Word Association Tests for Political Science

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Ze Han† Naijia Liu‡ Rory Truex§

Abstract

The standard practice to measuring political attitudes is to ask survey respondents to map their feelings onto a quantitative scale determined by the researcher. This approach, while widespread, suffers from a number of well-known problems. Such questions can be cognitively demanding, scales are different across cultures and even individuals of the same culture, and complex attitudes are reduced to a single number. In this paper, we advance the use of Word Association Tests (WATs), where respondents are presented a series of cue words and asked to provide other words that come to mind as quickly as possible. This approach more directly maps to how attitudes actually operate in the human mind, and it provides a richer set of data than a standard survey question. The paper develops and demonstrates the utility of WATs through an analysis of Chinese citizens' attitudes towards the Chinese Communist Party (CCP).

Keywords: survey; public opinion; sensitive questions; Word Association Test; China; Chinese Communist Party

Word Count: 9873

†Ph.D. Student, Department of Politics, Princeton University. zeh@princeton.edu.

‡Ph.D. Candidate, Department of Politics, Princeton University. naijial@princeton.edu.

§Assistant Professor of Politics and International Affairs, Princeton University. rtruex@princeton.edu. This material is based upon work supported by the Department of Politics, the School of Public and International Affairs, and the Paul and Marcia Wythes Center on Contemporary China at Princeton University. Our gratitude goes to Quentin Beazer, Dan Corstange, Simon de Deyne, Michelle Dion, Yue Hou, Kimuli Kisara, John Marshall, Andrew Nathan, Margaret Roberts, Arturas Rozenas, Arthur Spirling, Yiqing Xu and participants in seminars and panels at Columbia University, New York University, APSA and the PolMeth 2021 Summer Meeting. Any remaining errors are our own.

The standard practice to measuring political attitudes is to ask survey respondents to map their feelings into a quantitative scale determined by the researcher. Consider the following question commonly used in the study of Chinese politics (Lu and Dickson 2020; Ratigan and Rabin 2020; Shen and Truex 2021):

> *On a scale of 1 to 10, with 10 meaning very satisfied and 1 meaning not satisfied at all, how satisfied are you with the work of the following?*
>
> a. *Central government officials*

Respondents are meant to take their feelings about the central government, reduce them down to a single number, and report that number back faithfully to the researcher. This question format is commonplace in the discipline. In American politics, researchers analyze "feeling thermometer" questions from the American National Election Studies (ANES) that require respondents to assess political figures on a 101-point scale (Hetherington 1998; Winter and Berinsky 1999). Scholars of international relations employ similar measures of citizens' attitudes towards foreign countries (Gries et al. 2020). In the past five years (2017-2021), 162 articles in the *American Political Science Review*, *American Journal of Political Science*, and *Journal of Politics* have featured an analysis of survey data that measures political attitudes using quantitative scales. This represents roughly 15% of the articles in the top general interest journals in the field.[1]

Anyone who has taken a survey knows that the standard approach suffers from a number of problems. Such questions can be cognitively demanding. We might not have well-defined attitudes on every topic, and even if we did, placing those beliefs into a single quantitative dimension can feel arbitrary (Berinsky 1999, 2004; Berinsky and Tucker 2006). Scales are different for different people, and this can make comparison difficult (Brady 1985; King et al. 2004). Perhaps most importantly, we lose a lot of information when we ask people to reduce their attitudes to a single number or response.

[1]This calculation does not include short articles, letters, or book reviews.

Our primary criticism of existing question techniques is that they do not map well to psychologists' understanding of the human mind. One of the more important developments in political psychology has been the confirmation of the so-called "hot cognition" hypotheses – the idea that effectively all concepts in working memory are affectively tagged in some way (Redlawsk 2002; Lodge and Taber 2005). When a citizen thinks of herself, or democracy, or her political leaders, she thinks of a combination of positive and negative things.

These links are what most of us would call attitudes (Truex and Tavana 2019). In their simplest definition, attitudes are an association between a concept and an attribute (Lane et al. 2007; Lodge and Taber 2005). When we ask a standard survey question, we are asking the respondent to summarize this complex set of associations and feelings into a single answer, usually a number. This is an unnatural exercise, especially for respondents that are less educated, less quantitatively oriented, or just less practiced in answering survey questions (Berinsky 2004, 2008; Krosnick 1991; Tourangeau, Rips and Rasinski 2000). Many respondents might not even possess real opinions at the level of a standard survey question, instead responding with whatever ideas happen to be top of mind (Zaller and Feldman 1992).

The purpose of the current study is to propose the use of Word Association Tests (WATs) as a richer, cognitively revealing way of measuring attitudes. WATs have a long history in the field of psychology and were originally used as a personality diagnostic (Sharp 1991; Galton 1879). Taking a WAT is relatively simple, as respondents are not constrained by the demands of syntax in natural language (Szalay and Deese 1978; Prior and Bentin 2008). A list of cue words is presented one at a time to the research subject, who is asked to respond as quickly as possible with associated words that come to mind. The resulting data is a vector of response words for each respondent, for each cue word. The researcher can also collect metadata on how long respondents took to type in words and complete the task.

In this paper, we develop an adapted version of a Word Association Test, which will allow us to measure the semantic associations of different groups towards actors and concepts of interest. To our knowledge, this is the first test of its kind used in political science.

Substantively, our interest diverges from typical WATs that aim to explore how word meaning or semantic information in general is stored in memory (Anisfeld and Deese 1967; McRae et al. 2005; Vinson and Vigliocco 2008). We construct a WAT to measure attitudes towards the Chinese Communist Party (CCP) among Chinese citizens (in mainland China and Hong Kong. The aim of this paper is more methodological than substantive. Our goal is to show the utility of the WAT approach and provide a "how to" guide that will allow other researchers to use word association in other political contexts.

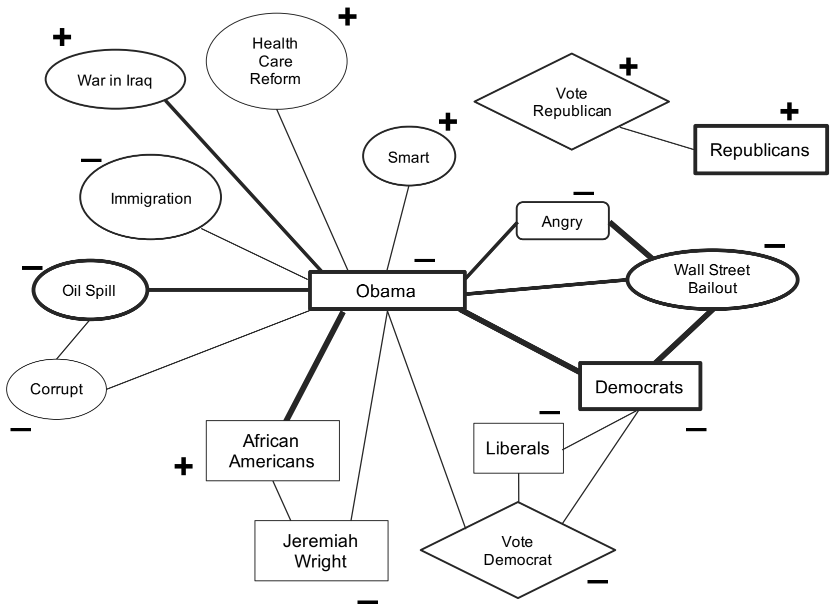
Attitudes and Memory

Every person possesses a body of preexisting knowledge which is stored in a vast long-term memory. Even though such information might not be front of mind, we have not deleted the knowledge of the color of our first car, or the directions to the movie theater, or the names and actions of our political leaders. When needed or "activated," these stored pieces of information are moved into working memory, where it can be used for conscious thinking and reasoning (Anderson 1983; Collins and Loftus 1975). The space in our working memories are quite small – about 7 (plus or minus 2) bits of information (Miller 1956). Long term memory, in contrast, is thought to be essentially limitless (Lodge and Taber 2013). Much of what we "know" might lie outside of our conscious awareness for long periods of time, and we might not even know we know it.

Memories are stored in a vast array of networked associations. Each piece of information is linked to countless other pieces of information, which are in turn linked to countless other pieces of information. When a concept is activated by some external stimulus, other linked pieces of information may be activated as well (Anderson 1983; Collins and Loftus 1975). For example, the concept of graduate school might bring the following related concepts quickly to mind: problem sets, comprehensive exams, job market, paper, job talk, seminar, carrel, desk, code, professor. One can do this for effectively every concept in memory.

We can visualize this idea with a mental map, where concepts in memory are drawn with

Figure 1: Example of "Mental Map"



links to each other that represent associations. Figure 1, which is reproduced and amended slightly from Lodge and Taber (2013), shows the cognitive structure of a hypothetical American citizen approaching the 2012 election. Different types of memory objects are denoted with different shapes, and the lines between the objects denote associations of varying strength. The memory objects are tagged with either a positive or negative affect. Figure 1 shows a mental map of a hypothetical Republican voter with negative associations with Barack Obama.

Our memories are an exceedingly complex web of information, and even representing just a few concepts and links on paper can quickly get unwieldy. Note that all figures of this nature – including the co-occurrence network that we will present in this paper – are incomplete. Each concept in memory is linked to still more concepts, which are in turn linked to other concepts, creating an effectively infinite network. And while it may not be possible to collect the full network, we can do better than standard survey questions, which reduce all of these relationships down to a single number.

Word Association Tests

Word Association Tests (WATs) allow us to build out cognitive maps for different groups of citizens, for different political concepts of interest. WATs were originally devised by Francis Galton in 1879 and later refined by Carl Gustav Jung to reveal subjects' "unconscious complexes" (Sharp 1991). Galton (1879) developed several psychometric experiments using word associations with the goal of quantifying the process of the human mind. He constructed a list of 75 printed words (trials) and then recorded each subject's associations when reading each of them. The trials had a maximum response period of about 4 seconds. He concluded that associations formed in childhood were better established than associations formed later in life.

Jung subsequently developed Galton's methods and introduced a refined WAT in 1903, primarily with the purpose of improving the accuracy of diagnosis in psychiatry (Berry et al. 1998). His original motivation was to examine whether patterns of interconnected thoughts and images around a particular idea could distinguish different kinds of patients (Escamilla et al. 2018; Sharp 1991). From 1903 to 1906, he conducted a series of WATs to identify the existence of the things that "people cannot or will not speak about" (Jung 2014).

At present, WATs are actively used in a range of fields, including psychology, physiology, education, marketing, and computer science. Researchers have used WATs to map associative memory structures (Shono, Ames and Stacy 2016; Steyvers, Shiffrin and Nelson 2005), explore brain activation patterns (Escamilla et al. 2018; Petchkovsky et al. 2013), assess conceptual change in education (Hovardas and Korfiatis 2006; Gulacar et al. 2015), examine consumers' perceptions toward products (Krumreich et al. 2019; Rojas-Rivas et al. 2018), and classify text documents (Agnihotri, Verma and Tripathi 2018; Santoni and Pourabbas 2016).

WATs can vary in length and design depending on the goals of the researcher. In "controlled" WATs, often used in neuropsychology, the subject's response is restricted to certain categories or word classes (Johnson et al. 2012; Malek-Ahmadi, Small and Raj 2011; Ross et al. 2007). In "free" WATs, respondents can provide whatever word comes to mind (de Andrade et al. 2016; Judacewski et al. 2019; Rojas-Rivas et al. 2018). In "continuous" WATs, the cue word is presented to the subject only once, and she is asked to give as many associations as possible in a pre-specified period of time (Brown and Ogle 1966, Matthews 1967, Silverstein and Harrow 1982, Silverstein and Chaifetz 1984). In "successive" WATs, the list of stimulus words is presented several times, often with the goal of measuring the stability of the subject's responses (Pons and Baudet 1979, Pons et al. 1986, Rosen and Russell 1957).

We know that with traditional survey questions, minor differences in question wording can make a big difference in outcomes. Some questions are too restrictive, while others are not constrained enough and include vague words and phrases that make responding difficult (Tourangeau, Rips and Rasinski 2000). WATs rarely include grammatical ambiguity and complicated syntax, and respondents can interpret the prompt relatively easily. WATs also do not involve quantitative scales of any kind and avoid the known issues of such questions – scale label effects, response contraction bias, and reference point effects, among others (Krosnick 1991; Roberts et al. 2014; Tourangeau, Rips and Rasinski 2000).

This is not to say WATs do not present their own methodological challenges. Throughout the paper we flag challenges and potential solutions based on our experience designing and using the WAT for this project.

Research Design

We administered two WATs designed to measure Chinese citizens attitudes towards the Chinese Communist Party. The first ("Study 1") was administered on March 9-10, 2020 to a sample of 1,189 Chinese citizens in mainland China, of whom 616 (51.81%) identified as female and 573 (48.19%) identified as male. The mean age was 36.9 years (SD $\approx$ 11.19). The second ("Study 2") was administered on May 21-June 10, 2020 to a sample of 1,019 Hong Kong residents of Chinese ethnicity, of whom 568 (55.74%) identified as female and 450

(44.16%) identified as male. The mean age was 37.19 years (SD $\approx$ 11.29).

Both studies were administered online in partnership with a local Chinese marketing company. All respondents were over the age of 18 and had to take the survey on a laptop/desktop computer. Apart from slight differences in the demographic and political attitude questions, the two surveys were identical, to facilitate a comparison between Hong Kong and mainland China. The Supporting Information provides the full questionnaire.

After a standard set of demographic questions, each participant completed a short WAT designed to take about six minutes. The instructions said that a cue word would appear on the screen and told the respondent that she would have 20 seconds to type all words that came to mind. Each participant was presented with a list of 18 cue words. This is considered a "free" and "continuous" WAT – there were no restrictions placed on response words, and each cue word appeared only once.

Some of the design decisions for our WAT merit further discussion. We wanted to give respondents enough time to provide multiple words in response to the cue word, but still limit the time such that the spontaneity and automaticity of the exercise was maintained. For example, if each cue word had a time limit of one minute, this would give respondents enough time to think through their responses and perhaps self-censor on more sensitive items. But if trials were restricted in five seconds, we might get only one word responses, or perhaps no responses at all. Relatedly, there is a question of how many cue words to include in a WAT. The more cue words, the more data to analyze, but the more likely the task would induce fatigue among respondents. After interviews with participants that piloted the survey, we felt that 20 seconds and 18 cue words were appropriate for our survey context. The number of cue words and the time for each trial are in line with best practices in various fields (De Deyne and Storms 2008; De Deyne, Navarro and Storms 2013; De Deyne et al. 2019; Gulacar et al. 2015; Li and Wang 2016; Vivas et al. 2019).

A second issue is what words to include among the cue words. To start with, we identified a set of "core" cue words that were the substantive focus of the study. We wanted to learn how precisely Chinese citizens thought about the regime and other important political concepts. There were five core cue words that were provided to all respondents:

China (中国)

Chinese Communist Party (共产党)

Central government (中央政府)

Me (我)[2]

Democracy (民主)

Note that we do not include the names of specific leaders or their associated ideological contributions (i.e. the "Three Represents" ("三个代表") or Jiang Zemin), as this would be too sensitive to do in the Chinese survey administration environment. In mainland China it is acceptable to ask citizens their levels of trust in government and the CCP, as well as their assessments of democracy in the country (Dickson 2016; Li 2004; Lu and Dickson 2020; Pan and Xu 2018).

If respondents only saw the five core cue words above, this might be a bit too obvious, and perhaps turn off some types of people from participating entirely. Our intuition was to include an additional set of "distractor words" that would reduce the overall sensitivity of the exercise. To avoid the scenario where cue words are unknown to participants, we included the most frequent Chinese words used in daily life. We relied on CharDB, a Chinese database that covers word frequencies, and randomly chose 95 cue words from the top 500 most frequent words.[3]

Our cue word set includes five core words and 95 others that come from everyday life. Each respondent saw the five core words and thirteen randomly chosen from the list of 95. The order of the trials was randomized for each respondent. The full list of words is available

[2]The "me" cue word was included for research for a separate project and will not be analyzed in detail in this paper.

[3]We filtered out all one character Chinese words in the CharDB database because most of single character Chinese words are function words. We saved the 500 most frequent Chinese words and filtered out all "stop words" (Lo, He and Ounis 2005). We randomly drew 95 words from the remaining 344 Chinese cue words.

in the Supporting Information.

For each respondent i and cue word c, the data include a vector of words W_{ic} that the respondent inputted as associating with the cue word. This vector varies in length across respondents and across words, which will we use as a variable, $count_{ic}$. Our core substantive analysis will focus on a simple associative strength measure, $p(r|c)$, which is the probability of responding with word r when given word c as a cue (De Deyne et al. 2019).

The data also includes two latency measures for each trial, $latency.firstclick_{ic}$ and $latency.submit_{ic}$. The former represents the time it took in seconds for the respondent i to enter their first response for the cue word c. The latter represents the time it took to submit the trial – respondents had the option to submit before the twenty seconds had elapsed.

Analysis

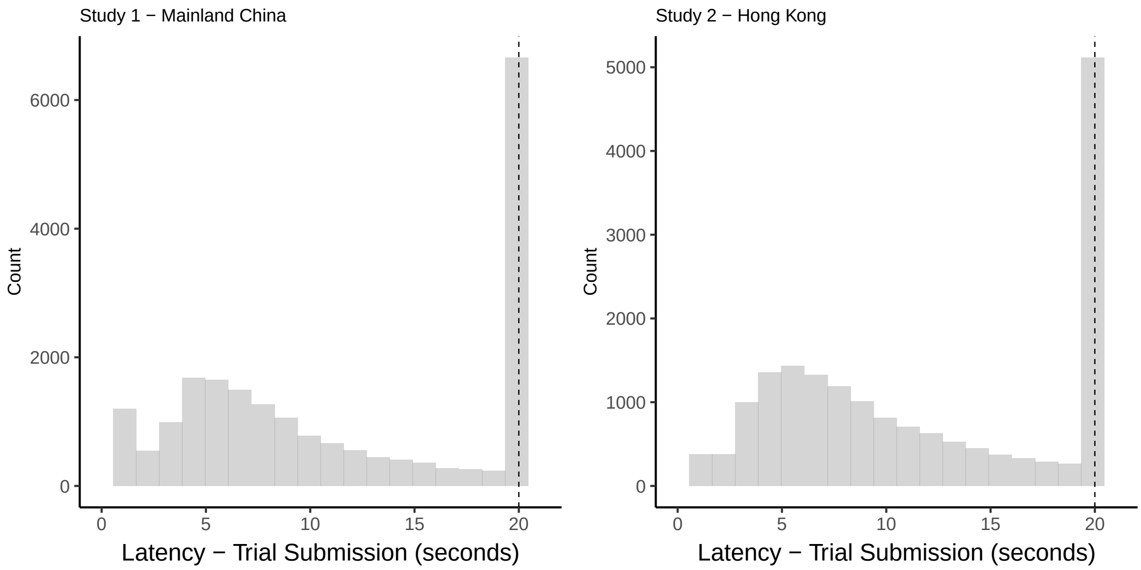
In the remainder of the article, we will focus on showing readers different steps in analyzing WAT data and some of the possibilities for visualization. Where appropriate we will also highlight some of the key substantive findings on public opinion in China.

Step 1: WAT Diagnostics

As with any set of responses to a novel question technique, researchers should first assess how respondents understood the task and identify any patterns or irregularities in the data. We would recommend a close analysis of submission patterns, specifically how long respondents take, how many words they submit, and whether key cue words are outliers on any of these variables.

Figure 2 shows a histogram of *latency.submit* for all respondents I across the full set of cue words J for the two studies. We see a bimodal distribution – nearly identical across the mainland China and Hong Kong samples – with peaks around 5.5 and 20 seconds. This suggests that respondents participated in the WAT in different ways. Most respondents followed the directions and took the full 20 seconds per trial, while others clicked submit much earlier.

Figure 2: Histogram of Submission Latency for All Trials



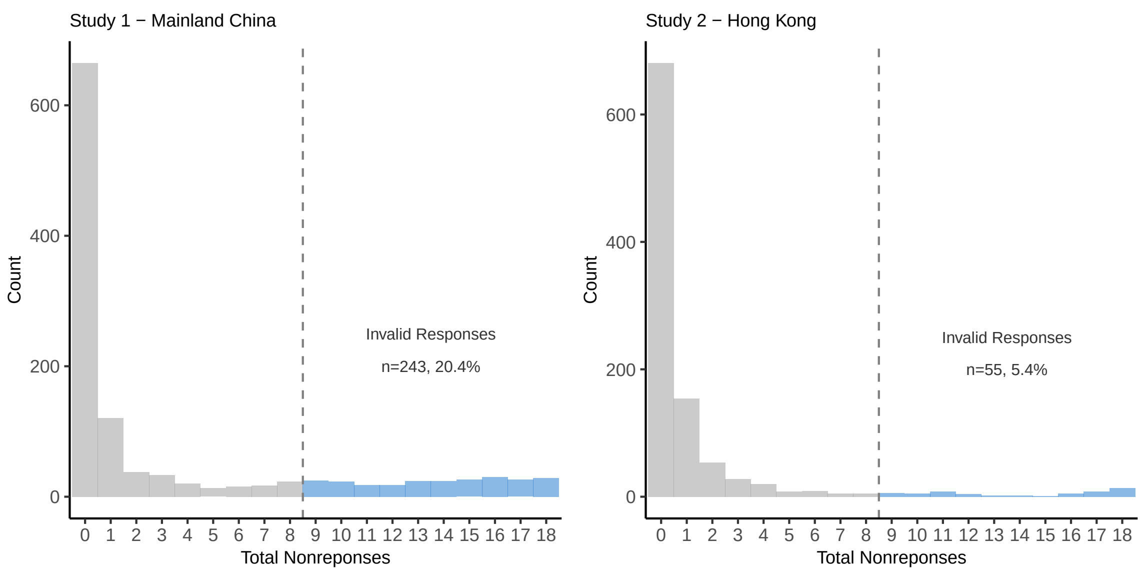
Note: Figure shows the histogram of the latency in seconds for the time it took a trial to be submitted. The allotted time was 20 seconds.

Not surprisingly, the time to submission was systematically related to the number of response words provided. Respondents that took the full 20 seconds provided an average of 3.682 (Study 1) and 3.240 (Study 2) response words in the mainland and Hong Kong samples, respectively. Respondents that took less than 10 seconds provided an average of 0.932 (Study 1) and 1.125 (Study 2) words in response.

This type of behavior is probably unavoidable given the nature of online surveys, where respondents often seek to work through surveys quickly to receive the cash payment. One alternative approach would have been to make the 20 seconds mandatory for all respondents – to not let respondents advance to the next trial until 20 seconds elapsed. We chose not to do this because we feared that this would annoy some respondents and create an attrition problem. As constructed, our WAT follows the recommendations of Salganik (2019), a "greedy" but not burdensome survey that allows respondents to provide varying amounts of data.

Researchers considering Word Association Tests should be aware that the instrument is much more time consuming than a standard Likert scale survey question. Our WAT took respondents an average of 3.43 minutes for respondents from mainland China and 3.52 minutes for respondents from Hong Kong – by design it should have taken 6 minutes. This can crowd out other questions or induce respondent fatigue, as suggested in our own diagnostics (see Figure 4). It might be possible to produce shorter WATs with similar properties, in the same way that psychologists have developed the "Brief IAT" to trim down administration times of the implicit association test (Sriram and Greenwald 2009). For example, we included 13 distractor cue words in our WAT, providing data that we did not really need or analyze. A shorter WAT which uses only the core words of interest might be more desirable depending on the research context.

Figure 3: Nonresponse Histogram



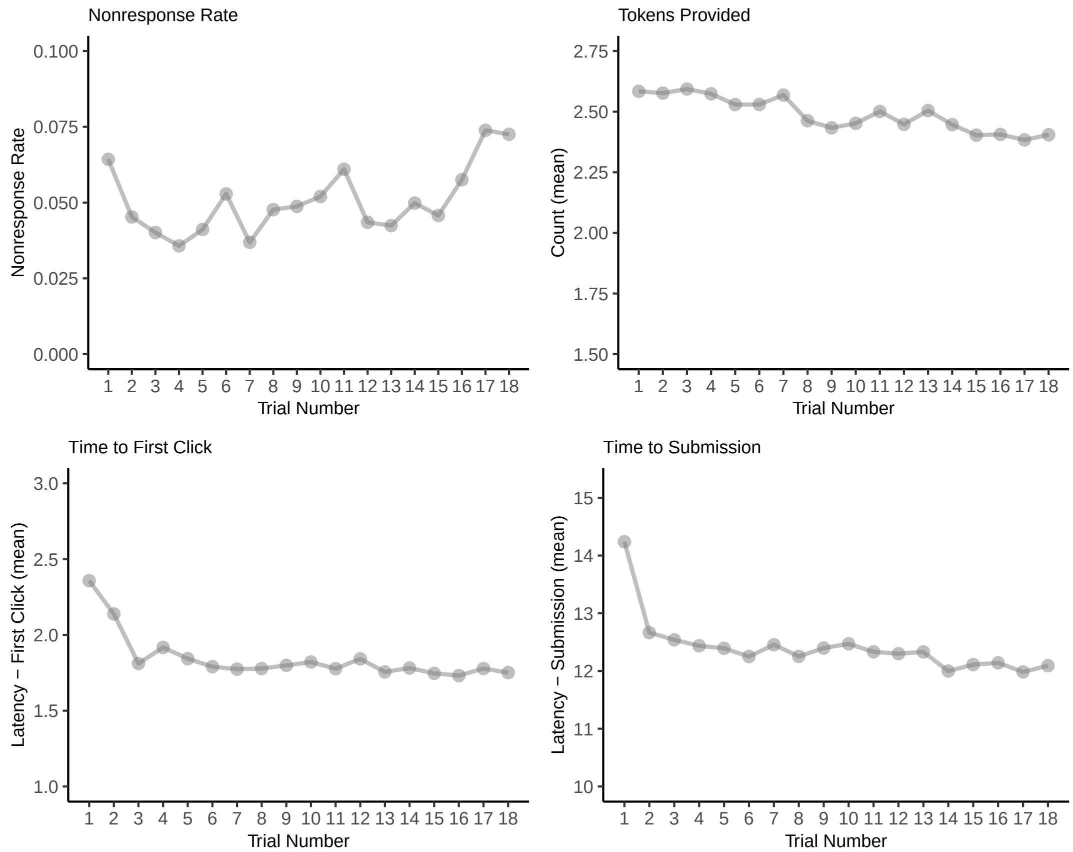
Note: Figure shows a histogram of the total number of nonresponses per respondent for the 18 WAT trials. Respondents that had a nonresponse rate greater than 50% were omitted from the analysis.

Researchers should also analyze nonresponse patterns at the respondent and cue word level. Figure 3 shows a histogram of the total number of nonresponses per respondent for the 18 WAT trials. We observe some respondents did not appear to take the WAT portion of the survey seriously at all. In mainland China, roughly 20.4% of respondents provided no answers to more than 50% of the WAT trials. In Hong Kong, about 5.4% of respondents showed that behavior pattern. Some level of item non-response to WAT cue words is understandable – respondents might not know a particular word, or they might struggle to come up with a response in the allotted time. But that level of non-response indicates "speeder" behavior. This data was unusable and will be excluded from the remainder of the analysis.[4] Note that the issue of repeated item non-response affects most online surveys, and it does not appear as though our survey was particularly vulnerable to the problem.

In Figures 4 and SI1 in the Supporting Information, we also consider response patterns by trial number, which allows us to assess whether respondents changed how they took the WAT as they progressed through the 18 trials. In both Hong Kong and mainland China, nonresponse rates increased, time to provide the first response shortened, and submission times were faster for later trials. For the first half of trials, respondents in Study 1 provided an average of about 2.54 tokens. By the second half, they provided about 2.44. This difference is not large but suggests researchers should be careful in constructing longer WATs, as there begin to be some costs in data quality. Shorter WATs, in the territory of 10 to 12 trials, might be more successful.

[4]A related issue which analysts should check for is "matching behavior," whereby the respondents simply inputs the cue word as the response word. This indicates a misunderstanding of the task. Roughly 2.1% of trials (442 in total) in mainland China had a matching response, and 5.4% of trials (995 in total) in the Hong Kong study were matching responses. These trials were excluded from the analysis.

Figure 4: Performance Diagnostics by Trial Number (Study 1 - Mainland China)



Note: Figure shows the mean nonresponse rate, latency to submission, and tokens provided by the trial order number. Data is from Study 1, and is filtered to exclude respondents that engaged in "speeder" behavior (non-responses to more than 50% of trials).

Our hope in constructing this survey is that the WAT technique reduces the sensitivity of assessing attitudes towards actors like the CCP or Chinese government (Ratigan and Rabin 2020, Shen and Truex 2021).[5] One way to assess this is to compare the latency, count, and nonresponse measures for all the words included in the WAT. If a question item is sensitive, we would expect respondents to pause slightly longer before answering, and perhaps provide fewer associated words as a result. We might also see higher rates of non-response (Ratigan

[5]We believe WATs hav potential as a sensitive question technique. Experiments have shown that WAT participants tend to provide the first word in their mental lexicon, rather than deliberate or strategic responses (Playfoot et al. 2018).

and Rabin 2020, Shen and Truex 2021).

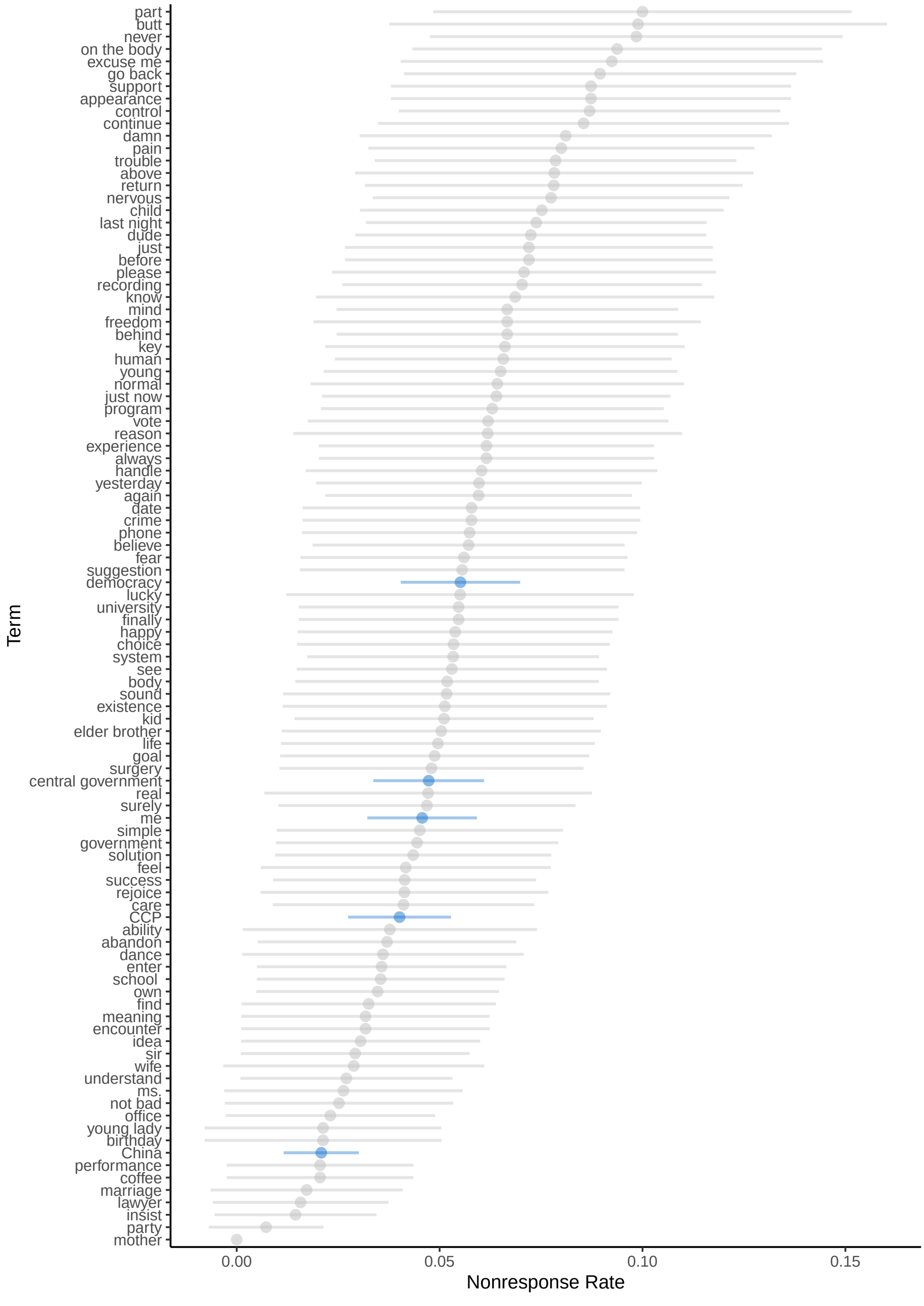
Figure 5 shows the non-response rate for all cue words used in our WAT for the mainland China sample (Study 1), and Figures SI2 and SI3 in the Supporting Information show the mean *count* and $latency.firstclick$.[6] We see that our five core words – China, CCP, central government, me, and democracy – are not outliers on these measures. It does not appear to be the case that respondents provide less data in response to the explicitly political cue words.

This can be assessed more systematically using a simple regression analysis, and we would recommend researchers conduct these sorts of diagnostic tests. The WAT metadata variables on nonresponse, response latency, and responses provided can be used as outcome variables in a regression with data at the trial level. Respondent-level covariates can also be incorporated, providing insight into participation patterns.

Table 1 shows the results of this exercise using the data from mainland China. A few notable patterns emerge. First, the core cue words appear to produce slightly more participation among respondents – the nonresponse rates for China, CCP, and central government are significantly lower than for other cue words, and the total response words provided are significantly higher. Based on prior research on public opinion in China, this is opposite of what we would expect if these questions were sensitive (Ratigan and Rabin 2020, Shen and Truex 2021). Table SI1 in the Supporting Information shows the equivalent analysis for the Hong Kong data, where such questions are not at all sensitive and a similar result obtains.

[6]Figures SI4 and SI5 show the equivalent figures for the Hong Kong sample (Study 2).

Figure 5: Non-response Rates for All Cue Words (Study 1 - Mainland China)



Note: Figure shows the non-response rates for all cue words presented in the WAT. Data is from Study 1 (Mainland China) and is filtered to exclude respondents that engaged in “speeder” behavior (non-responses to more than 50% of trials). Core cue words are shown in blue. Note that all respondents saw these words, which is why the point estimates have smaller confidence intervals than the other words.

Table 1: Determinants of Response Patterns (Study 1 - Mainland China)

	Outcome		
	nonresponse	*latency.submit*	*count*
	(1)	(2)	(3)
cue: CCP	-0.013	0.633	0.339
	(0.008)	(0.233)	(0.095)
cue: China	-0.037	0.037	0.418
	(0.008)	(0.233)	(0.095)
cue: Central Government	-0.013	0.484	0.177
	(0.008)	(0.233)	(0.095)
cue: Democracy	-0.004	-0.074	-0.110
	(0.008)	(0.233)	(0.095)
cue: Me	-0.007	-0.614	0.176
	(0.008)	(0.234)	(0.094)
female	0.008	0.157	0.131
	(0.003)	(0.107)	(0.043)
age	0.003	-0.049	-0.029
	(0.000)	(0.006)	(0.002)
minority	0.027	-1.802	-0.339
	(0.011)	(0.335)	(0.138)
lowed	0.065	-1.791	-0.854
	(0.004)	(0.133)	(0.054)
rural	-0.018	0.968	0.212
	(0.005)	(0.154)	(0.062)
ccp	-0.001	0.569	0.032
	(0.004)	(0.123)	(0.050)
n	15,172	15,172	15,172

Note: Table shows regressions of WAT metadata on demographic covariates and cue word indicators. The non core cue words represent the excluded category. Data is from Study 1, and is filtered to exclude respondents that engaged in "speeder" behavior (non-responses to more than 60% of trials) or provided no responses or matched responses towards the cue. Data is organized on the trial level. All models estimated using OLS. Standard errors shown in parentheses.

In line with previous results in the field that employ direct question techniques (Ratigan and Rabin 2020, Shen and Truex 2021), we also observe that citizens representing marginalized groups in China are more reticent on surveys. Respondents that were older, less educated and from minority groups provided significantly fewer words in response to the WAT cues. Thus it appears that the WAT approach does not solve the "silent voices" problem identified by Berinsky (2004), and efforts to aggregate and interpret such data must acknowledge biases in participation.

Table 2: TTR and HTR for Studies 1 and 2

	Study 1 - Mainland		Study 2 - HK	
	TTR	HTR	TTR	HTR
cue: CCP	0.297	0.281	0.377	0.362
cue: China	0.302	0.277	0.385	0.375
cue: Central Government	0.343	0.320	0.359	0.343
cue: Democracy	0.286	0.269	0.334	0.314

Note: Table shows the type-token ratio ("TTR") and the hapax legomenon-token ratio ("HTR") for the four core cue words for Study 1 and Study 2. The data is filtered to exclude respondents that engaged in "speeder" behavior (non-responses to more than 60% of trials) or provided no responses or matched responses towards the cue. The data suggests there is more lexical richness in the Hong Kong corpus.

In the analysis of WAT data, researchers frequently report two measures of lexical richness. The first is the type-token ratio ("TTR"), which takes the number of different words ("types") over to the total number of words in the corpus ("tokens"). An alternative measure is the ratio of the number of words that occur only once ("hapax legomenon") to the number of tokens (De Deyne, Navarro and Storms 2013; Baker, Hardie and Mcenery 2006). In natural language corpora, lexical richness positively correlates with the type-token ratio ("TTR") and the hapax legomenon-token ratio ("HTR"). Table 2 shows these two measures for the mainland China and Hong Kong studies, for the four core cue words of interest. We see that across the board, the Hong Kong corpus has more lexical richness– respondents provide a more diverse set of answers to the political cue words. This tells us something about the diversity of political thought in Hong Kong relative to the mainland.

Step 2: Frequency Analysis and Subgroup Comparisons

The natural next step for a WAT analysis is to consider the frequencies and associative strength $p(r|c)$ measure of different response words and look for substantive patterns therein. Table 3 shows the most common responses among mainland Chinese respondents (Study 1) to three cue words of primary interest: central government, CCP, and China. Overall, the roughly 1000 respondents provided 586, 581, and 585 unique words in response to being presented the cues of central government, CCP, and China, respectively. On average respondents provided about 2.0 to 3.0 words per cue in the allotted 20 seconds (see Figure SI3 in the Supporting Information). Table 3 shows all response words that were provided by at least 1% of the respondents.[7]

We see words that are attitudinal in nature. It is striking how positive the associations are – words like great (伟大), leadership (领导), long live (万岁), excellent (优秀), pretty good (不错), powerful (强大) and trust (信任) feature prominently. We might be tempted to attribute this pattern to preference falsification or self-censorship, but the WAT diagnostics above do not suggest that these terms were overly sensitive. We did not observe respondents taking longer to enter a response, or entering fewer responses, or refusing to enter responses altogether. These results accord with the general consensus in the China field that CCP leaders and the central government enjoy a deep reservoir of political support among the

[7] It is standard practice in WAT studies to clean the responses and filter out some respondents to improve the quality of the data. For example, for the CCP cue word, we first excluded participants that engaged in "speeder" behavior (243 or 20.4% of participants) or provided no responses to the cue (57 or 4.79% of participants). Second, we conducted a series of spell-checks and transformed unequivocal Pinyin and English words into simplified Chinese parallel corpora. This affected 14 responses (0.52%) and 10 responses (0.37%), respectively. Third, we created a list of synonyms and unified the same cluster of responses into a singular form, which involved 42 responses (1.57%). Fourth, we removed matching responses, where the respondent simply provided the cue word as the response. This involved 25 responses (0.93%). This left 2,543 responses (94.86%) from 922 participants (77.54%).

Table 3: Most Common Responses for Regime Cue Words (Study 1 - Mainland China)

Cue Word: Central Government			Cue Word: CCP			Cue Word: China		
Response	Freq	p(r|c)	Response	Freq	p(r|c)	Response	Freq	p(r|c)
country	69	0.074	China	89	0.094	powerful	170	0.186
leadership	59	0.063	leadership	59	0.062	motherland	91	0.100
authority	45	0.048	people	51	0.054	great	89	0.098
CCP	41	0.044	great	51	0.054	country	73	0.080
people	40	0.043	party member	44	0.047	let's go	33	0.036
centralization of authority	36	0.039	ruling party	36	0.038	people	27	0.030
right	31	0.033	Kuomintang	32	0.034	development	27	0.030
powerful	30	0.032	Mao Zedong	30	0.032	great power	24	0.026
China	24	0.026	democracy	30	0.032	prosperity	24	0.026
management	22	0.024	country	28	0.030	United States	24	0.026
trust	21	0.023	long live	25	0.026	CCP	23	0.025
highest	20	0.022	political party	22	0.023	unity	23	0.025
mechanism	20	0.022	serve the people	21	0.022	history	22	0.024
policy	16	0.017	socialism	18	0.019	mother	19	0.021
organ	16	0.017	powerful	17	0.018	pride	17	0.019
power	16	0.017	red	16	0.017	democracy	16	0.018
democracy	16	0.017	government	15	0.016	population	15	0.016
Beijing	15	0.016	in power	14	0.015	home	15	0.016
implementation	14	0.015	excellent	12	0.013	boom	15	0.016
State Council	13	0.014	unity	11	0.012	world	14	0.015
politics	13	0.014	pretty good	10	0.011	economic	14	0.015
core	13	0.014	support	10	0.011	peace	13	0.014
concentrated	12	0.013				nationality	13	0.014
Xi Jinping	11	0.012				patriotic	12	0.013
great	11	0.012				proud	12	0.013
correct	11	0.012				long live	11	0.012
reliable	10	0.011				safety	11	0.012
force	10	0.011				socialism	11	0.012
local	10	0.011				red	11	0.012
rule	10	0.011				Chinese flag	10	0.011
						terrific	10	0.011
						bounteous	10	0.011
						long	10	0.011
						culture	10	0.011
						deep love	10	0.011
						fine	10	0.011

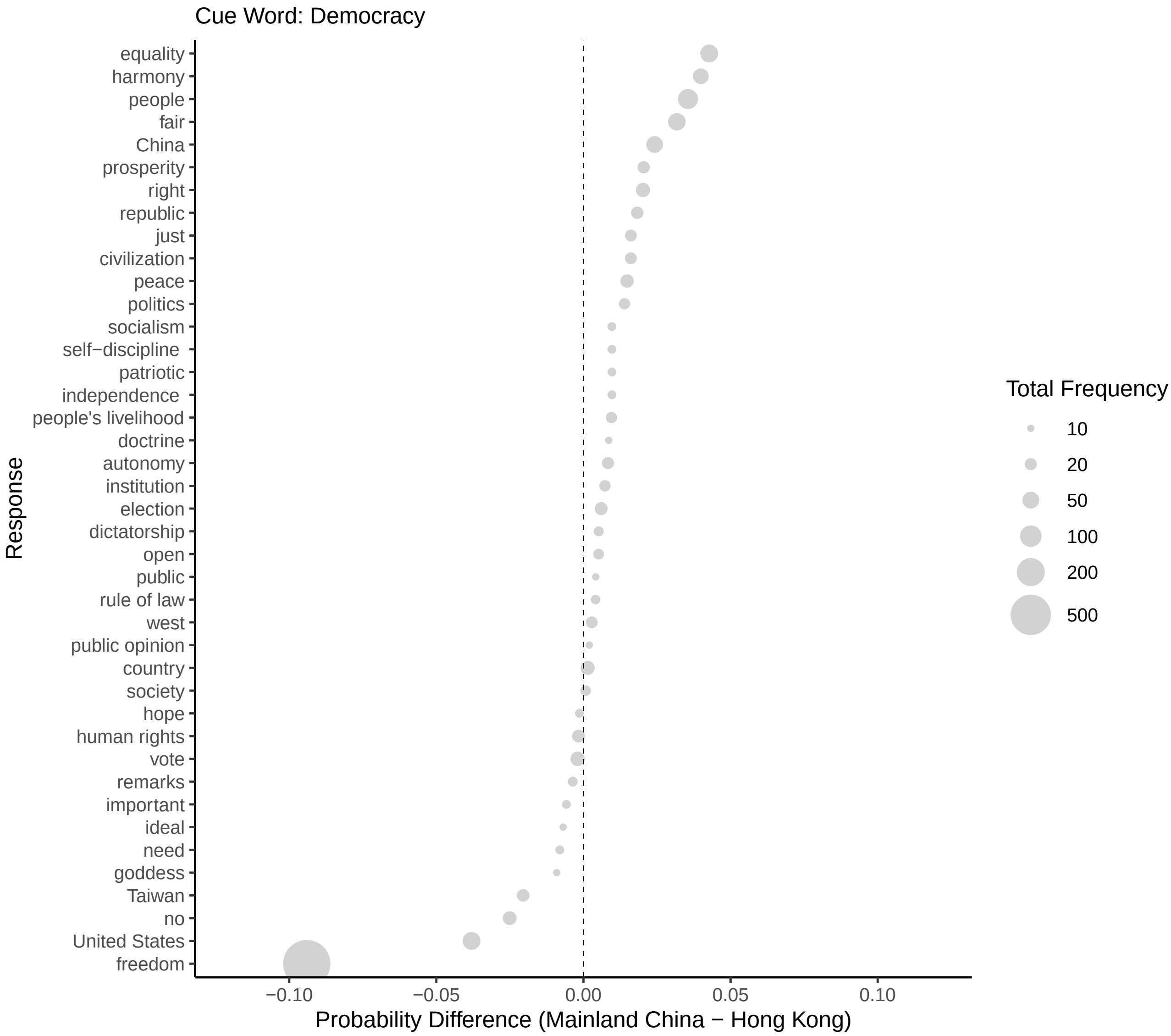
Note: Table shows most frequent responses for the cue words central government, CCP, and China. Data is from Study 1, and is filtered to exclude respondents that engaged in "speeder" behavior (non-responses to more than 50% of trials) or provided no responses towards the cue. Only words that had 10 or more responses ($p(r|c) > 0.01$) are shown.

population (Dickson 2016; Li 2004; Lu and Dickson 2020; Tang 2005; Truex 2017).

The WAT data allows a deeper glimpse into the cognitive basis for regime support among mainland Chinese citizens. Readers that are not China specialists might be surprised to see that the word "democracy" (民主) is one of the most commonly provided responses to the cues of CCP, central government, and China in Study 1. CCP propaganda and indoctrination materials describe the regime in the language of "socialist democracy' (社会主义民主), "Chinese-style democracy" (中国式民主), and "people's democratic dictatorship" (人民民主专政) (Nathan 2015). In 2013, the regime introduced twelve "Core Socialist Values" (社会主义核心价值观), stating that China should be "prosperous, democratic, civilized, and harmonious" (富强, 民主, 文明, 和谐) and embrace "freedom, equality, justice, and the rule of law" (自由,平等, 公正, 法治)." The CCP frames democracy as defined by substantive outcomes, not procedural processes. In this view, a government is democratic if it improves the material well being of the population (Guang 1996; Perry 2008), and the CCP's version of democracy is predicated on responsiveness to "the people" (Perry 2015).

Figure 6 presents another way of visualizing WAT data and comparing subgroups of interest. The chart shows the difference in the probability of response words for the democracy cue between the mainland China and Hong Kong samples, $p(r|c)_{Study1} - p(r|c)_{Study2}$. Response words with positive values are more common among respondents in mainland China, and response words with negative values are more common in Hong Kong. For ease of presentation, the figure only shows response words that appeared at least 10 times across the two samples, and the size of the point indicates the overall frequency of the response. This figure can be made for any cue word to compare any two subgroups.

Figure 6: Mainland China-Hong Kong Response Comparison for Democracy Cue



Note: Figure shows the difference in the probability of response words across the mainland China and Hong Kong samples for the democracy cue word. Words with values greater than zero are more common in mainland China; words with values less than zero are more common in Hong Kong. Data is filtered to exclude respondents that engaged in “speeder” behavior (non-responses to more than 50% of trials). Only words that appeared in 10 or more responses across the two samples are shown.

We see vastly different conceptions of democracy in mainland China and Hong Kong. In Hong Kong, respondents appear closer to the Western, liberal definition of the term.

Response words like freedom (自由), human rights (人权), and vote (投票) are more common in Hong Kong, and respondents also appear to associate the concept with democratic societies, namely the United States and Hong Kong. The word "no" or "do not have" (没有) is also very common, indicating the salience of Hong Kong's struggle for political rights. Citizens in mainland China, who experience substantial political indoctrination and face a constrained media environment, tend to replicate the conceptual associations provided by the regime. They tend to associate China with democracy, and they also reproduce other "Core Socialist Values" – equality (平等), harmony (和谐), prosperity (富强), and so forth. Words like people (人民), people's livelihood (民生), and socialism (社会主义) also reflect the CCP's socialist conception of the term.

The data also allows us to see different comparisons of patriotism and identity. Figure SI6 in the Supporting Information shows a probability difference chart for the China cue word. For respondents in mainland China, the response word set is almost uniformly positive. Concepts like powerful (强大), great (伟大), development (发展), rich and strong (富强), prosperity (繁荣), and terrific (厉害) convey a collective sense of optimism about the direction of the country, and the words pride (自豪), proud (骄傲), and "let's go/come on" (加油) are also commonplace. Citizens also reveal a sense of identity and belonging with concepts like motherland (祖国), mother (母亲), and mine (我的). Hong Kong respondents again provide a preponderance of negative words – words like dictatorship (独裁), autocratic (专制), and rubbish (垃圾).

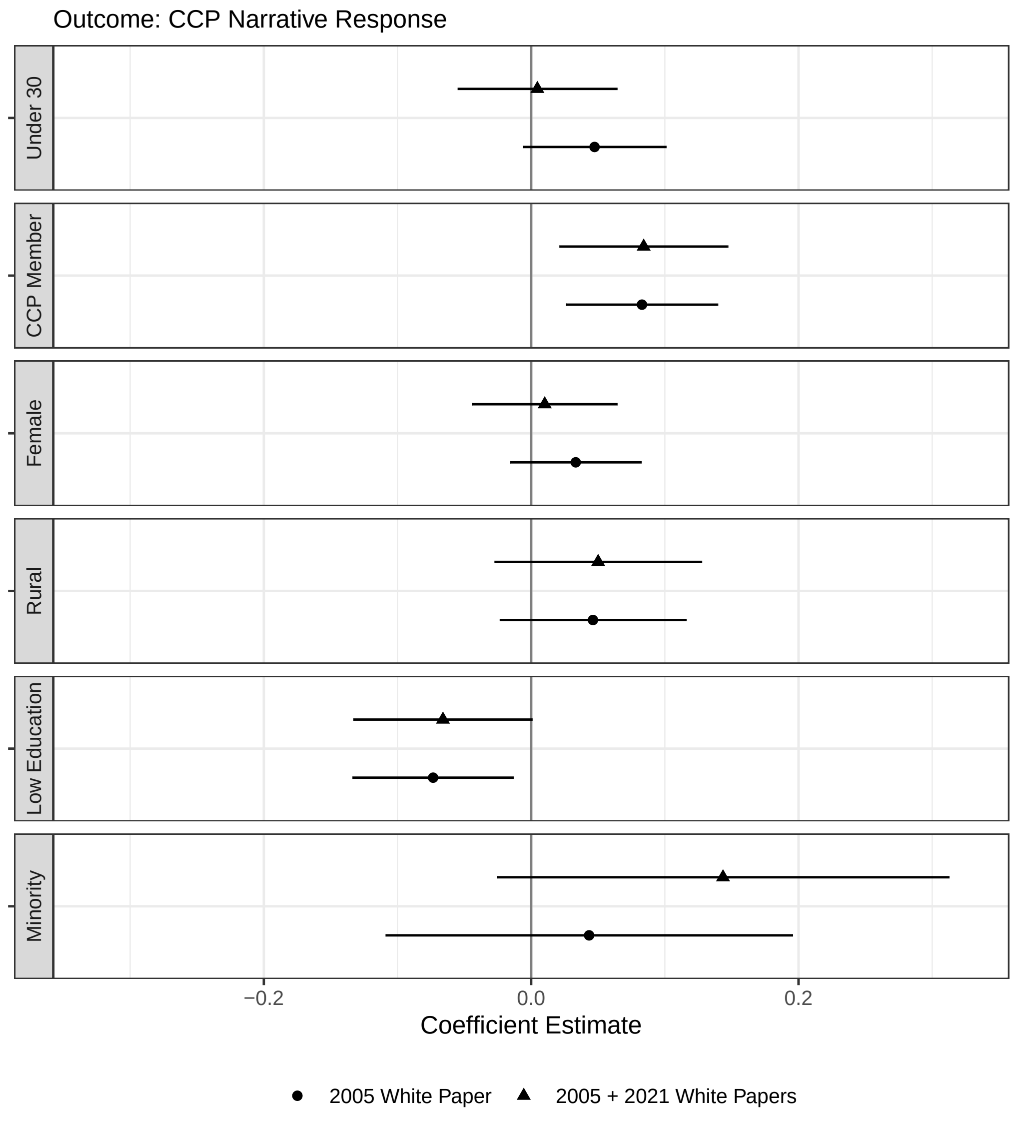
These visual frequency comparisons are useful, but researchers may want to test whether differences between groups are statistically significant, or to incorporate the WAT data into a multivariate framework. The question then is how to aggregate the WAT responses such that they could be used in a regression, while still retaining some of the richness of the information that differentiates WAT data.

We recommend a dictionary based approach, whereby response words are assigned manually to different categories by the analyst based on substantive knowledge of the case (de Andrade et al. 2016).[8] The resulting variable can then be used in standard regression model.

For example, in our case, China scholars would be interested to know what types of Chinese citizens have cognition that most closely reflects CCP narratives. To assess this, we first analyzed white papers on democracy published by the Chinese government. Since 1991, China's State Council has issued two white papers that exclusively focus on the concept of democracy: *Building of Political Democracy in China* (2005) and *China: Democracy that Works* (2021). Considering the timing of our survey, we chose to focus on the 2005 white paper and identified the 20 words that most commonly co-occurred with the word democracy (民主). Among others, this list includes words like CCP (中国共产党), the people as masters of the country (当家作主), China (中国), and socialism (社会主义). These words were tagged as indicators of a "CCP narrative response." We then created an indicator variable for respondents that provided one of those words in their responses to the cue word democracy– about 15% of respondents in mainland China did so. We incorporated this binary outcome variable into a linear probability model that included standard covariates of interest. As a robustness check, we generated a new list of 20 words examining the two 2005 and 2021 papers together and re-ran the regression.

[8] An alternative approach would be to estimate a structural topic model on the responses (Roberts et al. 2014), though we found this less tractable given the sparsity of the WAT data relative to a standard text document.

Figure 7: Determinants of CCP Narrative Responses (Study 1 - Mainland China)



Note: Figure shows the outcome of regressions of an indicator for a CCP narrative response on demographic covariates. Data is from Study 1 and is filtered to exclude respondents that engaged in clickthrough behavior (non-responses to more than 50% of trials).

Figure 7 shows the results of the dictionary analysis. We observe that CCP members are more likely to reproduce CCP language around democracy, and respondents that were less educated were less likely to use the language of socialist democracy. This hints at the importance of political education and indoctrination in the Chinese system (Cantoni et al. 2017) and dovetails with classic assertions made by Geddes and Zaller (1989)– citizens that have greater exposure to Party narratives appear more likely to internalize them at a subconscious level.

Step 3: Co-occurrence Analysis

The power of the Word Association Test is that it allows us to better map citizen cognition around key concepts of interest. For any population, we can identify response words associated with a cue word we are interested in, and in turn identify response words associated with those response words, and then response words associated with those response words, and so on ad infinitum. This type of analysis is called mapping a co-occurrence or collocation network (Meara 2016; Watts and Strogatz 1998). It is the closest we can get to constructing the type of mental map shown in Figure 1 with real data.

Note that this exercise is similar in spirit to word embedding, where researchers study the sentence structure and co-occurring probability among words in text documents– newspaper reports, speeches, social media posts, and so forth (Mikolov et al. 2013; Rheault and Cochrane 2020; Rodriguez, Spirling and Stewart 2021; Rodriguez and Spirling 2022). Our data is structured slightly differently, as WAT responses skip the sentence/paragraph structure and get at the co-occurring step directly. But WAT data could potentially be used in training models or as a spot check for word embedding results.

A co-occurrence network graph generally contains nodes that denote words and edges that link nodes i and j if the research subjects associate j with the cue i. It is up to the researcher to decide how to measure associations, and what constitutes a strong enough association to include as an edge on the graph. The edges can also be directed or weighted to reflect response frequency (De Deyne and Storms 2008; Newman 2012; De Deyne et al. 2019). Researchers will also need to decide how many nodes to show, and what order of association to depict. For example, a "first order" co-occurrence network would only show words that are associated with the cue word of interest. A "second order" co-occurrence network would show those words that are associated with the cue word of interest, and words that are in turn associated with those words.

Figure 8 shows a "second order" co-occurrence network for the CCP cue word for our sample from mainland China. The set of nodes in the network represent all words that respondents highly associate with the CCP (first order) and all words highly associated with those words (second order). This created a set of nodes; an edge is depicted between two nodes if $p(r|c) > .02$ for that cue-response pair.[9]

To produce this analysis, we supplemented our WAT data with existing word norms data collected by the Small World of Words (SWOW) project (De Deyne et al. 2019), which is one of many projects conducted by psychologists and linguists to map the mental lexicon of speakers of major languages. Our WAT data has Chinese citizens' associations with key concepts like the CCP, China, and democracy, but we do not know what they associated with words like red (红色), hero (英雄), emperor (皇帝) or the many other response words produced in our dataset. The SWOW researchers have some limited data available for a range of cue words for mainland China (about 120 responses per cue word), and we used that data to augment our network. This was sufficient for our purposes, but other researchers might find it possible to design an adaptive WAT, where response words provided by one respondent become cue words for other respondents.

[9]The network is visualized using the R igraph function using a force-directed layout algorithm. We found Niekler and Wiedemann's tutorial especially useful: `https://nballier.github.io/tm4ss.github.io/Tutorial_5_Co-occurrence.html`.

Figure 8: Second Order Co-occurrence Network for CCP Cue

Note: Figure shows a second order co-occurrence network for the CCP cue word for the mainland China sample (Study 1). The solid edge lines are from the WAT data, and the thinner dotted lines are from the SWOW data. Data is filtered to exclude respondents that engaged in "speeder" behavior (non-responses to more than 50% of trials) or provided no responses towards the cue.

Figure 8 shows distinct clusters of ideas – the core associations Chinese citizens have with the regime. We see a strong association between CCP and China, which is in turned linked to country (国家), national flag (国旗), government (政府), and more emotive expressions of nationalism like motherland (祖国), mother (母亲), and let's go (加油). Another cluster centers around people, which is linked to democracy, which is term linked to freedom, equality, and harmony – the "Core Socialist Values" region of the cognitive network. Another cognitive path links the CCP to the KMT regime, which brings up concepts like civil war (内战), opposition (反对), Chiang Kai-Shek (蒋介石), and Taiwan (台湾), among others. We also see clear links between the CCP and various CCP leaders, with Mao Zedong (毛泽东) occupying the most central position in the network. These individuals are in turn linked to words like leadership/leader (领导), new China (新中国), great person (伟人), and thought (思想).

Our overarching reaction to Figure 8 is the congruence between citizen cognition in mainland China and narratives proffered by the Chinese government. If the CCP regime could draw its idealized version of how it wants Chinese citizens to think, it would probably look like the network in Figure 8.

Conclusion

The purpose of the current study is to demonstrate the value in measuring political attitudes using Word Association Tests. Our hope is not for WATs to supplant existing question techniques, but for other researchers to further develop the tool for use across an array of research areas. We are optimistic because the scope of potential applications for WATs in political science is quite broad. Our paper has focused on understanding regime support, a substantive question of longstanding interest to scholars of authoritarian politics (Chen and Dickson 2008; Geddes and Zaller 1989; Magaloni 2006; Reuter and Szakonyi 2015; Treisman 2011). In American politics, we can envision a WAT of voters' attitudes towards different political candidates (Dolan 2010; Kam 2007; Krosnick 1988). Scholars of international relations could use WATs to understand how citizens perceive other nations or specific foreign policies (Milner and Tingley 2013; Tomz and Weeks 2013). WATs can also be readily combined with experiments, allowing us to see how exposure to media or propaganda material shifts citizens' cognition around a concept of interest (Huang 2015). They may also have promise as an alternative to existing sensitive question techniques (Ahlquist 2018; Blair, Imai and Lyall 2014; Bullock, Imai and Shapiro 2011; Chou, Imai and Rosenfeld 2020; Corstange 2009; Rosenfeld, Imai and Shapiro 2015) or as a validation method for word embedding studies (Mikolov et al. 2013; Rheault and Cochrane 2020; Rodriguez, Spirling and Stewart 2021; Rodriguez and Spirling 2022). WATs have yet to make their way to political science, but in our experience they reveal something different about political thinking than what we would get with a standard survey question.

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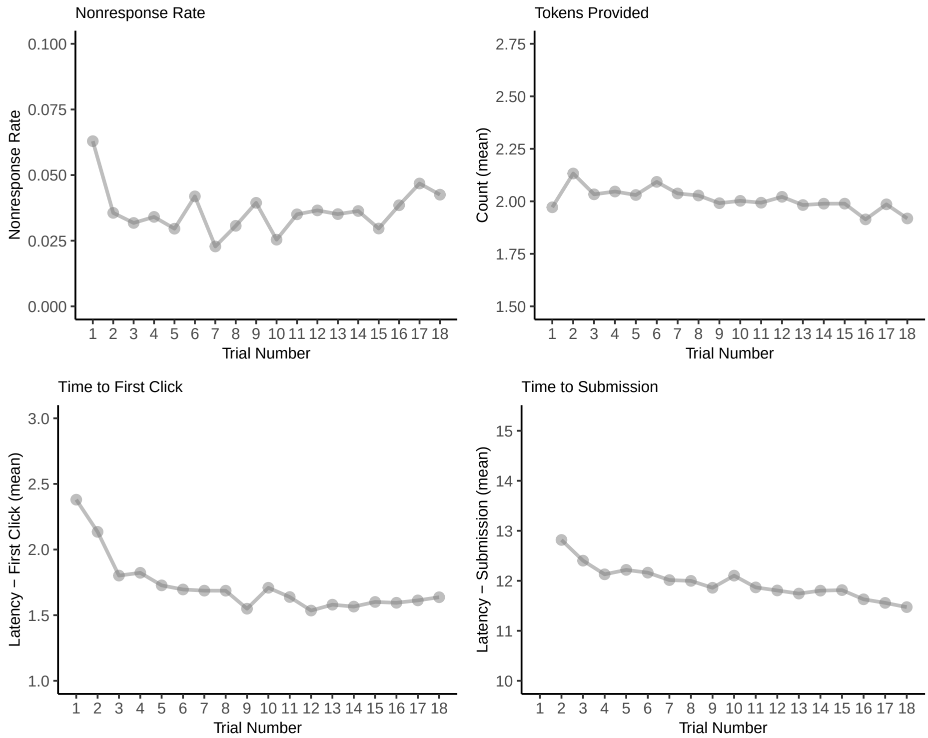
Supporting Information

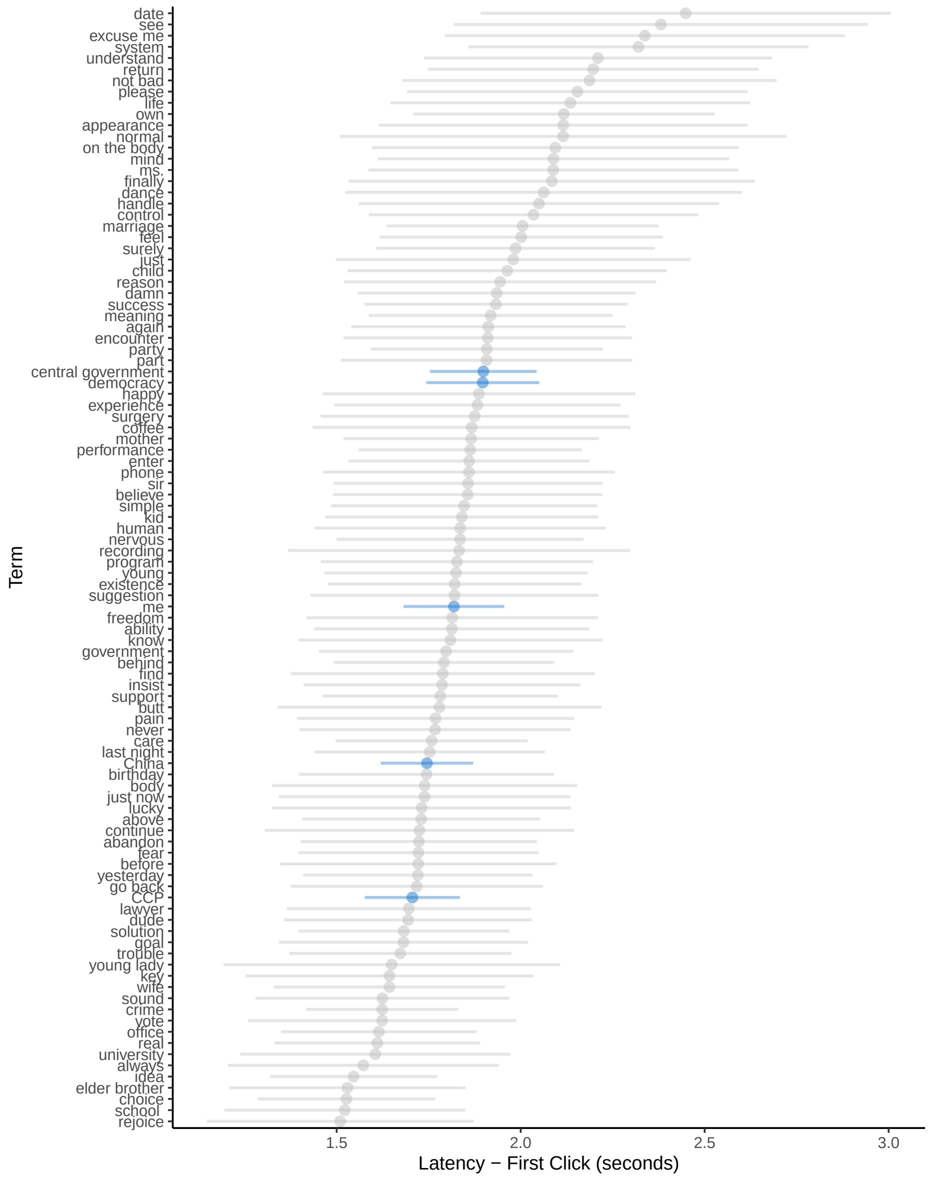
The Supporting Information contains the following:

Figure SI1: Key Performance Diagnostics by Trial Number (Study 2 - Hong Kong)



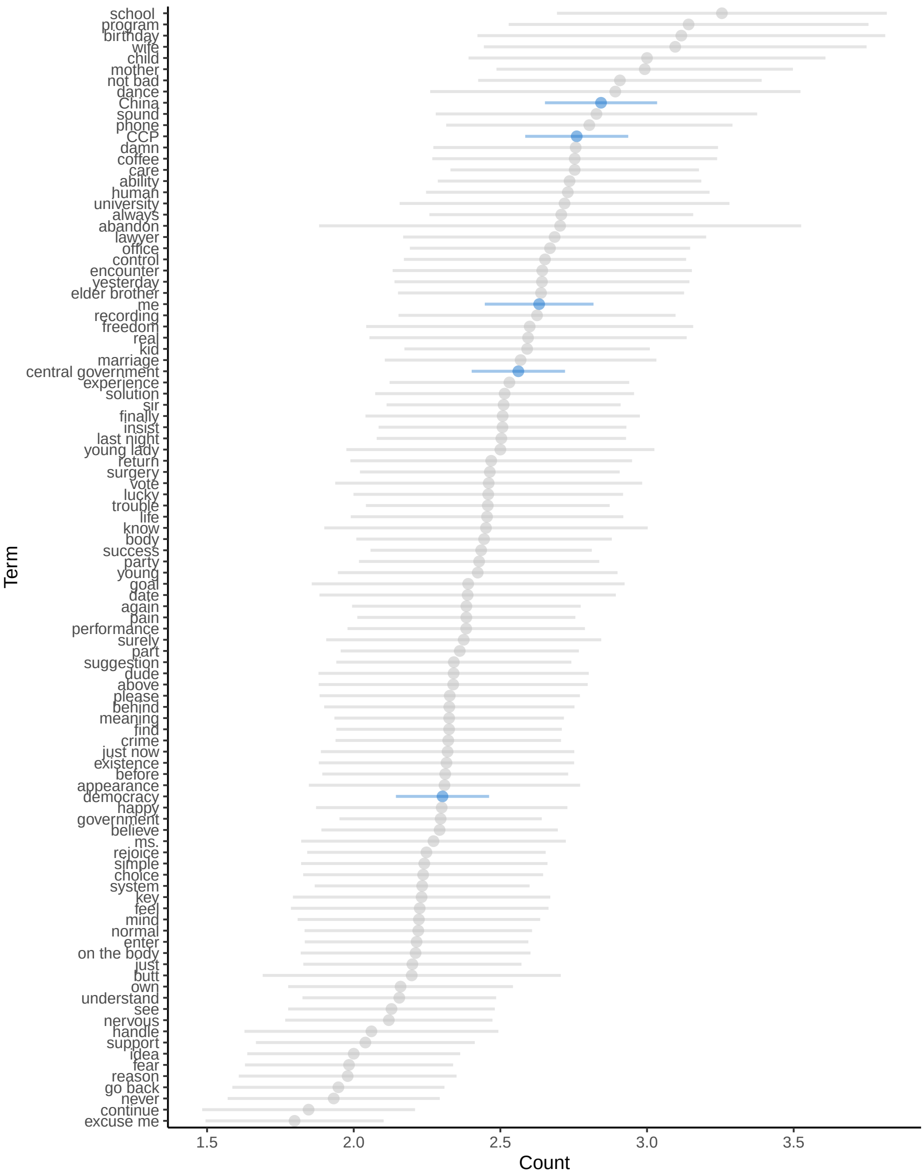
Note: Figure shows the mean nonresponse rate, latency to submission, and tokens provided by the trial order number. Data is from Study 2, and is filtered to exclude respondents that engaged in "speeder" behavior (non-responses to more than 50% of trials).

Figure SI2: Mean Latency to First Click for All Cue Words (Study 1 - Mainland China)



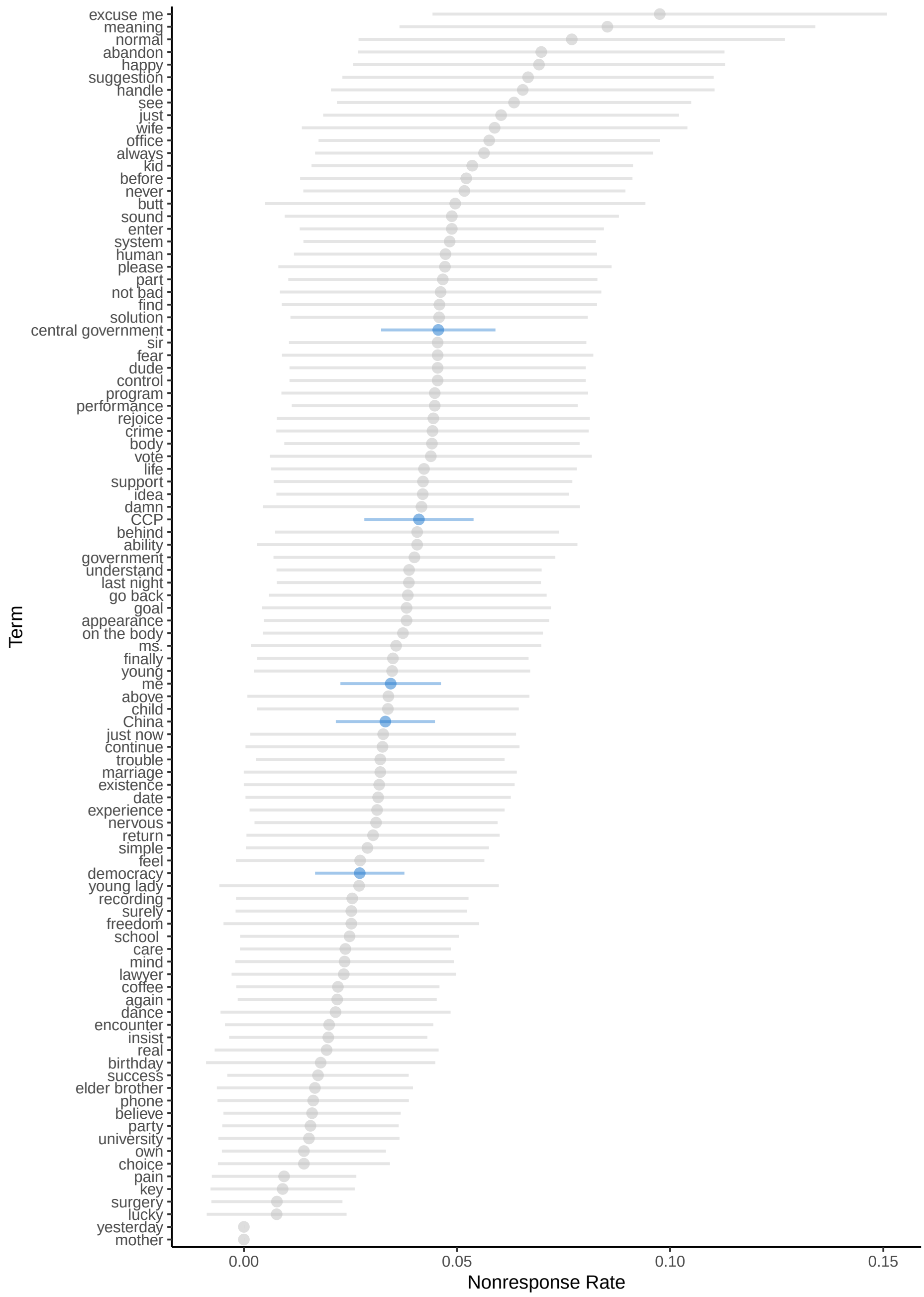
Note: Figure shows the mean of the latency to the first click for all cue words presented in the WAT. Data is from Study 1, and is filtered to exclude respondents that engaged in "speeder" behavior (non-responses to more than 50% of trials). Core cue words are shown in orange. Note that all respondents saw these words, which is why the point estimates have narrower confidence intervals than the other words.

Figure SI3: Mean Response Count for All Cue Words (Study 1 - Mainland China)



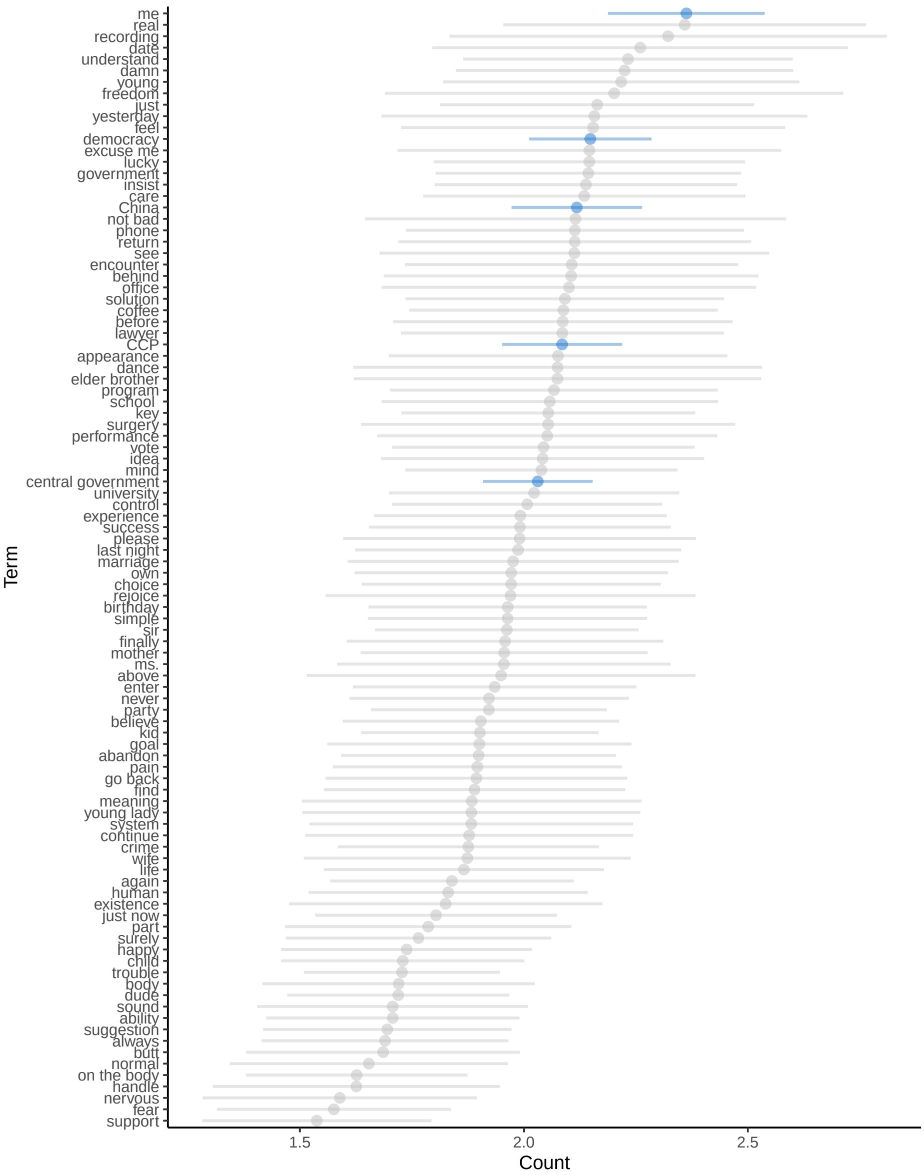
Note: Figure shows the mean response count for all cue words presented in the WAT. Data is from Study 1, and is filtered to exclude respondents that engaged in "speeder" behavior (non-responses to more than 50% of trials). Core cue words are shown in orange. Note that all respondents saw these words, which is why the point estimates have narrower confidence intervals than the other words.

Figure SI4: Non-response Rates for All Cue Words (Study 2 - Hong Kong)



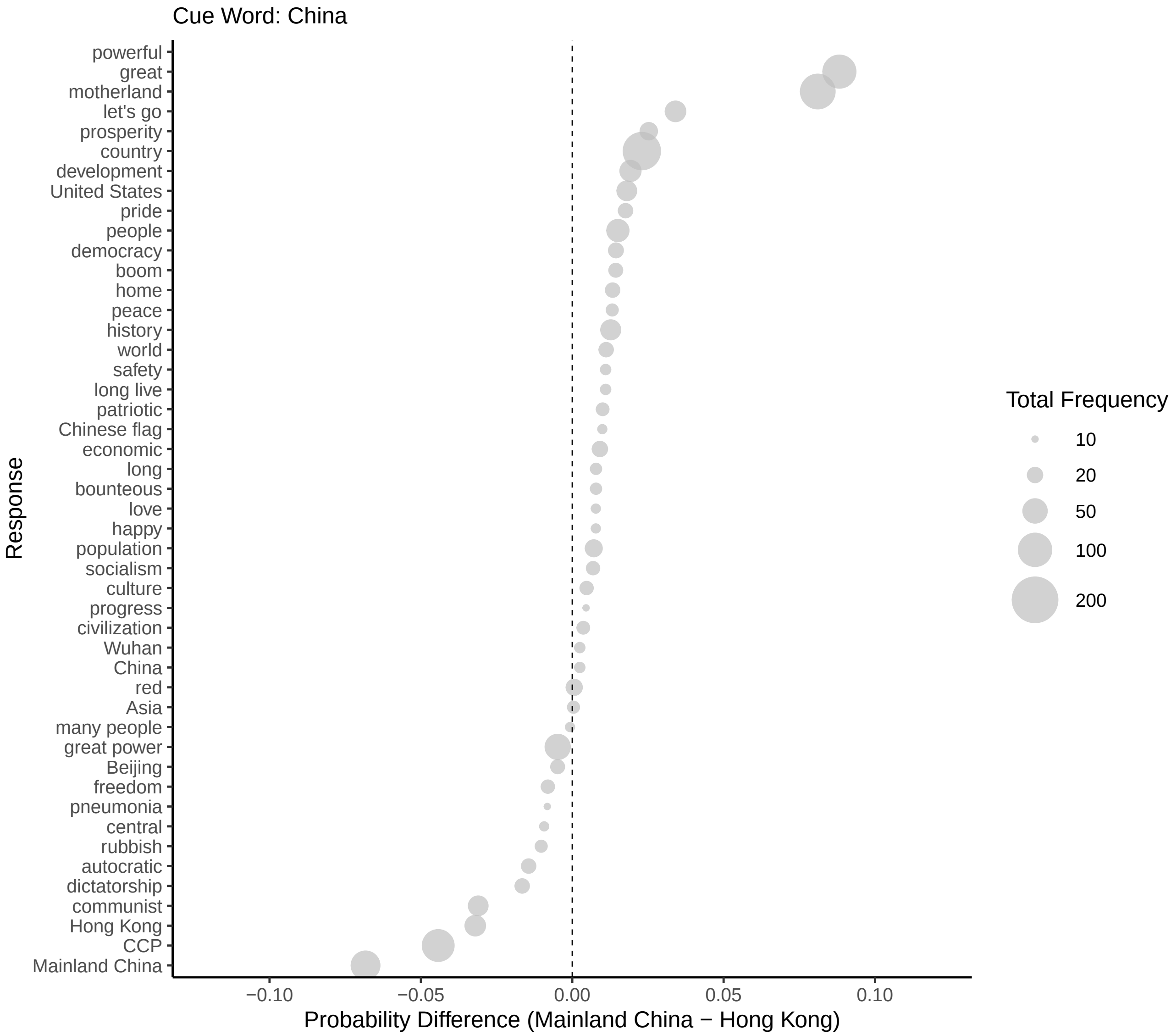
Note: Figure shows the non-response rates for all cue words presented in the WAT. Data is from Study 2 and is filtered to exclude respondents that engaged in "speeder" behavior (non-responses to more than 50% of trials). Core cue words are shown in orange. Note that all respondents saw these words, which is why the point estimates have narrower confidence intervals than the other words.

Figure SI5: Mean Response Count for All Cue Words (Study 2 - Hong Kong)



Note: Figure shows the mean response count for all cue words presented in the WAT. Data is from Study 2, and is filtered to exclude respondents that engaged in "speeder" behavior (non-responses to more than 50% of trials). Core cue words are shown in orange. Note that all respondents saw these words, which is why the point estimates have narrower confidence intervals than the other words.

Figure SI6: Mainland China-Hong Kong Response Comparison for China Cue



Note: Figure shows the difference in the probability of response words across the mainland China and Hong Kong samples for the China cue word. Words with values greater than zero are more common in mainland China; words with values less than zero are more common in Hong Kong. Data is filtered to exclude respondents that engaged in “speeder” behavior (non-responses to more than 50% of trials) or provided no responses towards the cue. Only words that appeared in 10 or more responses across the two samples are shown.

Table SI1: Determinants of Response Patterns (Study 2 - Hong Kong)

	Outcome		
	nonresponse	*latency.submit*	*count*
	(1)	(2)	(3)
cue: CCP	0.004	0.993	0.130
	(0.006)	(0.220)	(0.072)
cue: China	-0.004	0.120	0.167
	(0.006)	(0.213)	(0.069)
cue: Central Government	0.006	1.123	0.080
	(0.006)	(0.220)	(0.072)
cue: Democracy	-0.009	0.245	0.198
	(0.006)	(0.222)	(0.072)
cue: Me	-0.003	-0.006	0.410
	(0.007)	(0.231)	(0.075)
female	0.004	0.601	0.024
	(0.003)	(0.102)	(0.033)
age	0.001	0.023	-0.014
	(0.000)	(0.005)	(0.002)
lowed	0.017	-0.210	-0.291
	(0.003)	(0.108)	(0.035)
n	16,300	16,300	16,300

Note: Table shows regressions of WAT metadata on demographic covariates and cue word indicators. The non core cue words represent the excluded category. Data is from Study 2, and is filtered to exclude respondents that engaged in "speeder" behavior (non-responses to more than 60% of trials) or provided no responses or matched responses towards the cue. Data is organized on the trial level. All models estimated using OLS. Standard errors shown in parentheses.

Table SI2: Most Common Responses for Regime Cue Words (Study 2 - Hong Kong)

Cue Word: Central Government			Cue Word: CCP			Cue Word: China		
Response	Freq	p(r|c)	Response	Freq	p(r|c)	Response	Freq	p(r|c)
China	136	0.151	China	227	0.235	Mainland China	69	0.083
CCP	58	0.065	dictatorship	48	0.050	CCP	67	0.080
dictatorship	40	0.044	autocratic	36	0.037	country	55	0.066
power	27	0.030	rubbish	24	0.025	powerful	36	0.043
autocratic	26	0.029	bad	22	0.023	Hong Kong	33	0.040
Mainland China	24	0.027	no	18	0.019	communism	31	0.037
communism	23	0.026	totalitarian	15	0.016	great power	30	0.036
rubbish	23	0.026	one-party	14	0.015	motherland	18	0.022
people	21	0.023	communism	14	0.015	dictatorship	17	0.020
Xi Jinping	19	0.021	red	13	0.013	autocratic	16	0.019
totalitarian	19	0.021	freedom	12	0.012	people	14	0.017
Hong Kong	17	0.019	Xi Jinping	11	0.011	no	14	0.017
country	16	0.018	Mainland China	11	0.011	bad	12	0.014
Beijing	15	0.017	terrible	10	0.010	rubbish	12	0.014
no	15	0.017				freedom	12	0.014
authority	11	0.012				Beijing	11	0.013
bad	10	0.011				history	11	0.013
control	10	0.011				red	11	0.013
one-party	9	0.010				central	10	0.012
						development	10	0.012

Note: Table shows most frequent responses for the cue words Central Government, CCP, and China. Data is from Study 2, and is filtered to exclude respondents that engaged in "speeder" behavior (non-responses to more than 50% of trials) or provided no responses towards the cue. Only words that had 9 or more responses ($p(r|c) > 0.1$) are shown.

Note on Data Cleaning and Tokenization

1. Because responses to our core cue words contain both Chinese and English words, we used off-the-shelf machine translation tools to generate parallel corpora (simplified Chinese) and then manually checked every translation to ensure accuracy and consistency.

2. We reviewed and corrected all misspelling English responses. For example, "goverment" – "government."

3. In terms of Pinyin words, we changed most into simplified Chinese characters. For example, "zhong'guo" – "中国." Because some Pinyin words can refer to different groups of Chinese characters, those that were unclear remained in their original form.

Since responses to our core cue words contain many synonyms, we treated the following words as the same term:

1. 习, 习总, 习大大, 习近平, 习总书记, 习近平总书记, Xi Jinping

2. 毛, 毛泽东, 毛主席, 毛爷爷, Mao Zedong

3. 党, 我党, 中共, 共产党, 中国共产党, Chinese Communist Party (CCP)

4. 内地, 大陆, Mainland China

5. 大国, 强国, great power

6. 独裁, 专政, dictatorship

7. 支那, 中国, China

QUESTIONNAIRE **(MAINLAND CHINA)**	**问卷** **（中国大陆）**
INTRODUCTION AND CONSENT This survey is about your measuring your personality and cognitive reasoning. It is part of an academic research project being administered by an online marketing company. The survey is being conducted by academic researchers and will not be used or seen by the government in any way. Your participation is completely voluntary. If you agree to participate, you will answer some questions about yourself. You will then complete a short Word Association Test. The questions should take about 15 minutes to answer. If you complete the survey, you will receive a small payment. If you agree to participate, you may refuse to answer any of the questions or leave the survey at any time. Your participation in this study will be confidential. Any identifying information will be accessible only to the researchers and will never appear in any sort of report that might be published or shared. Your personal identity will never be linked to your survey responses, so please answer as honestly as you can. By clicking on the arrow below, you are agreeing to participate in the survey.	**调查介绍和参与者同意书** 本调查是关于您个人性格和认知推理的测试。它由网络营销公司负责，是某项学术研究的一部分。本调查由学术研究人员开展，政府不会以任何方式对数据进行使用或查看。 您的参与完全自愿。如果同意参与，您将会回答一些问题并完成一个简短的词汇联想测试。完成回答需要大约 15 分钟。如果完成调查，您将会收到少量报酬。 如果同意参与，您可以拒绝回答本调查中的任何问题，也可以在任何时刻终止回答。您对本研究的参与将会被严格保密，只有研究人员才会接触到身份信息。并且，您的身份信息绝不会出现在任何出版物或共享报告里。您的个人身份绝不会与您的调查回答相互关联，所以请您尽可能诚实回答。 单击下面的箭头，表明您同意参与调查。
SECTION I: **DEMOGRAPHICS** First, please answer some questions about your personal background.	**第一部分** **人口统计** 首先，请回答一些有关您的个人背景问题。
D1. What is your gender? <01> Male <02> Female <99> No answer	D1. 您的性别是？ <01> 男 <02> 女 <99> 不回答

D2. In what year were you born? ______	D2. 您出生于哪一年? ______
D3. In what province do you live? <01> Anhui <02> Beijing <03> Chongqing <04> Fujian <05> Gansu <06> Guangdong <07> Guangxi <08> Hainan <09> Hebei <10> Heilongjiang <11> Henan <12> Hong Kong <13> Hubei <14> Hunan <15> Inner Mongolia <16> Jiangsu <17> Jiangxi <18> Jilin <19> Liaoning <20> Ningxia <21> Qinghai <22> Shaanxi <23> Shandong <24> Shanghai <25> Shanxi <26> Sichuan <27> Taiwan <28> Tianjin <29> Tibet <30> Xinjiang <31> Yunnan <32> Zhejiang <33> Guizhou <34> Macau <99> No answer	D3. 您居住在哪个省份? <01> 安徽省 <02> 北京市 <03> 重庆市 <04> 福建省 <05> 甘肃省 <06> 广东省 <07> 广西壮族自治区 <08> 海南省 <09> 河北省 <10> 黑龙江省 <11> 河南省 <12> 香港特别行政区 <13> 湖北省 <14> 湖南省 <15> 内蒙古自治区 <16> 江苏省 <17> 江西省 <18> 吉林省 <19> 辽宁省 <20> 宁夏回族自治区 <21> 青海省 <22> 陕西省 <23> 山东省 <24> 上海市 <25> 山西省 <26> 四川省 <27> 台湾省 <28> 天津市 <29> 西藏自治区 <30> 新疆维吾尔自治区 <31> 云南省 <32> 浙江省 <33> 贵州省 <34> 澳门特别行政区 <99> 不回答

D4. Did you grow up in the countryside, a small town, or the city? <01> Countryside <02> Small town <03> City <99> Don't know	D4. 您是在农村、城镇还是城市长大？ <01> 农村 <02> 城镇 <03> 城市 <99> 不知道
D5. Do you currently have an agricultural household registration or a non-agricultural registration? <01> Agricultural <02> Non-agricultural <99> No answer	D5. 您当前是农业户口还是非农业户口？ <01> 农业户口 <02> 非农业户口 <99> 不回答
D6. What is your ethnicity? <01> Han <02> Minority <99> No answer	D6. 您属于哪个民族？ <01> 汉族 <02> 少数民族 <99> 不回答
D7. What is the highest level of education you have received? <01> Elementary or less <02> Elementary <03> Middle school <04> High school <05> Medium vocational <06> High level vocational <07> College <08> Masters <09> Doctorate <99> Refuse to answer	D7. 您的最高学历是? <01> 小学或以下 <02> 小学 <03> 初中 <04> 高中 <05> 职高/中专 <06> 大专 <07> 大学 <08> 硕士 <09> 博士 <99> 不回答

D8. What is/was your main occupation? <01> Farmer, animal husbandry, or fishery <02> Commerce, service trade worker <03> Individual industrial and commercial households <04> Owner of a private-owned business <05> Worker <06> Employee of government agency, party agency, or social organization <07> Manager <08> Serviceman or police officer <09> Professional/technical <10> Student <77> Other <99> No answer	D8. 您目前/退休前做什么工作？ <01> 农、牧、渔民 <02> 商业或服务业职工 <03> 个体工商户 <04> 私营企业主 <05> 工人 <06> 党政干部 <07> 管理人员 <08> 军人/警察 <09> 专家技术人员 <10> 学生 <77> 其它 <99> 拒绝回答
SECTION II: WORD ASSOCIATION TEST Now we would like you to complete a Word Association Test. You will have 20 seconds for each trial. There will be 18 trials in total. The Word Association Test will take 6 minutes. For each trial, you will see a target word. Please write in whatever other words come to mind when you see the target word. Please write down as many words as you can in the allotted 20 seconds.	**第二部分 词汇联想测试** 请您现在完成词汇联想测试。 怎么玩：屏幕上首先会出现一个词。在您看到屏幕上的词汇后，请输入您联想到的全部其他词语，越多越好！对于每个词汇，您有 20 秒的输入时间。您将先后看到 18 个词，本测试大约需要 6 分钟。
Target Word List (respondents will be randomly shown 18 words; words in red will be shown to all respondents)	目标词汇列表（受访者将会随机看到 18 个词汇，所有人都会看到红色词汇）
1. central government	1. 中央政府
2. democracy	2. 民主
3. me	3. 我
4. China	4. 中国
5. Chinese Communist Party	5. 共产党
6. know	6. 了解
7. sound	7. 声音
8. find	8. 找到
9. dance	9. 跳舞

10. crime	10. 犯罪
11. lucky	11. 幸运
12. just	12. 刚刚
13. handle	13. 处理
14. government	14. 政府
15. reason	15. 理由
16. insist	16. 坚持
17. surgery	17. 手术
18. elder brother	18. 哥哥
19. wife	19. 妻子
20. young lady	20. 小姐
21. Ms.	21. 女士
22. existence	22. 存在
23. birthday	23. 生日
24. pain	24. 痛苦
25. vote	25. 投票
26. key	26. 钥匙
27. marriage	27. 结婚
28. please	28. 拜托
29. continue	29. 继续
30. young	30. 年轻
31. butt	31. 屁股
32. suggestion	32. 建议
33. support	33. 支持
34. freedom	34. 自由
35. feel	35. 感到
36. damn	36. 他妈的
37. before	37. 之前
38. human	38. 人类
39. care	39. 关心
40. child	40. 小孩
41. never	41. 从没
42. lawyer	42. 律师
43. happy	43. 高兴
44. phone	44. 电话
45. system	45. 系统
46. mind	46. 介意
47. ability	47. 能力
48. coffee	48. 咖啡
49. sir	49. 长官
50. surely	50. 一定
51. not bad	51. 不错
52. party	52. 派对

53. own	53. 拥有
54. finally	54. 终于
55. normal	55. 正常
56. university	56. 大学
57. performance	57. 表现
58. meaning	58. 意思
59. dude	59. 老兄
60. recording	60. 记录
61. yesterday	61. 昨天
62. behind	62. 后面
63. idea	63. 想法
64. on the body	64. 身上
65. always	65. 一直
66. again	66. 重新
67. body	67. 身体
68. return	68. 回到
69. excuse me	69. 不好意思
70. kid	70. 小子
71. choice	71. 选择
72. goal	72. 目标
73. abandon	73. 放弃
74. nervous	74. 紧张
75. simple	75. 简单
76. part	76. 部分
77. real	77. 真的
78. school	78. 学校
79. see	79. 看到
80. appearance	80. 样子
81. above	81. 上面
82. last night	82. 昨晚
83. enter	83. 进入
84. encounter	84. 遇到
85. go back	85. 回去
86. experience	86. 经历
87. control	87. 控制
88. office	88. 办公室
89. life	89. 生命
90. mother	90. 母亲
91. rejoice	91. 开心
92. trouble	92. 麻烦
93. understand	93. 明白
94. program	94. 节目
95. date	95. 约会

96. just now	96. 刚才
97. success	97. 成功
98. fear	98. 害怕
99. solution	99. 办法
100. believe	100. 相信
SECTION III: **POLITICAL ATTITUDES** Now please answer some final questions about your attitudes.	**第三部分** **政治态度** 请回答一些有关您政治态度的问题。
M1. How interested would you say you are in political matters? <01> very interested <02> somewhat interested <03> not very interested <04> not at all interested <99> no answer	M1. 您如何评价您对政治事务的感兴趣程度？ <01> 非常感兴趣 <02> 有些感兴趣 <03> 不是很感兴趣 <04> 毫无兴趣 <99> 不回答
M2. Do you agree or disagree with the following statements? M2a. I am generally satisfied with government policies. <01> Strongly disagree <02> Disagree <03> Neither agree nor disagree <04> Agree <05> Strongly agree <99> No answer	M2. 您赞同下列陈述吗？ M2a. 我对政府政策总体满意。 <01> 非常不同意 <02> 不太同意 <03> 一般 <04> 比较同意 <05> 非常同意 <99> 不回答
M2b. The government cares what people like me think. <01> Strongly disagree <02> Disagree <03> Neither agree nor disagree <04> Agree <05> Strongly agree <99> No answer	M2b. 我认为政府关注像我这样人的想法。 <01> 非常不同意 <02> 不太同意 <03> 一般 <04> 比较同意 <05> 非常同意 <99> 不回答

M2c. I feel I have a pretty good understanding of the important political issues facing China. <01> Strongly disagree <02> Disagree <03> Neither agree nor disagree <04> Agree <05> Strongly agree <99> No answer	M2c. 我觉得我对中国面临的重大政治问题有充分了解。 <01> 非常不同意 <02> 不太同意 <03> 一般 <04> 比较同意 <05> 非常同意 <99> 不回答
M3. On a scale of 1 to 10, with 10 meaning very satisfied and 1 meaning not satisfied at all, how satisfied are you with the work of the following? M3a. National People's Congress <01> 1 – Not satisfied at all <02> 2 <03> 3 <04> 4 <05> 5 <06> 6 <07> 7 <08> 8 <09> 9 <10> 10 – Very satisfied <99> No answer	M3. 按照 1 至 10 的评价标准（ 10 表示非常满意，1 表示一点也不满意），您对以下方面的满意程度如何？ M3a. 全国人民代表大会的工作 <01> 1 – 一点也不满意 <02> 2 <03> 3 <04> 4 <05> 5 <06> 6 <07> 7 <08> 8 <09> 9 <10> 10 – 非常满意 <99> 不回答
M3b. Central government officials <01> 1 – Not satisfied at all <02> 2 <03> 3 <04> 4 <05> 5 <06> 6 <07> 7 <08> 8 <09> 9 <10> 10 – Very satisfied <99> No answer	M3b. 中央政府官员的工作 <01> 1 – 一点也不满意 <02> 2 <03> 3 <04> 4 <05> 5 <06> 6 <07> 7 <08> 8 <09> 9 <10> 10 – 非常满意 <99> 不回答

M3c. Local government officials <01> 1 – Not satisfied at all <02> 2 <03> 3 <04> 4 <05> 5 <06> 6 <07> 7 <08> 8 <09> 9 <10> 10 – Very satisfied <99> No answer	M3c. 地方官员的工作 <01> 1 – 一点也不满意 <02> 2 <03> 3 <04> 4 <05> 5 <06> 6 <07> 7 <08> 8 <09> 9 <10> 10 – 非常满意 <99> 不回答
M4. Are you a member of the Communist Party? <1> Yes <2> No <99> No answer	M4. 您是中共党员吗？ <01> 是 <02> 否 <99> 不回答
SECTION IV: PERSONALITY Please read each statement and decide how much you agree or disagree with that statement: 1 = strongly disagree 2 = disagree 3 = neutral (neither agree nor disagree) 4 = agree 5 = strongly agree	**第四部分 性格测试** 请您仔细阅读每一项陈述，决定您对这项陈述同意或不同意的程度: 1 = 非常不同意 2 = 不太同意 3 = 一般 4 = 比较同意 5 = 非常同意
H4. I feel reasonably satisfied with myself overall	H4. 整体而言我对自己还算满意。
H28. I feel that I am an unpopular person.	H28. 我觉得自己是个不受欢迎的人。
H52. I sometimes feel that I am a worthless person.	H52. 我有时觉得自己一文不值。

H10. I rarely express my opinions in group meetings.	H10. 在团体讨论中，我很少表达自己的意见。
H34. In social situations, I’m usually the one who makes the first move.	H34. 在社交场合里，我通常都是那个主动的人。
H58. When I’m in a group of people, I’m often the one who speaks on behalf of the group.	H58. 在团体中，我常是那个代表团体说话的人。
H16. I prefer jobs that involve active social interaction to those that involve working alone.	H16. 与独自工作相比，我更喜欢那些能与人互动的工作。
H40. The first thing that I always do in a new place is to make friends.	H40. 在一个新环境里，我做的第一件事总是去交朋友。
H22. On most days, I feel cheerful and optimistic.	H22. 大多数日子里，我都感到愉快和乐观。
H46. Most people are more upbeat and dynamic than I generally am.	H46. 大多数人都比平常的我要更乐观和更有活力。
CONCLUSION	**结束**
Thank you for participating in this survey. All your answers to the questions will be kept strictly confidential. Please contact cihuilianxiang@gmail.com with any questions or comments.	感谢您参与本调查。 您的答案将被严格保密。如有关任何问题或意见，请发邮件至cihuilianxiang@gmail.com。