpayers towards major tax issues, tax authorities, and other taxpayers. Ultimately, theories of tax morale seek to address why taxpayers *voluntarily* pay taxes. Luttmer and Singhal (2014) identify several categories of tax morale theories, two of which are suitable for our setting: peer effects and reciprocity. Language reflective of both mechanisms is highly evident in our data, as on average, users commonly express disapproval of other groups' tax behavior (peer effects) or frustration with the government's tax system and use of funds (reciprocity).

Peer effects can have either positive or negative influences on tax compliance, depending on whether taxpayers want to associate or disassociate with other taxpayers. As taxpayers become increasingly and publicly negative about tax issues, compliance decreases as taxpayers follow other taxpayers' examples of non-compliance (Hallsworth et al., 2017). In contrast, peer effects may induce taxpayers to disassociate with other taxpayers' activities. Social identity theory predicts that people self-categorize into groups with like-minded beliefs and then take actions that reinforce their social identity and distance themselves from those in other groups with different beliefs (e.g., Tajfel 1974).

equivalent to the number of tweets about American football or cats. Due to data restrictions beginning in March 2023, Twitter currently users have access only to tweets from the last seven days. We discuss these data restrictions in Section 4.1.

If some taxpayers disapprove of the tax-related stances or behaviors of an individual or group, they may seek to disassociate themselves from that individual or group.[4] Under this argument, the decline in tax sentiment on social media could be associated with greater tax compliance (e.g., Wenzel 2002; Wenzel 2004).

We also consider the role of reciprocity, which suggests that people's willingness to voluntarily pay taxes should increase in perceptions that the system is fair and the government will act in the citizens' interest (e.g., Giaccobasso et al., 2022). The notion of reciprocity predicts a direct association between tax sentiment and compliance. That is, under the notion of reciprocity, as tax sentiment worsens, tax compliance could also decrease as trust in the state erodes.

To empirically examine the link between the sentiment of tax issues on social media and tax compliance, we develop a novel method for estimating localized tax compliance. We build on the intuition in other studies that model abnormal or unexplained components of various variables (e.g., discretionary accruals or abnormal audit fees) in what Slemrod (2019) calls a "traces of income" approach to measuring tax compliance. We follow the guidelines in Chen et al., (2018) to estimate abnormal taxable income in a single model, in which reported taxable income is a function of factors related to economic income, as well as tax sentiment. To the extent that tax sentiment is significantly associated with reported taxable income, after controlling for factors of economic income, our results would suggest that tax sentiment is associated with tax compliance.

This analysis relies on both time-series and geographic variation. As a result, we gather data from government surveys of quarterly economic income at the county-year level, reported taxable income at the county-year level from the IRS, and the usage of Twitter in a given county-year. We

[4] For example, if individuals dislike the idea of Donald Trump avoiding taxes, for example, they may reduce their own avoidance behavior to disassociate themselves from Donald Trump and his supporters. Michelle Obama exemplified this general thought process in a 2016 Democratic National Convention speech where she famously said, 'When they go low, we go high."

follow prior literature in measuring overall Twitter activity (both tax and non-tax) at the county-year level (e.g., Kinder-Kurlanda et al., 2017 and Müller and Schwartz, 2023). Our fixed effect structure (county and year, or county and state-year) accounts for standard compliance determinants (e.g., tax rates, perceptions of detection risk, penalties) and our control variables account for changes in economic income (e.g., local economic measures like GDP and wages).

In summary, we find evidence consistent with negative peer effects and social identity theory, in that tax sentiment is negatively associated with reported taxable income after controlling for the economic conditions in the county. In other words, the evidence suggests that as the tone of tax discussion on social media worsens, local tax compliance increases—and only among the types of income that are easier to underreport (i.e., non-wage income, self-reported business income, and income from partnerships and S-corporations). In a falsification test, we find no association between tax sentiment and wage income, which has little room for discretion in tax reporting because of third-party reporting (Kleven et al., 2011). Collectively, these results are consistent with dissociative social identity theory, in that tax compliance is a reinforcing action one takes to disassociate oneself from aggressive tax practices reflected in social media.

We conduct several additional analyses to examine variation in peer effects in the data. First, we define several categories of tax-related tweet topics, examine the sentiment of tweets about these tax topics, then examine whether discussion of these tax topics is associated with more or less tax compliance. Of note, we find that localized discussions regard topics related to tax policy, taxing companies, tax fairness, and Donald Trump's taxes all have overwhelmingly negative sentiment, but are positively associated with tax compliance. Further, we find that the negative association between tax sentiment and tax compliance is concentrated within the time period of the Trump Administration. An interpretation of the results, therefore, suggests that as President Trump's perceived negative antics towards his own personal taxes were reflected in social media, it had the effect of increasing tax compliance.

Other analyses also provide corroborating evidence of negative peer effects in increasing local tax compliance. We find that the use of paid preparers moderates the influence of peer effects on tax compliance and that households with relatively more income exhibit a more negative association between tax sentiment and tax compliance. We find that counties that are more likely to socially disassociate with aggressive tax ideas reflected in social media (e.g., Democrat-majority counties) exhibit a more negative association between tax sentiment and tax compliance. Finally, we find that the results are consistent using both a quasi-natural shock to Twitter usage as well as a Bartik instrument, both of which strengthen the causal link between tax sentiment and local tax avoidance. Overall, the results paint a consistent picture of a negative association between tax sentiment and local tax compliance, supporting the notion that taxpayers increase tax compliance in order to disassociate themselves from a group of perceived tax avoiders, which is consistent with theories related to peer effects and social identity.

Our paper makes several contributions. First, the paper sheds new light on theories of tax morale that help fill in the evidential gaps as to why taxpayers voluntarily pay taxes. Tax morale is an extremely broad concept that essentially captures all non-pecuniary motivations for tax compliance (e.g., intrinsic motivation, reciprocity, peer effects, culture, information imperfections), and it is generally thought that proxies of tax morale and its mechanisms are strictly positively related to tax compliance. Our result, however, suggest that negative sentiment about tax issues on social media can actually be related to greater tax compliance. These robust results arise in our specific setting, social media, which is uniquely suited to examine peer effects and reciprocity as channels for voluntary tax compliance

Second, we develop a granular measure of tax sentiment using social media. In recent research, social media has been shown to influence the dissemination, amplification, and polarity of users' perceptions of important social issues, varying from grass roots protest campaigns and political fundraising to racism and xenophobia (e.g., Müller and Schwarz, 2023). In tax research, researchers have long sought to capture individuals' perceptions of tax issues but lack granular measures (e.g., localized or daily) that result from unprompted discourse. Our measure demonstrates substantial variation over time and places, and our descriptive evidence provides new insights into the issues, users, and conditions that drive variation in taxpayer sentiment on social media.

2. Background and Hypothesis Development

2.1. Tax Sentiment

We define tax sentiment as the tone of publicly expressed feelings and attitudes towards major tax issues and other taxpayers. As such, tax sentiment is a determinant of tax morale that captures the extrinsic, public-facing, or inter-social motivations for tax compliance. We measure tax sentiment using the general tone of all tax discussions on Twitter.

Tax sentiment, as we measure it, possesses unique features that capture tax morale channels related to either peer effects or reciprocity. First, because it is based on social media, it allows users to connect, debate, and share sentiments about tax issues with other users. Peer effects inherently rely on social interactions regarding taxation, which social media can capture broadly. Second, the setting (Twitter) exposes users to a wide variety of other taxpayers' actions and views, some of which they will agree with and others they will not. The variation in tax-related, user-generated content, derived from all sorts of users, including influencers, politicians, thought leaders, academics, or even vocal citizens, makes it a useful setting for examining peer effects.

Similarly, tax sentiment reflects users' attitudes and perceptions of a broad variety of tax issues, ranging from tax refunds to tax preparation to corporate taxation to outright tax evasion. Finally, it captures users' perceptions of the interaction between tax policy issues and other social issues, such as welfare, entitlements, legal boundaries, and human rights. These latter features allow the data to speak directly to the theory of reciprocity, which requires a measure of attitudes and perceptions of tax authorities and government use of tax dollars.

2.2. The Link between Tax Sentiment and Tax Compliance

What motivates taxpayers to voluntarily pay their taxes? Most research in this space starts with the work of Becker (1968) and Allingham and Sandmo (1972), both of which use rational, economic models of an individual who maximizes the expected utility of a tax evasion gamble. The intuition from these models is rather straightforward: an increase in the probability of detection or the penalty rate for getting caught increases the likelihood that the taxpayer complies with tax law. There are two challenges to this particular model. First, realized rates of compliance are much higher than would be predicted based on detection rates, penalties, and perceived risk aversion of taxpayers (e.g., Graetz and Wilde, 1985; Torgler, 2007; Alm, 2019). Second, the standard compliance model is based primarily on pecuniary incentives, which fail to recognize that individuals can derive utility from nonpecuniary sources. As a result, a growing literature has moved beyond the standard rational approach and considered more behavioral explanations for understanding tax compliance.

In public economics, the umbrella term for these non-pecuniary motives for tax compliance is *tax morale*. It represents the many plausible non-economic reasons why taxpayers remit more taxes than would be expected by rational models given a particular tax rate, detection risk, and penalty (e.g., Torgler, 2007; Luttmer and Singhal, 2014; Slemrod, 2019; Besley, Jensen, and Persson 2023).

However, measuring tax morale is not without its challenges. Because tax morale is inherently an "error term" concept that captures all compliance not attributable to rational incentives, it is difficult to observe or infer in real time.[5] Prior work has tried to proxy for tax morale, but the best available measures have been static and highly aggregated (e.g., Slemrod and Weber, 2012; DeBacker et al., 2015). Experimental work in the lab or field has provided some compelling evidence that taxpayer morale has implications for tax compliance (see Slemrod, 2019 for a review), but these studies also face challenges related to effect sizes, representativeness, priming, and external validity.[6] Further, some have argued that experimental manipulations of tax morale in the field or in the lab have lacked power, which has led to a series of null result findings regarding the prevalence of tax morale (e.g., Luttmer and Singhal, 2014). Tax authorities have also acknowledged the potential for tax morale to impact compliance, and have argued that understanding the tax morale of both individuals and entities will round out our understanding of tax compliance (OECD, 2019; OECD, 2022). But these same tax authorities have lamented the lack of data to better analyze important aspects of tax morale (OECD, 2019).

In short, while prior literature has examined several mechanisms for tax morale in small or experimental settings, it lacks broad sample evidence of what determines tax morale nationally. Our study seeks to provide that evidence. We focus on two behavioral mechanisms that could shed light on the implications of increasingly negative tax sentiment for tax compliance, each of which is highlighted as a major channel through which tax morale can operate by Luttmer and Singhal (2014).[7]

[5] Some elements needed to quantify tax morale are readily observable (e.g., current tax rates). Others are more problematic. For example, quantifying tax morale in real time would require knowing the amount of income a taxpayer will report in the future, their true income, and their perception of tax detection risk.

[6] Even in recent advances, such as open-ended surveys (Ferrario and Stantcheva, 2022), researchers prompt participants into thinking about specific issues that are of interest to the researcher, potentially biasing the responses and robbing the participants of expressing their true, unadulterated perspectives on tax issues.

[7] Luttmer and Singhal (2014) identify three other mechanisms that can affect tax morale, including intrinsic motivation, cultural factors, and information imperfections. The authors acknowledge that these mechanisms are not mutually exclusive and are in fact likely to interact and overlap with each other (p. 155) – we echo these acknowledgements. In focusing on peer effects and reciprocity, we choose to focus on the mechanisms that we believe best suit our setting and data. These are also mechanisms where the results from prior research are quite mixed, so we can add new evidence to the field.

The first is *peer effects*. Peer effects influence compliance by imposing pressures to conform to societal norms of paying (or not paying) one's taxes. Peer effects manifest via one's social identity, as a taxpayer's self-perceptions positively resonate with the ideas of some groups and negatively resonate with other groups' ideas. Social identity theory rests on the notion that individuals will identify as of being part of an in-group or out-group, and will also take actions to self-categorize or reinforce one's own identity with respect to a given group (Tajfel, 1974). For instance, a person wanting to identify as physically fit will often self-categorize with groups that represent fitness and take actions accordingly (e.g., by attending a gym). Consistent with the view that social identity is central to self-regulation (Oyserman, 2007), one's social identity could influence their tax-paying behavior. Specifically, as tax sentiment on social media reflects negative attitudes towards tax evasion, tax inequity, and those who evade taxes, it creates incentives for individuals to take actions to identify and associate themselves with a favorable in-group (e.g., the general public), as well as actions that disassociate themselves with an undesirable out-group (e.g., tax evaders or those who contribute to tax inequity). Through the lens of social identity theory, when public tax sentiment on social media is overwhelmingly negative, tax compliance is the mechanism by which individuals can associate themselves with a favorable in-group and distance themselves from an unfavorable out-group (Wenzel 2002). In other words, social identity theory would suggest that decreases in tax sentiment would be associated with increases in tax compliance.

The second behavioral mechanism by which tax sentiment could affect tax compliance is the notion of *reciprocity*, which suggests that taxpayer behavior depends on the extent to which taxpayers perceive that governments will act fairly and in taxpayers' interests (Slemrod, 2019; Cullen et al, 2021; Besley, 2021). If taxpayers trust and believe that governments will reciprocate trust and good behavior, then people are more likely to become "contingent consenters" who pay taxes despite the individual not having short-term, rational incentives to do so. Levi (1989) refers to this idea of compliance as one of "quasi-voluntary compliance," as taxpayers voluntarily choose to comply with taxes because of an implied social contract with the government.

The directional effects of these mechanisms on the association between tax sentiment and tax compliance is nuanced and depends on which effect is dominant in the data. On the one hand, the notion of reciprocity suggests that tax compliance is increasing in perceptions that the system is fair and the government will act in the citizens' interest (e.g., Giaccobasso et al., 2022). That is, under the notion of reciprocity, as tax sentiment worsens (which it has over the sample period), tax compliance could decrease as trust in the state decreases. On the other hand, to the extent that tax sentiment motivates taxpayers to reinforce their social identities by shunning certain aggressive tax practices or creates a social identity that disassociates with certain taxpayers (e.g., the wealthy or Trump), it can be negatively associated with tax compliance (e.g., Wenzel 2002). Thus, whether behavioral motives related to reciprocity or social identity dominate the association between tax sentiment and tax compliance is an empirical question.

These arguments lead to our hypothesis, stated in null form:

H1: Tax sentiment is not associated with tax compliance.

3. Measuring Tax Sentiment on Social Media

3.1. Background on Data

Researchers and pollsters have long used surveys to gather perceptions about various aspects of the tax system. Relative to these methods, our measure of tax sentiment from social media has several advantages for studying how taxpayer perceptions are associated with tax compliance. First, while surveys can provide a snapshot of solicited opinions for a sample of participants at discrete points in time, Twitter data captures ongoing and continuous tax sentiment over time and at the daily level for millions of users. Second, far more people use Twitter than any survey can possibly hope to capture. According to the Pew Research Center, 23% of Americans state that they use Twitter, of which approximately 70% say that they use Twitter as a source of news (Pew, 2021a; Pew 2021b). Further, while inferences using surveys are valid, surveys rarely capture sufficient geographic variation to reliably infer whether mechanisms of tax morale are related to tax compliance. Third, using Twitter eliminates demand effects—where survey questions or field experiment interventions prime participants into overstating the importance of the subject matter presented to them. Asay et al., (2024) provides evidence of this occurring in a tax setting. Twitter, on the other hand, does not involve researcher interventions and allows a window into the public's unvarnished perceptions about taxes.

The primary weakness of Twitter data is its potential lack of representativeness or generalizability. Relative to the general population, Twitter users are more likely to be young, wealthy, and college educated (Pew, 2021b). Further, Twitter users are more politically left-leaning than average, but perhaps less than one might expect (Pew, 2019). It is therefore likely that some of the inferences about what influences the tax sentiment of Twitter users may not generalize to the population more broadly. However, Pew Research discusses that Twitter users themselves exhibit a "sizeable diversity," highlighting the heterogeneity in demographics of Twitter users (Pew, 2019). That is, Twitter exhibits more demographic variation than pundits often give it credit for. Given the size and prevalence of social media, as well as its potential for virality, extremity and polarization, understanding the tax sentiment of this subset of the population is still a valuable exercise.

3.2. Data Collection and Criteria

At the time of our data collection, Twitter provided free access to its API for academics to collect up to 10 million tweets per month.[8] Users specified a query for keywords in a tweet and could

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[8] https://web.archive.org/web/20230520042703/https://developer.twitter.com/en/products/twitter-api/academic-research. This program ended in July 2023 and was replaced by a costly subscription service (e.g., the "Pro" subscription provides access to 1 million tweets per month at a cost of $5,000 per month) that only permits access to tweets over the prior seven days. We collected Twitter data between June 2022 and April 2023 under the discontinued academic program.

collect information about who made a tweet, when it was made, how many likes, retweets, and quotes it received, among other data.[9] We collect all tweets that mention the word "tax" between the years, 2014 and 2022.[10] This process yields a raw dataset of 186 million tweets with the word "tax" in them. Those tweets are liked over a billion times, suggesting a wide breadth of exposure for these tweets. Furthermore, the tweets provide basic information such as the author, the number of likes, the number of retweets, and, if the user has disclosed their location, the location where the tweet was made. We use these raw data only for Figure 1, all other figures and tables are based on more refined samples, which we discuss next.

For our primary sample, we require that tweets contain geo-location data identifying where the tweet was made in order to examine the relation between tax sentiment and tax compliance. This limits the analysis to about 3.1 million tax-related tweets that provide sufficient location information to be linked to a U.S. county. There are several other factors that support this decision. The first is tractability; by reducing the sample of tweets to 3.1 million with geo-location data, it becomes technically feasible to apply machine learning to develop our primary measure of tax sentiment. Second, by requiring geo-location data, we reduce the concern our results could be driven by automated bots, which have a prominent history on Twitter. Prior literature has found evidence that a significant amount of bot activity originates outside of the United States (e.g., Elmas et al., 2021); meaning that requiring a tweet to originate from the United States can mitigate concerns about bots.[11] Tables 2, and 4 to 11, and Figures 4 to 7 use this sample.

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[9] For a full list of all available data on tweet objects see: https://developer.twitter.com/en/docs/twitter-api/data-dictionary/object-model/Tweet

[10] The specific query that we run is: "(tax OR taxes OR taxing OR taxpayer OR taxman OR taxed) (-is:reTweet lang:en -is:nullcast)". Because there are frequent server errors when collecting tweets, often times code was interrupted and would need to be restarted by hand. If tweets were missed when restarting the query, this may lead us to miss a few tweets during the sample period. We have recollected data when there is more than a few second gap between tweets, but it is impossible to determine whether a few second gap between tweets is due to a data error or because there were in fact no such tweets.

[11] As an additional step to mitigate concerns about bots, we drop the top 0.1% of authors with the most tweets and any tweet that has been repeated verbatim 100 times or more.

Because the amount of attention any tweet receives is highly skewed, with a few select tax tweets being given nearly all of the attention on any given day, we construct a secondary sample of the top 1,000 most liked tweets per day, regardless of whether they contain geographic information or not. This likewise yields a sample of roughly 3 million tweets. While this sample does not exhibit geographic variation, it provides us with information about which tweets and users have been the most influential. Tables 1 and 3, and Figure 3 use this sample.

3.3. Measuring Tax Sentiment

Conceptually, tax sentiment reflects the tone of users' attitudes and perceptions of tax issues on social media. To operationalize this construct, we use machine learning to convert the tweets into a measure of tax sentiment. To do so, we employ a fairly unique machine learning methodology. Tweets are limited to very short sentences, with a limit of 140 or 280 characters. Further, tweets often use emojis, misspellings, sarcasm, and nuance. These issues combine to make it difficult to appropriately train data and to apply commonly-used measures of tone (e.g., Loughran and McDonald, 2011). Instead, to capture tax sentiment, we use a machine learning classification model from Barbieri et al., (2020) that was developed specifically for use on Twitter data and is based around the RoBERTa transformer-based language model (Liu et al., 2019). Transformer-based language models are initially trained on a large set of unlabeled textual data, and then can be further calibrated to perform well in specific contexts.[12] Barbieri et al., (2020) calibrate the RoBERTa model to classify sentiment on Twitter data. By being pretrained on Twitter, Barbieri et al.'s model is calibrated to provide accurate sentiment classifications on Twitter. By applying the Barbieri et al., (2020) model, we end up with a probability that a tweet is positive, negative, or neutral.[13]

[12] Other examples of transformer-based language models include generative pre-trained transformer (GPT, the foundation of ChatGPT) and bidirectional encoder representations from transformers (BERT).
[13] Before applying the Barbieri et al., (2020) model, we make tweets lower case, and then filter tweets to remove "@" references, link references, dollar values, and various symbols that do not convert to words.

We define *Tax Sentiment* as the probability that a tax tweet is positive minus the probability that it is negative; we take the average for a given county-year. The distribution of *Tax Sentiment* is centered at 0.5 (neutral), and ranges from 0.0 and 1.0, with 0.0 capturing highly negative tax tweets and 1.0 capturing highly positive tax tweets.

We also create several refined measures that capture variation in tax sentiment by topic. These measures relate to tax-related topics that we have identified as being potentially controversial and/or capture issues that social media users seem to talk about.[14] Note that all measures are within the set of tweets that already contain the word "tax," and therefore they capture categories linked to tax issues. The categories are defined as follows:

> *Taxing companies* – an indicator for all tax-related tweets that contain words related to companies (e.g., "company", "corporation", "business")
>
> *Trump returns* – an indicator for all tax-related tweets that contain words related to the release of Donald Trump's tax returns (e.g., "Trump" or "release", along with the word "return")
>
> *Taxing the rich* – an indicator for all tax-related tweets that contain words related to taxing the rich or wealthy (e.g., "the rich", "one percent", "*illionaire")
>
> *Tax inequity* – an indicator for all tax-related tweets that contain words related to inequity of taxes (e.g., "fair share", "rigged", "unfair")
>
> *Non-tax policy* – an indicator for all tax-related tweets that contain words related to non-tax policy or social issues (e.g., "military", "racism", "medicare")
>
> *Tax waste* – an indicator for all tax-related tweets that contain words related to wasting tax funds (e.g., "waste", "taxpayer money", "misspend")
>
> *Tax policy* – an indicator for all tax-related tweets that contain words related to tax policy (e.g., "TCJA", "tax increase", "tax cut")
>
> *Tax refunds* – an indicator for all tax-related tweets that contain words related to tax refunds (e.g., "refund", "bank account", "writeoff")

The exact measurement of these variables is detailed in Appendix A.

[14] Our set of categories and word lists is admittedly somewhat ad hoc. They are primarily based on the authors' examination of hundreds of tweets in the raw sample. However, the frequency with which these categories are discussed on social media and the reliability with which they capture a particular sign of sentiment suggest that they capture some of the more salient tax issues discussed on social media.

4. Descriptive Statistics and Validation

4.1 Importance of Taxes on Twitter

We begin by providing descriptive information about the prevalence of dialogue about taxes on Twitter. We first plot the trend in all tax-related tweets over the sample period. For this analysis only, we employ all raw tax-related tweets in the sample over the sample period, 2014-2022, including those without geo-location. In Figure 1, we show that the number of tax-related tweets has increased substantially over time, even while the total number of tweets has remained fairly stable. In 2014, the number of tax tweets in a given quarter was around 3.5 million. By the fourth quarter of 2022, the number of tax tweets had increased to 9.5 million – an increase of about 300%. To benchmark this against total Twitter activity, we roughly approximate the number of total tweets in each quarter by counting the number of tweets that contain the word "the".[15] At the beginning of the sample period, total tweets were about 1 billion before falling to about 650 million in 2017 and then increasing to 1.1 billion by the fourth quarter of 2022. Thus, we see that over the past decade, the fraction of social media attention paid to tax is generally increasing and that taxes are becoming a more salient issue on social media.

To further benchmark the importance of tax-related dialogue on Twitter, in Figure 2 we graph benchmark the number of tax-related tweets relative to tweets on other select topics: Israel/Palestine, U.S. Politics, Russia/Ukraine, Football, Cats, Basketball, Accounting, Financial Statements, and

[15] Likely due to privacy issues, Twitter does not release aggregate data on, or allow access to, the total number of tweets issued in a given day. Therefore, in Figure 1 only, in order to provide an approximation of the total number of daily tweets, we simply count the number of tweets that include the word "the" in them. In Figure 1, the orange line reports this approximation of total tweets. While this likely understates the number of tweets in absolute terms, it is also likely to be highly correlated with the total number of tweets.

Restatements. Appendix A contains the exact words that we used to identify tweets in each topic. For this figure, we pull all tweets related to each topic over the six-day period March 9-14, 2024.[16]

In Panel A, we graph the quantity of tweets in each topic. Of these topics, the most common are Israel/Palestine (10.1m tweets), U.S. Politics (8.5m tweets), and Russia/Ukraine (4.6m tweets). There are 2.2m tax-related tweets, roughly equal to the number of tweets about football and cats. Very few tweets mention accounting-related words. To get a sense of how important these topics are on Twitter in aggregate, in Panel B we estimate the proportion of tweets on each topic to the total number of tweets from March 9-14, 2024.[17] Tweets on Israel/Palestine, U.S. Politics, and Russia/Ukraine represent 23.7%, 20.1%, and 10.8%, respectively, of our estimated tweet population. Further, the quantity of tax related tweets is considerable (5.1%). For comparative purposes, there is one tweet about taxes for every 4.6 (2.1) tweets that mention Israel/Palestine (Russia/Ukraine). This analysis demonstrates that taxes are a salient issue on Twitter and within an order of magnitude of the pressing issues and topics of the day.

4.2 Social Media Users

To shed light on who drives tax-related discussions on social media and our *Tax Sentiment* variable, we examine characteristics of the most prolific users. Specifically, using our raw full sample of tweets (i.e., not just the tweets with geo-location tags), we manually classify the top 1,000 authors with the most likes on tax-related tweets into a series of categories. First, we classify accounts as either representing an individual or an organization (e.g., CNBC, Fox News). Second, we classify accounts

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[16] We use this narrow window because we retrieved only tax-related tweets under the discontinued academic API (see footnote 10). In order to pull tweets related other topics, we can only access tweets from the past seven days (168 hours, ending at the exact time of the query) and are limited to five queries every 15 minutes; hence, to use a consistent time period across all topics, we tabulate the frequency of each topic over a six-day period.

[17] As in Figure 1, we again estimate this proportion because Twitter does not allow users to access to the total number of tweets or query certain words ("stop words"). However, between the time we ran the analysis for Figure 1, Twitter updated its API to include "the" in its list of restricted words. Thus, we estimate the population of tweets by identifying the number of tweets that contain the most common English word that is not a restricted word in the Twitter API (specifically, "have"). This process yields a total population of 42.5m tweets, and, although it certainly understates Twitter activity, our approach nonetheless helps quantify the importance of each topic.

as (1) politicians, (2) political personalities, (3) journalists, (4) celebrities, (5) academics, (6) social media influencers, (7) businesspersons, or (8) unknown. Politicians are individuals who currently hold or have previously held elected or politically-appointed government positions. Political personalities are individuals or organizations primarily involved in political commentary.[18] A journalist is a user who works at a media company (e.g., TV, newspaper, online news). A celebrity is a person who is famous from "traditional" methods, such as an actor, musician, author, athlete, etc. An influencer is a person who is famous due to being a social media influencer. A businessperson is a top executive, entrepreneur, lawyer, etc. We label a user as "unknown" if we cannot classify them into one of the above categories. The categories are not mutually exclusive.

In Table 1, Panel A we list the top 25 users with the most likes on tax tweets and display our categorizations, their total number of likes, and the average *Tax Sentiment* of their tweets (note that several individuals are repeated because they have made multiple accounts).[19] Robert Reich (the user with the most likes on tax tweets), for example, is categorized as a politician, political personality, academic, and businessperson. This table reveals that the users who appear to be most influential, based on likes, are Robert Reich, Bernie Sanders, Alexandria Ocasio-Cortez, Joe Biden, and Charlie Kirk. In Panel B, we display the average *Tax Sentiment* by group, their fraction of the total number of likes, and what fraction they make up of the top 1,000 most influential users. We show that the majority of influential users have political motives, either as politicians (17% of users) or as political personalities (50% of users). The fraction of likes accounted for by each category is mostly similar to the fraction of users in each category, although politicians punch above their weight with 32% of likes. The vast majority of users are also individuals (90%), not organizations (10%). In terms of sentiment,

[18] We treat Politicians and Political Personalities as mutually exclusive unless users qualify as both in different time periods. For example, Robert Reich is both a politician and a political personality because he has previously held a political office (e.g., Secretary of Labor) and his current Twitter activity is primarily involved in political commentary.
[19] We calculate the average sentiment of these users using the sample of the top 1,000 most-liked tweets per day.

political personalities are the most negative (*Tax Sentiment* of 0.33), followed by academics (*Tax Sentiment* of 0.34). Organizations are the most positive (*Tax Sentiment* of 0.45), consistent with media outlets, think-tanks, and other groups aiming to be more neutral. Politicians themselves are the second most positive, perhaps due to tweets that champion their own agendas and political wins.

Lastly, we examine the importance of each group over time. In Figure 3, we graph the percentage of likes attributable to each group over year-quarters from 2014 to 2022. In Panel A, we show that at the beginning of the sample, organizations garnered the majority of the likes on tax-related tweets. However, individuals become more influential over the sample period, and by 2022 they dominate the space, with 88% of all likes. This result may, in part, reflect consumers shifting away from traditional media sources toward social media, as well as novel information generated by individuals. In Panel B, we graph user groups over time and note several key trends. First, related to the trend in individuals versus organizations, journalists accounted for the majority of the likes in 2014 but have decreased considerably in importance. Second, politicians and political personalities have become more important over time—with politicians receiving the most likes of any group leading up to the 2016 presidential election, and political personalities largely maintaining the most likes since 2017. Third, businesspersons are garnering substantially more likes on tax tweets, increasing from 2% to 14% over the sample period.

4.3 Descriptive Statistics: Tax Sentiment

In this section, we examine descriptive statistics that shed light on and validate our *Tax Sentiment* measure. In Figure 4, we first plot the geographic location of Twitter users in our primary sample of tweets with geo-location enabled. We do not observe systemic variation in the distribution of users-per-capita across the U.S.

In Figure 5, we graph trends in *Tax Sentiment* over time. In Panel A, we find that *Tax Sentiment* decreases steadily over our sample period, and declines sharply in the second half of 2016—suggesting that discourse regarding Donald Trump and the 2016 U.S. presidential election may have driven part of the decline in *Tax Sentiment* (as will be discussed further below).

In Figure 6, we display the variation in our measure of *Tax Sentiment* using a histogram. The figure reveals that a much greater fraction of tweets is negative rather than positive. A significant fraction of tweets is neutral, with no particular tilt in sentiment. However, perhaps the most striking result in Figure 6 is the bimodal nature of the distribution of tax sentiment on social media. That is, the sentiment of many tax tweets is either extremely positive or extremely negative. These results demonstrate the polarity of tax issues on social media.

Next, we provide insights on the content of tax-related tweets and examine how they vary with *Tax Sentiment*. In Table 2, we present the top 10 two-word N-grams by *Tax Sentiment* quintile for all tweets that contain the word "tax." We omit the word "tax", then present the most common word pairings, for tweets classified as relatively positive to relative negative. In the leftmost column, the most common word pairings for the most positive sentiment tweets largely relate to taxpayers' joy at filing a tax return or receiving a refund. The word pairs include: "cannot wait", "free weekend", "last year", and "got return". In the rightmost column, the word pairings that are most common for highly negative tweets relate to waste of taxpayer dollars, taxing the rich, tax policy, and other non-tax policies. The word pairs include: "[tax]payer money", "middle class", "cut rich", "waste money", "donald trump", and "health care." These word pairings serve two purposes: first, to demonstrate the power of the data to detect variation in tax-related topics of interest on social media; and second, to provide some assurance on the validity of the sentiment measure.

In Table 3, we examine determinants of *Tax Sentiment* by regressing it on other granular macroeconomic and Twitter-specific measures. Specifically, as determinants we use: the daily level of the CBOE Volatility Index (*VIX*); an indicator for days on which there are news events that target tax issues related to individual firms, according to Asay et al., (2024) (*Tax New Day*); U.S. tax policy uncertainty (*Tax Policy Uncertainty*) from policyuncertainty.com, based on Baker et al., (2016); and Twitter-based Economic Uncertainty (*Twitter Uncertainty*) also from policyuncertainty.com. As the policyuncertainty.com measures are available monthly, we merge it on at the appropriate month level. *Tax Policy Uncertainty* is an index of the dollar-weighted number of tax code provisions that are scheduled to expire within 10 years. *Twitter Uncertainty* is an index of the number of tweets that contain keywords related to economic uncertainty.

We show that *Tax Sentiment* is significantly and negatively related to *Twitter Uncertainty* and *Tax Policy Uncertainty*, which suggests that as the extent of economic uncertainty language on Twitter and the magnitude of expiring U.S. tax code provisions increase, the sentiment of tax-related dialogue on Twitter becomes more negative. We find a marginally significant negative relation with *Tax News Day* in columns 3 and 4 with year fixed effects, suggesting that specific articles about firms' tax issues is negatively related to the overall *Tax Sentiment* on Twitter on that day. In terms of explanatory power, we find that these variables, without year fixed effects, explain between 37.8% and 47.3% of the variation in *Tax Sentiment*. In aggregate, these results provide validation of our *Tax Sentiment* measure—showing that it correlates with other general tax policy uncertainty and Twitter-specific uncertainty measures—and suggest that *Tax Sentiment* is distinct from the existing measures.

5. Tax sentiment and Tax Compliance

We next study how the sentiment of tax issues reflected on social media is associated with tax compliance. Our goal in this portion of the paper is to examine whether there are potential outcomes that are associated with changes in tax sentiment. The outcome we choose to focus on is local tax compliance, namely the tendency for taxpayers report their income consistent with expectations.

5.1. Model of Tax Compliance

To examine the association between tax sentiment and compliance, we need some measure or model of tax under-reporting, which is notoriously difficult to model, even with access to private data from tax authorities. We develop a novel approach that leverages our localized social media data, as well as public, localized income tax data. This approach leans on the methodologies used in prior research to examine or predict abnormal levels of some outcome variable, such as discretionary accruals (e.g., Dechow et al., 1995), excessive audit fees (e.g., Hribar et al., 2014), or over-investment (e.g., Biddle et al., 2009). The approach in prior research is often to model the normal level of the outcome variable (e.g., total accruals) in order to identify/predict abnormal levels of that variable (e.g., discretionary accruals). In a tax setting, Slemrod (2019) refers to this approach as a "traces-of-income" procedure that compares true income to a reported income figure.

Based on that intuition, we model reported taxable income as a function of local economic inputs that proxy for true economic income. Rather than use residual from that model as a proxy for abnormal income in a second regression, we follow the guidance in Chen et al., (2018) to use a single-step approach to include all economic inputs, as well as tax sentiment, in the model. We interpret any movements in reported taxable income associated with tax sentiment to represent some degree of tax under-reporting.[20]

Our specification for these tests is given by the following equation:

$$Reported\ Income_{c,t} = \beta_1 AbnSentiment_{t,c} + \sum \beta_n Economic\ Income_{c,t} + \gamma_t + \delta_c + \varepsilon_{c,t} \qquad (1)$$

To measure *Reported Income*, we use the IRS county-level Statistics of Income (SOI) data. Specifically, we examine several measures of income that can be underreported by taxpayers: (1) *Reported Non-Wage Income*, which is the aggregate of adjusted gross income (AGI) minus Form W-2 income in a county-year; (2) *Schedule C Business Income*, which is total reported Schedule C business income in a county-year; and (3) *Partnership and S-Corp Income*, which is total reported pass-through or S-corp income in a county-year. We include four proxies for *Economic Income*, including *Wages, Employment, GDP,* and

[20] To be clear, we are not stating that we demonstrate tax evasion; individuals and companies have a variety of legal ways of reducing their income tax burden (e.g., Dyreng et al. 2008). Instead, we are arguing that movements in taxable income relative to economic income indicates that individuals have implicitly undertaken strategies to reduce their tax burden.

Establishments, each of which is logged.[21] In these compliance tests, we modify *Tax Sentiment* by scaling it by the average Twitter sentiment in a given county-year according to TSGI, and renaming this variable *Abnormal Tax Sentiment*. This modification allows us to account for changes in overall sentiment on Twitter and thus capture abnormal changes in tax-related content. δ_c and γ_t are fixed effects for county, year, or state-year as indicated. In equation (1), β_1 is our coefficient of interest, as it captures deviations in reported income that are related to variation in tax sentiment, conditional upon other economic inputs to the model. In falsification tests, we replace the dependent variable in this model with *Reported Wage Income*, which is aggregate Form W-2 (wage) income in a county-year.

5.2. Tax Sentiment and Local Tax Compliance

Descriptive information of each of these variables is presented in Table 4. We find that the average *Reported Wage Income* is $2.1 billion, roughly twice the size of *Reported Non-Wage Income* ($0.9 billion). The average county-year has 2,410 business establishments and 32,660 workers, with GDP of $4.7 billion and wages reported to the BEA in surveys of $1.7 billion. We also include county-year-level descriptive statistics of *Abnormal Tax Sentiment*, the proportion of tweets related to our eight tax categories, and county-level average personality characteristics. Note that all county-level economic variables have large standard deviations, indicating that they are highly skewed towards large counties.

We present our results of estimating equation (1) in Table 5. For each dependent variable, we include two columns that vary the fixed effects structure In columns 1 and 2 where the dependent variable is *Reported Non-Wage Income*, β_1 is significant and negative, indicating that decreases in our

[21] First, using data from the Bureau of Economic Analysis (BEA), we collect annual real GDP data from the CAGDP1 file. Next, from the Bureau of Labor Statistics (BLS), we collect data from the Quarterly Census of Earnings and Wage (QCEW). From QCEW we use number of employees, total wages, and total number of establishments in a county as joint proxies of economic activity. Both the CAGDP1 file, and the QCEW file are based primarily on survey data, meaning they are independent of tax returns. GDP can be computed as the sum of compensation to employees, taxes on production and imports minus subsidies, and gross operating surplus. The largest fraction of this is compensation to employees which is primarily based on QCEW data. Although calculating county level GDP is complicated, relying on a series of estimates that use data from a variety of sources, the only component of which we are aware that also uses IRS data is the estimate of profit for non-farm sole-proprietorships. For more information about how county level GDP is calculated see: https://apps.bea.gov/scb/issues/2020/03-march/0320-county-level-gdp.htm

measure of tax sentiment are associated with increases in local tax compliance. The model's overall R-squared is very high (0.998) and driven by the fixed effects in a setting where changes over time are relatively small. The within R-squared indicates the extent to which the independent variables explain variation in our aggregate reporting income variables within a given fixed effect unit. For example, within a given county and year, *Abnormal Tax Sentiment* and the economic income variables explain 16.2% of the variation in column (1).[22] In columns 3 through 6, we narrow in on business income, which is where the bulk of underreporting occurs. For both *Schedule C Business Income* and *Partnership and S-Corp Income*, we continue to find a negation relation between *Abnormal Tax Sentiment* and tax compliance. In columns 7 and 8, we perform a falsification test that uses *Wage Income* as the dependent variable. Because wage income is subject to third-party reporting by employers, taxpayers have few viable options to not comply or underreport wage income (Kleven et al., 2011) We expect and do not find that *Abnormal Tax Sentiment* is associated with *Wage Income*.

Overall, these results are consistent with social identity theory. Tax sentiment reflects social pressures for individuals to shun certain aggressive tax practices or creates a social identity that disassociates with certain taxpayers (e.g., the wealthy or Trump), and therefore, tax sentiment is negatively associated with tax compliance. The sign of the coefficient is consistent with reductions in tax sentiment being met with increases in tax compliance as taxpayers seek to adequately report taxes when the tone of tax discussion worsens. The application of social identity theory as a motivation for voluntary tax compliance is much less developed in the literature and unique relative to the prevailing notion that peer effects induce compliance via social norms and peer pressure.

[22] To provide a bit more intuition, a high within R-squared would suggest that for a given county, changes in *Tax Sentiment* over time tend to correspond to changes in *Reported Non-Wage Income*. In contrast, a high between R-squared suggests that the variation between countries on average (i.e., some countries are big, some area small) explains the majority of the variation in *Reported Non-Wage Income*.

5.3. Categories of Tax Sentiment

Next, we examine the link between the discussion of certain tax subjects and tax compliance. This test seeks to shed light on whether the social media rhetoric related to certain tax topics is more related to tax compliance than are general categories. As these topics seem to capture more extreme degrees of sentiment, they provide some assurance that the results are related to tax sentiment (and not some other omitted factor). Further, this test provides insights on the proposed channels and mechanisms that explain our result, namely that local tax compliance increases with users' frustrations with and negativity toward certain tax aggressive practices and people who abuse them.[23]

In Figure 7, we first present the average *Tax Sentiment* for the major tax topics we measure: *Taxing companies*, *Trump returns*, *Taxing the rich*, *Tax inequity*, *Non-tax policy*, *Tax waste*, *Tax policy*, and *Tax refunds*. We primarily associate tweets about *Taxing companies*, *Trump returns*, *Taxing the rich*, and *Tax inequity* with the idea of peer-effects because tweets that use these terms are generally focused on other taxpayers that serve as an out-group. We associate tweets about *Non-tax policy*, *Tax waste*, *Tax policy*, and *Tax refunds* with idea of reciprocity because tweets that use these terms are generally focused at or reference the government or tax authority as the counter-party in traditional reciprocity arguments. For this figure, we standardize each of the measures by subtracting the baseline sentiment for the average tax sentiment of tweets that are not included in any of these categories. We find that seven of the eight categories exhibit negative relative tax sentiment (i.e., substantially below baseline sentiment). In particular, the categories related to *Taxing the rich*, *Tax inequity*, and *Tax waste* are strongly below the average baseline sentiment for sample tax tweets. On the other hand, we find that the average tax sentiment for *Tax refunds* is more positive than the baseline. We perform a similar analysis in Table 6

[23] We acknowledge recent work by Puklavec, Kogler, Stravrova, and Zeelenberg (2023) that also models tax-related topics on Twitter. This study also even examines the sentiment of topic-specific conversations. It, however, does not do anything to link tax-related discussion on Twitter to tax compliance, which is the central purpose of our study.

Panel A and show that this relation holds true at the county level even after including fixed effects and controls.

In Table 6 Panel B, we examine whether reported income is related to the fraction of tax tweets in a given county-year that discuss each of our categories. In both columns, we find positive and statistically significant coefficients on *Taxing companies*, *Trump returns*, and *Tax policy*, indicating that social media discussion of these topics is associated with increased reported income. In other words, as social media activity focuses on meaningful tax topics, local tax compliance increases. Given that these measures capture tax tweets that are extremely negative sentiment, these results are consistent with the interpretation that the sentiment is negatively associated with tax compliance. These results also support the underlying theory of dissociative social identity, in that tax compliance is a reinforcing action one takes to disassociate oneself from aggressive tax practices (such as corporate tax aggressiveness or Trump failing to release tax returns) highlighted in social media.

We also further explore the possibility that sentiment about Donald Trump's tax returns in particular drove the negative relation between tax sentiment and compliance. We create an indicator variable, *Trump Presidency,* which is an indicator equal to one for years in the Trump administration. In Table 6 Panel C, we repeat the analysis in Table 5 but include an additional term that is the interact ion of *Abnormal Tax Sentiment* and *Trump Presidency*. We find that the relation between *Abnormal Tax Sentiment* and *Reported Non-Wage Income* is driven by the years during the Trump presidency. Together with the topical analysis in Panel B, these results suggest that the extremely negative focus on Donald Trump's tax returns was associated with increases in tax compliance.

6. Additional Analyses

Our primary result suggests that negative social media sentiment reflects users' frustrations with the tax system and those who abuse it, which is associated with better compliance with taxes, consistent with social identity theory. To further test the mechanism through which this result operates, we perform several additional analyses.

6.1. Role of Tax Preparers

First, we consider whether other parties involved in the tax compliance process influence the interaction between tax sentiment and compliance. Specifically, we examine the role of tax preparers. This analysis aims to both validate our model of tax compliance as well as examine whether tax preparers moderate the relation between *Tax Sentiment* and compliance. Tax preparers are tasked with professional duties to act ethically and uphold tax rules, and they can face severe career consequences for knowingly helping taxpayers underreport their income. Hence, we expect the proportion of tax preparers in a county to be positively associated with greater tax compliance. Further, given that many paid preparers act in a fiduciary role, we predict that a greater presence of tax preparers will moderate the negative relation between *Abnormal Tax Sentiment* and tax compliance by removing the effects of taxpayers' behavioral biases that impact compliance.

In Table 7, columns 1 and 2, we regress our primary dependent variable (*Reported Non-Wage Income*) on the percentage of returns in a county-year that use a paid preparer (*Preparer %*, calculated using the SOI data). We also include the proxies of *Economic Income* and use either county and year fixed effects (column 1) or county and state-year fixed effects (column 2), as in Table 5. As expected, in both columns, we find that *Preparer %* is positive and statistically significant, indicating that a greater presence of tax preparers is associated with higher tax compliance. This result suggests that our tax compliance model captures its intended construct and varies consistently with factors associated with tax compliance.

In columns 3 and 4, we again vary the fixed effects and include as additional independent variables of interest *Abnormal Tax Sentiment* and the interaction of *Abnormal Tax Sentiment* and *Preparer %*. On the interaction in column 4, we find a positive and significant relation with *Reported Non-Wage*

Income. That is, when there is a greater prevalence of tax returns in a county that use tax preparers, the negative relation between *Abnormal Tax Sentiment* and *Reported Non-Wage Income* is moderated—and more than offset. Overall, our results suggest that tax preparers play an important role in supporting tax compliance and mitigating psychological factors associated with noncompliance.

6.2. Variation in Household Income

Next, we examine variation in household income to evaluate whether certain taxpayers (especially those who are more well off) have more incentives to disassociate with their social identity from other rich or aggressive taxpayers that were the subject of intense negative sentiment. To do so, we take advantage of the fact that the IRS releases their SOI county-year level data by the AGI of the returns. Specifically, the IRS provides tax return information by county-year for eight AGI categories, starting from the lowest (negative AGI) in column (1), to the highest (AGI >$200,000) in column (8). We repeat the analysis in Table 5 using each of these eight categories.[24] This test examines whether the results are weaker or stronger based on the income status of the average household.

In Table 8, we find that the negative association between *Abnormal Tax Sentiment* and reported non-wage income is significant in the highest four income partitions (i.e., AGI of $50,000 to $75,000, AGI of $75,000 to $100,000, AGI of $100,000 to $200,000, and AGI >$200,000). The effect among middle- and high-income brackets suggests that previously documented relations between tax sentiment and abnormal reported income are concentrated in middle class and wealthy taxpayers. This result lends some credence to social identity theory because high income taxpayers may have a greater incentive to disassociate from perceived tax evasion by the wealthy.

[24] Note that because groups with low AGI may have negative non-wage income, we switch from using one plus the log of non-wage income to using the inverse hyperbolic sine of non-wage income. Results are similar when dropping county-year-AGI category observations with negative non-wage income and using one plus the log of non-wage income.

6.3. Local Political Affiliations

In our next set of analyses, we examine local demographic variation to evaluate whether local political affiliations moderate the association between the sentiment of tax issues on social media and local tax compliance. In Table 9, we examine whether the negative association between tax sentiment and tax compliance is weaker or stronger based on political affiliation. If social identity theory is the dominant mechanism at work in our data, we expect that Republican counties will exhibit a weaker association, as they are less likely to be negatively influenced by negative tax issues on social media because their social identities are less threatened by the notion of avoiding taxes (i.e., their in-group is more averse to taxes than their out-group). Conversely, we expect that Democrat counties are more likely to exhibit a dissociative pattern with aggressive tax positions reflected in social media (i.e., their in-group is less averse to taxes than their out-group). To measure political affiliation within a county, we use the fraction of a county who voted for a Republican president in 2016. We find that the interaction of *% Republican* and *Tax Sentiment* is positive across specifications. In other words, we find that counties that are more likely to socially disassociate with aggressive tax ideas reflected in social media (e.g., Democrat counties) exhibit a more negative association between tax sentiment and tax compliance

6.4. Strengthening Inferences

While we are not making causal claims in this study, we nonetheless want to mitigate concerns that the negative association between tax sentiment and tax compliance is due to a spurious omitted variable, reverse causality, or some other factor. To minimize this possibility, we perform two additional tests.

First, to address the concern that any number of local factors may simultaneously affect both tax sentiment and tax compliance, we exploit national variation in tax sentiment. We posit that national changes in sentiment have heterogeneous effects on the local tax sentiment of individual counties. For example, some counties may pay more attention to news media or may find tax issues more salient than other counties. To identify this variation, we perform an out-of-sample beta estimation similar to a CAPM using 2022 Twitter data.[25] Specifically, we regress local tax sentiment in a given county on the average national tax sentiment for all tweets and measure the β_1 in the following regression:

$$Abnormal\ Tax\ Sentiment_{i,t} = \beta_0 + \beta_1 * National\ Abnormal\ Tax\ Sentiment_t + \varepsilon_{i,t} \qquad (2)$$

To reduce the influence of outliers, we then create a county-level indicator variable for the top quartile of counties with the highest β_1, and call this measure *Sentiment Sensitivity*. In Table 10 Panel A, we first show that, unsurprisingly, changes in *National Abnormal Tax Sentiment* have a greater effect on local *Abnormal Tax Sentiment* in counties with higher *Sentiment Sensitivity*.[26] In other words, the interaction between *National Abnormal Tax Sentiment* and *Sentiment Sensitivity* serves as variation in *Abnormal Tax Sentiment* that is exogenous to local conditions.

In Table 10 Panel B, we show that while this interaction does not have a statistically detectable effect on overall tax compliance, it does have a significant effect on reported income for S-Corporations and Partnerships. In other words, at least for this subset of taxable income, increases in tax sentiment that are exogenous to local conditions decrease tax compliance.

Second, thus far it is clear that tweets reflect news events that affect tax compliance, but it is still unclear whether and to what extent Twitter actively affects compliance. To test this, we exogenously shock the fraction of users in a county and demonstrate that as Twitter becomes more prevalent, the effects of Twitter become stronger. Said differently, when there is negative sentiment, increasing the presence of Twitter increases compliance.

[25] Tax data from the SOI is not yet available for 2022 so we are unable to construct compliance measures for 2022. Hence, we use 2022 Twitter data out-of-sample to measure the sensitivity of changes in local tax sentiment to changes in national tax sentiment. To do this, we require that each county have 50 days with a geolocated tax tweet in 2022. We then use those sensitive measures in our main sample window.

[26] A crucial weakness of this test is that *Sentiment Sensitivity* can only be estimated for a relatively small subset of counties. This is important because it significantly limits the power of the tests in both panels and is why this design is not used as our main analysis.

To implement this, we follow Müller and Schwarz (2023) and use the early adoption of Twitter based on local attendance at the 2007 South by Southwest festival as an exogenous instrument to the fraction of the population in a county that uses Twitter. Müller and Schwarz (2023) exploit the fact that the 2007 South by Southwest festival (SXSW) was a key event in the spread of Twitter. They show that in the month of the festival Twitter users tripled, meaning areas with greater exposure to the festival were more likely to have a larger increase in the number of users and the effects of local attendees at that event has affected the prevalence of local Twitter usage more than a decade later.

In Table 11 Panel A, we show that counties who had a greater increase in the number of followers of SXSW experienced a greater increase in the number of Twitter users per capita. Then, in Table 11, Panel B, we use the test from Panel A as the first stage of an instrument for the number of users per capita. We regress *Reported Non-Wage Income* on the interaction between the predicted value from Panel A with *Abnormal Tax Sentiment*. We find that increases in the number of users from the SXSW conference strengthens the negative relation between sentiment and compliance, and also suggesting that perhaps not only is Twitter reflecting the views of its users, but is actively influencing tax compliance.

In sum, across two tests, we show that even when using variation exogenous to local counties, changes in tax sentiment are associated with changes in compliance. Collectively, these tests add to the mosaic of evidence from our primary analyses and strengthen the inferences that the association between social media sentiment and compliance is negative.

7. Conclusion

We examine the determinants and implications of tax sentiment, a construct that captures the tone of taxpayers' discussions, attitudes, and perceptions of tax-related issues on social media. Prior research argues for the need to provide behavioral explanations for variation in tax compliance

(Slemrod 2019). We contribute to that literature by adding a novel metric that captures taxpayers' real-time views on tax issues, as manifested in a large sample of tweets.

Our examination of tax sentiment and attention aims first to shed light more broadly on important trends on social media discussions of taxes. We show that taxes have become an increasingly important topic on social media, but that the tone of these discussions is increasingly negative. Discussions around taxation of the rich and of wasting taxpayer dollars are particularly negative.

We also examine the link between tax sentiment and tax compliance. To do so, we develop a novel approach to estimating compliance that models reported taxable income as a function of economic income, both measured at the county-year level. Based on this design, we examine whether variation in *Tax sentiment* is associated with reported taxable income. We find that reported taxable income is decreasing in *Tax Sentiment*, suggesting the more negative discussions on social media are associated with higher tax payments. This pattern of results is consistent with our findings being driven by taxpayers' responding to social identity as a form of self-regulation (Oyserman 2007). In other words, tax compliance can be a reinforcing action one takes to disassociate oneself from aggressive tax practices reflected in social media. Overall, the results indicate that tax sentiment is negatively associated with tax compliance.

Understanding taxpayers' perceptions of tax issues is crucial to tax policy discussions, tax system design, and tax compliance. At the same time, social media has emerged as a major force to drive individual and community perceptions. This study represents the first to examine the extent to which social media sentiment is associated with tax compliance—and suggests that it might create peer effects that differ from prior theory on voluntary tax compliance.

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Appendix A: Variable Definitions and Data Sources

Variable	Definition	Data Source	Unit Of Observation
Tax Sentiment	The average positive sentiment score minus the negative sentiment score for a given tweet, where positive and negative sentiment scores are created using the Barbieri et al. (2020) model output. The score is rebalanced to be between 0 and 1 to be on the same scale as the TSGI sentiment score (i.e., add one then divide the total by 2).	Twitter, Barbieri et al. (2020)	Tweet
Abnormal Tax Sentiment	The average *Tax Sentiment* of tweets in a county-year (day) divided by the average probability a tweet is positive in a given county-year (day) according to TSGI.	Twitter, TSGI	County-Year and Day
Tax Salience	The fraction of tweets on a given day that are related to taxes where the denominator is calculated using the number of tweets on a given day that contain the word "the".	Twitter	Day
Tax Policy Uncertainty	The daily US tax policy uncertainty measure according to policyuncertainty.com	Baker et al. (2016), policyuncertainty.com	Day
Tax News Day	An indicator variable for days on which there is a news article targeting firms' taxes, following Asay et a., (2024)	Asay et al. (2024)	Day
Twitter Uncertainty	The daily US twitter policy uncertainty measure according to policyuncertainty.com	Baker et al. (2016), policyuncertainty.com	Day
VIX	Daily level of the CBOE Volatility Index	CBOE	Day
Reported Non-Wage Income	Total AGI in a county-year or county-agi class-year ("A00100") minus total wage income in a county-year or county-agi class-year ("A00200") in the IRS SOI County Data File	IRS SOI County Data File	County-Year and County-AGI Class-Year
Schedule C-Business Income	Total reported schedule C business income ("A00900") in a county-year in the IRS SOI County Data File	IRS SOI County Data File	County-Year
Partnership and S-Corp Income	Total reported Pass-Through or S-Corp income ("A26270") in a county-year in the IRS SOI County Data File	IRS SOI County Data File	County-Year
Preparer %	The fraction of tax returns in a given county-year that are prepared using a paid preparer ("PREP") in the IRS SOI County Data File	IRS SOI County Data File	County-Year
Reported Wage Income	Total wage income in a county-year ("A00200") in the IRS SOI County Data File	IRS SOI County Data File	County-Year
Employment	The natural log of 1 + "Annual Average Employment" in QCEW	BLS QCEW	County-Year
GDP	The natural log of 1 + county real GDP according to the BLS CAGDP1 file.	BEA CAGDP1	County-Year
Wages	The natural log of 1 + "Annual Total Wages" in QCEW	BLS QCEW	County-Year
Establishments	The natural log of 1 + "Annual Average Establishment Count" in QCEW	BLS QCEW	County-Year
Conscientious	The conscientiousness score of a county according to Giorgi et al. (2022)	Giorgi et al. (2022)	County
Agreeableness	The agreeableness score of a county according to Giorgi et al. (2022)	Giorgi et al. (2022)	County
Emotional Stability	The emotional stability score of a county according to Giorgi et al. (2022)	Giorgi et al. (2022)	County
Extraversion	The extraversion score of a county according to Giorgi et al. (2022)	Giorgi et al. (2022)	County
Openness	The openness score of a county according to Giorgi et al. (2022)	Giorgi et al. (2022)	County
Republican	The fraction of a county who voted Republican in 2016 according to the MIT Election data lab. See: https://electionlab.mit.edu/data	MIT Election Data Lab	County
Trump Presidency	An indicator variable for years 2017-2020	None	County-Year
Users Per Capita	The number of Twitter users in a county according to Muller and Schwarz (2023)	Muller and Schwarz (2023)	County
Followers Post SXSW Per Capita	The number of followers of the SXSW account in a county in March 2007 SXSW according to Muller and Schwarz (2023) divided by the population of a county according to the 2010 Census.	Muller and Schwarz (2023)	County
Followers Pre SXSW Per Capita	The number of followers of the SXSW account in a county in 2006 SXSW according to Muller and Schwarz (2023) divided by the population of a county according to the 2010 Census.	Muller and Schwarz (2023)	County
Sentiment Sensitivity	An indicator variable for whether the county-specific beta estimation procedure yielded a	Twitter, Barbieri et al. (2020)	County
National Abnormal Sentiment	The national average *Abnormal Tax Sentiment* in a givne year.	Twitter	Year

Variable	Definition	Data Source	Unit Of Observation
Tax Sentiment of Tagged Tweets	The average tax sentiment of tweets in which a given S&P 100 company is tagged in a given year.	Twitter, Barbieri et al. (2020)	Firm-Year
Proportion of Tagged Tweets	The fraction of tweets that tag a given S&P 100 company in a given year divided by the total tweets that tag S&P 100 companies in that year.	Twitter	Firm-Year
ROA	Net income (ib) divided by total assets (at)	Compustat	Firm-Year
Leverage	Total Liabilities (lt) divided by total assets (at)	Compustat	Firm-Year
MTB	End of year market capitalization (prcc_f*csho) divided by book equity (ceq)	Compustat	Firm-Year
Size	Natural log of one plus total assets (at)	Compustat	Firm-Year
Intangibles	Intangibles (intan) divided by total assets	Compustat	Firm-Year
R&D	R&D expense (xrd), zero filled, divided by total assets	Compustat	Firm-Year
Returns	Market returns over the previous years	CRSP	Firm-Year
Returns Volatility	Standard deviation of monthly returns over the previous year	CRSP	Firm-Year
Cash ETR	Taxes paid divided by pretax income. Set to missing when pretax income is less than 0. Set to 1 when greater than 1 and 0 when less than 0.	Compustat	Firm-Year
GAAP ETR	Tax expense divided by pretax income. Set to missing when pretax income is less than 0. Set to 1 when greater than 1 and 0 when less than 0.	Compustat	Firm-Year
Havens	An indicator variable for whether a firm has a subsidiary in a tax haven.	WRDS Subsidiaries Database	Firm-Year
UTB	Uncertain tax benefits (txtubend) divided by total assets (at)	Compustat	Firm-Year

Figure 2 Topic	Search List
Scaler	have
Israel/Palestine	israel OR palestine
US Politics	election OR politics OR democrat OR republican OR gop OR liberal OR conservative
Russia/Ukraine	russia or ukraine
Football	football OR nfl
Cats	cat OR kitty OR kitten
Taxes	tax OR taxes OR taxing OR taxpayer OR taxman OR taxed
Basketball	basketball OR nba
Accountant	accountant
Financial Statements	financial statement OR 10-k
Restatment	restatement

Tweet Category	Definition	Data Source	Unit Of Observation
Taxing Companies	At the tweet level, an indicator variable for if a tweet contains one of the following words: "corporation", "companies", "company", "businesses", "business tax", "enterprise", "firm", "corporate", "multinational", "shareholder", "stakeholder". At the county-year level, the fraction of tax tweets for whom the indicator at the tweet level is 1.	Twitter	Tweet and County-Year
Trump Returns	At the tweet level, an indicator variable for if a tweet contains the word "trump" or "release" and the word "return". At the county-year level, the fraction of tax tweets for whom the indicator at the tweet level is 1.	Twitter	Tweet and County-Year
Taxing the Rich	At the tweet level, an indicator variable for if a tweet contains one of the following words: "the wealthy", "the rich", "one percent", "1%", "1 percent", "illionaire", "middle class", "poor". At the county-year level, the fraction of tax tweets for whom the indicator at the tweet level is 1.	Twitter	Tweet and County-Year
Tax Inequity	At the tweet level, an indicator variable for if a tweet contains one of the following words: "fair share", "unfair", "not fair", "unjust", "rigged","unequal","equalit","not equal", "equit". At the county-year level, the fraction of tax tweets for whom the indicator at the tweet level is 1.	Twitter	Tweet and County-Year
Non-Tax Policy	At the tweet level, an indicator variable for if a tweet contains one of the following words: "vaccine", "covid", "diversity", "dei", "blm", "black lives", "school", "curriculum", "racism", "racist", "discriminat", "racial", "justice", "climate", "gun control", "gun violence", "shooting", "lgbt", "lesbian", "gay", "bisexual", "transgender", "queer", "health care", "social security", "medicare", "healthcare", "doctor", "immigration", "migrants", "military", "police", "abortion", "inflation", "employment", "jobs", "worker", "union", "workforce", "work force". At the county-year level, the fraction of tax tweets for whom the indicator at the tweet level is 1.	Twitter	Tweet and County-Year
Tax Waste	At the tweet level, an indicator variable for if a tweet contains one of the following words: "waste", "wasting", "stole", "misuse", "exploit", "squander", "misspend", "misspent", "steal", "excess", "pork", "reckless", "splurge". At the county-year level, the fraction of tax tweets for whom the indicator at the tweet level is 1.	Twitter	Tweet and County-Year
Tax Policy	At the tweet level, an indicator variable for if a tweet contains one of the following words: "tax cut", "tax increase", "cut tax", "decrease tax", "raise tax", "lower tax", "tax policy", "tax bill", "tcja", "sales tax", "property tax", "gas tax", "carbon tax", "tax plan". At the county-year level, the fraction of tax tweets for whom the indicator at the tweet level is 1.	Twitter	Tweet and County-Year
Tax Refunds	At the tweet level, an indicator variable for if a tweet contains the words "tax return" and the Trump indicator is 0, or if a tweet contains one of the following words: "refund", "bank account", "donation", "deduction", "credit", "rebate", "writeoff", "write off". At the county-year level, the fraction of tax tweets for whom the indicator at the tweet level is 1.	Twitter	Tweet and County-Year

Figure 1: Trends in Tax-Related Twitter Volume

This figure graphs the quarterly total number of tax related tweets from Q1 2014 to Q4 2022. *Tax tweets* is the total number of tweets in a given quarter that contain the word "tax". *Total tweets* is an approximation of the total number of tweets in a given quarter (as captured by the total number of tweets that contain the word "the"). This figure uses the raw sample of 186 million tweets.

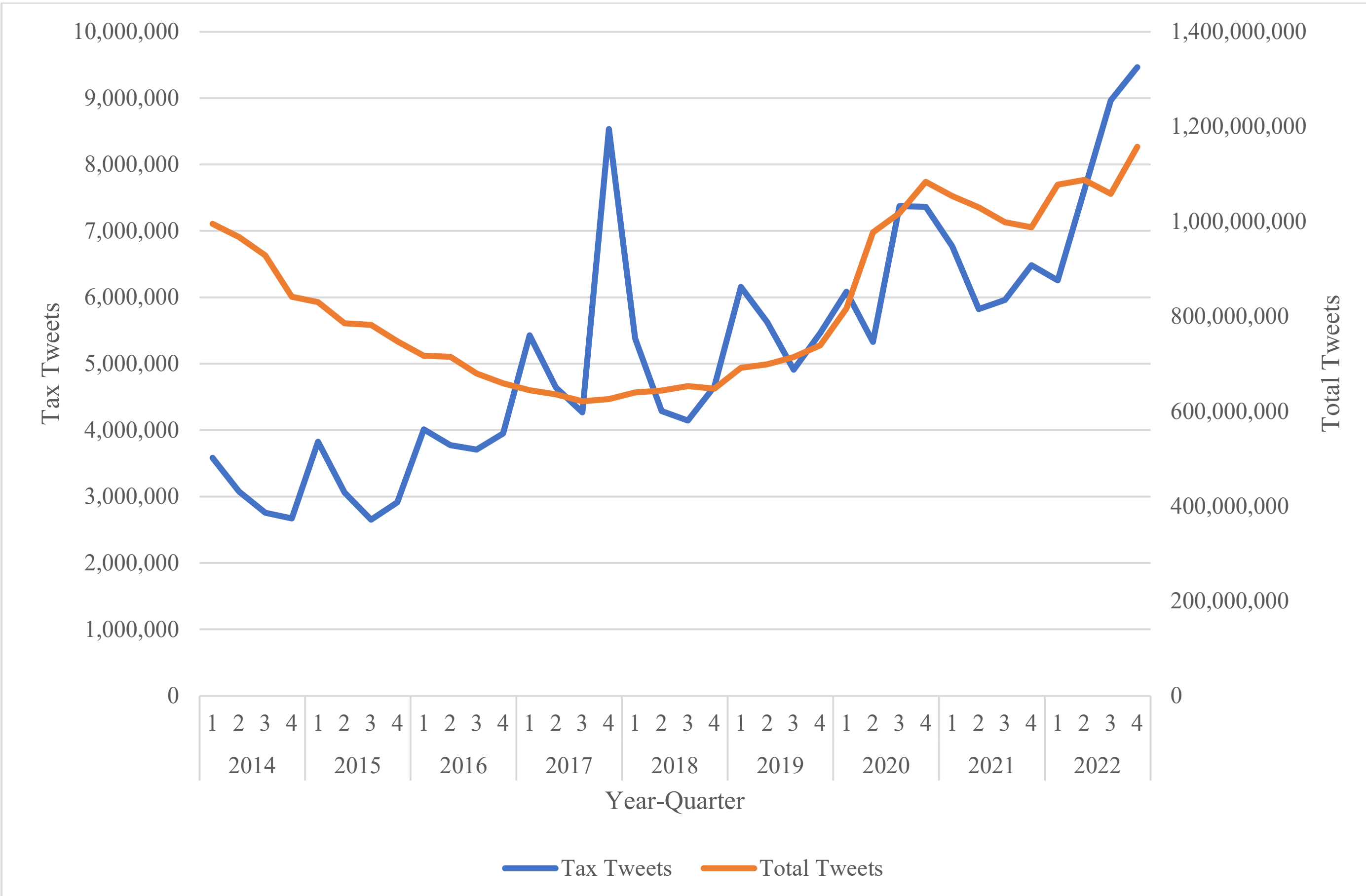
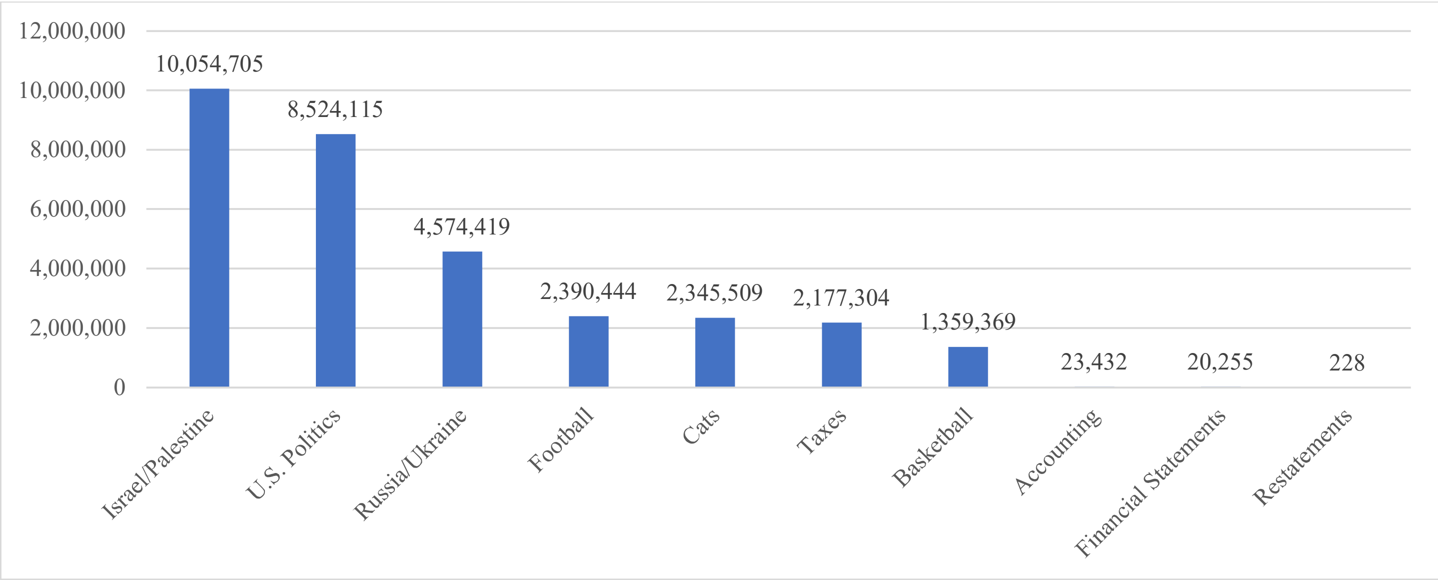


Figure 2: Comparison of Twitter Topics

This figure graphs the total number and percentage of tweets related to specific topics from March 9-14, 2024 (out-of-sample). We use this narrow window because Twitter removed academic access to its API in March 2023 and currently only allows queries on activity from the last seven days. Panel A includes the total number of tweets related to Israel/Palestine, U.S. political parties, Russia/Ukraine, football, cats, taxes, accounting, financial statements, and restatements. The specific words included in each search are listed in Appendix A. Panel B estimates the proportion of total tweets related to each topic. Because Twitter does not permit API users to determine the total number of Tweets, we estimate the denominator of this proportion by counting the total number of tweets that contain the most common word in the English language that is not classified as a stop word by Twitter ("have"), as stop words cannot be queried.

Panel A: Number of Tweets



Panel B: Proportion of Tweets

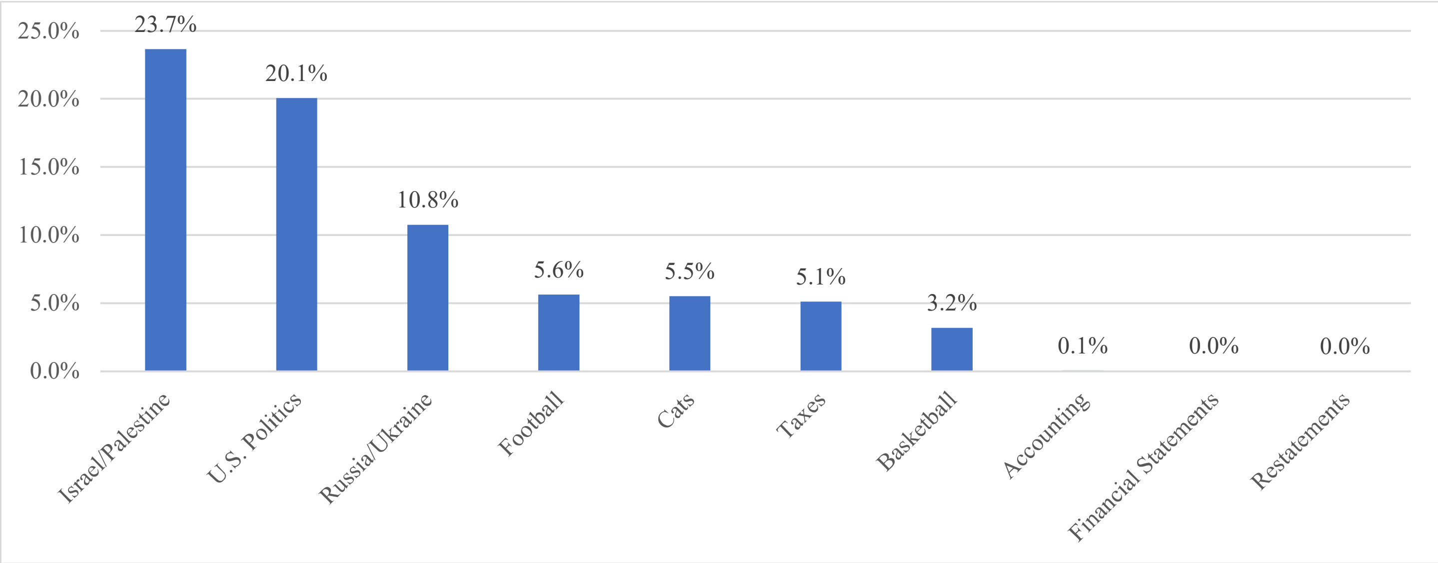
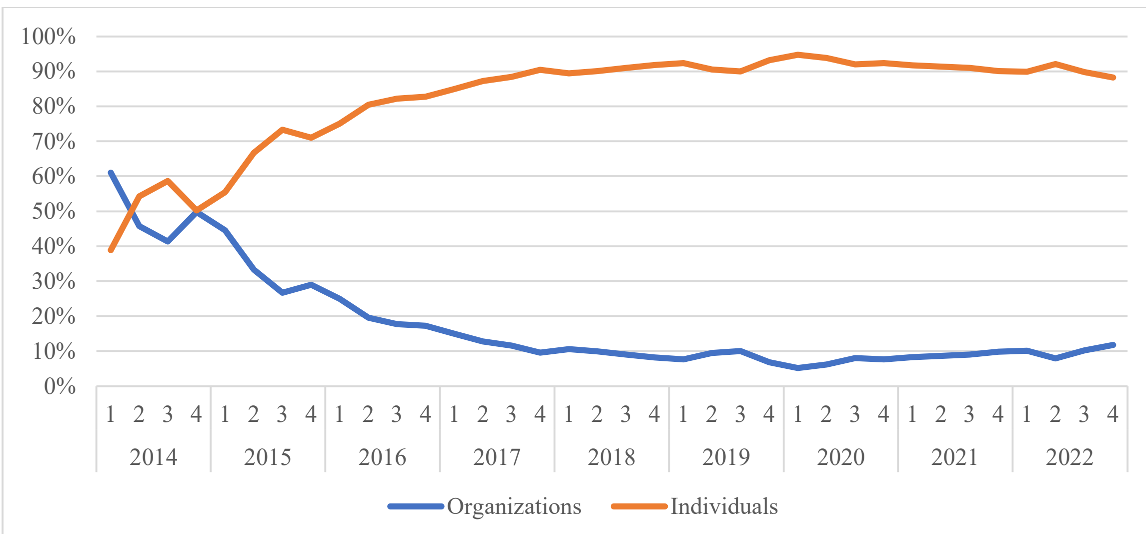


Figure 3: Trends in User Likes

This figure graphs the proportion of likes on tax-related tweets attributable to each user group from 2014 to 2022. We begin with the raw sample of 186 million tweets. However, for computational tractability, we keep only the 1,000 most liked tweets each day and analyze their authors (i.e., users). In Panel A, we classify users as either representing an individual or an organization (e.g., CNBC, Fox News). In Panel B, we classify users as (1) politicians, (2) political personalities, (3) journalists, (4) celebrities, (5) academics, (6) social media influencers, (7) businesspersons, or (8) unknown. Politicians are individuals who currently hold or have previously held elected or politically-appointed government positions. Political personalities are individuals or organizations primarily involved in political commentary. A journalist is a user who works at a media company (e.g., TV, newspaper, online news). A celebrity is a user who is famous from "traditional" methods, including as an actor, musician, author, athlete, etc. An influencer is a user who is famous due to being a social media influencer. A businessperson is a top executive, entrepreneur, lawyer, etc. We label a user as "unknown" if we cannot classify them into one of the above categories. The categories are not mutually exclusive.

Panel A: Organizations vs Individuals



Panel B: User Groups

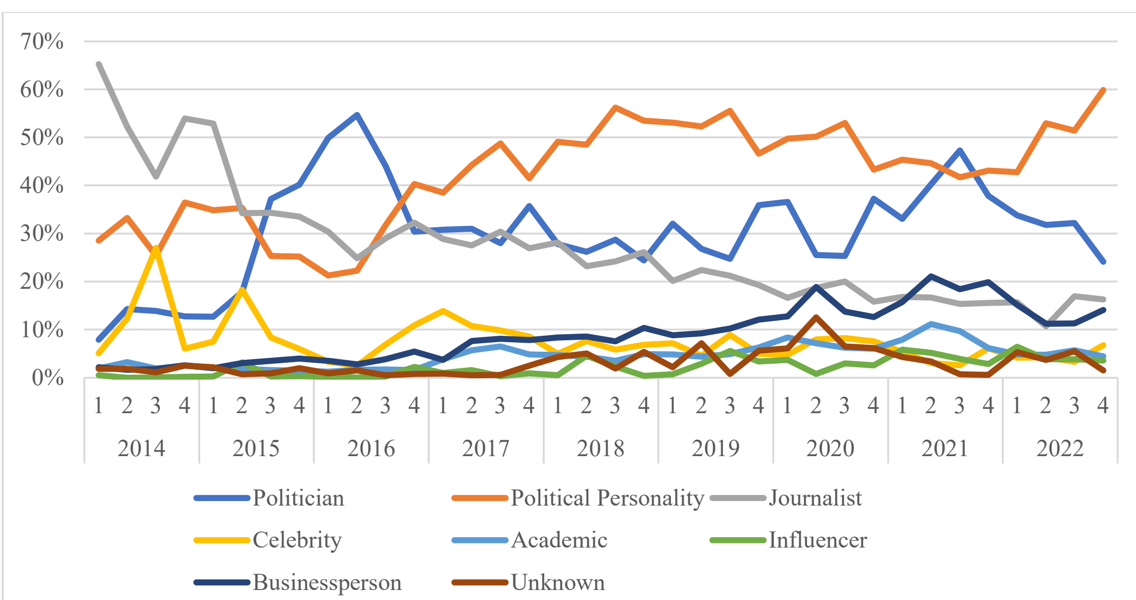


Figure 4: Choropleth of Tweets

This figure plots the number of tweets that contain the word "tax" in 2020 divided by the number of people in the county. This figure uses our primary sample of the 3.1 million tweets that have geo-location enabled.

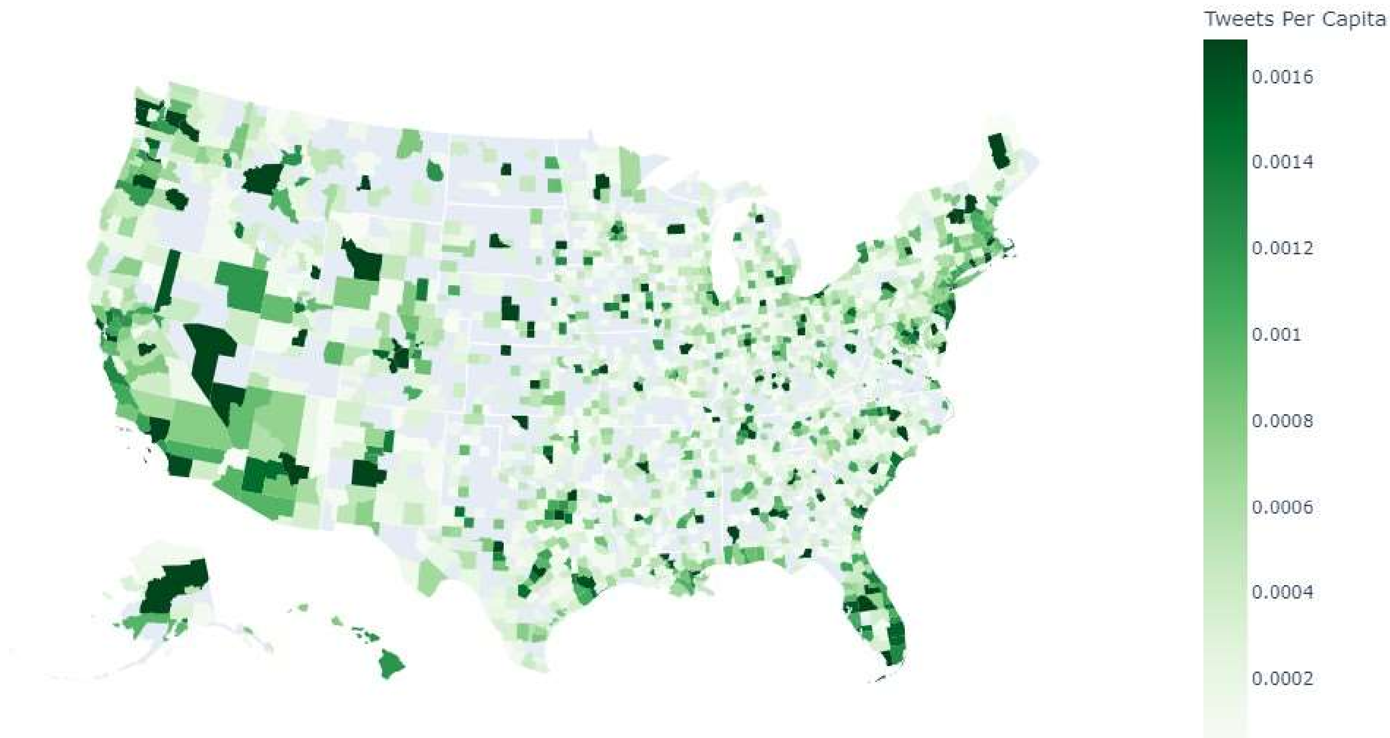


Figure 5: Trends in Tax Sentiment

This figure graphs the average of *Tax Sentiment* of tweets that contain the word "tax" by year-quarter. *Tax Sentiment* is the average probability in a given county-year that a tweet is positive according to the Barbieri et al. (2020) model output. The distribution of *Tax Sentiment* is centered at 0.5 (neutral), and scaled between 0.0 and 1.0, with 0.0 capturing highly negative tax tweets and 1.0 capturing highly positive tax tweets. This figure uses our primary sample of the 3.1 million tweets that have geo-location enabled.

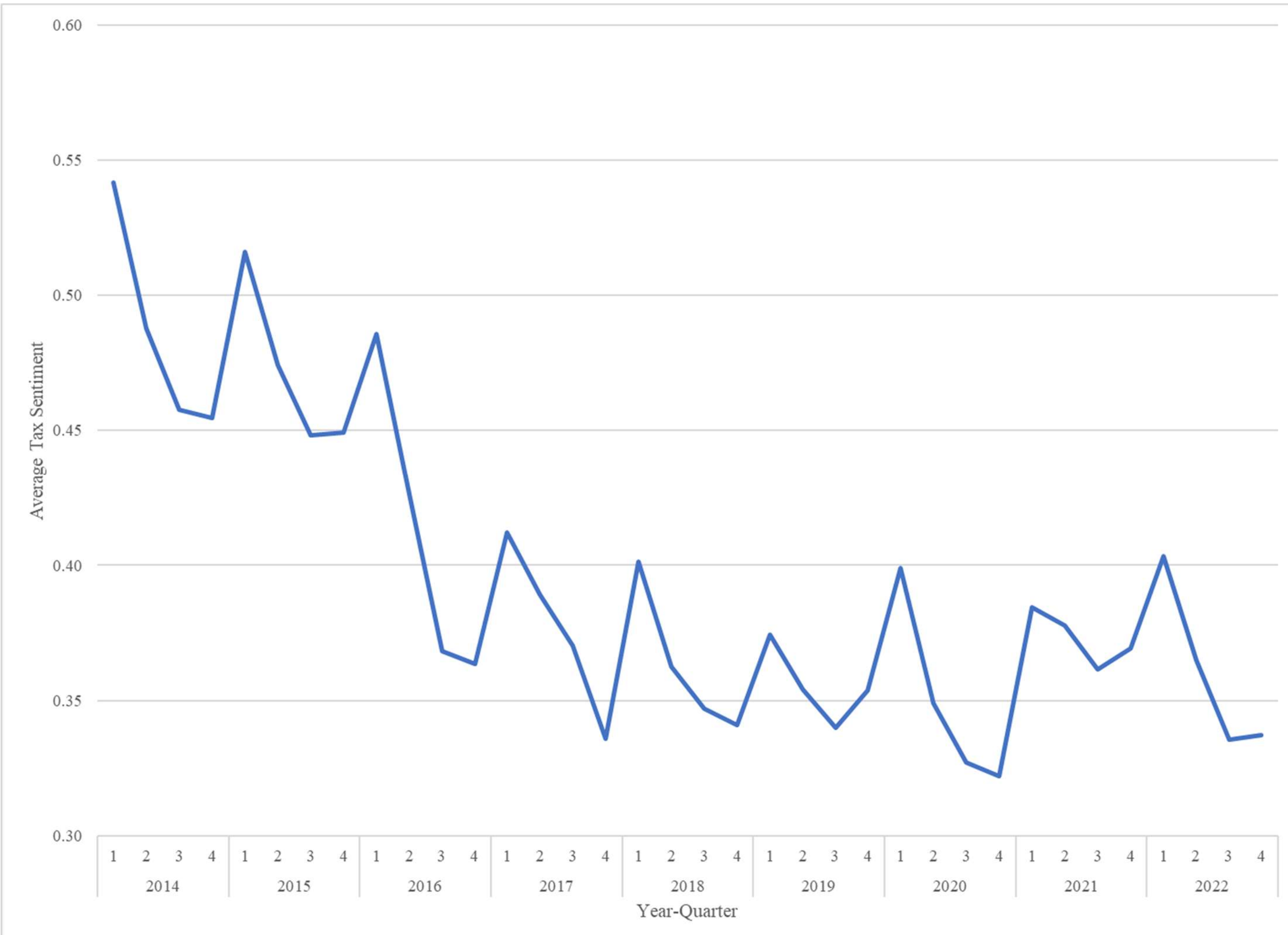


Figure 6: Histogram of Tax Sentiment

This figure graphs a histogram of *Tax Sentiment* for all tweets that contain the word "tax." *Tax Sentiment* is the average probability in a given county-year that a tweet is positive according to the Barbieri et al. (2020) model output bin size for the histogram is 0.02. The distribution of *Tax Sentiment* is centered at 0.5 (neutral), and scaled between 0.0 and 1.0, with 0.0 capturing highly negative tax tweets and 1.0 capturing highly positive tax tweets. This figure uses our primary sample of the 3.1 million tweets that have geo-location enabled.

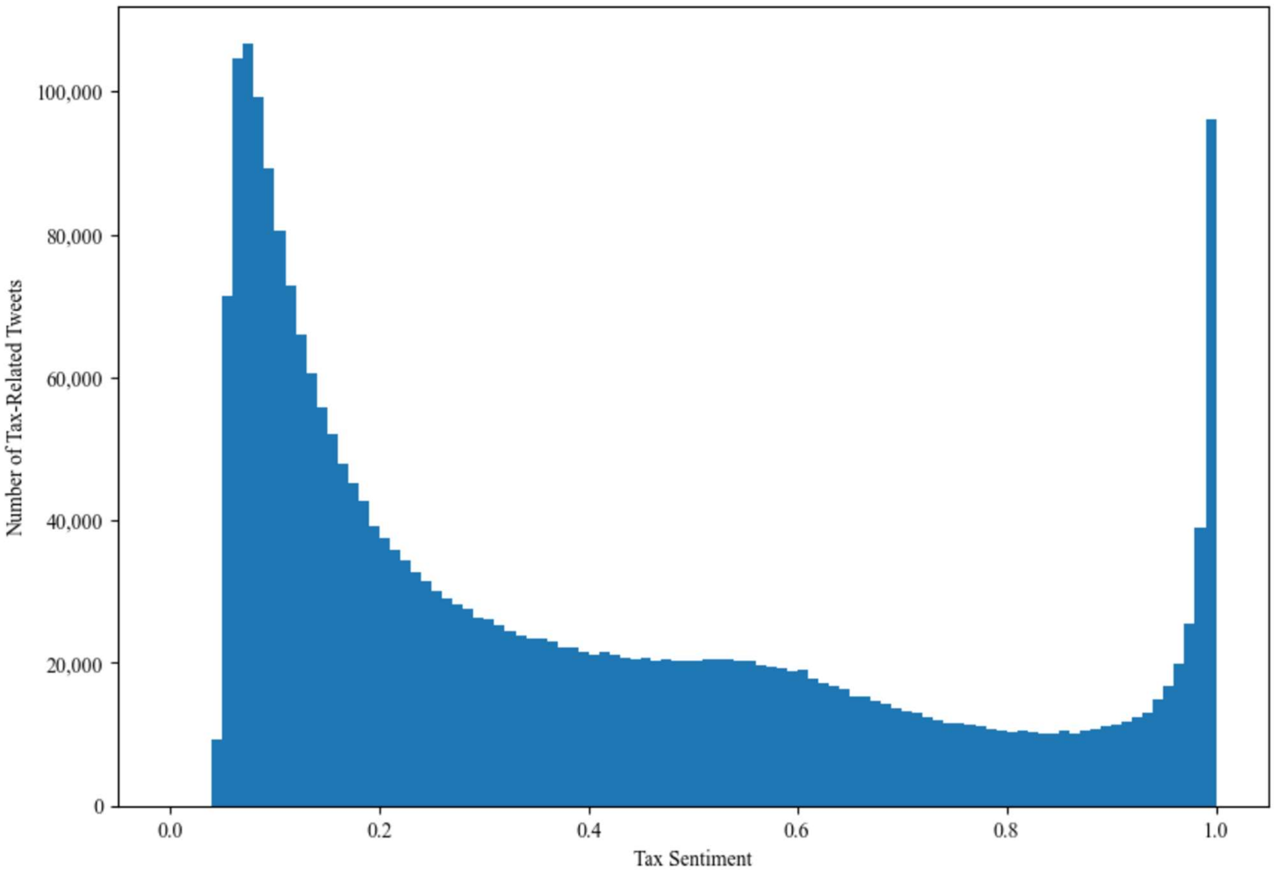


Figure 7: Tax Sentiment by Topic

This figure graphs the average *Tax Sentiment* for each of the eight categories for tweets that contain the word "tax". The precise definition of each category and other variables is listed in Appendix A. *Tax Sentiment* is the average positive sentiment score minus the negative sentiment score, where positive and negative sentiment scores are created using the Barbieri et al. (2020) model output. In the figure, a category's average *Tax Sentiment* is displayed relative to a baseline group by taking the difference between the average sentiment of the category's tweets and the average sentiment of tweets that do not belong to any of the eight categories. This figure uses our primary sample of the 3.1 million tweets that have geo-location enabled.

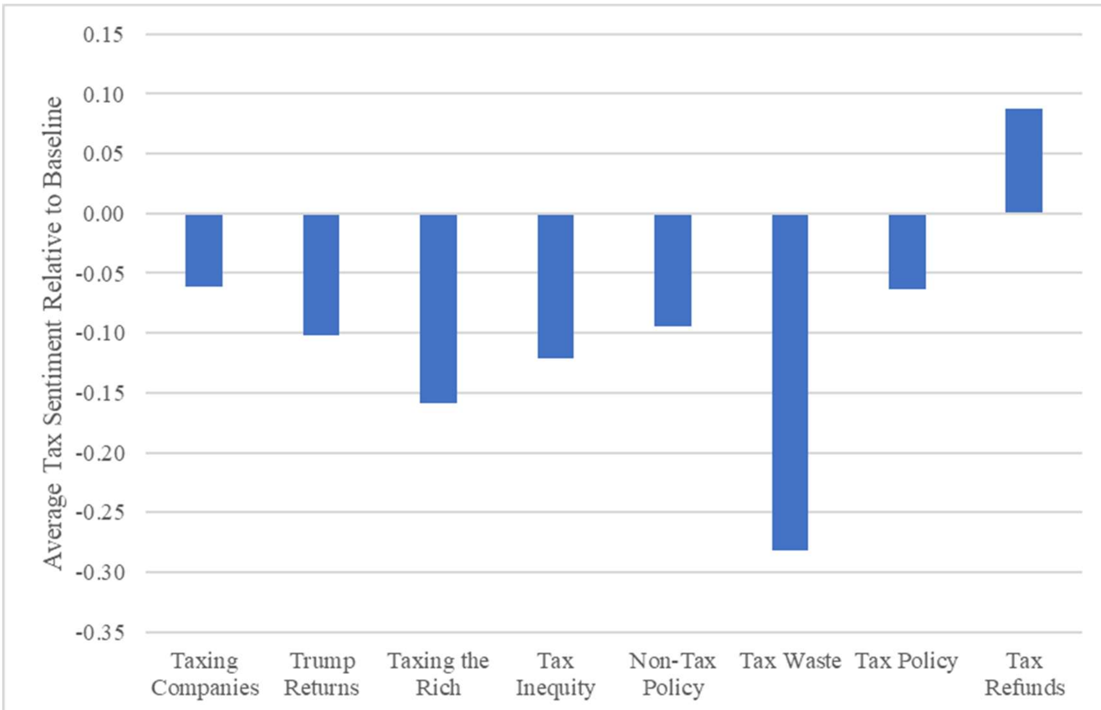


Table 1: User-level Descriptive Statistics

This table presents descriptive statistics on Twitter users in our sample. In Panel A, we tabulate the 25 users from 2014 to 2022 with the most likes on tweets containing the word "tax", the *Tax Sentiment* of their tweets, their total likes, and our categorization of user type. In Panel B, we tabulate by group the average *Tax Sentiment*, the proportion of users, and the proportion of likes. Total Likes is the total number of likes on tax tweets by that user. *Tax Sentiment* is the average positive sentiment score minus the negative sentiment score for the a given user's tax tweets that are in the top 1,000 most liked tweets per day, where positive and negative sentiment scores are created the Barbieri et al. (2020) model output. We classify users as either representing an individual or an organization (e.g., CNBC, Fox News). We also classify users as (1) politicians, (2) political personalities, (3) journalists, (4) celebrities, (5) academics, (6) social media influencers, (7) businesspersons, or (8) unknown. Politicians are individuals who currently hold or have previously held elected or politically-appointed government positions. Political personalities are individuals or organizations primarily involved in political commentary. A journalist is a user who works at a media company (e.g., TV, newspaper, online news). A celebrity is a user who is famous from "traditional" methods, including as an actor, musician, author, athlete, etc. An influencer is a user who is famous due to being a social media influencer. A businessperson is a top executive, entrepreneur, lawyer, etc. We label a user as "unknown" if we cannot classify them into one of the above categories. The categories are not mutually exclusive.

Panel A: Users with Most Likes

Name	Username	*Tax Sentiment*	Total Likes	Organization	Politician	Political Personality	Journalist	Celebrity	Academic	Influencer	Businessperson	Unknown
Robert Reich	RBReich	0.35	18,981,518	0	1	1	0	0	1	0	1	0
Bernie Sanders	BernieSanders	0.36	12,045,018	0	1	0	0	0	0	0	0	0
Bernie Sanders	SenSanders	0.34	11,715,660	0	1	0	0	0	0	0	0	0
Alexandria Ocasio-Cortez	AOC	0.29	8,264,610	0	1	0	0	0	0	0	0	0
President Biden	POTUS	0.60	7,788,233	0	1	0	0	0	0	0	0	0
Charlie Kirk	charliekirk11	0.32	7,250,373	0	0	1	0	0	0	0	0	0
Kyle Griffin	kylegriffin1	0.45	6,641,608	0	0	1	1	0	0	0	0	0
Joe Biden	JoeBiden	0.48	6,440,641	0	1	0	0	0	0	0	0	0
Dan Price	DanPriceSeattle	0.41	5,313,280	0	0	0	0	0	0	0	1	0
Elizabeth Warren	ewarren	0.46	4,607,704	0	1	0	0	0	0	0	0	0
David Corn	DavidCornDC	0.72	4,554,033	0	0	1	1	0	0	0	0	0
BrooklynDad_Defiant	mmpadellan	0.24	4,119,370	0	0	1	0	0	0	0	0	0
Kamala Harris	KamalaHarris	0.39	4,074,653	0	1	0	0	0	0	0	0	0
Citizens for Ethics	CREWcrew	0.35	3,809,374	1	0	1	0	0	0	0	0	0
Scott Dworkin	funder	0.26	3,770,509	0	0	1	0	0	0	0	0	0
Jon Cooper	joncoopertweets	0.40	3,137,623	0	0	1	0	0	0	0	0	0
Elon Musk	elonmusk	0.45	3,129,647	0	0	0	0	0	0	0	1	0
Elizabeth Warren	SenWarren	0.40	2,861,859	0	1	0	0	0	0	0	0	0
Rep. Jim Jordan	Jim_Jordan	0.35	2,697,708	0	1	0	0	0	0	0	0	0
Ted Lieu	tedlieu	0.33	2,678,098	0	1	0	0	0	0	0	0	0
Adam Schiff	RepAdamSchiff	0.35	2,514,827	0	1	0	0	0	0	0	0	0
Joy-Ann (Pro-Democracy) Reid	JoyAnnReid	0.34	2,483,872	0	0	1	0	0	0	0	0	0
Donald Trump Jr.	DonaldJTrumpJr	0.34	2,432,575	0	0	1	0	0	0	0	0	0
The Hill	thehill	0.45	2,296,042	1	0	0	1	0	0	0	0	0
George Takei	GeorgeTakei	0.33	2,261,304	0	0	0	0	1	0	0	0	0

Panel B: User Groups

Group	*Tax Sentiment*	Proportion of Users	Proportion of Likes
Organization	0.45	11.0%	9.4%
Individual	0.36	89.0%	90.6%
Politician	0.42	17.4%	31.8%
Political Personality	0.33	50.1%	48.6%
Journalist	0.40	22.3%	19.7%
Celebrity	0.35	8.0%	6.2%
Academic	0.34	2.3%	5.9%
Influencer	0.40	5.5%	3.1%
Businessperson	0.36	12.9%	12.6%
Unknown	0.35	8.2%	4.2%

Table 2: N-grams by Tax Sentiment Quintiles

This table presents the top 10 two-word N-grams by *Tax Sentiment* quintile for all tweets that contain the word "tax." *Words* is the text of the two-word N-gram. *Fraction* is the fraction of tweets that contain the listed two-word N-grams. Columns display the quintile of a tweet's *Tax Sentiment,* with Quintile 1 (Q1) having the most positive relative sentiment and Quintile 5 (Q5) having the most negative relative sentiment. *Tax Sentiment* is the probability a tweet is positive according to the Barbieri et al. (2020) model output. For purposes of displaying the n-gram, the word "tax" and its derivatives are removed from the tweets. This table uses our primary sample of the 3.1 million tweets that have geo-location enabled.

Q1 (highly positive)		Q2		Q3		Q4		Q5 (highly negative)	
Words	Fraction	Words	Fraction	Words	Fraction	Words	Fraction	Words	Fraction
cannot wait	1.1%	middle class	1.0%	middle class	1.7%	middle class	2.1%	payer money	2.2%
free weekend	1.0%	trump return	0.6%	cut rich	0.7%	payer money	1.1%	middle class	1.9%
middle class	0.8%	donald trump	0.6%	social security	0.7%	cut rich	1.0%	american people	0.9%
last year	0.6%	last year	0.5%	donald trump	0.6%	social security	0.9%	cut rich	0.9%
got return	0.6%	social security	0.5%	payer money	0.6%	health care	0.8%	waste money	0.9%
bank account	0.5%	release return	0.5%	health care	0.6%	donald trump	0.6%	health care	0.8%
president trump	0.5%	release returns	0.5%	fair share	0.5%	american people	0.6%	social security	0.8%
small business	0.5%	health care	0.4%	last year	0.5%	rich people	0.5%	waste payer	0.7%
health care	0.4%	new york	0.4%	rich people	0.5%	last year	0.5%	million dollar	0.6%
get back	0.4%	fair share	0.4%	release return	0.5%	fair share	0.5%	donald trump	0.5%

Table 3: Tax Sentiment and Macroeconomic Conditions

This table presents determinants of average daily *Tax Sentiment* across the sample period, 2014 and 2022. *VIX* is a measure of market uncertainty, captured by the daily level of the implied option volatility from the CBOE. *Tax News Day* is an indicator variable for days on which there is a news article targeting firms' taxes, following Asay et a., (2024). *Tax Policy Uncertainty* and *Twitter Uncertainty* are policy uncertain measures from policyuncertainty.com, following Baker et al., (2016). *Tax Salience* is the fraction of tweets on a given day that are related to taxes. *Tax Sentiment* is measured as the average probability on a given day that a tweet is positive according to the Barbieri et al. (2020) model output. This table uses our sample of tax tweets that are in the top 1,000 most liked tweets per day. All variables are defined in Appendix A.

	Tax Sentiment			
	(1)	(2)	(3)	(4)
Tax Salience		-6.206***		-1.329
		(-6.718)		(-1.482)
VIX	0.001	0.001	0.001	0.001
	(1.675)	(0.792)	(1.597)	(1.569)
Tax News Day	-0.003	0.002	-0.011*	-0.010*
	(-0.449)	(0.342)	(-1.826)	(-1.735)
Tax Policy Uncertainty	-0.000*	-0.000**	-0.000	-0.000
	(-1.961)	(-2.246)	(-0.364)	(-0.363)
Twitter Uncertainty	-0.000***	-0.000***	-0.000***	-0.000***
	(-4.889)	(-4.795)	(-2.758)	(-2.894)
Year FE	No	No	Yes	Yes
Observations	2,265	2,265	2,265	2,265
R-Squared	0.378	0.473	0.665	0.668

Table 4: County-level Descriptive Statistics

This table presents descriptive statistics at the county-year level between 2014 and 2020. Variables that are not ratios or percentages are presented in unlogged form. This table uses our primary sample of the 3.1 million tweets that have geo-location enabled. All variables are defined in Appendix A.

	Count	Mean	SD	Q1	Q2	Q3
Reported Non-Wage Income	21,455	918,904	2,496,286	63,572	165,556	520,333
Partnership & S-Corp Income	21,241	170,331	505,480	7,270	22,675	80,234
Schedule C Business Income	21,317	91,565	249,081	6,159	16,113	51,459
Reported Wage Income	21,455	2,073,760	5,456,814	154,925	390,168	1,192,152
Abnormal Tax Sentiment	21,455	0.71	0.27	0.58	0.70	0.78
Taxing Companies	21,455	1.9%	4.7%	0.0%	0.0%	1.8%
Trump Returns	21,455	1.1%	3.6%	0.0%	0.0%	0.0%
Taxing the Rich	21,455	2.7%	6.5%	0.0%	0.0%	2.7%
Tax Inequity	21,455	0.3%	1.2%	0.0%	0.0%	0.0%
Non-Tax Policy	21,455	5.9%	11.4%	0.0%	0.0%	9.1%
Tax Waste	21,455	1.6%	4.5%	0.0%	0.0%	1.0%
Tax Policy	21,455	7.3%	14.2%	0.0%	0.0%	10.1%
Tax Refunds	21,455	7.2%	14.3%	0.0%	0.0%	9.7%
Preparer %	21,455	57.4%	9.9%	50.2%	56.7%	64.4%
Agreeableness	13,906	0.04	0.45	-0.28	0.04	0.36
Conscientious	13,906	-0.06	0.56	-0.41	-0.08	0.31
Emotional Stability	13,906	0.15	0.53	-0.21	0.16	0.50
Extraversion	13,906	-0.06	0.39	-0.33	-0.04	0.22
Openness	13,906	0.11	0.73	-0.44	0.01	0.59
% Republican	21,329	64%	15%	55%	67%	75%
Employment	21,455	32,660	84,792	2,185	6,261	19,704
GDP (1000's)	21,455	4,672,072	12,526,848	362,368	935,622	2,680,433
Wages (1000's)	21,455	1,651,941	4,867,640	78,883	239,959	818,035
Establishments	21,455	2,410	5,877	241	574	1,587

Table 5: Tax Sentiment and Local Tax Compliance

This table models local tax reporting as a function of factors related to economic income, as well as tax sentiment. The dependent variable, *Reported Non-Wage Income*, is a county-year's total reported adjusted gross income less W-2 income. *Schedule C Business Income* and *Partnership and S-Corp Income* are the total amount of business income from schedule C and partnership and S-Corp in come report in a county-year, respectively. *Abnormal Tax Sentiment* is a relative measure of *Tax Sentiment*, measured as the average probability in a given county-year that a tweet is positive according to the Barbieri et al. (2020) model output divided by the average probability a tweet is positive in a given county-year according to TSGI. *Employment*, *Wages,* and *Establishments* are the natural log of total employment, wages, and establishments in a county. *GDP* is a county-year's natural log of real GDP. All columns include county fixed effects. Columns include year and state-year fixed effects as labeled. Standard errors are clustered by state. This table uses our primary sample of the 3.1 million tweets that have geo-location enabled. All variables are defined in Appendix A.

Dep. Var	Reported Non-Wage Income		Partnership and S-Corp Income		Schedule C Business Income		Reported Wage Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abnormal Tax Sentiment	-0.034***	-0.029***	-0.063***	-0.055***	-0.025***	-0.014**	-0.005	-0.004
	(-3.052)	(-2.987)	(-2.878)	(-2.765)	(-3.227)	(-2.203)	(-1.571)	(-1.652)
Employment	-0.246	-0.181	-0.278	-0.362	-0.237	-0.090	0.014	-0.059
	(-1.617)	(-1.230)	(-0.838)	(-1.349)	(-1.598)	(-0.760)	(0.175)	(-0.939)
GDP	0.215***	0.183***	0.234*	0.178**	0.076	0.047	0.135**	0.089**
	(3.236)	(5.415)	(1.697)	(2.172)	(0.751)	(0.575)	(2.434)	(2.651)
Wages	0.533***	0.364***	0.890**	0.800**	0.462***	0.238**	0.189***	0.173***
	(5.766)	(6.075)	(2.521)	(2.619)	(3.484)	(2.115)	(4.406)	(5.268)
Establishments	0.325***	0.420***	0.210	0.252*	0.459***	0.523***	0.364***	0.400***
	(4.317)	(7.068)	(1.357)	(1.866)	(4.093)	(5.654)	(8.007)	(8.802)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
State-Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	21,455	21,455	21,238	21,238	21,316	21,316	21,455	21,455
R-Squared	0.998	0.998	0.993	0.993	0.997	0.998	1.000	1.000
Within R-Squared	0.162	0.116	0.0816	0.0514	0.0974	0.0601	0.467	0.391

Table 6: Tax Compliance and Topical Measures of Tax Sentiment

This table examines uses various categories of tweets to determine the mechanism through which *Abnormal Tax Sentiment* affects tax compliance. All panels present regressions at the county-year level between 2014 and 2020. In Panel A, the dependent variable, *Abnormal Tax Sentiment,* is a relative measure of *Tax Sentiment*, measured as the average probability in a given county-year that a tweet is positive according to the Barbieri et al. (2020) model output divided by the average probability a tweet is positive in a given county-year according to TSGI. The listed independent variables are the proportion of tax tweets in a given county-year that are categorized by topics. The precise definition of each category and other variables is listed in Appendix A. Panel B presents a regression of *Reported Non-Wage Income* on these same categories. The dependent variable, *Reported Non-Wage Income*, is a county-year's total reported adjusted gross income less W-2 income. Panel C presents a regression of *Reported Non-Wage Income* on *Abnormal Tax Sentiment* interacted with *Trump Presidency*, which is an indicator equal to one for years 2017 to 2020. In all panels, economic Controls include *Employment, Wages, Establishments,* and *GDP*. In each panel, column (1) includes county and year fixed effects, and column (2) includes county and state-year fixed effects. Standard errors are clustered by state. This table uses our primary sample of the 3.1 million tweets that have geo-location enabled. All variables are defined in Appendix A.

Panel A: County Level Determinants of Tax Sentiment

	Dep. Var	Abnormal Tax Sentiment	
		(1)	(2)
Peer Effects	*Trump Returns*	-0.412***	-0.407***
		(-6.327)	(-6.068)
	Taxing the Rich	-0.448***	-0.432***
		(-10.878)	(-10.575)
	Tax Inequity	-0.315**	-0.312**
		(-2.365)	(-2.345)
	Taxing Companies	-0.139***	-0.133***
		(-3.425)	(-3.198)
Reciprocity	*Non-Tax Policy*	-0.148***	-0.146***
		(-4.898)	(-4.655)
	Tax Waste	-0.839***	-0.836***
		(-18.258)	(-18.166)
	Tax Policy	-0.003	-0.011
		(-0.076)	(-0.347)
	Tax Refunds	0.288***	0.283***
		(11.626)	(10.985)
County FE		Yes	Yes
Year FE		Yes	No
State-Year FE		No	Yes
Economic Controls		Yes	Yes
Observations		21,455	21,455
R-Squared		0.690	0.700
Within R-Squared		0.0970	0.0938

Panel B: Category Determinants of Tax Compliance

Dep. Var	Reported Non-Wage Income	
	(1)	(2)
Trump Returns	0.133**	0.087*
	(2.419)	(1.902)
Taxing the Rich	0.035	0.010
	(0.958)	(0.369)
Tax Inequity	0.050	-0.014
	(0.469)	(-0.195)
Taxing Companies	0.099***	0.070**
	(2.714)	(2.261)
Non-Tax Policy	0.012	0.019
	(0.610)	(1.246)
Tax Waste	0.018	0.008
	(0.567)	(0.340)
Tax Policy	0.041***	0.035***
	(4.327)	(3.955)
Tax Refunds	-0.019*	-0.005
	(-1.766)	(-0.537)
County FE	Yes	Yes
Year FE	Yes	No
State-Year FE	No	Yes
Economic Controls	Yes	Yes
Observations	21,455	21,455
R-Squared	0.998	0.998
Within R-Squared	0.163	0.117

Panel C: Trump Presidency

Dep.Var.	*Reported Non-Wage Income*	
	(1)	(2)
*Abnormal Tax Sentiment*Trump Presidency*	-0.048***	-0.021*
	(-3.649)	(-1.811)
Abnormal Tax Sentiment	-0.012	-0.019
	(-0.978)	(-1.489)
County FE	Yes	Yes
Year FE	Yes	No
State-Year FE	No	Yes
Economic Controls	Yes	Yes
Observations	21,455	21,455
R-Squared	0.998	0.998
Within R-Squared	0.163	0.116

Table 7: Tax Preparers and Tax Compliance

This table models local tax reporting as a function of paid tax preparation levels. The dependent variable, *Reported Non-Wage Income*, is a county-year's total reported adjusted gross income less W-2 income. *Preparer %* is the fraction a tax returns in a county-year that are prepared using a paid preparer. *Abnormal Tax Sentiment* is a relative measure of *Tax Sentiment*, measured as the average probability in a given county-year that a tweet is positive according to the Barbieri et al. (2020) model output divided by the average probability a tweet is positive in a given county-year according to TSGI. *Employment*, *Wages,* and *Establishments* are the natural log of total employment, wages, and establishments in a county. *GDP* is a county-year's natural log of real GDP. Column (1) includes county and year fixed effects, and column (2) includes county and state-year fixed effects. Standard errors are clustered by state. This table uses our primary sample of the 3.1 million tweets that have geo-location enabled. All variables are defined in Appendix A.

Dep. Var	*Reported Non-Wage Income*			
	(1)	(2)	(3)	(4)
Preparer %	1.387***	1.165**	1.274***	0.926**
	(3.127)	(2.474)	(2.818)	(2.076)
Abnormal Tax Sentiment			-0.116*	-0.213***
			(-1.698)	(-4.458)
*Preparer %*Abnormal Tax Sentiment*			0.148	0.328***
			(1.256)	(4.475)
Employment	-0.214	-0.167	-0.203	-0.159
	(-1.432)	(-1.135)	(-1.364)	(-1.094)
GDP	0.213***	0.179***	0.209***	0.175***
	(3.174)	(5.113)	(3.186)	(5.192)
Wages	0.502***	0.351***	0.494***	0.340***
	(6.064)	(5.713)	(5.996)	(5.717)
Establishments	0.299***	0.367***	0.299***	0.367***
	(3.761)	(5.290)	(3.760)	(5.248)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
State-Year FE	No	Yes	No	Yes
Observations	21,455	21,455	21,455	21,455
R-Squared	0.998	0.998	0.998	0.999
Within R-Squared	0.180	0.127	0.183	0.133

Table 8: Tax Compliance and Tax Sentiment, by Household Income Level

This table models local tax reporting as a function of factors related to economic income as well as tax sentiment, partitioned by household income. The dependent variable, *Reported Non-Wage Income*, is the inverse hyperbolic sine (to allow for negative values) of a county-year's total reported adjusted gross income less W-2 income for tax returns between the IRS's eight AGI thresholds. *Abnormal Tax Sentiment* is a relative measure of *Tax Sentiment*, measured as the average probability in a given county-year that a tweet is positive according to the Barbieri et al. (2020) model output divided by the average probability a tweet is positive in a given county-year according to TSGI. Economic controls are the same as in Table 6. Regressions include county and state-year fixed effects. Standard errors are clustered by state. This table uses our primary sample of the 3.1 million tweets that have geo-location enabled. All variables are defined in Appendix A.

Dep. Var.	Reported Non-Wage Income						
AGI	$1-$10K	$10K-$25K	$25K-$50K	$50K-$75K	$75K-$100K	$100K-$200K	>$200K
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Abnormal Tax Sentiment	-0.036**	0.010*	0.001	-0.017***	-0.021***	-0.035***	-0.040***
	(-2.476)	(1.833)	(0.103)	(-4.569)	(-6.378)	(-7.309)	(-3.033)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,104	21,374	21,392	21,380	21,353	21,338	19,729
R-Squared	0.994	0.999	0.998	0.999	0.999	0.999	0.997
Within R-Squared	0.0152	0.0409	0.0566	0.0504	0.0814	0.0613	0.144

Table 9: Tax Compliance, Tax Sentiment, and Local Characteristics

This table models local tax reporting as a function of factors related to economic income, as well as tax sentiment interacted with measures of local political affiliations. The dependent variable, *Reported Non-Wage Income*, is a county-year's total reported adjusted gross income less W-2 income. *Abnormal Tax Sentiment* is a relative measure of *Tax Sentiment*, measured as the average probability in a given county-year that a tweet is positive according to the Barbieri et al. (2020) model output divided by the average probability a tweet is positive in a given county-year according to TSGI. Economic controls are the same as in Table 6. Political affiliation is proxied for by the fraction of a county that voted Republican in 2016. Column (1) includes county and year fixed effects, and column (2) includes county and state-year fixed effects. Standard errors are clustered by state. This table uses our primary sample of the 3.1 million tweets that have geo-location enabled. All variables are defined in Appendix A.

Dep.Var.	*Reported Non-Wage Income*	
	(1)	(2)
*Abnormal Tax Sentiment*Republican*	0.349***	0.217**
	(3.531)	(2.554)
Abnormal Tax Sentiment	-0.256***	-0.168**
	(-3.513)	(-2.654)
County FE	Yes	Yes
Year FE	Yes	No
State-Year FE	No	Yes
Economic Controls	Yes	Yes
Observations	21,329	21,329
R-Squared	0.998	0.998
Within R-Squared	0.172	0.121

Table 10: Bartik Instrument

This table presents a Bartik instrument that is used to control for the endogenous relation between tax sentiment and tax compliance. All panels present regressions at the county-year level between 2014 and 2020. *Sentiment Sensitivity* is an indicator variable for whether the county-specific beta estimation procedure yielded a beta that was in the top 25% of all counties for which betas were estimated. The beta estimation procedure uses a sample from 2022 of counties who have tax tweets on more than 50 distinct days. For each day, we regress the average national abnormal tax sentiment on the county-day's abnormal tax sentiment. The betas from this regression are then used to construct the county-specific *Sentiment Sensitivity. National Abnormal Sentiment* is defined as the national average *Abnormal Tax Sentiment* for a given year. *Abnormal Tax Sentiment* is a relative measure of *Tax Sentiment*, measured as the average probability in a given county-year that a tweet is positive according to the Barbieri et al. (2020) model output divided by the average probability a tweet is positive in a given county-year according to TSGI. *Reported Non-Wage Income*, is a county-year's total reported adjusted gross income less W-2 income. *Schedule C Business Income* and *Partnership and S-Corp Income* are the total amount of business income from schedule C and partnership and S-Corp in come report in a county-year, respectively. Economic Controls include *Employment, Wages, Establishments,* and *GDP.* All columns include county fixed effects. Columns include year and state-year fixed effects as labeled. Standard errors are clustered by state. This table uses our primary sample of the 3.1 million tweets that have geo-location enabled. All variables are defined in Appendix A.

Panel A: Relevance Test

Dep. Var	Abnormal Tax Sentiment	
	(1)	(2)
*National Abnormal Sentiment*Sentiment Sensitivity*	0.045*	0.050*
	(1.745)	(1.797)
County FE	Yes	Yes
Year FE	Yes	No
State-Year FE	No	Yes
Economic Controls	Yes	Yes
Observations	2,883	2,869
R-Squared	0.902	0.919
Within R-Squared	0.0265	0.0319

Panel B: Outcomes Test

Dep. Var	Reported Non-Wage Income		Schedule C Business Income		Partnership and S-Corp Income	
	(1)	(2)	(3)	(4)	(5)	(6)
*National Abnormal Sentiment*Sentiment Sensitivity*	-0.026	-0.023	0.011	0.041	-0.128***	-0.097**
	(-1.138)	(-0.835)	(0.366)	(1.281)	(-3.383)	(-2.137)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
State-Year FE	No	Yes	No	Yes	No	Yes
Economic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,883	2,869	2,882	2,868	2,879	2,865
R-Squared	0.996	0.997	0.997	0.998	0.988	0.990
Within R-Squared	0.162	0.0932	0.155	0.0899	0.0828	0.0398

Table 11: SXSW Shock

This table examines the effects of the South by Southwest festival on tax compliance. Panel A regresses the number of Twitter users per capita (*Users Per Capita)* in a county on the number of followers in that county of the South by Southwest festival per capita before (*Followers Pre SXSW Per Capita*) and after (*Followers Post SXSW Per Capita*) the 2007 festival. The dependent variable of Panel B, *Reported Non-Wage Income*, is a county-year's total reported adjusted gross income less W-2 income. *Abnormal Tax Sentiment* is a relative measure of *Tax Sentiment*, measured as the average probability in a given county-year that a tweet is positive according to the Barbieri et al. (2020) model output divided by the average probability a tweet is positive in a given county-year according to TSGI. Economic Controls include *Employment, Wages, Establishments,* and *GDP*. Columns (1) and (2) of Panel B use the actual number of *Users Per Capita,* while columns (3) and (4) use the predicted value of *Users Per Capita* from Panel A. All columns include county fixed effects. Columns include year and state-year fixed effects as labeled. Standard errors are clustered by state. This table uses our primary sample of the 3.1 million tweets that have geo-location enabled. All variables are defined in Appendix A.

Panel A: Relevance

Dep. Var.	Users Per Capita
Followers Post SXSW Per Capita	983.489***
	(8.774)
Followers Pre SXSW Per Capita	2,056.619***
	(7.443)
Observations	3,069
R-Squared	0.129

Panel B:

Dep. Var	Reported Non-Wage Income			
	(1)	(2)	(3)	(4)
*Abnormal Tax Sentiment*Users Per Capita*	-9.883***	-7.022***	-14.920**	-13.025
	(-5.007)	(-3.545)	(-2.327)	(-1.425)
Followers Pre SXSW Per Capita			13,994.513	12,132.690
			(0.719)	(0.466)
Abnormal Tax Sentiment	0.038***	0.022**	0.072*	0.064
	(3.245)	(2.028)	(1.766)	(1.075)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
State-Year FE	No	Yes	No	Yes
Economic Controls	Yes	Yes	Yes	Yes
OLS	Yes	Yes	No	No
IV	No	No	Yes	Yes
Observations	21,448	21,448	21,448	21,448
R-Squared	0.998	0.998	0.998	0.998
Within R-Squared	0.172	0.122	0.169	0.122