Journal of Economic Behavior and Organization 212 (2023) 1242–1254

Contents lists available at ScienceDirect

Journal of Economic Behavior and Organization

journal homepage: www.elsevier.com/locate/jebo

What we tweet about when we tweet about taxes: A topic modelling approach

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ARTICLE INFO

Article history:
Received 15 March 2022
Revised 20 January 2023
Accepted 7 July 2023

Keywords:
Taxation
Topic modeling
Machine learning
Social media
Information diffusion
Sentiment analysis

ABSTRACT

Recent literature on taxation suggests that a "service and client" approach by the authorities is required in order to establish a synergistic tax climate between taxpayers and tax offices and thus enhance voluntary tax compliance. The present study investigates whether lay people's conceptions about taxation reflect such a synergistic (vs. an antagonistic) climate. Applying an unsupervised machine learning approach (i.e., topic modeling) to over a million tax related tweets from 2010 to 2020, we identified 30 topics with different content. Using the theoretical framework differentiating between synergistic and antagonistic tax climate, we were able to further categorize these topics into four broader groups: 1. *Opinions about Tax Politics*, 2. *Enforcement (antagonistic climate)*, 3. *Information & Service (synergistic climate)*, and 4. *Emotions*. The most frequently observed group was *Information & Service (synergistic climate)*, which also steadily gained prominence during the past decade. We proceeded by analyzing the information diffusion properties and sentiment of the tweets associated with the four groups. *Information & Service* tweets had the most positive sentiment but were shared the least, while tweets regarding *Opinions about Tax Politics* were shared most often. In sum, the results suggest that lay people's conceptions about taxation – as discerned from conversations on social media (Twitter) – largely reflect a synergistic (vs. an antagonistic) climate, and contribute to the literature on tax climate and social media.

1. Introduction

The moment a society introduces taxes, tax evasion is guaranteed to be in the slipstream. It is problematic because a) it reduces the available money that governments can use for social welfare and other citizen services, and b) it can undermine the tax morale of otherwise law-abiding citizens. Hence, it comes as no surprise that authorities, policymakers and tax researchers have been trying for decades to understand taxpayer's attitudes and behavior (Alm et al., 2012; Kirchler, 2007). When it comes to understanding tax compliance (and thus evasion), existing literature converges on two different types of determinants: deterrence-based factors, such as the severity of fines or the probability of audit, and social and psy-

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https://doi.org/10.1016/j.jebo.2023.07.005

chological factors, such as social norms, trust, and fairness perceptions (Kogler et al., 2015; Murphy, 2003; Torgler, 2003; Wenzel, 2004). While deterrence factors are assumed to be essential in enforcing compliance, psychological factors, such as high trust in authorities, are necessary to foster voluntary tax compliance and to establish a synergistic interaction climate between taxpayers and authorities (Kirchler et al., 2008).

There are different ways in which one can investigate lay people's beliefs and attitudes toward taxation, including citizen perceptions of the climate between taxpayers and authorities. Some studies have explored so-called "social representations," for instance by documenting people's mental taxation-related associations or everyday conversations about taxes (see, for instance, Fetchenhauer, 2004; Kasper et al., 2018; Lewis, 1982; Olsen et al., 2017; Onu and Oats, 2016). These studies find that tax compliance motivation depends considerably on beliefs, attitudes, and social norms of taxpayers (Hallsworth et al., 2017; Kogler and Kirchler, 2020; Wenzel, 2005), and these are all expressed in people's communication about the fairness, appropriateness, and effectiveness of taxation. Typically, these studies ask participants to express their thoughts and feelings with respect to taxation, or ask them to discuss those among themselves, record these conversations and analyze them. The present study takes a novel and complementary approach to investigating people's conversations about taxes by assessing the content of over a million tax-related tweets posted between 2010 and 2020. The approach is novel as it is unobtrusive (we use naturally occurring conversations) and allows for high precision due to an exceptionally large data basis (we use over a million tweets).

1.1. Enforcement vs. service paradigm

Research on attitudes and social norms with respect to taxation is by no means new (Schmölders, 1960; Vogel, 1974). Many studies focused on classical economic deterrence factors, such as the level of fines and the probability of audits (Allingham and Sandmo, 1972; Srinivasan, 1973; Yitzhaki, 1974). Some recent studies pinpoint the practical importance and usefulness of these deterrence factors (e.g., Boning et al., 2020; Kleven et al., 2011; Slemrod, 2019). However, during the last two decades, alternative, social and psychological factors, have slowly started receiving more attention. Accordingly, more recent investigations examined how tax compliance decisions are influenced by trust (e.g., Batrancea et al., 2019; Kogler et al., 2013), service quality (e.g., Gangl et al., 2013), emotions (e.g., Coricelli et al., 2014; Enachescu et al., 2019), fairness perceptions (e.g., Murphy and Tyler, 2008), attitudes (e.g., Braithwaite, 2003), and social norms (e.g., Hallsworth et al., 2017; Wenzel, 2005).

Some approaches combine classic deterrence and psychological factors. For example, the most prominent one – the Slippery Slope Framework – integrates both the classical economic and newer psychological factors to offer a conceptual tool to understand tax compliance behavior (Kirchler et al., 2008). It assumes two main dimensions as main determinants of tax compliance: trust in and power of authorities. Trust is claimed to be influenced by the previously mentioned alternative factors, while power mainly depends on economic factors (e.g., deterrence factors). While both trust and power reinforce tax compliance, trust leads to voluntary compliance, while power yields enforced compliance.

Accordingly, trust determines whether the climate between taxpayers and tax authorities can be characterized as antagonistic (with authorities adopting a "cops and robbers" attitude), or synergistic (authorities adopting a "service and clients" attitude). Accordingly, a synergistic climate is beneficial for a number of reasons. First, control and audits are often cost-intensive, and taxpayers in a synergistic climate voluntarily contribute to the public good (Kirchler et al., 2008). Second, the perception of constant surveillance signals distrust and might thus foster resistance (Cialdini, 1996; Frey, 2003). Third, promoting voluntary compliance is likely more effective in preventing aggressive tax planning and tax avoidance (Kirchler et al., 2014). Overall, this suggests that a synergistic climate entailing a service-oriented approach educating and supporting taxpayers is more promising than an antagonistic approach forcing taxpayers to comply.

The idea of a service-oriented approach has since been adopted by many tax offices around the world. Some of them now increasingly assist citizens throughout the taxpaying procedure. The service-oriented approach involves, for instance, taxpayer education, increased assistance, phone services, and improved websites, as successful examples of tax administration reforms in Singapore (Alm and Torgler, 2011) or Sweden (Stridth and Wittberg, 2015) demonstrate. This improvement of the service has led to increased public approval. More recently some tax administrations started using advanced analytics to improve their services.[1] For example, the Singapore tax administrations implemented text mining techniques to track and identify certain trends in taxpayer queries, ultimately allowing for more specific guidance (campaigns, information on website, updates) to the taxpayers (OECD, 2016).

However, research exploring the prevalence of a synergistic vs. antagonistic climate remains scarce. One exception is a recent study by Lozza and Castiglioni (2018) who showed that differences between a synergistic and an antagonistic tax climate are reflected in the language of tax-related articles in local newspapers. An analysis of newspaper articles in Italy and the Italian speaking canton of Ticino in Switzerland found that the Swiss newspapers more frequently used such words as "information," "client," "agreement," "negotiate," "assistance," and "help", which are indicative of a synergistic climate. In contrast, the Italian newspapers more often used words like "inspection," "supertax," "audits," and "evasion," which are indicative of an antagonistic climate. In contrast, the current study focuses on lay people's conceptions of taxes and aims

[1] It is important to mention that the vast majority of these advanced analytics are being used for enforcement purposes (e.g., audit) and that the service aspect only just started evolving.

at documenting the prevalence of service- and enforcement-related perceptions (i.e., synergistic vs. antagonistic interaction climate) by studying naturally occurring conversations on Twitter.

1.2. Lay conceptions of taxes

Most studies on taxpayer's conceptions have been conducted in rather artificial environments, where people were explicitly asked about their associations with taxes and tax-related stimulus words (e.g., Kirchler, 1998; Stark et al., 2016). This carries the risk of demand effects and might result in socially desirable answers. Indeed, self-reported compliance is not necessarily associated with actual compliance (Elffers et al., 1992). We set out to investigate naturally occurring conversations on Twitter, which are not bound to a specific domain, and where people can freely express their opinions, without prior instruction to do so. We build upon and extend Onu and Oats' (2016, 2018) examinations of lay peoples' conversations about taxes in natural settings. While Onu and Oats (2016, 2018) applied qualitative analysis techniques to analyze the interactions about taxes in specific employment groups, we apply an unsupervised machine learning method (i.e., topic modeling) to examine and classify the conversations about taxes on social media. The machine learning approach allowed us to process unprecedentedly large amounts of conversation data (over a million tax-related tweets).

1.3. The present research

The main goal of the present study was to identify and classify messages about taxation on social media, specifically, Twitter. We explored what kind of information the analysis of social media data could potentially provide to the tax administration. We used topic modeling to classify the content of the tax-related tweets. Topic modeling automatically discovers certain "topics" in naturally occurring text, on the basis of the probability of certain words co-occurring in tweets. The content of these topics can then be interpreted and labeled (manually). For example, if a topic mostly contains words like "rich," "system," "stop," "economy," and "poor," it is likely to be about inequality and redistribution. The topic modeling assigns each tweet a probability of belonging to a certain topic, also indicating the topic's most representative tweets, which may help understanding the topic content and assigning it a label (Silge and Robinson, 2017).

In topic modeling, words can be part of multiple topics; as a result, topics that share more common words, are more similar. Topics can therefore be combined into overarching groups. We used the differentiation between a synergistic and antagonistic approach as the framework for categorizing the topics (obtained via machine learning, i.e., topic modeling) into groups.

In the present study, we pursue several objectives. First, we study the prevalence of the identified groups, and the extent to which their relative frequency has changed over the last decade. We also study how people engage with the tweets that fall into different groups. Specifically, we assess how often user-generated messages are shared with others (i.e., how often tweets are retweeted), revealing the information diffusion patterns associated with each identified group (Suh et al., 2010). Finally, we assess the sentiment (i.e., positive vs. negative valence) and document the potential differences in the use of positive and negative language among the identified groups.

2. Method

2.1. Data collection

We gathered English language tweets with the hashtags #tax, #taxes, and #taxation that were posted by Twitter users in the 11 years from 2010 to 2020 (see also, Puklavec et al., 2023). That was done in two steps: First, identification numbers of messages were pulled using a Python-based scraper for social networking services (snscrape; JustAnotherArchivist, 2021). Second, using these identification numbers, we pulled the content of the messages and the associated metadata (e.g., time of creation) using an R script and Twitter's Application Programming Interface (API). The data were collected in January 2021 and are openly available[2] along the corresponding scripts at https://osf.io/mhypt/.

2.2. The dataset

To make sure that the tweets in our dataset originate from individual users (and not bots or company advertisements), we followed the following procedure. First, we examined the distribution of tweet numbers per user and discovered that some users posted enormous amounts of messages (max = 172,046, while the most common number of tweets per user was 1, see Figure S-1 in online supplement), which is nearly impossible without the involvement of automated processes. Therefore, we removed the top 1% of the users with the most tweets. This left the users that posted up to 75 messages in total (under the taxation related hashtags) during the 11-year period. In the second step, we identified users who had posted identical messages several times and removed these users as well, as this is one of the main indicators of bots (Kabakus and Kara, 2017). The resulting dataset consisted of 1,336,694 unique tweets from 514,341 users.

[2] The Twitter Developer Policy does not allow openly sharing of the messages itself. Included are the message identification numbers, which have to be "rehydrated" using the Twitter API.

2.3. Analysis strategy

2.3.1. Topic modelling

To classify the content of the tax-related tweets, we used a topic modeling approach. Topic modeling is an unsupervised machine learning method for classification of documents (in this case; tweets), which treats each document as a mixture of topics, and each topic as a mixture of words. Fitting such a topic model results in assigning each tweet a probability of belonging to a certain topic, and the probability of a specific word coming from a certain topic (Silge and Robinson, 2017). To fit the topic model, we used the R package “stm” (Roberts et al., 2019).

2.3.2. Data pre-processing

Following methodological recommendations (e.g., Hvitfeldt and Silge, 2021), we completed several pre-processing steps before submitting the tweets to the topic modeling. First, we transformed all words to lowercase and split the words that contained separators (e.g., underscores, hyphens) into single elements (e.g., “tax-avoidance” was split into “tax” and “avoidance”). The following features were removed from the text: punctuation (e.g., dots, commas), symbols (e.g., hashtags, @-signs), numbers (or words that start with numbers), URL links, HTML tags (which mostly represent emoticons in the Unicode format). Furthermore, we removed words containing two or less characters, as their meaning is often unidentifiable without a bigger context (e.g., “go”, “re”, “mr”, “dr”, etc.). Additionally, we removed the words containing the “tax”-stem as they were present in any single tweet in our dataset, and certain categories of words (articles, pronouns, prepositions, conjunctions, filler words, and auxiliary verbs[3]), because due to their frequent use, they do not add much discriminating value when classifying naturally occurring text. Finally, all the words were stemmed (e.g., the words “earn”, “earning”, and “earnings” were turned into the stem “earn”), allowing for better a classification of etymologically related terms.

After the pre-processing steps, some of the tweets were still identified as identical (e.g., messages that were exactly the same in content, but contained a different URL link). To make sure that the final dataset included unique tweets, we calculated the cosine similarity between each tweet and removed the tweets with a similarity score of 99% or higher, keeping only one of them. The final dataset thus consisted of 1,160,412 unique tweets from 472,227 users.

2.3.3. Choosing the number of topics

In topic modeling, choosing an optimal number of topics is important. A small number would lead to an overrepresentation of too distinct tweets within a single topic, whereas a large number would lead to very distinctive representation of the tweets, making it harder to summarize the findings. The procedure we used is often adapted in topic modeling, as there is no “one-size-fits-all” approach which can be used to determine the correct numbers of topics (Roberts et al., 2019).

We started by fitting a topic model using an algorithm (Mimno and Lee, 2014) to automatically identify the optimal number of topics. We used the resulting number as a starting point and proceeded by running models with a different number of topics around this starting point (cf. Roberts et al., 2019). We then compared the estimated held-out likelihood[4] and residuals of the models to select a smaller number the best fitting models. These were models with 25, 30, and 35 identified topics (see Figure S-2 in online supplements). Finally, we used a combination of semantic coherence (most probable words in a topic co-occur together frequently; Mimno et al., 2011) and exclusivity indicators (words being common in one topic and rare within others; Airoldi and Bischof, 2016) to identify the optimal number of topics for our dataset. We selected the model with the highest values on both indicators (see Figure S-3 in online supplements). This selected model identified 30 topics.

2.3.4. Validating the topics

While the topic modeling assigns a probability of certain tweets belonging to a topic, and certain words being more probable in a specific topic than in others, topic labeling needs to be done manually. Labeling was based on studying the list of the most frequently used words in each topic and the 50 most representative tweets (as identified by the model) from each topic. The first author has proposed the initial labels, which have been then validated by the other authors. Finally, disagreements were discussed among the authors, resulting in consensus for a final set of labels (see Table 1).

2.3.5. Information diffusion

We used the retweet count of a tweet as a proxy for assessing information diffusion of the message. The retweet count has become an established practice when assessing information diffusion of tweets (e.g., Suh et al., 2010). Retweet count is usually heavily skewed, because most messages receive zero retweets (in our sample, ~81%). To account for such an over-dispersed dependent variable ($M = 0.62$, $\sigma^2 = 102.95$), we used negative binomial models in the respective analyses.

[3] Sources for those words are the quanteda R package (Benoit et al., 2018) and the Linguistic Inquiry and Word Count dictionary (Pennebaker et al., 2015).

[4] The held-out likelihood estimation compares model performance in a hold-out sample (similar to cross-validation procedures; Roberts et al., 2019).

Table 1
Topics, Corresponding Labels, Terms, Example Tweets, and Topic Groups.

Groups	Label	Terms	Example tweet
G1: Opinions about tax politics	US Tax Policy	Cut, rais, obama, gop, economi	Tell Obama not to raise taxes. #tpp #sgp #twisters #teaparty #rnc #tcot #catcot #liberty #taxes #obama
	International Politics and Taxation	Public, payer, gov, privat, nhs	This is #Taxistan! Tax tax everywhere! #Pakistan #Budget2015 #BudgetDhoka #pakistanbudget #PTI #PMLN #tax #IMF
	Spending of US Tax Money	Work, american, fund, million, dollar	With our #Tax dollars #Turkey and #Azerbaian are paying #Terrorists to behead #Armenians #SanctionTurkey #terrorism #Islamic_Terrorist #TerroristAttacks #StopErdogan #StopAliev
	Inequality And Redistribution	Rich, system, stop, econom, poor	Tax the rich. Wealth tax. Tax the rich. Wealth tax. Tax the rich. Wealth tax. Tax the rich. Wealth tax. Tax the #rich. #Wealth #tax.
G2: Enforcement	Tax Money Use	Say, spend, support, canada, health	@RepLarryBucshon Don't spend my #tax$ on #horseslaughter. #80% say ban it. Strong bipartisan support. #KeepMoranAmendment. Thx (Smoore, IN)
	Corporate Tax Avoidance, Dodging, Loopholes, Havens	Corpor, compani, avoid, big, billion	@Google Dutch Sandwich Shielded 16 Billion Euros From Tax #google #dutch #sandwich #tax #tech #technology thoughtbees
	US State Legislation (Property, Budget, Reliefs, Pension, Oil)	State, properti, bill, increas, budget	Tax rises for landlords set to cause 30 percent hike in rent prices #tax #rent #landlord
	Tax Evasion & Fraud	Hmrc, bank, fraud, evas, face	Footballer Lionel Messi will face trial for alleged #tax fraud after his appeal against the charge is rejected.
G3: Information & service	Global Taxation Discussions	Discuss, global, develop, talk, futur	Presentation by Vitor Gaspar (@IMFNews) on #Global #Fiscal Developments and #Tax #Capacity in #Developing Countries.
	Questions About Taxation	Question, pleas, ask, join, answer	Dangit, City Of Seattle, why do your W-2 s have 0 s and Os that are indistinguishable? #taxday #taxes #seattle
	Studying Taxation & Tax Law	Watch, good, resid, non, studi	Library at 10AM:o #ForeverAlone #midterms #exams #tax #cramming @ Robarts Library
	Job Advertisement	Job, look, manag, office, appli	#Tax Senior with #NFP Exp. Job at Gables Search Group – Woodcliff Lake, NJ #Indeed #jobs" #jobsearch #hiring #careers RT GablesSearch
	Tax News (Changes, Reports, Laws)	New, chang, read, law, report	How does the new #tax law affect cross-border #MnA deals? @MoldenhauerCurt explains in @BloombergBNA
	Tax On Cryptocurrency	Capit, regul, bitcoin, trade, gain	Portuguese Crypto users Not Taxed for Capital Gains #cryptocurrency #cryptocurrencynews #cryptonews #Bitcoin #BTC #ETH #Portugal #Taxhaven #Taxes #capitalGains #cryptousers #cryptotrading
	Tax Filing & Preparation	Get, time, day, free, today	It's not too early to get a jump on the coming tax season! Get Started on Your 2017 #Tax Preparation Today
	Accounting Services (Advertisement)	Busi, account, financ, servic, help	Connected Accounting – offering affordable and reliable #bookkeeping and #accounting services for small to medium size businesses #accounts #payroll #tax #smallbusinesses #supportlocal #southpeninsula
	Taxability & Exemptions	Give, sale, keep, onlin, exempt	Eye on Retail: Should online retailers collect sales tax? - #ecommerce #taxes #retail
	Information for Employers (Social Security, Insurance, Benefits, Payroll)	Benefit, employ, inform, insur, payrol	Independent contractors vs. employees: Are your workers classified correctly? #taxes #employees
	Tax Planning (Time)	Year, plan, end, last, week	Protect your beneficiaries inheritance from unnecessary taxes with a strategic estate plan: #WednesdayWisdom #estateplanning #taxes #trusts #wills #inheritance
	Tax Education	Educ, school, good, video, idea	The best way to teach kids about taxes is to eat 30% of their ice cream. #taxes #icecream #cherryontop #chocolatefudge #whippedcream
	Tax Credits & Refunds (Vehicles, Energy, Travel, Lotteries)	Credit, car, cash, win, loan	To qualify for an #electricvehicle #taxcredit, the #EV you purchase has to be for the purpose of you #driving the #vehicle, not reselling it. The EV must be driven in the U.S., and built by qualified #automakers. #electriccar #electriccars #Evs #electricvehicles #taxes #carsales
	Tax Services & Support (Information & Deadlines)	Ir, file, return, know, need	U.S. Extends Particular person Tax Submitting Deadline from April 15 to July 15 #april #deadline #extends #filing #individual #july #tax
	Saving and Investing Money (Stock & Real-Estate)	Money, save, invest, way, home	Taxes don't have to be scary. I can sell your house and save you money at the same time! #houseexpert #tax #thehelpfulagent #aleemsellschicago #themoreyouknow #aleemproperty #realestate #realestateagent #agentaleem #atproperties

(*continued on next page*)

Table 1 (*continued*)

Groups	Label	Terms	Example tweet
G4: Emotions	Attitudes and Opinions about Taxes	Peopl, think, mani, live, care	#LifesSimpleTruth: There are 2 types of people who complain about #taxes: men and women;)
	Social Representations of Taxes	Pay, want, govern, much, paid	#Taxes are what we pay for civilized society and because of that I believe everyone should pay their fair share
	Emotions And Taxes	One, go, life, feel, man	FUCK ALL YOU FUCKING FUCKS GO FUCK A DICK. #taxes #taxreturn #brokebitchprobs #fuckeverything
G0: Miscellaneous	Trump: Policy & Ethics	Trump, realdonaldtrump, potus, lie, russia	Why is President Trump so SCARED of anyone seeing his TAXES if h"s NOT LYING about them? @FoxNews @realDonaldTrump @WhiteHouse @POTUS @CNN @NBCNews @foxnewsalert #Trump #taxes #scared
	Tax Burden in India	Incom, rate, gst, india, reduc	Govt slashes #tax rates in all slabs for individuals. Up to 5 lacs— No tax 5 −7.5 lacs— 10% income tax 7.5–10 lacs— 15% income tax 10 −12.5 lacs— 20% income tax 12.5–15 lacs— 25% income tax Above 15 lacs income— 30% #BudgetSession2020 @nsitharaman
	Tax News (Trump Tax Files)	News, thank, trump, show, releas	#DonaldTrump #NeverTrump #Taxes #CubaGoodingJr Donald Show Me The Taxes #HillaryClinton
	Random: Policy & Leftovers	N/A	N/A

Note. To keep the tweet messages as anonymous as possible, all links from the message were removed. The terms represent the five most frequent terms (stemmed) associated with each topic.

2.3.6. Valence

We used sentiment analysis to assess the valence (positive vs. negative) of each topic. We used the Valence Aware Dictionary and sEntiment Reasoner method (VADER; Hutto and Gilbert, 2014) which is specifically attuned for microblog-like content (Twitter messages) to compute the valence compound score of each tweet. The valence compound score represents the sum of the valence scores of each word in the tweet. The score is normalized to range between −1 (most negative) and 1 (most positive) to represent the overall sentiment of a given tweet. We compared the topic groups in how they differ by valence scores.

3. Results

First, we present the results of the topic modeling, namely the identified topics and the larger groups they fell into. Second, we examine the prevalence of the topic groups in general and to what extent the conversation content (i.e., group relative prevalence) changed over the last decade. Third, we determine the popularity of the different groups by looking at which topic group was shared the most by Twitter users. Last, we determine which groups yield more positive (vs. negative) content.

3.1. Identifying topics and the topic groups

Table 1 shows the 30 topics as identified by the (automatic) topic modeling approach. Each topic has a corresponding label and example tweet. To further categorize the topics into smaller groups, we computed the Jensen-Shannon Divergence (similarity between topic probability distributions) between topics and then used multidimensional scaling to represent the inter-topic distances (Sievert and Shirley, 2014). The results are shown in Fig. 1.

As the main framework we used the differentiation between topics related to a synergistic (service-oriented) and an antagonistic (enforcement-oriented) tax climate. Not every topic could be classified as falling into one of the two dimensions,[5] which is why we extended the classification into four separate groups. The resulting groups were 1. *Opinions about Tax Politics*, 2. *Enforcement*, 3. *Information & Service*, and 4. *Emotions*. Topics 2 (*Enforcement*) and 3 (*Information & Service*) represent the enforcement-orientation and service-orientation, respectively. The *Enforcement* group contained topics that were related to enforcement information, for example, topics about corporate tax evasion and tax legislation. The *Information & Service* group contained topics related to sharing information (e.g., news, job offers, accounting services), tax knowledge (e.g., tax exemptions, tax credits, answering questions), and education (e.g., tax filing, learning about taxation). The group *Opinions about Tax Politics* contained topics that were related to political discussion, for example, U.S. and international politics referring to taxation. And finally, the *Emotions* group contained topics related to emotions, social representations, attitudes, and opinions about taxes. These groups are used in all of the forthcoming analyses.

[5] Four topics were dropped entirely (indicated in Table 1 as "G0: Miscellaneous"), as their content was too specific, and could not be directly associated with any of the remaining topics.

Fig. 1. Multidimensional Scaling with Topic Distances.
Note. The size of the circles represents the overall prevalence (number of tweets) of the respective topic.

3.2. Prevalence of topics

To identify which topics are most representative of discussions on Twitter, we first allocated each tweet to a single topic by taking the largest probability from the topic model (of a tweet belonging to a specific topic). The frequency of tweets per group is shown in Fig. 2. We find that the majority of tweets about taxation belonged to the group representing *Information & Service* tweets (∼56%), followed by tweets about *Enforcement* (∼17%), *Opinions about Tax Politics* (∼14%), and *Emotions* (∼13%), respectively.

Next, we computed the proportions of tweets falling into these groups for each year, to identify how discussions about taxation have evolved during the last decade. The results are represented in Fig. 3. The relative number of tweets about *Information & Service* has been consistently rising during the last decade while the relative number of tweets about *Opinions about Tax Politics* has been decreasing. Tweets about *Enforcement* experienced a peak mid-decade, whereas the relative number of *Emotions* tweets did not change over time.

3.3. Topics and information diffusion

Next, we examined whether the tweets that belong to a certain topic group are more or less likely to be shared with others. For this purpose, we examined how belonging to one of the four topic groups predicts the retweet count of the tweets (see Table 2). We used a negative binomial regression to account for the overdispersion of the dependent variable (retweet count). The predictors in the regression were dummy coded topic groups. Since we were interested in comparing topic groups representing a synergistic and an antagonistic climate, we chose the *Information & Service* topic group as the reference category.

In comparison to the topic group *Information & Service* all other groups predicted higher retweet counts. Tweets belonging to the groups *Opinions about Tax Politics, Enforcement,* and *Emotions* were associated with an 84%, 40% and, 22% higher retweet count (compared to *Information & Service*), respectively. Regressions with alternative reference groups revealed that

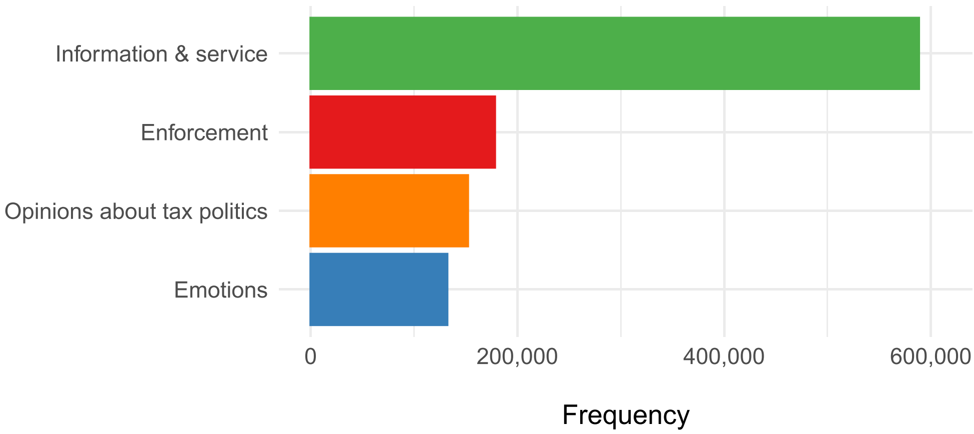

Fig. 2. Frequency of Tweets per Topic Group.
Note. The X-axis represents the raw frequencies.

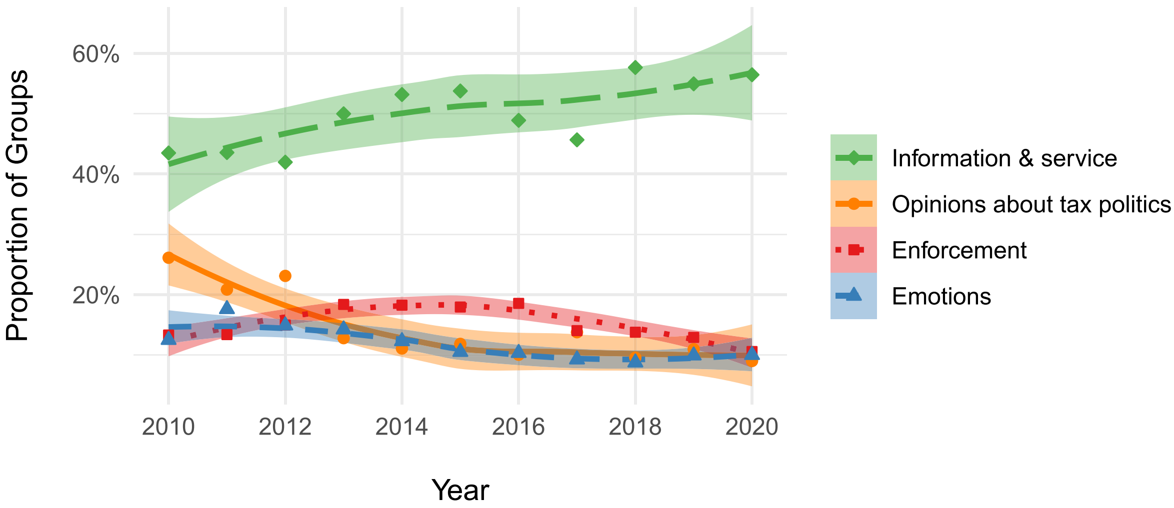

Fig. 3. Relative Share of Topic Groups from Years 2010 to 2020.
Note. The error bars represent the 95% confidence interval.

Table 2
Negative Binomial Regression for Topic Groups Predicting Retweet Count.

	Model 1		Model 2	
Predictors	Incidence Rate Ratios	95% CI	Incidence Rate Ratios	95% CI
Intercept	0.49 ***	0.48 – 0.49	0.27 ***	0.27 – 0.28
Opinions – Politics	1.84 ***	1.81 – 1.87	1.67 ***	1.64 – 1.70
Enforcement	1.40 ***	1.38 – 1.42	1.38 ***	1.35 – 1.40
Emotions	1.22 ***	1.20 – 1.25	1.20 ***	1.17 – 1.22
Follower count			1.00 ***	1.00 – 1.00
URL			1.19 ***	1.18 – 1.21
Media			2.47 ***	2.43 – 2.51
Observations	1050,734		1050,734	

Note. *** $p < .001$. CI = Confidence interval. The dependent variable is the retweet count of the respective tweet. Opinion – Politics, Enforcement, and Emotions are dummies of the topic groups, with Information & service as the reference group. The follower is the count of followers of the respective user. URL: 1 = tweet contains URL link, 0 = tweets does not contain URL link. Media: 1 = tweet contains media, 0 = tweet does not contain media.

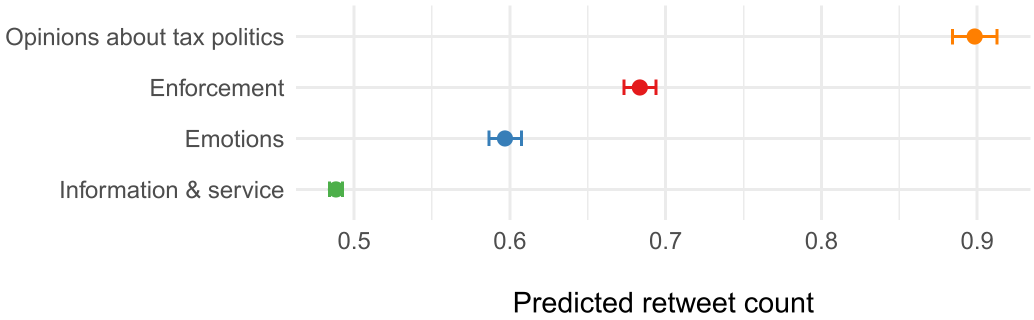

Fig. 4. Predicted Retweet Count per Topic Group.
Note. The error bars represent the 95% confidence interval.

Table 3
Linear Regression for Topic Groups Predicting Valence.

	Model 1		Model 2	
Predictors	Estimates	95% CI	Estimates	95% CI
Intercept	0.19 ***	0.19 – 0.19	0.17 ***	0.17 – 0.17
Opinions – Politics	−0.20 ***	−0.20 – −0.19	−0.19 ***	−0.19 – −0.18
Enforcement	−0.17 ***	−0.18 – −0.17	−0.17 ***	−0.17 – −0.16
Emotions	−0.14 ***	−0.15 – −0.14	−0.14 ***	−0.14 – −0.13
Follower count			−0.00 **	−0.00 – −0.00
URL			−0.00	−0.00 – 0.00
Media			0.07 ***	0.07 – 0.07
Observations	1050,734		1050,734	
R^2 / R^2 adjusted	0.043 / 0.043		0.047 / 0.047	

Note. *** $p < .001$, ** $p < .01$. CI = Confidence interval. The dependent variable is the VADER valence score of the respective tweet. Opinion – Politics, Enforcement, and Emotions are dummies of the topic groups, with Information & service as the reference group. The follower is the count of followers of the respective user. URL: 1 = tweet contains URL link, 0 = tweets does not contain URL link. Media: 1 = tweet contains media, 0 = tweet does not contain media.

those three groups also significantly differ from each other (see Tables S-1 to S-3 in online supplements), with *Enforcement* tweets being shared more than *Emotions* tweets, and *Information & Service* tweets being shared least often. The predicted retweet count of each group is illustrated in Fig. 4. This pattern remained the same after controlling for the follower count of the respective user and whether the tweet contained any media or URL links (see Table 2, Model 2), which represent common control variables in research on information diffusion on Twitter (e.g., Suh et al., 2010).

3.4. Topic content sentiment

Finally, we compared the tweets belonging to each topic group on the dimension of valence. Table 3 shows linear regression results with the VADER compound score (indicating valence) as the dependent variable. Again, we were interested in comparing topic groups representing a synergistic and an antagonistic climate and chose the *Information & Service* topic group as the reference. Tweets belonging to the *Information & Service* group contained the most positive message content, followed by *Emotions, Enforcement,* and *Opinions about Tax Politics* tweets. Running the regression with different reference groups revealed that those three groups also significantly differ from each other (see Tables S-4 to S-6 in online supplements). Importantly, only the *Information & Service* group has a predominantly positive valence, whereas the remaining groups' valence ranged from negative to positive, with a mean around 0, indicating neutral valence scores (see Fig. 5). After controlling for possible confounding variables (follower count, and whether the tweet contained any URL links or media), the results remained robust (see Table 3, Model 2).

4. Discussion

Academic research on taxation has proposed that the climate between taxpayers and the tax office can be described as either synergistic or antagonistic, which is assumed to have downstream consequences for compliance (Alm and Torgler, 2011; Kirchler et al., 2008). The current study sought to determine whether this distinction – between synergistic and antagonistic climate – is reflected in lay people's conceptions about taxation by classifying conversations about taxation on the social media platform Twitter. Applying an unsupervised machine learning approach ("topic modeling") to the dataset of 1,160,412 unique tweets posted over the 11-year period from 2010 to 2020 by 472,227 unique users, we identified 30 initial topics that – using the distinction between synergistic and antagonistic tax climate as a guiding theoretical framework –

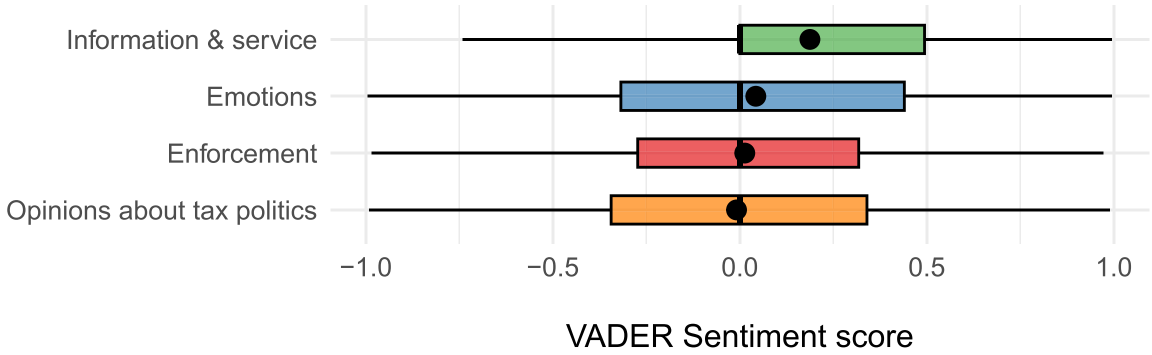

Fig. 5. Valence Scores per Topic Group.
Note. The figure depicts box plots. The black circles represent the mean valence score. The black vertical lines represent the median valence score.

were further classified into four different topic groups: *Enforcement* (antagonistic climate), *Information & Service* (synergistic climate), *Opinions about Tax Politics*, and *Emotions*.

Besides mapping the content of tax-related conversation on Twitter, our dataset spanning 11 years allowed us to identify which topic groups gained vs. lost in prominence over the last decade. Results show that the biggest frequency, and also an increase over time, is observed in *Information & Service* tweets dedicated to sharing information about taxes (e.g., news about taxation, information on filing and preparing tax reports) and providing service to taxpayers (e.g., offering accounting services). In fact, half (i.e., 15) of the 30 topics were classified as part of the group *Information & Service* that represents a synergistic tax climate. This showcases that the claimed importance of a "client and service" attitude (e.g., Alm and Torgler, 2011; Kirchler et al., 2008) is observable in lay people's conversations on social media. The increasing frequency of tweets in this topic group over the last decade is interesting and may have several reasons. One explanation might be that more and more individuals and companies are using social media to engage with questions regarding taxation, by individuals either seeking help, or companies using Twitter as a marketing tool to promote their services. Another explanation could be that dealing with taxes is becoming increasingly difficult, requiring more help from social networks. For example, the U.S. federal tax code is steadily growing more complex, exceeding 10 million words in 2015 (Greenberg, 2015). Nonetheless, both arguments speak for individuals increasingly seeking information and help, pinpointing the importance of providing service to taxpayers.

Even though *Information & Service* tweets were most frequent, the analyses of retweet patterns (i.e., information diffusion) revealed that they get retweeted the least, in comparison to the other topic groups. One reason for this retweet count could be of purely methodological nature: as more than half of the tweets in our dataset fall into this topic group, the topics in this topic group might be more diverse (relative to other groups), resulting in high heterogeneity in retweet count associated with different topics within this topic group. Another reason might be that the *Information & Service* tweets are simply not exciting or interesting enough to share with other people. *Information & Service* tweets could just be addressing very specific questions or issues rendering them of low importance to the larger community. Interestingly, the most frequently shared tweets were from the topic group *Opinions about Tax Politics*. There is reason to assume that taxation topics in a political context are more likely to contain uncivil language (e.g., Theocharis et al., 2020) than, for example, tweets about providing information and services. Also, there is evidence showing that emotionally charged tweets get retweeted more often (e.g., Stieglitz and Dang-Xuan, 2014), which would explain the information diffusion patterns observed in the present study.

The examination of the valence of the tweets in the various topic groups showed rather large variations. Most of the tweets in the dataset were of neutral valence, while additionally the topic groups about *Emotions, Enforcement,* and *Opinions about Tax Politics* showed large variation in terms of valence, ranging from extremely negative to extremely positive. This finding is not surprising given the large number of tweets in our dataset, as they contain a wide variety of opinions that are being shared on social media. In contrast, the largest topic group, *Information & Service,* showed predominantly positive valence scores. This finding aligns with the assumption that positive attitudes prevail in the synergistic tax climate, and could be a potential explanation of why tweets in the *Information & Service* group were retweeted less. Drawing from the word-of-mouth and negativity bias literature, negative information is often more likely to affect people's behavior, thus potentially also affecting what people consider worth sharing (e.g., Arndt, 1967; Hennig-Thurau et al., 2015; Robertson et al., 2022; Rozin and Royzman, 2001). This could explain the lower retweet count in the *Information & Service* topic group, as those tweets were more positive in comparison to tweets of other topic groups.

4.1. Limitations

The present study is a demonstration that Twitter data offers a valuable tool for studying naturally occurring conversations and thus providing a window into lay people's conceptions of taxation. This of course comes with certain limitations.

For instance, the ubiquity of bots on social media represents might contaminate the dataset making it unsuitable for the analyses of human online behavior. Importantly, we took many steps to identify and remove bots (see method section) and thus ensure the dataset quality.

Based on the restricted length of the tweets, messages on Twitter can be classified as microblog content. Currently there is a limit of 280 characters per message (which was 140 characters before 2017) and messages are usually adjusted to fit the character count, for example, with more frequent use of abbreviations (Boot et al., 2019). This could have especially affected our valence analysis, making it particularly hard to correctly classify some special cases of emotionally laden messages (e.g., containing emoticons, which are transformed into Unicode notation). Yet, we are certain that this issue could not have substantially biased our conclusions since the VADER scores that we used to measure valence has been specifically developed for valence classification of microblog-like content (Hutto and Gilbert, 2014).

Finally, the current study only examined English language tweets, which potentially limits the conclusions to English-speaking countries. In the domain of taxation, it is apparent that there can be many cultural differences in both, the tax climate and the possibility to talk about it (free speech). These differences may stem from different political systems, economic systems, social climates, etc. (e.g., Alm and Torgler, 2006; Torgler and Schneider, 2004). An argument for a broader application of the study's conclusion is a cross-national analysis using scenarios describing service-oriented tax offices, showing very consistent cross-cultural patterns of such an orientation resulting in higher levels of trust (Batrancea et al., 2019).

4.2. Implications

Our results suggest that text analysis of social media data might be of interest to tax administrations. While some tax administrations have recently discovered the value of text analysis of formal conversations between tax office and taxpayers (e.g., using text mining for taxpayer inquiries; OECD, 2016), herein, we showed that the analysis of naturally occurring conversations on social media might be useful as well. For example, an overview of the topics that are most frequently discussed might help policy makers to identify domains where people need most help (i.e., ask most questions about). As many tax offices around the world are interested in providing sufficient services to the taxpayers, social media might be a valuable tool to identify fields where improvement is needed. Tax authorities might also consider using social media more frequently for providing information to taxpayers, although a thorough analysis of this specific kind of communication is needed before making any claims about its effectiveness. We hope that future studies will continue this stream of research.

Another important finding of the study is the mere fact, that the majority of tax related tweets is about seeking service and information (rather than discussing evasion, avoidance, fines and audits). The present findings thus point in the direction that service information might be more relevant to people than enforcement information. Some experimental studies have obtained similar evidence (e.g., Enachescu et al., 2019), yet the current analysis is the first to detect this pattern in lay people's, naturally occurring, conversations on social media. It also aligns with the fact that most taxpayers have a positive attitude towards paying taxes anyway (e.g., Braithwaite, 2003).

Conclusion

The present study analyzed conversations about taxation on social media. The findings indicate that the majority of messages are dedicated to providing and seeking information and services (*Information & Service* group), and that this group of topics gained prominence during the past decade, indicating the significance of the core elements of a synergistic tax climate. Ironically, while *Information & Service* topics are more frequent and contain more positive language in comparison to other topic groups, they are being shared less than other topic groups. Taken together, these results contribute to the literature on tax psychology by emphasizing the importance of service-orientation as reflected in lay people's conceptions about taxation. The results also suggest that conversations on social media can be analyzed in a systematic way and could be a potential source of information for tax administrations who seek to improve the quality of their services.

Declaration of Competing Interest

We have no conflict of interest to disclose. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

Žiga Puklavec: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft. **Christoph Kogler:** Conceptualization, Writing – review & editing. **Olga Stavrova:** Conceptualization, Methodology, Writing – review & editing. **Marcel Zeelenberg:** Conceptualization, Writing – review & editing.

References

Airoldi, E.M., Bischof, J.M., 2016. Improving and evaluating topic models and other models of text. J. Am. Stat. Assoc. 111 (516), 1381–1403. doi:10.1080/01621459.2015.1051182.

Allingham, M.G., Sandmo, A., 1972. Income tax evasion: a theoretical analysis. J. Public Econ. 1 (3–4), 323–338. doi:10.1016/0047-2727(72)90010-2.

Alm, J., Kirchler, E., Muehlbacher, S., Gangl, K., Hofmann, E., Kogler, C., Pollai, M., 2012. Rethinking the research paradigms for analysing tax compliance behaviour. CESifo Forum 13 (2), 33–40.

Alm, J., Torgler, B., 2006. Culture differences and tax morale in the United States and in Europe. J. Econ. Psychol. 27 (2), 224–246. doi:10.1016/j.joep.2005.09.002.

Alm, J., Torgler, B., 2011. Do ethics matter? Tax compliance and morality. J. Bus. Ethics 101 (4), 635–651. doi:10.1007/s10551-011-0761-9.

Arndt, J., 1967. Word of Mouth Advertising: a Review of the Literature. Advertising research foundation, New York.

Batrancea, L., Nichita, A., Olsen, J., Kogler, C., Kirchler, E., Hoelzl, E., Weiss, A., Torgler, B., Fooken, J., Fuller, J., Schaffner, M., Banuri, S., Hassanein, M., Alarcón-García, G., Aldemir, C., Apostol, O., Bank Weinberg, D., Batrancea, I., Belianin, A., Bello Gómez, F.d.J., 2019. Trust and power as determinants of tax compliance across 44 nations. J. Econ. Psychol. 74. doi:10.1016/j.joep.2019.102191.

Benoit, K., Watanabe, K., Wang, H., Nulty, P., Obeng, A., Müller, S., Matsuo, A., 2018. Quanteda: an R package for the quantitative analysis of textual data. J. Open Source Softw. 3 (30). doi:10.21105/joss.00774.

Boning, W.C., Guyton, J., Hodge, R., Slemrod, J., 2020. Heard it through the grapevine: the direct and network effects of a tax enforcement field experiment on firms. J. Public Econ. 190, 104261. doi:10.1016/j.jpubeco.2020.104261.

Boot, A.B., Tjong Kim Sang, E., Dijkstra, K., Zwaan, R.A., 2019. How character limit affects language usage in tweets. Palgrave Commun. 5 (1). doi:10.1057/s41599-019-0280-3.

Braithwaite, V., 2003. Dancing with tax authorities: motivational postures and non-compliant actions. In: Braithwaite, V. (Ed.), Taxing Democracy. Ashgate Aldershot, pp. 15–39. doi:10.4324/9781315241746.

Cialdini, R.B., 1996. Activating and aligning two kinds of norms in persuasive communications. J. Interpret. Res. 1 (1), 3–10. doi:10.1177/109258729600100102.

Coricelli, G., Rusconi, E., Villeval, M.C., 2014. Tax evasion and emotions: an empirical test of re-integrative shaming theory. J. Econ. Psychol. 40, 49–61. doi:10.1016/j.joep.2012.12.002.

Elffers, H., Robben, H.S.J., Hessing, D.J., 1992. On measuring tax evasion. J. Econ. Psychol. 13 (4), 545–567. doi:10.1016/0167-4870(92)90011-U.

Enachescu, J., Olsen, J., Kogler, C., Zeelenberg, M., Breugelmans, S.M., Kirchler, E., 2019. The role of emotions in tax compliance behavior: a mixed-methods approach. J. Econ. Psychol. 74, 102194. doi:10.1016/j.joep.2019.102194.

Fetchenhauer, D., 2004. *Different Perspectives on Prosocial and Antisocial Behavior* [Kumulative Habilitation, Ruhr-Universität Bochum] Bochum.

Frey, B.S., 2003. Deterrence and tax morale in the European Union. Eur. Rev. 11 (3), 385–406. doi:10.1017/S1062798703000346.

Gangl, K., Muehlbacher, S., de Groot, M., Goslinga, S., Hofmann, E., Kogler, C., Antonides, G., Kirchler, E., 2013. "How can I help you?" Perceived service orientation of tax authorities and tax compliance. FinanzArchiv /Public Finance Anal. 69 (4), 487–510. doi:10.1628/001522113X675683.

Greenberg, S., 2015. Federal Tax Laws and Regulations are Now Over 10 Million Words Long October 8. Tax Foundation. https://taxfoundation.org/federal-tax-laws-and-regulations-are-now-over-10-million-words-long/.

Hallsworth, M., List, J.A., Metcalfe, R.D., Vlaev, I., 2017. The behavioralist as tax collector: using natural field experiments to enhance tax compliance. J. Public Econ. 148, 14–31. doi:10.1016/j.jpubeco.2017.02.003.

Hennig-Thurau, T., Wiertz, C., Feldhaus, F., 2015. Does Twitter matter? The impact of microblogging word of mouth on consumers' adoption of new movies. J. Acad. Market. Sci. 43 (3), 375–394. doi:10.1007/s11747-014-0388-3.

Hutto, C.J., Gilbert, E.E., 2014. VADER: a parsimonious rule-based model for sentiment analysis of social media text. Eighth International Conference on Weblogs and Social Media (ICWSM-14).

Hvitfeldt, E., Silge, J., 2021. Supervised Machine Learning for Text Analysis in R. CRC Press.

JustAnotherArchivist (2021). *Snscrape* [Computer software]. https://github.com/JustAnotherArchivist/snscrape

Kabakus, A.T., Kara, R., 2017. A survey of spam detection methods on Twitter. Int. J. Adv. Comput. Sci. Appl. 8 (3). doi:10.14569/ijacsa.2017.080305.

Kasper, M., Olsen, J., Kogler, C., Stark, J., Kirchler, E., 2018. Individual attitudes and social representations of taxation, tax avoidance and tax evasion. In: Hashimzade, N., Epifantseva, Y. (Eds.), The Routledge Companion to Tax Avoidance Research. Routledge, pp. 289–303.

Kirchler, E., 1998. Differential representations of taxes: analysis of free associations and judgments of five employment groups. J. Socio-Econ. 27 (1), 117–131. doi:10.1016/s1053-5357(99)80080-8.

Kirchler, E., 2007. The Economic Psychology of Tax Behaviour. Cambridge University Press doi:10.1017/CBO9780511628238.

Kirchler, E., Hoelzl, E., Wahl, I., 2008. Enforced versus voluntary tax compliance: the "slippery slope" framework. J. Econ .Psychol. 29 (2), 210–225. doi:10.1016/j.joep.2007.05.004.

Kirchler, E., Kogler, C., Muehlbacher, S., 2014. Cooperative tax compliance: from deterrence to deference. Curr. Dir. Psychol. Sci. 23 (2), 87–92. doi:10.1177/0963721413516975.

Kleven, H.J., Knudsen, M.B., Kreiner, C.T., Pedersen, S., Saez, E., 2011. Unwilling or unable to cheat? Evidence from a tax audit experiment in Denmark. Econometrica 79 (3), 651–692. doi:10.3982/ECTA9113.

Kogler, C., Batrancea, L., Nichita, A., Pantya, J., Belianin, A., Kirchler, E., 2013. Trust and power as determinants of tax compliance: testing the assumptions of the slippery slope framework in Austria, Hungary, Romania and Russia. J. Econ. Psychol. 34, 169–180. doi:10.1016/j.joep.2012.09.010.

Kogler, C., Kirchler, E., 2020. Taxpayers' subjective concepts of taxes, tax evasion, and tax avoidance. In: van Brederode, R.F. (Ed.), Ethics and Taxation. Springer, Singapore, pp. 191–205. doi:10.1007/978-981-15-0089-3_8.

Kogler, C., Muehlbacher, S., Kirchler, E., 2015. Testing the "slippery slope framework" among self-employed taxpayers. Econ. Govern. 16 (2), 125–142. doi:10.1007/s10101-015-0158-9.

Lewis, A. (1982). *The psychology of taxation*. M. Robertson.

Lozza, E., Castiglioni, C., 2018. Tax climate in the national press: a new tool in tax behaviour research. J. Soc. Polit. Psychol. 6 (2), 401–419. doi:10.5964/jspp.v6i2.937.

Mimno, D., Lee, M., 2014. Low-dimensional embeddings for interpretable anchor-based topic inference. In: Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP). Doha, Qatar.

Mimno, D., Wallach, H.M., Talley, E., Leenders, M., McCallum, A., 2011. Optimizing semantic coherence in topic models. In: Proceedings of the Conference on Empirical Methods in Natural Language Processing. Edinburgh, United Kingdom.

Murphy, K., 2003. Procedural justice and tax compliance. Austr. J. Soc. Issues 38 (3), 379–408. doi:10.1002/j.1839-4655.2003.tb01151.x.

Murphy, K., Tyler, T., 2008. Procedural justice and compliance behaviour: the mediating role of emotions. Eur. J. Soc. Psychol. 38 (4), 652–668. doi:10.1002/ejsp.502.

OECD, 2016. Advanced Analytics for Better Tax Administration: Putting Data to Work. OECD Publishing, Paris doi:10.1787/9789264256453-en.

Olsen, J., Kogler, C., Stark, J., Kirchler, E., 2017. Income tax versus value added tax: a mixed-methods comparison of social representations. J. Tax Admin. 3 (2), 87–107 urn:nbn:nl:ui:12-e8d1ecd6-b18a-4c53-b7a0-95c6fe34d404.

Onu, D., Oats, L., 2016. Paying tax is part of life": social norms and social influence in tax communications. J. Econ. Behav. Organ. 124, 29–42. doi:10.1016/j.jebo.2015.11.017.

Onu, D., Oats, L., 2018. Tax talk: an exploration of online discussions among taxpayers. J. Bus. Ethics 149 (4), 931–944. doi:10.1007/s10551-016-3032-y.

Pennebaker, J.W., Boyd, R.L., Jordan, K., & Blackburn, K. (2015). *The development and psychometric properties of LIWC2015.*

Puklavec, Ž., Stavrova, O., Kogler, C., Zeelenberg, M., 2023. The Role of Emotional and Moral Language in the Diffusion of Tax-Related Communication on Twitter. Manuscript submitted for publication.

Roberts, M.E., Stewart, B.M., Tingley, D., 2019. stm: an R package for structural topic models. J. Stat. Softw. 91 (2), 1–40. doi:10.18637/jss.v091.i02.

Robertson, C., Pröllochs, N., Schwarzenegger, K., Parnamets, P., Van Bavel, J.J., & Feuerriegel, S. (2022). *Negativity drives online news consumption* [Registered Report Stage 1 Protocol]. doi:10.6084/m9.figshare.19657452.v1.

Rozin, P., Royzman, E.B., 2001. Negativity bias, negativity dominance, and contagion. Pers. Soc. Psychol. Rev. 5 (4), 296–320 10.1207%2FS15327957PSPR0504_2.
Schmölders, G. (1960). *Das irrationale in der öffentlichen Finanzwirtschaft*. Suhrkamp.
Sievert, C., Shirley, K., 2014. LDAvis: a method for visualizing and interpreting topics. In: Proceedings of the Workshop on Interactive Language Learning, Visualization, and Interfaces. Baltimore, Maryland, USA.
Silge, J., Robinson, D., 2017. Text Mining with R: A Tidy Approach. O'Reilly.
Slemrod, J., 2019. Tax compliance and enforcement. J. Econ. Lit. 57 (4), 904–954. doi:10.1257/jel.20181437.
Srinivasan, T.N., 1973. Tax evasion: a model. J. Public Econ. 2 (4), 339–346. doi:10.1016/0047-2727(73)90024-8.
Stark, J., Kogler, C., Gaisbauer, H., Sedmak, C., Kirchler, E., 2016. Differentiating views of inheritance: the free association task as a method to assess social representations of wealth, inherit, and bequeath. Rev. Behav. Econ. 3 (1), 91–111. doi:10.1561/105.00000044.
Stieglitz, S., Dang-Xuan, L., 2014. Emotions and information diffusion in social media: sentiment of microblogs and sharing behavior. J. Manag. Inf. Syst. 29 (4), 217–248. doi:10.2753/mis0742-1222290408.
Stridth, A., Wittberg, L., 2015. From Feared Tax Collector to Popular Service Agency. Strömberg Distribution i Flemingsberg.
Suh, B., Hong, L., Pirolli, P., Chi, E.H., 2010. Want to be retweeted? Large scale analytics on factors impacting retweet in Twitter network. In: IEEE Second International Conference on Social Computing, 2010, pp. 177–184. doi:10.1109/SocialCom.2010.33.
Theocharis, Y., Barberá, P., Fazekas, Z., Popa, S.A., 2020. The dynamics of political incivility on Twitter. Sage Open 10 (2). doi:10.1177/2158244020919447.
Torgler, B., 2003. Tax morale, rule-governed behaviour and trust. Constitutional Polit. Economy 14 (2), 119–140. doi:10.1023/A:1023643622283.
Torgler, B., Schneider, F., 2004. *Does Culture Influence Tax Morale? Evidence from Different European Countries* (CREMA Working Paper No. 2004-17). Center for Research in Economics, Management and the Arts (CREMA). https://www.econstor.eu/handle/10419/214303.
Vogel, J., 1974. Taxation and public opinion in Sweden: an interpretation of recent survey data. Natl. Tax J. 27 (4), 499–513. https://www.jstor.org/stable/41861983.
Wenzel, M., 2004. The social side of sanctions: personal and social norms as moderators of deterrence. Law Hum. Behav. 28 (5), 547–567. doi:10.1023/B:LAHU.0000046433.57588.71.
Wenzel, M., 2005. Misperceptions of social norms about tax compliance: from theory to intervention. J. Econ. Psychol. 26 (6), 862–883. doi:10.1016/j.joep.2005.02.002.
Yitzhaki, S., 1974. Income tax evasion: a theoretical analysis. J. Public Econ. 3 (2), 201–202. doi:10.1016/0047-2727(74)90037-1.