Eliciting People's First-Order Concerns:
Text Analysis of Open-Ended Survey Questions

By Beatrice Ferrario and Stefanie Stantcheva[*]

Survey data is a key tool for understanding people's views on public policies. Surveys let us slip into people's minds and reveal otherwise invisible things such as attitudes, perceptions, reasonings, and beliefs. They can shed light on how people reason about important policies that shape their daily lives, such as health care, taxation, and trade policy. What efficiency and distributional impacts do people have in mind when thinking about these policies? What are their perceived goals and social objectives?

To some extent, we can learn about support for some policies by observing citizens' political behaviors. Yet, we lack data on their more detailed policy preferences, since voting rarely happens on specific and separate issues. Furthermore, it is difficult to infer the reasoning underlying people's policy views using observational data. Survey methods are thus an invaluable complement to our other research methods.

The backbone of surveys is often made of multiple-choice questions. The advantages of these questions are that answer options are standardized and streamlined across respondents and they easily lend themselves to quantitative analysis. However, in some settings, we may prime respondents to think about (and, subsequently, perhaps select) some answer options that they would otherwise not have thought about. Conversely, we may omit relevant options that we do not know about. In open-ended questions, respondents are not offered answer options, but rather an empty text en-

try field in which they can write freely. Open-ended survey questions can therefore circumvent some of the above-mentioned issues. By being less guided, they may teach us things that we may otherwise have missed and that we may not be used to thinking about as economists. The answers to these open-ended questions can be analyzed using text analysis methods to shed light on the first-order considerations that come to people's minds, without constraining them to think about a limited set of answer options.

This paper illustrates the design and use of open-ended survey questions, focusing on the topics of income and estate taxation.

An abundant literature leverages survey data to explore people's perceptions and preferences about tax policy and redistribution (Gimpelson and Treisman (2018), Hauser and Norton (2017), Alesina, Stantcheva and Teso (2018), Stantcheva (2021), Fisman et al. (2020), Cruces, Perez-Truglia and Tetaz (2013), Karadja, Mollerstrom and Seim (2017), Roth and Wohlfart (2018), and Hvidberg, Kreiner and Stantcheva (2020)). Perceptions (and misperceptions) of tax rates are documented in De Bartolome (1995), Gideon (2017), Ballard and Gupta (2018), Rees-Jones and Taubinsky (2019), Chetty, Friedman and Saez (2013), Feldman, Katuščák and Kawano (2016), and Stantcheva (2021).

Text analysis methods of non-survey data, such as online media and newspaper coverage, have been applied in finance (Antweiler and Frank (2004)), macroeconomics (Baker, Bloom and Davis (2016)), and political economy (Groseclose and Milyo (2005), Gentzkow and Shapiro (2010), Tesei, Durante and Pinotti (2018), and Gentzkow, Kelly and Taddy (2019)). Our goal is to apply these text analysis methods

to data derived from answers to open-ended survey questions. A few papers in political science (Roberts et al. (2014), Brugidou (2003)) leverage open-ended survey questions, and the practice is also starting to spread to economics (Stantcheva (2020), Houde and Wekhof (2021)).

In this paper, the data comes from two surveys on income and estate taxes, conducted in 2019 on 5140 U.S. residents aged 18 to 70. The sample is representative of the U.S. population along the dimension of gender, age, income, political affiliation, and employment (see Appendix OA-1). Section I presents the application of text analysis to open-ended survey questions. Section II summarizes key results about people's views on income and estate taxation.

I. Using Open-Ended Survey Questions

A. *What do Open-ended Questions Measure?*

Open-ended questions can go from broad to narrow. Broader open-ended questions are useful to elicit first-order, intrinsic concerns that people have before they are prompted to think of a particular policy aspect with more directed questions. Thus, it makes sense to start by asking people big picture questions such as the "main considerations" that come to their minds when they think about an issue (e.g, the income and estate tax). In our application, we then narrow the focus by asking people what a "good" tax system means to them and what its goals should be, as well as what their main perceived shortcomings of the current U.S. tax system are. Finally, one can ask targeted questions, such as about the effects on the U.S. economy and on different groups of people if the policy were changed (e.g., what would be the effects on the economy if taxes on high earners were raised).[1]

It is useful to think about what the answers to open-ended questions capture. The answers of respondents who have not previously thought carefully about the

topic may be "gut reactions." These reactions are informative, as they reflect what a respondent thinks and will keep thinking, absent more learning or targeted reflection. The answers of respondents who have already thought about the topic previously or take time to think about it during the survey before answering may reflect more profound views.[2] Either way, answers to open-ended questions capture the first-order considerations that matter to people and the aspects of an issue that are top of mind for them.

B. *Text Analysis Methods for Open-Ended Questions*

DATA PRE-PROCESSING

To prepare the data for text analysis, we first parse the answers to reduce the number of distinct text elements. We remove punctuation, excess spaces, numbers, misspelled words, and so-called "stop words," which are common words that carry no intrinsic meaning such as "and," or "the." The remaining words in each answer are then lemmatized to group all inflected forms of a word.[3] Words appearing in the question itself or that occur generically in answers can also be removed (e.g., "think," "believe," "should"). Appendix OA-5 describes the data pre-processing in detail. We now briefly present three text analysis methods, with more details in Online Appendix OA-6.

WORD CLOUDS

For each of the methods presented, a decision has to be made on the basic unit of analysis, i.e., the size of word groups that will be considered as a set. "n-grams" are groups of n words. In word clouds, the font size for each n-gram is proportional to its frequency. Word clouds are best used as a first step in visualizing the data and scanning answers quickly. Their weakness

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[1]Section OA-2 provides all the questions asked.

[2]The time spent on each question can be measured and it is possible to distinguish between these two types of responses.

[3]For instance, "policies" becomes "policy," "were" becomes "be."

is that they do not account for synonyms. Hence, topics for which there are many possible words to express the same thought may be artificially diluted, while niche topics that feature clear "buzzwords" may be inflated in importance.

Keyness analysis

Keyness analysis is based on a relative frequency analysis that compares the use of n-grams between two groups (a reference and a target/study group). The keyness scores of an n-gram are based on the χ^2 test statistic for the null hypothesis that the propensity to use the n-gram is the same for the reference and target groups. In a nutshell, the keyness score of a term measures how characteristic this term is of the reference group. Words that are common, but used relatively equally by the two groups do not have a high keyness score.

Topic Analysis

The topic analysis is based on a keywords-count model. Topics are defined by sets of keywords. To extract the topics and associated keywords, approaches range from manual to semi-supervised or unsupervised (see Online Appendix OA-4 for a summary of some key methods). In practice, given the shorter length of open-ended survey questions' answers and the manageable sample sizes, a more guided approach seems better. We recommend extracting the "Document-term matrix" (matrix of frequencies of terms in each answer), plotting the distributions of words (e.g., using word clouds), and checking many sample answers to better understand how words are used by respondents. Oftentimes, themes and commonly used words appear quite clearly from the frequency distributions. It is, however, important to do sensitivity checks on the topics delineated and on the keywords included. More decisions that need to be made (and which warrant sensitivity analysis) include whether to count a topic that is mentioned multiple times by a respondent only once or not, and whether to filter out differences in answer lengths

across groups by computing topic distributions within groups.

II. Application: How Do People Think About Taxes?

To apply these methods to how people think about income and estate taxation, we focus on answers to the broad question "what are your main considerations" when thinking about income or estate taxes, respectively. The other open-ended questions are analyzed in Online Appendix OA-9. Figure 1 shows the word clouds derived from the responses. For the income tax, respondents intuitively express disagreement with the current levels of taxes and views

(a) Income Tax
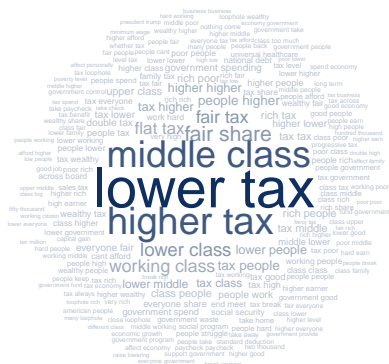
(b) Estate Tax

Figure 1. : Word Clouds for Income and Estate Tax

Note: The figure shows word clouds based on the text analysis of answers to the open-ended question about respondents' main considerations on the tax systems. See Section OA-5 of the Appendix for details on pre-processing steps and Section I for a summary of the method.

on the direction in which to change them ("lower tax" or "higher tax," depending on the groups they refer to) and concern about the impacts on the "middle class." For the estate tax, respondents' first-order reaction centers around "double taxation" and the fairness of the estate tax, followed closely by concerns about the "middle class" and "family."

A. Key topics mentioned

Figure 2 shows the distribution of topics in respondents' answers by political affiliation. For the income tax, there are eight distinct topics: *Distribution, Fairness, Government Spending, Social Insurance, Efficiency, Loopholes, Flat Tax, Public Goods*, and *Don't Know* (the labels are chosen by us and need not be words used by respondents). For instance, the *Distribution* topic contains keywords such as "middle class," "low income, "millionaire." The *Fairness* issue contains the words "fair" and "unfair." *Public goods* captures "infrastructure," "education," and "health care." *Efficiency* is represented by words such as "hurt economy," "work less," "competition," and "spend less," among others. The final category is for respondents who express that they do not know enough about the policy to give a meaningful answer. Appendix OA-7 lists the full set of keywords identifying each topic, and example answers are in Appendix OA-8. An answer is counted as mentioning a topic if it contains at least one of the topic keywords and answers can contain multiple topics.

The topics of *Distribution* and *Fairness*, as well as *Government Spending* and *Loopholes* are some of the most frequently mentioned ones. The *Efficiency* topic does not appear to be top of mind for most people. These results echo the findings of Stantcheva (2021) that distributional and fairness considerations dominate efficiency ones in shaping people's tax policy views, using a finer decomposition analysis that leverages a series of (non-open-ended) survey questions. Thus, people's responses to the open-ended questions already provide meaningful insights into what matters to them.

Figure 2. : Topic Analysis of Income and Estate Tax by Political Affiliation

Note: The figure shows within party affiliation distribution of topics in the question about respondents' main considerations on the tax systems. The bars represent the number of times topic X was mentioned over the number of times any topic was mentioned by political group G. Topics are indicator variables based on a keywords-count model. See OA-7 for the full list of keywords defining each topic.

For the estate tax in Panel B, the topics are similar to those from the income tax survey. Specific to the estate tax is the *Double Tax* topic, captured by keywords such as "already taxed, " already paid," and "taxed/paid twice" and the *Grieve* topic, which is captured by terms such as "grieve," "bury," and "funeral." The distribution of topics is again heavily centered around issues of *Distribution* and *Fairness,* but the *Double Tax* also carries a lot of weight. Much rarer are mentions of government spending, efficiency, loopholes, death, or public goods. Furthermore, more people express a lack of knowledge for the estate tax than for the income tax (32% of respondents as compared to 28%).

B. Political differences in topics mentioned

It is useful to plot topic distributions for different groups, to see whether first-order concerns are heterogeneous across respondents. Figure 2 does this by political affiliation, while Online Appendix OA-9 provides

cuts by age, income, or education groups. Political leanings are captured by both the vote in 2016 (Clinton vs. Trump) and by a self-reported degree of conservatism vs. liberalism (see OA-3 for details). The four main categories that emerge are Clinton Liberals, Clinton Moderates, Trump Moderates, and Trump Conservatives.

There are clear political differences in the topics mentioned. Issues related to *Distribution* are much more prevalent on the left of the political spectrum than on the right: they represent 50% of topics mentioned by Clinton Liberals and 25% by Trump Conservatives. *Government spending*, on the other hand, is a more pressing concern for respondents on the right, accounting for less than 4% of topic mentions for Clinton Liberals and 22% for Trump Conservatives. *Efficiency* is not frequently mentioned by any political group. Perhaps surprisingly, *Fairness* mentions are evenly distributed across the political spectrum. This is because, even though everyone cares about fairness, the meaning of this concept greatly differs across respondents: fairness is in the eye of the beholder.

Figure 3 shows the keywords that are most specific to Democrats and Republicans. Consistent with the topic distribution, the keywords on the Democrat side center around issues of *Distribution* ("poor rich," "lower class," "middle class," and "tax wealthy"). Republicans tend to emphasize *Government Spending, Government Waste, and the Economic Costs* ("people work," "economy spend").

For the estate tax, there are also clear differences in the topics mentioned by political leanings. *Distribution* issues are most prevalent among Clinton Liberals and diminish rapidly and monotonically towards Trump Conservatives. Conversely, *Double Taxation* concerns are prevalent among Trump Conservatives, but quite rare among Clinton Liberals. The mentions of *Fairness* are again evenly distributed across the political spectrum. These patterns are confirmed by the keyness analysis (Panel B of Figure 3).

In the Appendix, Figure OA-2 shows the distribution of responses to the question "Who gains if taxes on high earners were increased?" Among Democrats, prevalent answers are "the middle class" and "everybody." Among Republicans, common answers are "nobody" and "government and politicians." These reflect beliefs in
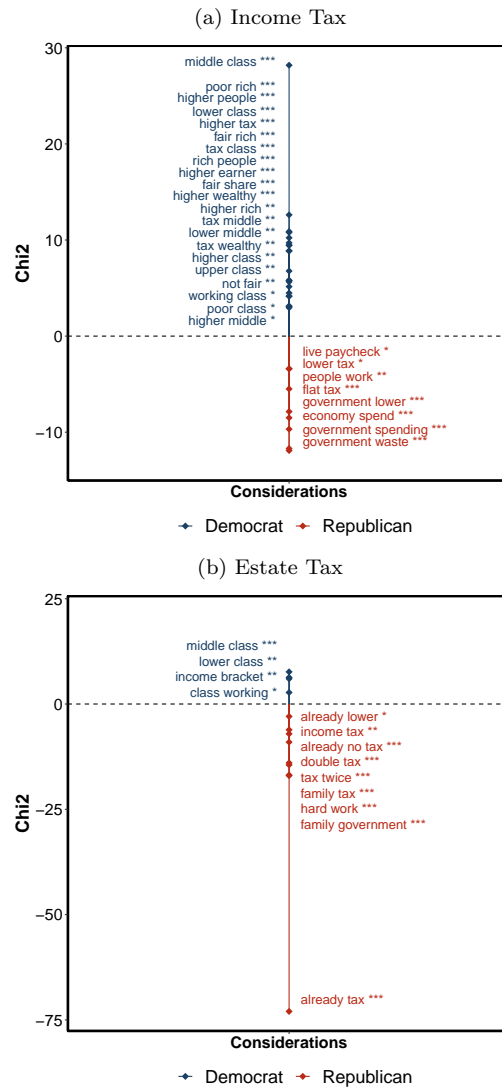

Figure 3. : Keywords of Income and Estate Tax by Political Affiliation

Note: The figure shows differential association of keywords in answers to the question about respondents' main considerations on the tax systems, by political affiliation. The score reported for a set of two words is the χ^2- test statistic, testing the null hypothesis that the occurrence of the given set is equal across Democrats versus Republicans. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See Online Appendix Section OA-6.2 for details on the computation.

"trickle-down" economics. Figure OA-6 shows similar perceived winners and losers from estate tax increases.

When it comes to the perceived shortcomings of the income tax, Figure OA-3 shows that keywords specific to Democrats relate to *Loopholes* and *Tax Breaks for the Rich and Corporations*, while for Republicans they center around *Government Spending* and *Work* (i.e., that taxes discourage work and that it is unfair to tax hard-working people).

C. Patterns by Age, Income, and Education

These methods can be applied to analyze heterogeneity across any groups of interest. Online Appendix OA-9 shows keyness and topic analyses across age, education, and income groups. These heterogeneities are generally smaller than those by political affiliation. Consider age patterns as an example. Older respondents' concerns with income taxes are characterized by terms related to *Government Waste, Budget, Social Security*, and the *Complexity* and *Loopholes* of the tax code (see Panel B of Figure OA-3), as well as worries about possible *Double Taxation* from the estate tax (see Panel B Figure OA-5). Younger respondents' concerns surrounding the income tax relate to *Cost of Living, Affordability* and *Healthcare*, and they are more likely to express a lack of knowledge about the estate tax.

III. Conclusion

Open-ended survey questions offer the potential to elicit people's first-order considerations on policy issues. By not constraining respondents to a given set of answer choices, they avoid priming them to think of otherwise non-salient options or omitting relevant options. Open-ended questions can range from broader to more targeted. Leveraging recent advances in text analysis, their answers can be visualized and quantitatively studied to shed light across many areas of economics.

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