The Elements of Cultural Power: Novelty, Emotion, Status, and Cultural Capital

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Abstract:

Why do certain ideas catch on? What makes some ideas more powerful than others? Using a novel dataset that traces Chinese netizens' discussion of American politics on an online forum, this study examines key predictors of cultural power – novelty, emotion, status, and linguistic features – using an innovative diachronic word-embedding method. The study finds a curvilinear relationship between novelty and resonance, as well as a positive relationship between status and cultural power. Contrary to theoretical expectations, moderate emotions, whether positive or negative, are found to be more effective in evoking resonance than more intense emotions, possibly due to the mediating effect of the forum's "group style." Thus, it appears that while extreme sentiments towards the U.S. may exist, they are not likely to be resonant, at least among more educated Chinese netizens. The study also finds significant effects of linguistic features such as lexicon diversity and the use of English in Chinese discussions. This suggests a Bourdieusian "cultural-capital signaling and selection" path to cultural power, which has not been considered in most studies of resonance.

INTRODUCTION

Cultural power affects how people perceive social realities, shaping social actions through “persuasion” rather than coercion or material incentive. That is, cultural power can reinforce, change, or even create the perspectives we hold about how the world works. While “persuasion” itself is not free of the influence of political and economic power, the qualities of the cultural object itself – be it a speech, a melody, or a visual motif – are important in determining its cultural efficacy. But what are the factors that determine an object’s cultural efficacy? Why are some cultural objects more “catching” than others (Schudson 1989)? Although sociologists have developed some theories of such cultural power, few empirical efforts have been made to systematically examine and revise these theoretical claims, leading to piecemeal progress in our sociological knowledge about cultural power.

This paper reviews and synthesizes theories and research of cultural power and empirically tests a set of propositions about how the qualities of a cultural object may affect its efficacy. Specifically, this paper invokes the concept of resonance in social interactions to understand what makes some ideas stand out in the political discussions among Chinese internet users as they “puzzle out” (McDonnell, Bell, and Tavory 2017: 3) the rise of Trump during the 2016 U.S. General Election.

Doing so, this paper addresses two problems in the current literature on cultural power. First, while various theories have been devised, from Aristotle’s general theory of persuasion (Aristotle 1857), to Griswold’s theory of the power of multivocality (Griswold 1987), to Bourdieu’s treatises on linguistic practice and symbolic power (Bourdieu 1992), little empirical research synthesizes and tests these propositions systematically. Recent work that asks similar questions – for example, what makes pop culture popular (Salganik, Dodds, and Watts 2006;

Askin and Mauskapf 2017; Toubia, Berger, and Eliashberg 2021), what makes some publications have more scientific impact (Uzzi, Stringer, and Jones 2013), and what contributes to successful engagements in civil organizations (Bail 2016a; Paxton, Velasco and Ressler 2020) – tend to focus on a particular mechanism of cultural power, such as cultural power realized through novelty or emotion. While individual mechanisms are building blocks towards a general theory, we do not know whether these mechanisms hold when other factors are considered or the relative importance of these individual elements.

The second problem in this literature is the inaccurate measurement of one of its key predictors: novelty. While novelty has been the focus of much social science research (Uzzi et al. 2013; Foster, Rzhetsky and Evans 2015; Shi and Evans 2020), the actual method of measurement is detached from its theoretical definition. Novelty, which denotes experience against a *pre-existing* knowledge structure, is often measured as novelty compared to a cultural object's contemporaneous competitors rather than compared to the pool of knowledge a subject has typically had as she encountered the cultural object. While the current operationalization of novelty measures novelty of a certain kind, it departs from the theoretical construct of the concept, which is the novelty of the cultural object experienced by the audience *given what they know* when encountering the object. In other words, novelty is adjudicated synchronously when it is experienced by the audience diachronically.

This paper addresses these two weaknesses by examining the elements of the cultural power of ideas in real-world interactions. First, using a dataset collected from a political discussion forum that is time-labeled, this study models the effect of key predictors of cultural power –novelty, emotion, status, and linguistic features – based on the theory of resonance (McDonnell et al. 2017) and the Bourdieusian insights on linguistic capacity (Bourdieu 1992).

Second, to address the measurement problem of novelty, this study develops a measure of novelty using diachronic word-embedding models that effectively resolves the problem of measurement by measuring a text's novelty against the pre-existing "discourse establishment" rather than its contemporaneous competitors.

To anticipate the findings, the study confirms the curvilinear relationship between novelty and resonance, yet also finds that the effect of novelty does not begin decreasing until the level of novelty gets quite high. Therefore, novelty has a positive effect throughout the vast majority of the distribution. Second, contrary to expectation, emotion does not have a simple positive linear relationship with cultural power. Rather, slight or moderate emotions are most effective. This result is likely driven by the specific "group style" and speech norms of the discussion forum from which the data is sourced (Eliasoph and Lichterman 2003). This discrepancy reveals two theoretical oversights in the sociology of emotion: first, the causal connection between emotion and resonance is likely to be mediated by local interaction norms: the group style the community developed; second, to capture the relationship between emotion and resonance, it might be more productive to attend to different institutionalized *types* of emotions rather than only to a valence scale that runs from negative to positive or from neutral to intensive.

Third, a Bourdieusian mechanism of cultural power –"cultural capital signaling and selection" – is found in this study. The use of a diverse vocabulary and a relevant foreign language effectively increases the resonance of a text when these practices are not overplayed, most likely because the audiences associate these practices with greater linguistic and social capacities in the context of the discussion forum. This element of cultural power has been overlooked by previous research because in those studies, the sample of cultural objects being studied has been prescreened to meet a certain standard of sophistication –plays that theaters deem good enough to stage (Griswold 1986), theories that economists deem good enough to consider as viable policy guidance (Block and Somers 2014), or organizations that media deem to be legitimate enough to contact (Bail 2012; 2014). However, once we observe the unmediated process of idea selection, objectified cultural capital plays a role in how the audience experiences and evaluates the cultural object. Lastly, these findings also provide insights to understanding popular views of the U.S. among more educated Chinese internet users. While the forum has been portrayed as the hub of fanatical Chinese Trump fans in popular journalistic accounts, a closer look at the competition of ideas in this platform suggests that while these voices might exist they were unlikely to be resonant. Synthesizing theories and research of cultural power, this study provides new evidence and new methods for cultural sociologists to understand the elements of cultural power in social interactions.

CULTURAL POWER AND RESONANCE IN INTERACTION

To capture the insight that some ideas are more powerful than other competing ones, and to find how a discursive field gets "settled" (Bail 2012:855) by one voice rather than another, cultural sociologists have increasingly invoked the metaphor of *resonance* (Snow et al. 1986; Griswold 1987; Schudson 1989; McDonnell 2014; Mohr et al. 2020). This conceptualization approaches the problem of cultural power at the *micro interactional level*, asking which elements in the interaction between the cultural object and the individual are crucial to generating resonance.[1] It sees cultural power as created in the *interaction* between a cultural object and its socially embedded "interpreters," particularly when the cultural object can help people "puzzle through" a problem they face or construct (McDonnell et al. 2017: 1-9).

The prototype of this perspective was first adumbrated by Griswold (1987). She argues that cultural power is determined by how a cultural object's content and quality are perceived by an audience with a particular set of propositions, problems, and concerns in the social reality they live in. In her study on the success of novels by George Lamming among literary critics in West India, the U.K., and the U.S., she discovered that works that invoked diverse interpretations were most esteemed by reviewers. Thus, Griswold argued that the power of a cultural object does not come from its content, but from the way it *interacts* with its audience. Ideas or cultural objects that are multi-vocal or ambiguous are more likely to have a higher impact across time and space because their content is more likely to reverberate with various audiences, who may find the cultural object meaningful in sharply contrasting ways.

Reformulating Griswold's theory of cultural power at the cognitive level, McDonnell et al. (2017:3) define resonance as an "emergent process" that entails a cognitive experience of problem-solving for the subject. This experience is affected by three factors. First, the *optimal cognitive distance* factor predicts that an idea is more likely to resonate when it deploys an analogy that is neither "too close" nor "too distant" given the actors' shared cultural schema. Second, the *emotionality* factor predicts that a higher emotional intensity will make resonance more likely. Third, the *structural power and status of the interlocutor* will also likely be positively related to resonance. That is, more centrally-located and more prestigious actors are more likely to create resonant objects. These three theoretical propositions consist of the first three hypotheses regarding the determinants of cultural power that this study examines.

By understanding resonance as a process, this new theorization resolves the long-lasting methodological challenge to studies of resonance –the problem of the "selection on the dependent variable" problem. That is, we cannot infer what makes an idea successful based on a sample of successful ideas (Ferree 2003; Salganik et al. 2006; Bail 2014; Mohr et al. 2020). As we cannot observe failed ideas, we do not know if our argument holds true for negative cases, and often revert to circular logic, where an idea is successful since it is resonant, and we know it is resonant since it was successful. The key to solving this problem is to anchor the analytical focus not on the features of successful ideas but on the *process* through which both successful and failed ideas are observed (Bail, Brown, and Mann 2017). The new theorization from McDonnell et al. (2017) offers possibilities to address the selection bias because resonance is not evaluated by the known outcome but by features of the *interactional process*. Following this conceptualization, this study views resonance as an emergent process in which actors feel that an idea provides a solution to a problem. Such cognitive experience can be caused by a novel combination of conceptions or ideas in the actor's conceptual map, and/or intensified emotion. Contextual factors may also come into play in the form of the structural power or status of the actor, or linguistic features that may affect how an audience experiences an idea.

RESONANCE AND NOVELTY

The first element of resonance this paper aims to examine is *novelty*. In the interactional perspective of cultural power, novelty refers to the experience of the subject when one encounters a cultural object that invokes concepts or symbols that are unlinked or weakly associated in one's cultural schema. The *optimal cognitive distance* hypothesis proposed by Griswold (1987) and McDonnell et al. (2017) argues that an idea is more likely to resonate when it deploys an analogy that is neither "too close" nor "too distant" given the actors' shared cultural schema. For example, the metaphor that "Juliet is the sun" is more likely to resonate as compared to "Juliet is a girl" (too close) or "Juliet is a frying pan" (too distant) (Griswold 1987: 1112; McDonnell et al. 2017). The audience is more likely to feel the "fit" when an idea puts together things that are not previously connected in the audience's mind but are also not too distant so that the audience can "work out" the metaphor or analogy and feel the "reward of resonance" (McDonnell et al. 2017: 6).

According to such a definition, the novelty of an idea can be measured by how different one message is from others in the discursive field in terms of its choice of concepts and the connections an interlocutor draws between such concepts. At the cognitive level, this conceptualization assumes that individuals enact their cultural schema in their speech practices, and actors in the interaction share a cultural schema that contains a map of associations and categorizations to a degree that they can effectively adjudicate whether an idea is making a banal or novel statement (DiMaggio 1997; Ignatow 2009).

If the optimal cognitive distance thesis is true, we should expect to observe the maximum popularity occurs at some intermediate level of novelty. I thus predict:

H1. An idea's novelty is curvilinearly related to resonance with the highest resonance at intermediate levels of novelty.

RESONANCE AND EMOTIONALITY

The second element of resonance is *emotionality* (or, rather, the intensity of emotion). There are two distinct ways that emotion is related to resonance in McDonnell et al. (2017)'s theorization. First, emotion is a critical part of the *experience* of resonance. Various emotions accompany the process of resonance, from the "anxiety and frustration individuals face" in problem-solving, to "the excitement of finding a novel solution" (McDonnell et al 2017:6; McDonnell 2014). Second, emotion can be a *causal factor* that makes resonance more likely. In other words, cultural objects that embody more intense emotions are more likely to make interlocutors experience resonance. In what follows, I will focus on this second way emotion shapes resonance, as my focus is on factors that lead to the creation of cultural power.

Extensive research in psychology, political science, sociology, and even natural language processing (NLP) have shown that emotional arousal can intervene in the cognitive process of learning and understanding, and an idea can be resonant just by heightening its emotional appeal (Brader 2005; Erisen et al. 2014; McDonnell et al. 2017).

In political psychology, Brader's study (2005) of political campaign ads found that the usage of music and images that evoke enthusiasm and fear can affect one's evaluation of political candidates. Similarly, Erisen et al. (2014) found that people's political reasoning is "biased systematically" by the emotions that were aroused in the earliest "affect priming" stage of the experiment (187). In NLP research, the use of sentiment words is found to significantly predict whether a Reddit user changes a poster's view (Tan et al. 2016).

In sociology, Bail's study (2012) on the post-9-11 rise of anti-Muslim organizations on mainstream media found that by displaying fear and anger, anti-Muslim fringe organizations were able to attract public attention and initiated a reorganization of media reporting from more neutral voices to predominantly anti-Muslim sentiment. Related to Bail's study, Paxton, Velasco, and Ressler (2020) discover that non-profit organizations that expressed a more intense positive emotion are associated with more donations and volunteers. While Bail's study (2012) finds a positive relation between *negative* sentiments and cultural power, Paxton et al.'s study (2020) finds *positive* sentiments doing the work. Thus it seems that it is the intensity rather than the direction of emotion that leads to resonance.

Therefore, as extant research suggests that it is the intensity rather than the direction of emotion that positively predicts resonance, the second hypothesis states:

H2. Ideas with more intense emotions, regardless of the direction of emotion (positive or negative), are more likely to be resonant.

RESONANCE AND STATUS

Third, resonance arises from *interaction* and depends on the actors' structural positions in the interaction. Higher-status or "centrally located" actors are more likely to create resonance (McDonnell et al. 2017: 8). This echoes earlier studies on organizational isomorphism and diffusion (DiMaggio and Powell 1983; Strang and Meyer 1993). Diffusion is more likely to happen when actors conceive of themselves as engaged in a "cultural linkage" with each other. Therefore, changes within one actor are likely to diffuse to culturally linked others (Strang and Meyer 1993:490). Among actors in a field, those seen as "more legitimate or successful" are more likely to motivate mimics than others (DiMaggio and Powell 1983: 152).

Empirical research supports this hypothesis. Salganik et al. (2006) found that the presence of distinction markers affects the outcome of a cultural selection process. Bail (2016b) also demonstrates that advocacy organizations that create "cultural bridges" (measured by the overlapped usage of topical words) are much more likely to stimulate conversations than those that do not. In a study on an online debate forum, Debate.org, Durmus, and Cardie (2019) show that the participants' forum activeness (e.g. number of comments, votes, friends) and their network centrality are positively related to the likelihood of winning a debate. Therefore, the third hypothesis stipulates that:

H3. Individuals with higher status are more likely to generate resonant ideas.

RESONANCE AND LINGUISTIC FEATURES

Linguistic features of speech are a crucial element of cultural power. While the interactionist theory of resonance reviewed earlier did not consider linguistic features as a determinant, Bourdieu (1992) has argued that linguistic competence directly affects the power of one's speech, which has recently been rediscovered in natural language processing (NLP) literature. According to Bourdieu (1992), linguistic features such as grammar, vocabulary, and the choice of languages and dialects are enactment of one's "linguistic capital" –an important dimension of cultural capital (72). The symbolic power of linguistic practices has to be understood in the specific "linguistic field" or "linguistic market" that entails its own expectations, rules, and valuations. Consequently, the effect of one's utterances is determined by two factors: (1) one's "linguistic capacity" to generate "grammatically well-formed sentences" (Thompson 1992:18), and (2) one's "social capacity" to recognize the specific linguistic field and utilize her linguistic competence accordingly (Bourdieu 1992; Thompson 1992).

Recent NLP literature corroborates Bourdieu's "linguistic capacity" thesis. For example, in a study about Reddit's "Change My View" community, Tan et al. (2016) find that the length and the vocabulary diversity of a post are statistically significant in predicting a reply's probability of successfully changing a user's view. Durmus and Cardie's study (2019) on Debate.org yielded similar results. They found that features of a debater's language, including post length, number of positive and negative words, and lexical diversity will increase the classification precision of the machine learning model in predicting the success of a debater's post.

Accordingly, this study considers two linguistic features. The first is the effect of lexical diversity. This feature indexes the diversity of the vocabulary deployed in a given text. Different from novelty, which measures the originality of concept combination, lexical diversity focuses on the mere diversity of words. For example, one can imagine a post that engages with a conventional idea but draws on a variety of closely associated concepts and terms to convey the argument. Compared to a post that engages with the same conventional idea but has a much smaller vocabulary, the former post will have a higher lexical diversity than the latter as the former uses more distinct words, whereas their novelty is tied.

The specific mechanisms through which lexical diversity affects resonance are not fully clarified in extant research. A high level of lexical diversity may suggest sophistication and thus is preferred (Bradac, Konsky and Davies 1976; Hosman 2002). But such complexity may work against the persuasiveness of a text if it obscures the clarity of an argument (Ta et al. 2022). For example, both Tan et al. (2016) and Ta et al. (2022) have identified a negative effect of lexical diversity on the persuasiveness of a text. Ta and her colleague (2022) explains this as a "navigating" role played by lexical repetition. Repeated words can serve as "textual markers" that help audience navigate through the structure of a complicated argument (Ta et al. 2022:896). Given the inconclusive evidence, my hypothesis will propose the effect of lexical diversity to work consistently with recent NLP studies, which is:

H4-1. Messages that use a more diverse lexicon will be less likely to resonate.

In addition to the diversity of one's vocabulary, this study will also consider the effect of foreign language usage in communication as this is a distinct feature of the empirical case which will be laid out in the next section. Foreign language usage in communication often occurs in bilingual or multilingual settings, and in interactions that concern cross-cultural topics (Gal 1987). Bourdieu (1992) sees the usage of language as a forceful demonstration of one's cultural capital, particularly in a social context where a particular language is deemed by the audience as having a higher status (79). Geipel, Hadjichristidis, and Surian (2016) also find that the use of a foreign language can affect the way people make moral evaluations. In an interactional setting where the topic being conversed is relevant to a specific foreign culture, the usage and reception of the foreign language are an indispensable part of the users' experience of (non)resonance and therefore should be taken into account.

Since the usage of a foreign language is a display of one's cultural capital of the foreign culture being discussed and thus can make the author of a text appear more credible, I predict:

H4-2. When discussing a topic relevant to a foreign culture, messages that use a higher proportion of the respective foreign language are more likely to be resonant.

THE CASE: CHINESE NETIZENS PUZZLING THROUGH TRUMP'S RISE

To study the process of resonance, I leverage a case of political interaction that traces how users in a Chinese political forum "puzzle through" (McDonnell et al. 2017:1) American politics over a two-year period (2016-2017) when Trump and the 2016 presidential election was a popular topic in the Chinese virtual public sphere.[2]

The forum where the data was collected is China's most prominent question-and-answer (Q&A) forum, Zhihu, which attracts more than 8.2 million daily visitors and is ranked China's seventh most used social network (Statista 2021). Similar to the American Q&A website, Quora, this forum hosts discussions on a wide gamut of topics ranging from natural science to relationship advice. Compared to Sina Weibo –the Chinese equivalent of Twitter that most studies on Chinese online discourse are based on – this Q&A forum is a forgotten treasure that offers much richer text data in Chinese netizens' deliberation of social, political, economic, and cultural issues, as users of this Q&A website are more likely to engage with extended debate and knowledge sharing than users of Sino Weibo (See Appendix G).

In particular, during the 2016 U.S. General Election, the enthusiastic political discussions that unfolded in this community even attracted attention from U.S. media. In fact, Zhihu is reported as the hub of fanatical Chinese Trump supporters as posts that passionately praised Trump were frequently seen in the platform (Dychtwald 2016; Fu 2016; Carlson 2018). Thus, to understand how the U.S. is discussed and perceived by the Chinese public as Trump came to power, discussion text from this forum serves as an important source for analysis.

Similar to other studies that use social media data, this study does not claim that the data is representative of the Chinese population. Rather, it approximates the Chinese "middle class" views as the users of this forum are shown to be more educated, higher income, and more likely to live in urban areas than the average Chinese citizens (Peng 2016; CNNIC 2021; Statista 2021). This bias towards the Chinese middle class is also a feature of Weibo –by far the most studied Chinese social media platform (Fu and Chua 2013). While these urban educated Chinese are not the majority of the total Chinese population,[3] they often play an important role in social policy development in China. Studies and news reports show that the Chinese middle class is at the forefront in initiating and participating China's recent political protests and activism on issues such as pollution (Qiu 2008; Li 2010:75), property rights (Wang et al. 2013), and the "996 work culture" (Yip 2021). The fact that in most such cases, the government took prompt action to acknowledge their concerns through policy-making suggests the prominent political importance possessed by this group.

In addition, the data is also collected with both the state censorship and the participants' "self-censorship" in place, although recent studies have consistently shown that the actual proportion of censored speech on Chinese social media is extremely low (King, Pan, and Roberts 2013; King, Pan, and Roberts 2014; Lu, Pan, and Xu 2021). Moreover, state censorship is less of a problem in this analysis than it would be if the discussions under study were about Chinese domestic politics since discussions of foreign politics are much less censored (King et al. 2013).

The extensive political discussions about U.S. politics on the forum allow us to trace the evolution of the Chinese users' view of the U.S., a topic that is under scholarly debate. On the one hand, research shows that the Chinese public's anti-Americanism is on the rise, and increased exposure to the social realities of Western democracies in recent decade has led to increasing doubts about liberal democracy as a viable political model among Chinese netizens on Weibo (Shi, Lu, and Aldrich 2011; Zhang Forthcoming). On the other hand, other studies have found that Chinese people's attitudes towards the U.S. are quite favorable when it comes to U.S. domestic politics and its social institutions. The more educated Chinese middle class tends to hold even more positive views than less affluent groups (Johnston 2004; Guan et al. 2020). The mixed evidence on the Chinese public's view of the U.S. begs for additional empirical study to understand what kind of sentiment towards the U.S. is more likely to be popular in Chinese netizens' deliberation of the U.S.

Moreover, studies of Chinese people's sentiment towards the U.S. have always relied on an oversimplified dichotomous measure (positive vs. negative), ignoring the fact that the intensity of emotion may matter more than the direction of it (Guan et al. 2020; Lu et al. 2021). In addition, besides emotion, the other elements of cultural power are rarely considered in such studies. Most studies focus on understanding how sentiments are distributed in public discourse, rather than what kind of discourse and sentiment are culturally most *powerful*. Therefore, by leveraging this novel dataset that captures elaborated debate about American politics, this study can improve the current understanding of how the Chinese public's view of the U.S. evolved and what features of a text contribute to resonance among Chinese netizens as they discuss American political issues.

Beyond its substantive importance, this case is also a valuable example of political interactions where resonance is minimally confounded by one's pre-existing political opinion. Few studies have addressed determinants of resonance in political interactions other than the role of emotion (Brader 2005; Bail 2012; Erisen, Lodge, and Taber 2014; Bail 2014). The key challenge is that resonance in political interactions is often more like a cause than an effect. People are more likely to converse in communities whose political views resonate with theirs and reproduce such resonance through further interactions (Mutz and Martin 2001; McPherson, Smith-Lovin, and Cook 2001; Huckfeldt, Johnson, and Sprague 2004). To overcome this challenge, we can study competitions of political ideas among individuals who enter a "political idea market" with the potentially confounding prior preference held constant; the case under study is such a scenario. Because the discussion participants, as Chinese middle class living in urban areas, share similar political attitudes towards the U.S. (Johnston 2004; Li 2010), were not politically involved in the U.S. presidential election, and were generally unfamiliar with the specifics of American politics, the case minimizes the effect of individuals' pre-existing political affiliations, opinions, or economic interests on finding a particular idea resonant. With tens of thousands of posts that received dramatically different numbers of "upvotes," this case provides an opportunity to examine what factors most effectively produce resonance in political interactions.

DATA AND METHOD

Data

This study uses a dataset of political discussions of U.S. politics on a widely used Chinese question-and-answer (Q&A) platform. This platform is similar to the American Q&A website, Quora, in its setup. Users can post questions and answers to topics of interest to them, and each question and its answers are labeled with the topic it relates to (Figure 1). For foreign politics, the discussion volume of U.S. related topics in this forum steadily increased from 2011 to 2015, with a significant boost in 2016 and a slight decline in 2017 (Table 1). The heightened discussion volume in 2016 was most likely caused by the controversial Republican presidential candidate, Donald Trump, who triggered heated debates about U.S. politics not only in this forum but in the Chinese public sphere in general (Dychtwald 2016; Carlson 2018). As shown in Table 1, before 2016, the average number of daily questions and answers about U.S. politics was quite small, with fewer than 3 questions and 20 answers posted every day. In 2016, the figures surged to 20 questions and 181 answers. In 2017, although user activeness declined to about 8 questions and 114 answers, this level of participation is still much higher than the pre-2016 period.

[Insert *Table 1 Discussion Volumes of the Forum (2011-2017)* here]

The author wrote a web crawler that collected the questions, answers, and other meta information for all content that is labeled by any of the following topic tags: "U.S. Politics," "2016 U.S. Election", "U.S. Society," "U.S. Economy," and "China-U.S. Comparison." [4] The data was then filtered to keep answers in response to questions that have 5 or more answers and answers posted by the end of 2017. [5] This resulted in a corpus of 84,259 unique answers. This time-labeled corpus is used to train diachronic word-embedding models, as will be discussed in the Measurement subsection. Then, answers posted between 2016 and 2017 that contain at least two concepts after concept extraction are kept for calculating novelty and other key predictors which are used for statistical modeling (see Measurement). The final dataset used for modeling contains 75,079 unique answers (Figure 1).[6]

[Insert *Figure 1 Data Collection & Subset Workflow with Demo of Webpage Structure* here]

Since this corpus is time-labeled and contains the entire universe of the discussion of U.S. politics that occurred in this forum since its inception, it allows the researcher to monitor the change in discourse over time in response to the forum deliberations and the real-world events. As will be discussed in the next subsection, leveraging the time-labeled observations, diachronic word-embedding models can be trained and used to measure novelty according to its theoretical definition. With tens of thousands of posts that received dramatically different numbers of "upvotes," this dataset provides an opportunity to examine what factors most effectively produce resonance.

Measurement

This study aims to examine the effect of novelty, emotionality, status, and linguistic features on resonance, controlling for other potentially relevant characteristics. The key *dependent variable*, resonance, is operationalized as the number of upvotes a post receives (similar to "likes" on U.S. social media). This information is collected when each answer is scraped. Compared to studies that can directly observe the experience of resonance through expressions of heightened emotions such as rapid speech, raised voices, and display of excitement (McDonnell 2014:261), the measure of upvotes in this study relies on the assumption that the action of upvoting is linked to an unobserved cognitive process –the experience of resonance.[7] In many studies, such binary outcomes are usually the best available proxy for the experience of cultural power despite the assumptions it entails, as researchers only have access to *outcomes* of people's cognitive process –likes, shares, consumptions (Salganik et al. 2006; Bail 2016a; Askin and Mauskapf 2017; Casas and Williams 2019). Future research is needed to understand the extent to which the assumption might be violated, and how it might affect results. In this study, I follow the practice of previous research and use upvote as a proxy of the experience of resonance.

There are four sets of independent variables that are of particular interest to this study. First, this study operationalizes *novelty* by measuring the extent to which the concepts a post engages are close or distant in a high dimensional semantic space (Shi and Evans 2020). Here, the semantic space is pre-defined by the entirety of the discourse that occurred before the given post. Novelty, in this conception, is a "diachronically moving target." What was considered novel a year - or even a month - ago may be considered banal today. The challenge is to approximate the true novelty of a given text by measuring it within the discursive space at the point in time it is written. To achieve this goal, this study applies diachronic word-embedding modeling, capturing meaning changing over time (Kim et al. 2014; Rodman 2020).

Word-embedding models represent each word in a given corpus as a vector. These word vectors can be computed using different word-embedding model implementations, most commonly *Word2Vec* (used in this paper) and *GloVe*. The core idea of word-embedding models is to "learn" the relationship between words by examining each target word and its local context words. The learning process is performed through a neural network that leverages stochastic gradient descent and backpropagation to minimize the incorrect predictions about the target and context words occurrence in the given corpus (Mikolov, Yih, and Zweig 2013; Rong 2016; Rodman 2020).[8] The resultant vector representations of words are shown to encode semantic information that can successfully solve various natural language processing problems, including analogy tests, part-of-speech tagging, named-entity-recognition, among others (Mikolov 2013; Garg et al. 2018; Rodriguez and Spirling Forthcoming).

The steps involved in calculating novelty diachronically are summarized in Figure 2. First, a word-embedding model, M_{start}, is trained using the entire corpus (all discussions from 2011 to 2017).[9] Then, the entire corpus is divided into sub-corpus by week.[10] This resulted in 106 year-week corpora. Third, to obtain a vector representation of the semantic relationship for each point in time, a new word-embedding model is trained using the previous time point's model for initialization and the current year-week sub-corpus for training. Using this method, each year-week is represented with a vector space that reflects the relationship between words at their specific point in time. To account for the randomness in the *Word2Vec* (W2V) modeling result obtained for each time point, the bootstrapping method is applied with 150 iterations at each time point (Rodman 2020). Thus, novelty is calculated by taking the bootstrap sample mean. A confidence interval of the novelty measure is also obtained by taking the 5% and 95% values in the bootstrap samples.

[Insert *Figure 2 Diachronic Measure of Novelty* here]

Then, the novelty of time point T_t is calculated using the vector space trained at time point T_{t-1}. This way, one can effectively measure the novelty of a post not against its contemporaneous competitors, but the "discourse establishment" it speaks to because novelty is always experienced in relation to an *existing* cognitive mapping of concepts and their associations (DiMaggio 1997; Strauss and Quinn 1997; McDonnell et al. 2017). In other words, novelty is not measured by comparing how novel a post is with posts that are created at the same time point, but by comparing it with what *has been* said and posted in the public sphere. This way of measuring more accurately reflects the theoretical definition of novelty in the theory of resonance than measuring novelty by comparing a text with its counterparts generated at the same time point.

The diachronic word-embedding model obtained at each time point reflects not only the discourse that occurred in this time point, but also carries along the semantic relations that occurred in all previous time points. In general, concepts that have been more frequently used together in this forum will be closer in the semantic space, whereas those that are rarely discussed together will be further away. At each time point, adjustments of the word-embedding models means that concepts that are discussed together in the current texts slice will be reflected in the resultant model, whereas concepts that are discussed together previously but not in the current texts slice will either have an unchanged or attenuated relationship, depending on how the rest of the concept network changes. Therefore, the diachronic word-embedding model reflects not only the current text slice, but also the discourse that occurred up to the current time point through the cumulatively evolved semantic network relations.

Intuitively, one can think of the diachronic word-embedding model as working similarly to human memory: the present and the recurring events are most readily retrievable in comparison to rare or distant past events (Schudson 1989). Thus, concepts that have been discussed together in the most recent past, and concepts that are discussed together frequently in this forum will both obtain relatively low novelty scores. This realistically reflects the cognitive "carrying capacity" of the forum users (Hilgartner and Bosk 1988:59), as it does not assume or require that the participants know the entire discourse history of the forum. Rather, it emphasizes recurring discourses and more recent ideas. When the target post embeds those concepts, the novelty will be lower than those that do not.

Not all words in a post are used to calculate the novelty. In this study, concept words are defined as words with a Part-of-Speech (POS) tag of nouns, verbs, adjectives, or idioms,[11] and only words with such POS tags are used to calculate novelty (stop words[12] are removed). This is a decision made after examining a random sample of the forum posts with each segmented word and its POS tag. It is found that words tagged as nouns, verbs, adjectives, or idioms are most likely to represent key concepts of the argument. In addition, since this study measures the novelty of concept word *combinations*, at least two concepts are needed. Thus, posts that engaged with less than two concepts are removed. Novelty is measured following Shi and Evans (2020):

$$\text{Novelty}(Doc_i) = -\log \sum_{d}^{D} \prod_{n}^{N} v_{nd}$$

In this measure, Doc_i is the ith document in the sub-corpus, v_{nd} is the word-embedding value of concept n at dimension d. This measure relies on the assumption that the W2V space reveals a latent high dimensional space where the loadings each word has on each dimension indicates the probability that the word's meaning belongs to that dimension (Xing et al. 2014; Kim and Shin 2017; Kozlowski, Taddy and Evans 2019). Accepting such an understanding, the novelty measure indicates how likely one observes the combination of concepts in a defined word-embedding space.

To validate the effectiveness of the diachronic measure of novelty, I examined the change of novelty score over time for posts with similar content. Since posts that engage with different concepts are not directly comparable, I searched for posts that are almost identical copies with only minor edits. Figure 3 shows three such cases with the posts and their English translations displayed at the top of each panel, and their novelty score point estimates with confidence intervals on the bottom.

[Insert *Figure 3 Post Content and Novelty Score Across Time* here]

The left panel shows a short post that is a parody of a famous line in the classic Chinese history writing, *Records of the Grand Historian*. It is used on the forum as a slogan, either sincerely or ironically, to support Trump. The middle panel shows a post that recites a Chinese political idiom, a phrase often used by past Chinese Communist Party leaders as a motto to show one's loyalty to the country and Party regardless of personal gain or loss. In this forum, this line is also often used, either sincerely or ironically, to praise a political leader (sometimes Trump, sometimes others). The right panel is a post that tries to show how a Parisian newspaper changed their political stance over the course of six days as Napoleon arrived in Paris and dethroned the Directory. The post is used to prove how the mainstream media serve as the mouthpiece of the dominant political establishments, and is evoked on the forum when people discuss U.S. news media. All of the three posts appear in the data multiple times in almost identical forms, suggesting that multiple users have used the same content to answer different questions at different points in time.

In all examples, the novelty score trends downwards as time progresses, despite the deviations of two data points in the Napoleon panel. This is because both posts had introduced one or two new concepts to the original text, leading the novelty score to increase as such combinations are relatively less common. This validation shows that the diachronic novelty measure is effective in penalizing concept combinations that have appeared before while rewarding novel concept co-occurrence.

It should be noted that the measure of novelty used in this study is an indirect measure of “cognitive distance.” It assumes that cultural schemas, as “organized network of associations” (Mohr et al. 2020: 25), are embodied in people’s narratives through their use of concepts (Ignatow 2009). While it is possible to measure “cognitive distance” directly through measuring individuals’ schematic associations (Hunzaker and Valentino 2019), this cognitive measure requires experimental settings that are costly and not always viable in studies that use social media data. Therefore, the novelty measure in this study rests on the assumption that the network of concepts in discourse provides an approximation of the shared cultural schema (Ignatow 2009).

The second independent variable of interest is *emotionality*, which is measured using a Chinese sentiment prediction package “bixin” which has a test accuracy[13] of above 0.82 on a mixed corpus of customer reviews, Weibo tweets, general news, and financial news in Chinese.[14] The raw sentiment score ranges from -1 (negative) to 1 (positive), and I operationalize this measure to a categorical variable that captures *both* the intensity and the direction of the emotion.

As discussed earlier, while current literature suggests that it is the intensity rather than the direction of the emotion that leads to a higher chance of one experience resonance, the direction of emotion is often monitored in research about Chinese netizen's view of the U.S. (Guan et al. 2020; Lu et al. 2021). Therefore, to be able to engage with the literature, a measure that captures both intensity and direction is preferred.

Based on the percentile of a post's sentiment score, it is categorized using a 7-level emotionality scale. The top and bottom 10% are categorized as "extremely positive" and "extremely negative" (scoring above 0.99 or below -0.99 in the raw sentiment measure). Those between 70% and 90% (scoring between 0.18 to 0.99) and 10% to 30% (scoring between -0.99 to -0.25) are labeled as "moderately positive" and "moderately negative," respectively. Those scored between 50% to 70% (0.001 to 0.18) and 30% to 50% (-0.25 to -0.001) are defined as "slightly positive" and "slightly negative." Those at the 50th percentile (-0.001 to 0.001) are defined as "neutral." As a robustness check, I also used the absolute value of the sentiment score as a continuous measure of emotionality and the findings hold (see Appendix C).[15]

The third set of independent variables measure *status*. I leverage the user's number of followers and a "prestige marker" provided by the forum (a "top writer" badge awarded to users whose answers had been recommended by the forum's editors) to test the third hypothesis. Therefore, two measures are used: (a) a user's number of followers, which is log-transformed as the distribution is skewed[16] and (b) a dummy variable indicating if the user has a "top writer" badge awarded by the forum's editors. For anonymous users, measure (b) – whether the user has a "top writer" badge – is coded as "False" regardless of whether or not the actual user is a "top writer." I do this because when users choose to answer a question anonymously, their "prestige badge" disappears, meaning that the status marker is veiled when users browse the text and decide if the post resonates.

The last group of independent variables describes linguistic characteristics of the text that might influence resonance. First, the *lexical diversity* of a post is measured by a post's Type-Token Ratio (TTR) following previous research (Tan et al. 2016; Ta et al. 2022). The TTR is calculated by dividing the number of unique tokens (i.e. Chinese words) by the number of all tokens of a document. It measures how diverse the language is by looking at how many unique words appeared in the text.[17] The second linguistic feature of interest is *the usage of a foreign language,* and in this study, it refers to Chinese forum users' usage of English in their discussion of U.S. politics. This is measured by the number of English words divided by the sum of the number of English words and the number of Chinese characters. Although the primary language is Chinese on the forum, it is almost unavoidable for the discussants to use some English words or expressions when talking about American politicians, institutions, and social problems. In China, the ability to command the language is still associated with higher social status, with less than 20% of the population equipped with English proficiency beyond simple greetings (Wei and Su 2012; Appendix H). Furthermore, only less than 4% of the population has the ability to read and write English freely (Wei and Su 2012). Therefore, the usage of English is associated with higher social status and thus is considered an important linguistic feature in this empirical case.

Controls

Control variables will be included in the models to account for differences in the questions and author characteristics including (1) the *lengths of the post* as measured by the number of characters ; (2) the *topic* a post engages with, which is defined as the topic tag attached to the question this post is responding to, which is a categorical variable of five topic tags -2016 election, U.S. Politics, U.S. Society, U.S. Economy, China-U.S. Comparison;[18] (3) *question characteristics* which are measured by (a) the number of answers a question has, and (b) the number of views a question has. Both variables are log-transformed because of skewed distribution. These question characteristics control for the effect of question popularity, i.e. a post to a more popular question may get more upvotes; (4) gender of the user –a categorical variable of male, female, or unknown. (5) *time distance* to the 2016 U.S. General Election day – an integer variable indicating a post's time distance, in terms of days, from the 2016 election day to control for the effect of time dependencies as people's interest in U.S. politics might peak around election day and decline as the time distance increases. Table 2 displays the descriptive statistics of both the key variables of interest and control variables.

Modeling Strategy

The main question for this research is what kinds of answers resonate with the platform's users. Given the overdispersed distribution of upvote counts, I model the relationship between resonance and its predictors using a zero-inflated negative binomial (ZINB) count regression (Moghimbeigi et al. 2008; Fox 2015). Many prior studies use negative binomial regression to model overdispersed count data (Evans 2008; Foster, Rzhetsky and Evans 2015; Bail 2016b). But, unlike the typical negative binomial distribution the number of zeros is inflated in my data (see Appendix A for distributions), and it is reasonable to assume the data generation process for zero-upvote and non-zero-upvote posts invovle distinct mechanisms. For example, there may be a "threshold" of word count or the number of followers below which the post is unlikely to get any visibility. In this case, ZINB regression is a preferable choice because it assumes that the data-generation processes for zeros versus non-zeros could be different (Moghimbeigi et al. 2008; Fox

2015). Using ZINB, the expected number of upvotes a post receives is modeled with a covariant vector containing the measures discussed before.

To account for the possibility of a curvilinear relationship between novelty and upvote, the covariant vector contains a quadratic term for *novelty*. Because the raw score of novelty has a relatively large range, to reduce multicollinearity with the quadratic term, the novelty score is standardized to have a mean of 0 and a standard deviation of 1, and then squared to obtain the quadratic term. Both (the standardized measure of) novelty and its squared term are entered in the equation. Similarly, to reduce multicollinearity with novelty and with length's quadratic term, answer length is standardized to have a mean of 0 and a standard deviation of 1. To check for nonlinearity for our key predictors, squared terms of Author's Follower Count (logged), Lexical Diversity, and English Usage are also modeled.

FINDINGS

Table 2 provides descriptive statistics for all variables. Because this study assumes a different data generation process for the inflated number of zeros, summary statistics for non-zero upvote posts and zero-upvote posts are displayed respectively, with the overall summary statistics displayed in the last column. Across key continuous measures (Novelty, Author Follower Count, Lexical Diversity, and English Usage), we can see that the non-zero upvote group has a higher mean than the zero upvote group except for Lexical Diversity. This seems to confirm the results of Tan et al. (2016) and Ta et al. (2022) that Lexical Diversity is negatively associated with cultural power. For the categorical measure of Emotionality, the non-zero upvote group has more posts concentrated in the "moderately positive/negative" and "slightly positive/negative" categories, whereas the zero-upvote posts are more likely to be either "neutral" or "extremely positive/negative." This pattern seems to contradict my hypothesis, suggesting that higher emotional intensity does not lead to more cultural power.

Correlations (R) between key variables are shown in Table 3. There is a relatively high correlation between Answer Length and Novelty, at 0.68. This suggests that longer posts are associated with a higher probability of drawing on more distant concepts.[19] Answer Length is negatively associated with Lexical Diversity. This suggests that longer posts also tend to include more repetitive use of words, such as common stop words (e.g. "the", "a", both Length and Lexical Diversity are measured with stop words included).

[Insert *Table 2 Descriptive Statistics of Model Variables* here]

[Insert *Table 3 Correlation of Continuous Variables* here]

The result of the modeling is shown in Table 4. Model 1 is a simple model that only includes the three theoretical predictors as proposed in McDonnell et al. (2017) – Novelty, Emotionality, and Author's Status without adding Novelty's squared term. Model 2 added Novelty's squared term to test for the curvilinear relationship between novelty and resonance. These two simple models show four tentative findings: (1) Novelty is positively related to resonance when a curvilinear relationship is not modeled; (2) however, when Novelty's squared term enters the equation, it is significant and negative, revealing that there is a curvilinear relationship between novelty and resonance; (3) in contrast to H2 (more intensive emotion will lead to more cultural power), slight or moderate emotions seem to perform better than neutral or extreme emotions, as the positive effect of emotion declines as emotion intensifies; and (4)

Author's Status is positively associated with resonance in terms of Author's Follower Count (logged) and the prestigious "Top Writer" badge.

Model 3 included linguistic features as predictors. Adding Lexical Diversity and English Usage to the model, Model 3 finds statistically significant relationships between Lexical Diversity and resonance as predicted in H4-1 (negative association), and English Usage and resonance as predicted in H4-2 (positive association). This seems to confirm my hypotheses about linguistic features, that increased diversity of vocabulary decreases the likelihood of resonance, whereas increased use of English increases the cultural efficacy.

Model 4 added Answer Length as a control on top of Model 3. Once Answer Length is considered, the effect of novelty decreases considerably. This is expected as the two variables are correlated at 0.68 (Table 3). Yet the effect of Novelty and its square are still statistically significant, which assures us that there is a curvilinear relationship between Novelty and resonance.

To check for nonlinearity for key predictors, squared terms of Author's Follower Count (logged), Lexical Diversity, and English Usage are modeled to see if there are statistically significant nonlinear relationships in Model 5. It is found that both Lexical Diversity and English Usage have statistically significant and negative coefficients for their squared terms, whereas Author's Follower Count (logged) has a statistically significant and positive coefficient for its squared term. This result is shown in the column of Model 5 in Table 4. As we can see, while the main effect of Lexical Diversity is negative, adding a squared term suggests that the effect of Lexical Diversity will likely remain positive until it reaches an optimal point. Similarly, English Usage also presents a statistically significant curvilinear relationship with resonance.

For Author's Follower Count (logged), in contrast, the squared term's coefficient is statistically significant and positive, resulting in a positive effect of author status across all observed values. The coefficients of the Author Top Writer dummy are significant from Model 1 to 4, but once the squared term of logged Author Follower Count is added, the significance of the dummy variable disappears. This is most likely because the Author Top Writer dummy picks up the effect of the squared term of Author's Follower Count (logged) before it is added to the model, and because there are insufficient number of observations that have the "Top Writer" badge (only 0.8% and mostly appeared in the non-zero upvote posts in the dataset). The pattern of the coefficients of Emotionality dummies does not change as I add these squared terms as well as the control variable Answer Length.

Comparing the Bayesian Information Criterion (BIC) for Model 4 and Model 5, the lower BIC of Model 5 suggests a better fit when squared terms of these variables entered the equation.[20] These surprising results suggest that in addition to disconfirming H2 (more intense emotion will have a positive effect on resonance), one might also reject H4-1 (lexical diversity has a negative effect on resonance) and H4-2 (use of English has a positive effect on resonance).

Model 6 is the full model including all control variables. The effects of key predictors and key controls do not change much after adding the additional controls in Model 6. The full model shows that Novelty, Lexical Diversity, and English Usage all have curvilinear relationships with resonance, whereas Status (measured by logged Author's Follower Count) is positively related to resonance. Emotionality presents a nuanced pattern that suggests both the intensity and the direction of the emotion matters in the data. Compared to Neutral posts, posts that are "Slightly Negative" perform the best, seconded by those that are "Moderately Negative." As intensity increases, the effect of emotionality declines, and the effects of "Extremely Positive" and

“Extremely Negative” are not statistically different from that of neutral posts. This pattern is visually illustrated in Figure 4, which plots the coefficients of the Emotionality dummies in Model 6.

[Insert *Table 4 Modeling Results (Negative Binomial Component of ZINB)* here]

[Insert *Figure 4 Model 6 Coefficients of Emotionality Dummies* here]

[Insert *Figure 5 Coefficients of Model 6 Using Novelty Dummies* here]

In addition to these models, an additional modeling exercise is performed to cross-validate the curvilinear relationship between novelty and resonance. In this model, dummy variables are created by categorizing each observation based on the range of its standardized novelty score. As depicted in Figure 5, the coefficient plot for this novelty-dummy model, we observe that the effect of novelty steadily increases as novelty gets higher, until it reaches its maximum effect when novelty is 1 to 2 standard deviations (SD) away from the mean (from 92nd to 98th percentile). After that, the effect starts to decrease.

The novelty-dummy model further clarifies the positive effect of Novelty on resonance in most of the distribution in the data. Thus the declined effect of Novelty beyond the inflection point pertains to only a small proportion of cases at the very top of the distribution. There are about 2,946 cases that have an “optimal novelty” between 1 to 2 SD (standard deviation) away from the mean, with only about 2,608 cases scoring higher than 2. However, the rarity of the cases is consistent with the over-dispersed distribution of novelty, with 75% of the posts scoring less than the mean. Thus, in most of the distribution, novelty is associated with enhanced resonance.

Figure 6 shows the predicted number of upvotes for key independent variables according to the results of Model 3, 5, and 6, while other covariates are fixed at the mean. The full model is depicted with the black solid curve. Novelty, as shown on the top-left grid, has an effect at about 30 upvotes at its optimal value when all the control variables are added, which is between 4 to 5 SD from the mean. This approximates the novelty-dummy modeling results, as shown in Figure 5.

[Insert *Figure 6 Predicted Number of Upvotes of Key IVs and Controls, by Models* here]

Figure 6 also demonstrates how the intensity and direction of emotion affect resonance. Two patterns emerge. First, the trend of the predicted effect of emotion is approximately symmetric with respect to the "Neutral" category. That is, the expected number of upvotes increases by about 10 from "Neutral" to either "Slightly Positive" or "Slightly Negative." Then, the predicted number of upvotes starts to decline as emotion intensifies, for both positive and negative emotions. Second, negative emotion is consistently in the lead over positive emotion across the three emotionality categories by a small margin. The result suggests that: (1) *regardless of the direction of the emotion*, the intensity of emotion, instead of having a positive linear relationship with resonance, presents an approximate curvilinear relationship that rewards slight or moderate expression of emotion the most; and (2) when the direction of the emotion is considered, negative emotion holds a small advantage over positive emotion in the data. Modeling exercises that use a continuous measure of emotionality also yield a curvilinear relationship (Appendix C).

In terms of the effect of author status, Figure 6 demonstrates a decelerating positive effect of Author's Follower Count on expected upvote, with a positive return of an additional increase of 1,000 followers diminishes from about 2 upvotes to less than 1 upvote once the Author's Follower Count hits 2,000. Importantly for my analysis, the effect remains positive across all observed values.

The nonlinear relationship between resonance and Lexical Diversity as well as English Usage both have a notable impact on upvotes, with an optimal value of Lexical Diversity amount to an increase of more than 40 upvotes compared to the lowest predicted value, and that of English Usage is about 30 upvotes.[21]

DISCUSSION

The modeling results allow an evaluation of the hypotheses. First, this study finds a curvilinear relationship between novelty and resonance (i.e. H1 is confirmed). Yet the point where the effect of novelty is overturned is far above the median at a percentile above 90%, so that novelty has a positive effect in the vast majority of the distribution. In other words, there is a high bar for a text becoming "too novel" to the extent that it will be detrimental to its cultural power.

In a previous study by Askin and Mauskapf (2017) that found a curvilinear relationship between novelty and popularity in the production of popular music, there is also a rarity of the "optimal novelty" in the dataset. In their study, novelty is measured by the "typicality" (the reverse of novelty) of a song comparing to other songs released in the previous 52 weeks in a high-dimensional sonic feature space (Askin and Mauskapf 2017). Conceptually, both their and my measurements aim to capture how similar a cultural object is compared to an existing pool of cultural objects. In their findings, songs that achieved optimal novelty are at the long tail of the sample distribution (Askin and Mauskapf 2017:920,928).[22]

Combining their study with this one, the tentative conclusion is that the optimal point of novelty is likely to be in the far right tail of the novelty distribution. In other words, instead of thinking of novelty's optimal effect as somewhere in the middle, it is more plausible that the optimality occurs somewhere closer to "strangeness" than banality. To reiterate the example used by both Griswold (1987) and McDonnell et al. (2017), while "Juliet is the sun" is deemed as achieving an optimal cognitive distance that is neither too strange nor too banal, if we were able to obtain a "discourse establishment" data that represents the cultural schema that Shakespeare's work spoke to, we might find that it probably was *quite novel* to associate a female lover with the sun before Shakespeare articulated it that way and that the novelty enhanced resonance.

Second, the modeling results do not find a positive linear relationship between emotionality and resonance (i.e. H2 is rejected). Rather, there is evidence showing a curvilinear relationship between emotionality and resonance, with emotionally moderate speech found to be more effective than emotionally intense speech or emotionally neutral speech. In addition, negative emotion tends to have a stronger positive effect than positive emotion across different levels of emotionality.

This is a rather unexpected result given that previous studies about emotionality and political interaction consistently demonstrate that emotionality is positively associated with resonance (Brader 2005; Erisen et al. 2014). In addition, as journalistic commentaries have repeatedly emphasized the intensely fervent pro-Trump sentiment found in this community (Dychtwald 2016; Fu 2016; Carlson 2018). It turns out that while the extreme sentiments were picked up by reporters, the community members themselves did not find ideas with extreme emotions resonant. Instead, opinions expressed with moderate emotions were favored.

This unexpected finding might be explained by the "filtering" or mediation effect of "group styles" in the relationship between emotion and resonance (Eliasoph and Lichterman 2003). As defined by Eliasoph and Lichterman (2003), group styles are "recurrent patterns of interaction that arise from a group's shared assumptions about what constitutes good or adequate participation in the group setting" (737). A critical dimension that defines a group style is its “speech norms” –what kinds of topics, in what form, with what emotions are appropriate given the group setting (Eliasoph and Lichterman 2003:739). As groups differ, the effectiveness of intense emotions in interactions may vary. As Eliasoph and Lichterman haven shown, in the suburban activist group ACES, members followed “an unspoken rule that speech should sound reasonable” and often avoided expressions with anger or rage (2003:755). Schudson (1989) also provides an interesting example of the “group style” of the science community where members prefer a speech norm that may not be effective elsewhere: “[i]n science, the duller, the better” (167). Similarly, in the case of this discussion forum, it is possible that users have developed a group style constituted by a speech norm that promotes the sharing of logical, well-crafted opinions rather than speech that appeals to heightened emotions. The fact that the forum attracts the more educated, urban professional Chinese middle class that is more concerned with foreign politics may act as a filter, creating a group that is willing to engage in extensive debate about foreign affairs in a manner where ideas and opinions are deliberately conveyed with moderate emotions.

Therefore, the result of this study should not be interpreted as a refutation to the theory of emotion and resonance. Rather, it is more likely that it identifies an important *mediator* to the general theoretical claim that intense emotion makes resonance more likely. It is possible that group styles will mediate this relationship, as the speech norms that emerged from repeated group interactions may prefer moderate emotions to intense ones.

Further, the finding of this study also questions how emotion should be understood, theorized, and measured. As many have pointed out, emotions do not fall on a simple one-dimensional spectrum of negative to positive or neutral to intense (Brader and Marcus 2013; McDonnell 2014:262 footnote 12 to 14). The *types* of emotion people experience in social interactions matter. In a recent study on Twitter images, Casas and Williams (2019) leveraged a five-category emotional structure and found that while there is a positive relationship between emotional intensity and cultural efficacy (measured by retweets) for fear, disgust, and enthusiasm, such a relationship is absent for anger or sadness. This demonstrates that emotion types may play a role in determining cultural efficacy. Similarly, in my study, it could be that the most effective type of emotion that is truly being conveyed by the author and felt by the audience is not perceived by "amount," but as a type that we commonly describe as careful, prudent, or collected. In a different group setting such as the alt-right discussion board on the anonymous forum 4Chan, anger and rage –as emotional types –could be valued more than any other types of emotion.

In social and political psychology, there are several well-researched "families of emotions" that put emotion types into loosely clustered families (Brader and Marcus 2013: 175). More recent political psychology literature argues that it might be more effective to understand emotions in an "affective space" with at least three dimensions (Brader and Marcus 2013; Marcus et al. 2017). Cultural sociologists should expand upon such efforts to develop a theory and measurement of emotion that goes beyond a one-dimensional scale. By improving our theorization of emotion, we will be able to test if the relationship between emotion and resonance also depends on how emotions are measured and categorized. It is possible that it is the intensity of *a particular type* of emotion, rather than the emotion of any kind, that makes resonance more likely depending on the group or interactional setting.

In terms of the interlocutor's status, one of the two measures – Author's Follower Count – supports the hypothesis that status positively predicts resonance (H3). The other status measure – the "Top Writer" badge – does not have a robust effect in the full model. Nonetheless, the positive relationship between Author's Follower Count and upvote is consistent with previous studies on status and resonance.

Hypothesis H4-1, that Lexical Diversity is negatively related to resonance is rejected. The modeling results suggest a curvilinear rather than a negative linear relationship. It appears that when one draws on a more diverse vocabulary but does not overplay it, it helps the text to achieve higher cultural power. Lastly, hypothesis H4-2 that foreign language usage is positively related to resonance is also rejected because this study finds a curvilinear rather than positive linear relationship. In the context of Chinese discussion of American politics, modest usage of English helps an answer build credibility. But as the proportion of English continues to increase beyond a certain point, a post's chance to create resonance declines.

Lexical diversity and the usage of foreign language seem to suggest a "cultural-capital signaling and selection" mechanism in creating resonance. The author signals their knowledgeability through a diverse vocabulary and the deployment of a relevant foreign language. At the same time, the audiences select posts whose enacted cultural capital effectively demonstrate credibility without going so far as to make the content too difficult to understand. The signaling and selection thus reproduce linguistic markets that "imposes themselves as a system of specific sanctions and censorships" (Bourdieu 1992: 37).

From the standpoint of the speaker, this echoes Bourdieu's thesis (1992) that symbolic power is tied to both the linguistic *and* social capacity mobilized in interactions. The speaker needs not only competence with an expansive vocabulary and a relevant foreign language (the linguistic capacity), but also an awareness of *when to stop* (the social capacity). From the standpoint of the audiences, this confirms Schudson's proposition (1989) that the audiences play an active role in evaluating and thus creating cultural power. Specifically, crucial to the experience of resonance is a match between object features and the local “aesthetic conventions” (Schudson 1989: 167). The “cultural-capital signaling and selection” mechanism is not only about the author signaling cultural capital through linguistic or other object features, but also about the audiences actively selecting on the kind and amount of cultural capital that they value the most in the interactional situation.

Importantly, the “cultural-capital signaling and selection” mechanism should not be confused with the “speaker status” path to cultural power, although these two could be correlated. The former refers to the experience of resonance arising from the audiences’ evaluation of an object’s features, whereas the latter is about the speaker’s structural position and the audiences’ evaluation of the speaker’s pre-existing status as she enters a social interaction (such as one’s titles and disclosed credentials). A speaker with higher status could be more likely to mobilize highly-valued cultural capital, but as shown in this and other studies (Bradac et al. 1976; Tan et al. 2016; Durmus and Cardie 2019), holding the speaker’s status as constant, different deployment of linguistic features can affect the likelihood of resonance. These two are therefore analytically distinct elements of cultural power.

Previous studies have examined cultural capital as an independent cause for various life outcomes such as educational attainment, marital selection, friendship ties, and hiring decisions (DiMaggio and Mohr 1985; Rivera 2012; Lewis and Kaufman 2018). Yet the effect of cultural capital embedded in the cultural object is considered less in the study of ideas and their cultural power. The selection on the dependent variable is likely to obscure the consideration of these elements, as studies of the competition of ideas tend to observe competing ideologies and discourses that approximate each other in their sophistication of articulation, because there was usually a gate-keeping mechanism in place –for example, what was chosen for stage performances

(Griswold 1986), what was published (Griswold 1987), what qualified as theories that merit scholarly debate (Block and Somers 2014), or what is worth broadcasting by the news media (Ferree 2003; Bail 2012). However, once we observe the unmediated process of idea selection, objectified cultural capital plays a role in how the audience experiences and evaluates the cultural object.

To briefly conclude, this study confirms a curvilinear relationship between novelty and resonance, as well as a positive effect of status on resonance, as suggested by extant literature on cultural power (McDonnell et al. 2017). However, this study does not find a positive association between emotional intensity and resonance, most likely because the way emotion affects resonance is mediated by "group styles" (Eliasoph and Lichterman 2003). Future research is needed to clarify how group styles might mediate the causal connection between emotion and resonance, possibly by a new conception of "emotion types" that goes beyond a simple sentiment scale. This paper also confirms an additional "cultural capital signaling and selection" mechanism to cultural power: the use of a diverse vocabulary and a relevant foreign language increases the resonance of a text when these practices are not overplayed, most likely because the audiences associate these practices with greater linguistic and social capacities.

Methodologically, this paper introduces a new method to sociology that utilizes word-embedding models dynamically. The method has been recently introduced to political science (Rodman 2020). Its potential in exploring various sociological inquiries using word-embedding models with a time dimension makes it a valuable addition to the sociological toolbox. With such an improvement, novelty measured in this study reflects its dynamic relation to the ever-changing discourse structure. Subsequent research that aims to better understand resonance through computational methods can attend to the following two limitations of this research. First, one can develop a more accurate method for concept extraction than selecting on the Part-of-Speech (POS) tagging; this approach could select concepts that may not be perceived as key concepts by the audience. A content-specific approach would be preferred. For example, one may apply tf-idf[23] keywords extraction or topic modeling to create a concept list (although it might overlook concept combinations that are rare but novel). Second, it is worth further complicating our understanding of novelty. The key question is: the novelty of what? This study demonstrates the novelty of concept combination, developed from the theoretical proposition made about an optimal cognitive distance. However, novelty can also be created by combining different topics (DiMaggio et al. 2018) and it is worth exploring how these two different kinds of novelty relate to each other and to resonance.

Substantively, this paper provides one of the most up-to-date examinations of the Chinese public's view of the U.S. particularly after Trump's rise to power. Contrary to popular accounts that assumed the popularity of the Trump craze among Chinese netizens, the study finds that such extreme sentiments were not well received in this forum joined by more educated users. Instead, ideas that are moderate in emotion are most likely to be resonant. In addition, while previous research has found that the Chinese middle class holds more positive attitudes towards the U.S. than those who are less well-off (Johnston 2004), this study finds that slightly and moderately negative posts are more effective than those that are positive, which raises the question about whether there is a rising trend of anti-American sentiment even among Chinese middle class over the past decade. Particularly, as government responses to COVID-19 have been highly politicized in China (Zhang Forthcoming), it is politically important to build a better understanding of what kinds of emotion towards the U.S. are culturally most powerful among different social classes in China. At the same time, the study also demonstrates that such research should go beyond a dichotomous sentiment measure because a simple negative-positive categorization might result in a mischaracterization of the Chinese public's view of the U.S.

There is still much to be learned about the cognitive and interactional process leading to resonance. The findings of this research raise questions about some of the core assumptions we have held in our theorization. Besides thinking about emotion along a sentiment score scale, how else can we define and measure different types of emotion? Is intensity the most important aspect of emotion that affects the experience of resonance? What other signals of cultural capital are picked up by observers and how do they affect the cultural power of ideas? How do local norms and expectations intervene in the creation of cultural power? Indeed, as sociologists strive to answer these questions, they also engage in a creative process of problem-solving; a process that searches for both scientific facts and imaginative theorizations that can "resonate" with our everyday experience of cultural power.

NOTES

1. While there have been many strands of research devoted to this inquiry at the macro, historical level, asking how and why certain ideologies emerged to become hegemonic over certain historical periods (for example, Wuthnow 1989, Somers and Block 2005), this paper focuses on understanding resonance in the *micro process of interaction*.

2. Data from the earlier period (2011 to 2015) are also used in training the word-embedding model.

3. Scholars estimate the Chinese middle class makes up 20% to 40% of the total population, see Li 2010.

4. U.S. related topics are defined as questions and answers that are labeled by any of the following topic tags: "U.S. Politics," "2016 U.S. Election," "U.S. Society," "U.S. Economy," and "China-U.S. Comparison." While only the "U.S. Politics" and the "2016 U.S. Election" tags are explicitly about U.S. politics, the other three tags contain discussions about the social and economic aspects of the American society, and about the comparisons between U.S. and Chinese social institutions, which are often quite political. As a robustness check, Appendix F presents modeling results that only include posts tagged with "U.S. Politics" and "2016 U.S. Election" topic tags.

5. Note that this study focuses on the resonance of *answer posts*, instead of the resonance of *questions*. Therefore, the exclusion of questions based on a question's popularity does not mean the exclusion of answer posts based on an answer post's popularity. All answer posts, regardless of their number of upvotes or comments, as long as they are responding to a question that garnered more than five answers, are kept in the data. Questions with less than five answers

usually do not attract enough attention from the forum users and thus the upvotes of the question's answer posts may not accurately distinguish the resonance power of the answer posts.

6. Specific sample size change for each cleaning step: Total answer count from 2011 to mid-2020: 246,073; Answers to questions with at least 5 answers: 226,070; Answers posted by the end of 2017 (i.e. data used for training the diachronic word-embedding models): 84,259; Answers between 2016 to 2017 (i.e. data used for statistical modeling): 79,719 with 4,640 (5.8%) removed due to insufficient concept numbers, resulting in 75,079 observations. Answers between 2011 to 2015 are used to train a word-embedding model that "knows" the "discursive establishment" to which answers posted in 2016 and later were responding. Coding files for web-scraping, diachronic word-embedding models, as well as the data and code used for statistical analysis are made available for replication exercises at github.com/di-zhou/resonance_rep.

7. Users may upvote for various reasons. For instance, some might upvote because the post is authored by a friend, as a mistake, or even just to troll. Biases can also go the other way: Some might be stingy with upvotes despite experiencing resonance, while others do not upvote because they do not want others in their social network to find out what they resonate with. Another potential issue of using upvote and other binary outcomes as proxies for resonance is that it treats the experience as dichotomous rather than a process that can vary by intensity. This prevents researchers from capturing the various degrees of resonance experienced by the users. As stated in the text, these assumptions require future research to understand the extent to which these assumptions might affect results.

8. For a more detailed explication of word-embedding models and how it applies to social science research, please see Garg et al. (2018), Kozlowski et al. (2019), Rodman (2020), and

Rodriguez and Spirling (Forthcoming). For technical explanations of the computation of word vectors, see Mikolov et al. (2013), Mikolov, Yih, and Zweig (2013), and Rong (2016).

9. Stopwords are not removed in the training of all W2V models. Only URLs, punctuations, and numbers are removed. Hyper-parameters of the W2V model are set as the following: dimension = 100, minimum count of words = 0, iteration = 200, skip gram = TRUE, negative sample size = 5, context window = 20. The author also performed a sensitivity test using a minimum count of words = 10 (others remain the same). The conclusion holds for the test. See Appendix D for modeling results of the sensitivity test.

10. Which time unit to use is arguable. Although it is most ideal to obtain the most fine-grained time-slice possible, it is computationally less efficient when the number of discussions is too small within each time slice. This study chooses year-week as the unit as it balances between precision and efficiency. (As shown in Table 1, the average number of daily answers from 2016 to 2017 ranges from 113 to 181, whereas the weekly average will be larger than 700.) The week number refers to the number of complete seven day periods that have occurred between the date and January 1st, plus one. For example, posts created on Jan. 8th, 2016 has a year-week value of 2016-02.

11. The Chinese NLP package "Jieba" is used for segmentation and POS tagging (Sun 2020). Chinese idioms are mainly four-character Chinese words. Similar to English idioms, Chinese idioms are widely used in writing and spoken language to express various meanings. A major difference is that most of the Chinese idioms consist of four Chinese characters (although some special expressions have less or more than four characters).

12. Stop words are extremely common, mostly functional words that themselves carry little substantive meaning. For example, conjunctions, articles, modal particles that add mood to the

text. Stop words are not removed for training W2V models or calculating sentiments but are removed when calculating novelty.

13. "Test accuracy" is defined as the ratio of correct predictions to all predictions. In this context, a test accuracy of above 0.82 means that in the test data set (data that are not used to train the machine learning model, but are set aside to test the performance of the model), more than 82% of them have received a sentiment classification from the machine learning model that are same to the gold standard –which is the sentiment classification assigned by human coders.

14. To access the package: https://github.com/bung87/bixin (last accessed for data analysis in November 2020)

15. As shown in Appendix C, the continuous measure of emotionality ranges from 0 to 1, with 0 represents minimum emotionality and 1 the maximum. The modeling results using this continuous measure instead of the categorical measure also yields a curvilinear relationship.

16. A small number, 0.001, is added to these variables before log-transformation to avoid zeros.

17. In this study, TTR is measured on a text that is segmented using "Jieba" (Sun 2020) with minimal pre-processing –that is, only URLs, punctuations, and numbers are removed, whereas stop words are kept.

18. A question can be labeled with multiple topic tags. Only the main topic tag, which is the first topic tag attached to the question, is used.

19. By our definition, the length of a post is associated with novelty probabilistically. In the simplest model, one can assume that all authors are equally knowledgeable and share the same cultural schema which embeds various concepts and their associations. In addition, one assumes that as the author develops a text, s/he will need to draw more concepts from the "concept network." In this case, as an author develops a longer post, the number of concepts will increase,

and as the number of concepts increase, the probability of capturing dissimilar concepts increases. An analogy would be to draw floating particles from an enclosed box. There could be 99 black particles and one red particle. As one increases the number of particles for each draw, the probability of capturing the rare co-occurrence of black and red increases.

20. A limitation exists in only modeling up to the 2^{nd} degree but not higher polynomial terms of the predictors, because a polynomial setup with degrees 3, 4, or even higher will usually fit the data better because of its flexibility in shapes. A method to address this caveat is to create dummies of the variable of concern and see what trend the coefficients present, which is performed and showed for the Novelty variable later in this section. At the same time, while higher-order terms increase model fit, they are more difficult to interpret. It is important to carefully design models to balance these two considerations.

21. In addition, nonparametric regression that relaxes the curvilinear assumption and allows for more flexible nonlinear forms suggests that Novelty and Lexical Diversity broadly fit the curvilinear assumption, while English Usage may have additional local maximums at the near-zero point. In brief, the results do not contradict the conclusions drawn from the ZINB modeling results.

22. Askin and Mauskapf's study (2017) measured "typicality" instead of novelty to gauge how novel a pop song is compared to others. Typicality (the reverse of novelty) is measured by the weighted average of a song's cosine similarity to every other song released in the previous 52 weeks, with the cosine similarity calculated using a high-dimensional sonic feature space. In the distribution of the typicality score they presented, songs that scored at or below the optimal typicality value (around 0.55) are at the far left of the sample distribution (Askin and Mauskapf 2017: 920). And since a low typicality score indicates a high level of novelty and vice versa, this

pattern is consistent with my findings that posts scored at or above the optimal novelty value are at the far right of the sample distribution.

23. Tf-idf: term frequency–inverse document frequency, a measure that becomes larger when a word is more frequent in a given document but is less common in the entire corpus (collection of documents).

REFERENCES

Aristotle. 1857. *Treatise on Rhetoric: Literally Translated from the Greek*. United Kingdom: Bohn.

Askin, Noah, and Michael Mauskapf. 2017. “What Makes Popular Culture Popular? Product Features and Optimal Differentiation in Music.” *American Sociological Review* 82 (5): 910–44.

Bail, Christopher A. 2012. “The Fringe Effect: Civil Society Organizations and the Evolution of Media Discourse about Islam since the September 11th Attacks.” *American Sociological Review* 77 (6): 855–79.

———. 2014. *Terrified: How Anti-Muslim Fringe Organizations Became Mainstream*. Princeton, United States: Princeton University Press.

———. 2016a. “Cultural Carrying Capacity: Organ Donation Advocacy, Discursive Framing, and Social Media Engagement.” *Social Science & Medicine* 165 (September): 280–88.

———.. 2016b. “Combining Natural Language Processing and Network Analysis to Examine How Advocacy Organizations Stimulate Conversation on Social Media.” *Proceedings of the National Academy of Sciences* 113 (42): 11823–28.

Bail, Christopher A., Taylor W. Brown, and Marcus Mann. 2017. “Channeling Hearts and Minds: Advocacy Organizations, Cognitive-Emotional Currents, and Public Conversation.” *American Sociological Review* 82 (6): 1188–1213.

Bamler, Robert, and Stephan Mandt. 2017. “Dynamic Word Embeddings.” *ArXiv:1702.08359 [Cs, Stat]*, July. http://arxiv.org/abs/1702.08359.

Block, Fred, and Margaret R. Somers. 2014. *The Power of Market Fundamentalism: Karl Polanyi’s Critique*. Cambridge, United States: Harvard University Press.

Bourdieu, Pierre. 1992. *Language and Symbolic Power*. Translated by Gino Raymond and Matthew Adamson. Cambridge, UK: Polity Press.

Bradac, James J., Catherine W. Konsky, and Robert A. Davies. 1976. "Two Studies of the Effects of Linguistic Diversity upon Judgments of Communicator Attributes and Message Effectiveness." *Communication Monographs* 43 (1): 70–79. https://doi.org/10.1080/03637757609375917.

Brader, Ted. 2005. "Striking a Responsive Chord: How Political Ads Motivate and Persuade Voters by Appealing to Emotions." *American Journal of Political Science* 49 (2): 388–405.

Carlson, Benjamin. 2018. "Why China Loves Trump." *The Atlantic*, March 2018. https://www.theatlantic.com/magazine/archive/2018/03/trump-china/550886/.

Casas, Andreu, and Nora Webb Williams. 2019. "Images That Matter: Online Protests and the Mobilizing Role of Pictures." *Political Research Quarterly* 72 (2): 360–75. https://doi.org/10.1177/1065912918786805.

CGSS (Chinese General Social Survey). 2018. http://cgss.ruc.edu.cn/English/Home.htm

Claudia Strauss, and Naomi Quinn. 1997. "Schema Theory and Connectionism." In *A Cognitive Theory of Cultural Meaning*. New York: Cambridge University Press.

CNNIC (China Internet Network Information Center). 2021. The 47th Survey Report of Chinese Internet Development. https://www.cnnic.com.cn/IDR/ReportDownloads/202104/P020210420557302172744.pdf

DiMaggio, Paul. 1997. "Culture and Cognition." *Annual Review of Sociology* 23: 263–87.

DiMaggio, Paul, Clark Bernier, Charles Heckcher, and David Mimno. 2018. "Interaction Ritual Threads: Does IRC Theory Apply Online?" In *Ritual, Emotion, Violence: Studies on the Micro-Sociology of Randall Collins*, edited by Elliott B. Weininger, Annette Lareau, and Omar Lizardo, 81–124. Routledge.

DiMaggio, Paul, and John Mohr. 1985. "Cultural Capital, Educational Attainment, and Marital Selection." *American Journal of Sociology* 90 (6): 1231–61.

DiMaggio, Paul J., and Walter W. Powell. 1983. "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields." *American Sociological Review* 48 (2): 147–60.

Durmus, Esin, and Claire Cardie. 2019. "Modeling the Factors of User Success in Online Debate." In *The World Wide Web Conference on - WWW '19*, 2701–7. San Francisco, CA, USA: ACM Press. https://doi.org/10.1145/3308558.3313676.

Dychtwald, Zak. 2016. "Why Chinese Netizens Cheer Trump." *Foreign Policy*, 2016. http://foreignpolicy.com/2016/11/07/why-chinese-netizens-cheer-trump-tropes-corrupt-official-versus-common-folk/.

Eliasoph, Nina, and Paul Lichterman. 2003. "Culture in Interaction." *American Journal of Sociology* 108 (4): 735–94.

Erisen, Cengiz, Milton Lodge, and Charles S. Taber. 2014. "Affective Contagion in Effortful Political Thinking." *Political Psychology* 35 (2): 187–206.

Evans, James A. 2008. "Electronic Publication and the Narrowing of Science and Scholarship." *Science* 321 (5887): 395–99.

Ferree, Myra Marx. 2003. "Resonance and Radicalism: Feminist Framing in the Abortion Debates of the United States and Germany." *American Journal of Sociology* 109 (2): 304–44.

Foster, Jacob G., Andrey Rzhetsky, and James A. Evans. 2015. "Tradition and Innovation in Scientists' Research Strategies." *American Sociological Review* 80 (5): 875–908.

Fox, John. 2015. *Applied Regression Analysis and Generalized Linear Models*. SAGE Publications.

Fu, King-wa, and Michael Chau. 2013. "Reality Check for the Chinese Microblog Space: A Random Sampling Approach." *PLOS ONE* 8 (3): e58356. https://doi.org/10.1371/journal.pone.0058356.

Fu, King Wa; Zhu, Yuner (2020): COVID-19 related Weibo Data from "Did the world overlook the media's early warning of COVID-19?". HKU Data Repository. Dataset. https://doi.org/10.6084/m9.figshare.12199038.v1

Gal, Susan. 1987. "Codeswitching and Consciousness in the European Periphery." *American Ethnologist* 14 (4): 637–53.

Garg, Nikhil, Londa Schiebinger, Dan Jurafsky, and James Zou. 2018. "Word Embeddings Quantify 100 Years of Gender and Ethnic Stereotypes." *Proceedings of the National Academy of Sciences* 115 (16): E3635–44. https://doi.org/10.1073/pnas.1720347115.

Geipel, Janet, Constantinos Hadjichristidis, and Luca Surian. 2016. "Foreign Language Affects the Contribution of Intentions and Outcomes to Moral Judgment." *Cognition* 154 (September): 34–39.

Griswold, Wendy. 1986. *Renaissance Revivals: City Comedy and Revenge Tragedy in the London Theater, 1576-1980*. University of Chicago Press.

———. 1987. “The Fabrication of Meaning: Literary Interpretation in the United States, Great Britain, and the West Indies.” *American Journal of Sociology* 92 (5): 1077–1117.

Guan, Yichen, Dustin Tingley, David Romney, Amaney Jamal, and Robert Keohane. 2020. “Chinese Views of the United States: Evidence from Weibo.” *International Relations of the Asia-Pacific* 20 (1): 1–30.

Hilgartner, Stephen, and Charles Bosk. 1988. “The Rise and Fall of Social Problems: A Public Arenas Model.” *American Journal of Sociology* 94 (1): 53–78.

Hosman, Lawrence A. 2002. “Language and Persuation.” In *The Persuasion Handbook: Developments in Theory and Practice*, edited by James Price Dillard and Michael Pfau, 371–90. SAGE Publications.

Huckfeldt, Robert, Paul E. Johnson, Paul E. Johnson, and John Sprague. 2004. *Political Disagreement: The Survival of Diverse Opinions Within Communication Networks*. Cambridge University Press.

Hunzaker, M.B. Fallin, and Lauren Valentino. 2019. “Mapping Cultural Schemas: From Theory to Method.” American Sociological Review 84 (5): 950–81. https://doi.org/10.1177/0003122419875638.

Ignatow, Gabriel. 2009. “Culture and Embodied Cognition: Moral Discourses in Internet Support Groups for Overeaters.” Social Forces 88 (2): 643–69. https://doi.org/10.1353/sof.0.0262.

Johnston, Alastair Iain. 2004. “Chinese Middle Class Attitudes Towards International Affairs: Nascent Liberalization?” The China Quarterly 179 (September): 603–28. https://doi.org/10.1017/S0305741004000505.

Kim, Yoon, Yi-I Chiu, Kentaro Hanaki, Darshan Hegde, and Slav Petrov. 2014. “Temporal Analysis of Language through Neural Language Models.” In *Proceedings of the ACL*

2014 Workshop on Language Technologies and Computational Social Science, 61–65. Baltimore, MD, USA: Association for Computational Linguistics. https://doi.org/10.3115/v1/W14-2517.

Kim, Youngsam and Hyopil Shin. 2017. “Finding Sentiment Dimension in Vector Space of Movie Reviews: An Unsupervised Approach.” *Journal of Cognitive Science* 18 (1): 85–101.

King, Gary, Jennifer Pan, and Margaret E. Roberts. 2013. “How Censorship in China Allows Government Criticism but Silences Collective Expression.” *American Political Science Review* 107 (2): 326–43.

King, G., Jennifer Pan, and Margaret E. Roberts. 2014. “Reverse-Engineering Censorship in China: Randomized Experimentation and Participant Observation.” *Science* 345 (6199): 1251722–1251722.

Kozlowski, Austin C., Matt Taddy, and James A. Evans. 2019. “The Geometry of Culture: Analyzing the Meanings of Class through Word Embeddings.” *American Sociological Review* 84 (5): 905–49.

Lewis, Kevin, and Jason Kaufman. 2018. “The Conversion of Cultural Tastes into Social Network Ties.” *American Journal of Sociology* 123 (6): 1684–1742.

Li, Cheng. 2010. *China’s Emerging Middle Class: Beyond Economic Transformation*. Washington DC: Brookings Institution Press.

Li, Xiaoyue, and Bryan Tilt. 2018. “Perceptions of Quality of Life and Pollution among China’s Urban Middle Class: The Case of Smog in Tangshan.” *The China Quarterly* 234 (June): 340–56. https://doi.org/10.1017/S0305741017001382.

Lu, Yingdan, Jennifer Pan, and Yiqing Xu. 2021. “Public Sentiment on Chinese Social Media during the Emergence of COVID19.” *Journal of Quantitative Description: Digital Media* 1 (April). https://doi.org/10.51685/jqd.2021.013.

McDonnell, Terence E. 2014. “Drawing out Culture: Productive Methods to Measure Cognition and Resonance.” *Theory and Society* 43 (3/4): 247–74.

McDonnell, Terence E, Christopher A Bail, and Iddo Tavory. 2017. “A Theory of Resonance.” *Sociological Theory* 35 (1): 1-14.

McPherson, Miller, Lynn Smith-Lovin, and James M Cook. 2001. “Birds of a Feather: Homophily in Social Networks.” *Annual Review of Sociology* 27 (1): 415–44.

Mikolov, Tomas, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. “Efficient Estimation of Word Representations in Vector Space.” *ArXiv:1301.3781 [Cs]*, September. http://arxiv.org/abs/1301.3781.

Mikolov, Tomas, Wen-tau Yih, and Geoffrey Zweig. 2013. “Linguistic Regularities in Continuous Space Word Representations.” In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 746–51. Atlanta, Georgia: Association for Computational Linguistics. https://www.aclweb.org/anthology/N13-1090.

Moghimbeigi, Abbas, Mohammed Reza Eshraghian, Kazem Mohammad, and Brian Mcardle. 2008. “Multilevel Zero-Inflated Negative Binomial Regression Modeling for over-Dispersed Count Data with Extra Zeros.” *Journal of Applied Statistics* 35 (10): 1193–1202.

Mohr, John W., Christopher A. Bail, Margaret Frye, Jennifer C. Lena, Omar Lizardo, Terence E. McDonnell, Ann Mische, Iddo Tavory, and Frederick F. Wherry. 2020. *Measuring Culture*. Columbia University Press.

Mutz, Diana C., and Paul S. Martin. 2001. “Facilitating Communication across Lines of Political Difference: The Role of Mass Media.” *American Political Science Review* 95 (1): 97–114.

Paxton, Pamela, Kristopher Velasco, and Robert W. Ressler. 2020. “Does Use of Emotion Increase Donations and Volunteers for Nonprofits?” *American Sociological Review* 85 (6): 1051–83.

Peng, Lin. 2016. “Zhihu Guangzhou Brand Open Day launched, high income and high consumption are the biggest characteristics of Zhihu users”. *Nanfang Post* http://kb.southcn.com/content/2016-10/29/content_158614467.htm [Chinese]

Rivera, Lauren A. 2012. “Hiring as Cultural Matching: The Case of Elite Professional Service Firms.” *American Sociological Review* 77 (6): 999–1022.

Rodman, Emma. 2020. “A Timely Intervention: Tracking the Changing Meanings of Political Concepts with Word Vectors.” *Political Analysis* 28 (1): 87–111.

Rodriguez, Pedro L., and Arthur Spirling. (Forthcoming). “Word Embeddings: What Works, What Doesn’t, and How to Tell the Difference for Applied Research.” *The Journal of Politics*. https://doi.org/10.1086/715162.

Rong, Xin. 2016. “Word2vec Parameter Learning Explained.” *ArXiv:1411.2738 [Cs]*, June. http://arxiv.org/abs/1411.2738.

Rudolph, Maja, and David Blei. 2018. "Dynamic Embeddings for Language Evolution." In *Proceedings of the 2018 World Wide Web Conference on World Wide Web - WWW '18*, 1003–11. Lyon, France: ACM Press. https://doi.org/10.1145/3178876.3185999.

Salganik, Matthew, Peter Sheridan Dodds, and Duncan J. Watts. 2006. "Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market." *Science* 311 (5762): 854–56.

Schudson, Michael. 1989. "How Culture Works: Perspectives from Media Studies on the Efficacy of Symbols." *Theory and Society* 18 (2): 153–80.

Shi, Feng, and James Evans. 2020. "Science and Technology Advance through Surprise." *ArXiv:1910.09370 [Physics, Stat]*, January. http://arxiv.org/abs/1910.09370.

Shi, Tianjian, Jie Lu, and John Aldrich. 2011. "Bifurcated Images of the U.S. in Urban China and the Impact of Media Environment." *Political Communication* 28 (3): 357–76.

Snow, David A., E. Burke Rochford, Steven K. Worden, and Robert D. Benford. 1986. "Frame Alignment Processes, Micromobilization, and Movement Participation." *American Sociological Review* 51 (4): 464–81.

Somers, Margaret R., and Fred Block. 2005. "From Poverty to Perversity: Ideas, Markets, and Institutions over 200 Years of Welfare Debate." *American Sociological Review* 70 (2): 260–87.

Statista. 2021. "Social Networks: Zhihu in China 2021." Statista Global Consumer Survey – Brand Report.

Strang, David, and John Meyer. 1993. "Institutional Conditions for Diffusion." *Theory and Society* 22: 487–511.

Sun, Junyi. (2020). Jieba v0.42.1. January 20, 2020. https://github.com/fxsjy/jieba

Ta, Vivian P., Ryan L. Boyd, Sarah Seraj, Anne Keller, Caroline Griffith, Alexia Loggarakis, and Lael Medema. 2022. "An Inclusive, Real-World Investigation of Persuasion in Language and Verbal Behavior." *Journal of Computational Social Science* 5 (1): 883–903. https://doi.org/10.1007/s42001-021-00153-5.

Tan, Chenhao, Vlad Niculae, Cristian Danescu-Niculescu-Mizil, and Lillian Lee. 2016. "Winning Arguments: Interaction Dynamics and Persuasion Strategies in Good-Faith Online Discussions." *Proceedings of the 25th International Conference on World Wide Web - WWW '16*, 613–24. https://doi.org/10.1145/2872427.2883081.

Toubia, Olivier, Jonah Berger, and Jehoshua Eliashberg. 2021. "How Quantifying the Shape of Stories Predicts Their Success." *Proceedings of the National Academy of Sciences* 118 (26).

Thompson, John B. 1992. Editor's Introduction to *Language and Symbolic Power*, by Pierre Bourdieu, 13-43. Translated by Gino Raymond and Matthew Adamson. Cambridge, UK: Polity Press.

Uzzi, Brian, Satyam Mukherjee, Michael Stringer, and Ben Jones. 2013. "Atypical Combinations and Scientific Impact." *Science* 342 (6157): 468–72.

Wang, Zhengxu, Long Sun, Liuqing Xu, and Dragan Pavlićević. 2013. "Leadership in China's Urban Middle Class Protest: The Movement to Protect Homeowners' Rights in Beijing." *The China Quarterly* 214 (June): 411–31. https://doi.org/10.1017/S0305741013000374.

Wei, Rining, and Jinzhi Su. 2012. "The Statistics of English in China: An Analysis of the Best Available Data from Government Sources." *English Today* 28 (3): 10–14. https://doi.org/10.1017/S0266078412000235.

Wuthnow, Robert. 1989. *Communities of Discourse: Ideology and Social Structure in the Reformation, the Enlightenment, and European Socialism*. Cambridge, United States: Harvard University Press.

Xing, Chao, Dong Wang, Xuewei Zhang, and Chao Liu. 2014. "Document Classification with Distributions of Word Vectors." In *Signal and Information Processing Association Annual Summit and Conference (APSIPA), 2014 Asia-Pacific*, 1–5. https://doi.org/10.1109/APSIPA.2014.7041633.

Yao, Zijun, Yifan Sun, Weicong Ding, Nikhil Rao, and Hui Xiong. 2018. "Dynamic Word Embeddings for Evolving Semantic Discovery." In *Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining*, 673–681. WSDM '18. New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/3159652.3159703.

Yip, Waiyee. 2021. "China Steps in to Regulate Brutal '996' Work Culture." *BBC News*, September 1, 2021, sec. China. https://www.bbc.com/news/world-asia-china-58381538.

Zhang, Yinxian. Forthcoming. "Passive Political Legitimacy: How the Chinese Online Sphere Changed from Challenging to Bolstering the State in the 2010s." *The China Journal*.

TABLES

Table 1: Discussion Volumes of the Forum (2011-2017)

Year	Total Question Count	Average Questions Posted per Day	Total Answer Count	Average Answers Posted per Day	Total Active Days	% of Active Days of the Year
2011	40	0.11	1478	4.05	38	0.10
2012	108	0.30	1236	3.39	87	0.24
2013	257	0.70	2046	5.61	172	0.47
2014	415	1.14	2266	6.21	236	0.65
2015	970	2.66	6722	18.42	332	0.91
2016	7336	20.10	66192	181.35	364	1.00
2017	2850	7.81	41489	113.67	361	0.99

Note: Discussions include all posts that are labeled by any of the following topic tags: “U.S. Politics,” “2016 U.S. Election”, “U.S. Society,” “U.S. Economy,” and “China-U.S. Comparison.”

Table 2: Descriptive Statistics of Model Variables

	Non-zero upvote (N=49230)	**Zero upvote (N=25849)**	**Overall (N=75079)**
Answer Upvote			
Mean (SD)	67.3 (401)	0 (0)	44.1 (326)
Median [Min, Max]	6.00 [1.00, 36100]	0 [0, 0]	2.00 [0, 36100]
Novelty Score (Standardised)			
Mean (SD)	0.127 (1.16)	-0.242 (0.511)	0.00 (1.00)
Median [Min, Max]	-0.258 [-1.54, 17.5]	-0.376 [-1.04, 12.4]	-0.316 [-1.54, 17.5]
Emotionality			
Extremely Positive	5090 (10.3%)	4207 (16.3%)	9297 (12.4%)
Moderately Positive	9009 (18.3%)	3921 (15.2%)	12930 (17.2%)
Slightly Positive	5595 (11.4%)	1388 (5.4%)	6983 (9.3%)
Neutral	7240 (14.7%)	5949 (23.0%)	13189 (17.6%)
Slightly Negative	7825 (15.9%)	2085 (8.1%)	9910 (13.2%)
Moderately Negative	8907 (18.1%)	3642 (14.1%)	12549 (16.7%)
Extremely Negative	5564 (11.3%)	4657 (18.0%)	10221 (13.6%)
Status: Author Follower Count (in 1,000 and logged)			
Mean (SD)	-1.67 (3.56)	-3.73 (2.74)	-2.38 (3.44)
Median [Min, Max]	-1.63 [-6.91, 7.93]	-3.82 [-6.91, 5.47]	-2.45 [-6.91, 7.93]
Status: If Author is Top Writer			
Not top writer	48607 (98.7%)	25838 (100.0%)	74445 (99.2%)
Top writer	623 (1.3%)	11 (0.0%)	634 (0.8%)
Lexical Diversity (Type Token Ratio)			
Mean (SD)	0.859 (0.132)	0.920 (0.104)	0.880 (0.126)
Median [Min, Max]	0.879 [0.0233, 1.00]	0.976 [0.0250, 1.00]	0.909 [0.0233, 1.00]
English Usage ($\frac{N(Eng\_words)}{N(Eng\_words)+N(Chn\_character)}$)			
Mean (SD)	0.0144 (0.0711)	0.00683 (0.0486)	0.0118 (0.0644)
Median [Min, Max]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]
Answer Length (Number of character, standardised)			
Mean (SD)	0.111 (1.18)	-0.212 (0.408)	0.00 (1.00)
Median [Min, Max]	-0.213 [-0.341, 62.2]	-0.293 [-0.341, 31.0]	-0.255 [-0.341, 62.2]
Author Gender			
Female	5459 (11.1%)	2548 (9.9%)	8007 (10.7%)
Male	37367 (75.9%)	19101 (73.9%)	56468 (75.2%)
Unknown	6404 (13.0%)	4200 (16.2%)	10604 (14.1%)
Question Answer Count (in 100 and logged)			
Mean (SD)	-1.62(1.23)	-1.54 (1.24)	-1.66 (1.23)
Median [Min, Max]	-1.96 [-2.98, 4.01]	-1.71 [-2.98, 3.61]	-1.96 [-2.98, 4.01]
Question View Count (in 1,000,000 and logged)			
Mean (SD)	-3.11 (2.03)	-3.09 (2.08)	-3.19(2.04)
Median [Min, Max]	-3.17 [-6.68, 3.19]	-3.06 [-6.68, 2.76]	-3.28 [-6.68, 3.19]
Time Distance to Election (in day)			
Mean (SD)	43.9 (167)	53.9 (160)	47.4 (164)
Median [Min, Max]	0 [-306, 417]	2.00 [-306, 417]	1.00 [-306, 417]
Topic Category			
2016 U.S. Election	30266 (61.5%)	15038 (58.2%)	45304 (60.3%)
China-U.S. Comparison	854 (1.7%)	630 (2.4%)	1484 (2.0%)
U.S. Politics	16197 (32.9%)	9283 (35.9%)	25480 (33.9%)
U.S. Society	370 (0.8%)	134 (0.5%)	504 (0.7%)
U.S. Economy	1543 (3.1%)	764 (3.0%)	2307 (3.1%)

Table 3: Correlation of Key Continuous Variables

	Answer Upvote	Novelty	Author Follower(logged)	Lexical Diversity	Eng Usage	Answer Length
Answer Upvote	1.0000					
Novelty	0.2045	1.0000				
Author Follower (logged)	0.1292	0.1400	1.0000			
Lexical Diversity	-0.1443	-0.5373	-0.1733	1.0000		
Eng Usage	0.0222	0.0145	0.0277	-0.1471	1.0000	
Answer Length	0.1875	0.6830	0.1395	-0.5312	0.2555	1.0000

Table 4: Modeling Results (Negative Binomial Component of ZINB)

	Dependent variable: Answer Upvote					
	Models					
	(1)	(2)	(3)	(4)	(5)	(6)
Novelty	0.578***	0.775***	0.546***	0.367***	0.311***	0.239***
	(0.020)	(0.024)	(0.025)	(0.030)	(0.030)	(0.031)
Novelty^2		−0.042***	−0.030***	−0.028***	−0.026***	−0.024***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Emotionality (Ref: Neutral)						
Extremely Positive	−0.197***	−0.186***	−0.199***	−0.188***	−0.184***	−0.054
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Moderately Positive	0.598***	0.525***	0.350***	0.397***	0.321***	0.343***
	(0.041)	(0.041)	(0.042)	(0.042)	(0.042)	(0.041)
Slightly Positive	0.841***	0.720***	0.433***	0.446***	0.364***	0.430***
	(0.049)	(0.049)	(0.051)	(0.051)	(0.052)	(0.051)
Slightly Negative	0.950***	0.852***	0.598***	0.594***	0.508***	0.512***
	(0.044)	(0.045)	(0.046)	(0.046)	(0.046)	(0.046)
Moderately Negative	0.727***	0.667***	0.450***	0.465***	0.363***	0.432***
	(0.040)	(0.040)	(0.042)	(0.042)	(0.042)	(0.042)
Extremely Negative	0.004	0.018	0.026	0.030	−0.023	0.044
	(0.044)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Author Follower Count (in 1,000 and logged)	0.150***	0.150***	0.145***	0.143***	0.211***	0.198***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Author Follower Count (in 1,000 and logged)^2					0.017***	0.017***
					(0.001)	(0.001)
Author is Top-writer (Ref: Not Top-writer)	0.818***	0.795***	0.740***	0.747***	0.110	0.091
	(0.120)	(0.120)	(0.120)	(0.120)	(0.126)	(0.125)
Lexical Diversity			−0.272***	−0.203***	0.523***	0.511***
			(0.013)	(0.014)	(0.072)	(0.080)
Lexical Diversity^2					−0.044***	−0.045***
					(0.005)	(0.005)
English Usage			0.162***	0.102***	0.439***	0.314***
			(0.024)	(0.024)	(0.044)	(0.044)
English Usage^2					−0.065***	−0.049***
					(0.006)	(0.006)
Control: Answer Length				0.377***	0.401***	0.411***
				(0.041)	(0.039)	(0.040)
Other Control Variables	No	No	No	No	No	Yes
Constant	−9.004	−11.184	−9.401	−11.045	−14.663	−15.122
	(11.754)	(36.945)	(53.644)	(89.251)	(126.223)	(201.603)
Observations	75,079	75,079	75,079	75,079	75,079	75,079
Bayesian Inf. Crit.	479,405.800	478,957.500	477,814.300	477,490.000	476,057.300	470,298.100

Note: *p<0.05; **p<0.01; ***p<0.001

To show coefficients Lexical Diversity and English Usage have been multiplied by 10.

FIGURES

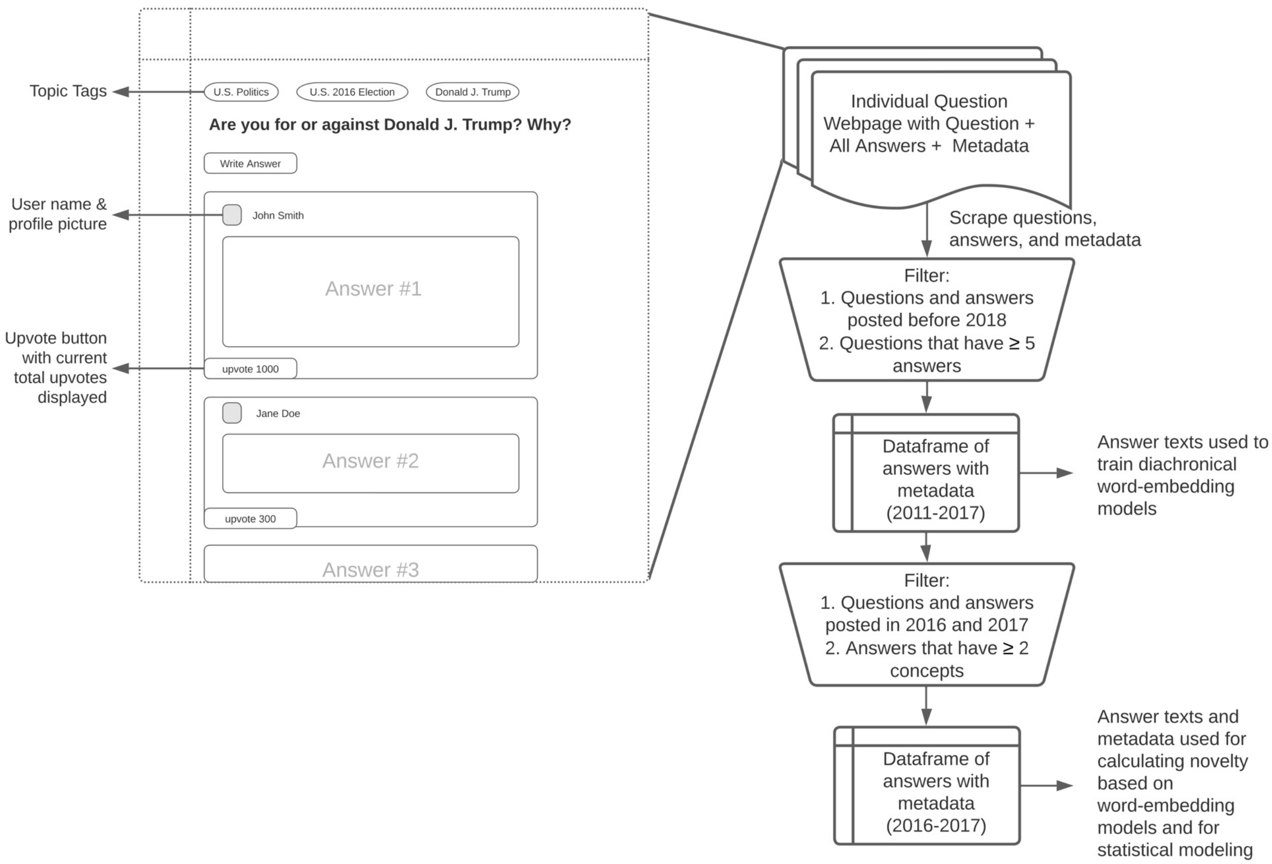

Figure 1 Data Collection & Subset Workflow with Demo of Webpage Structure

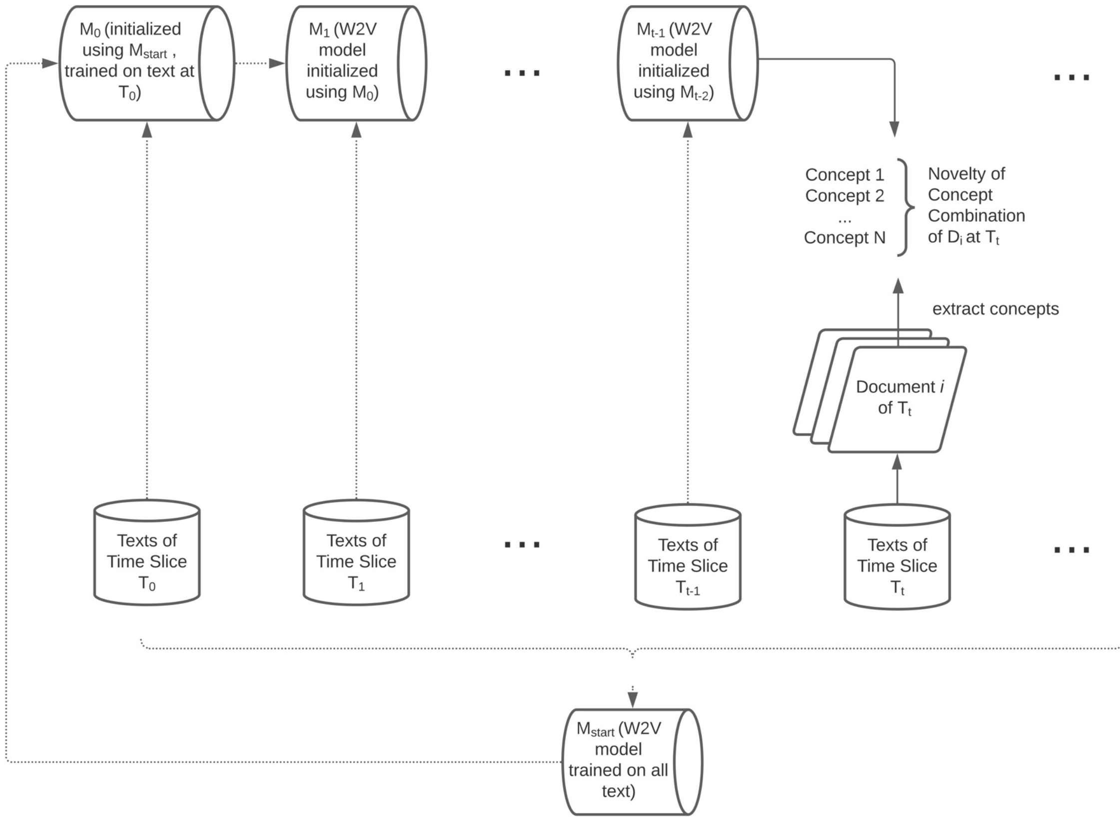

Figure 2 Diachronic Measure of Novelty

Note: Novelty of a document D_i at time T_t is calculated based on the concepts extracted from the document. The word-embedding model used to calculate novelty at time T_t is Model M_{t-1} . This model is trained using its previous time point's W2V model (M_{t-2}) for initialization and its own year-week sub-corpus (texts of time slice T_{t-1}) for training. The final novelty score of document D_i is the bootstrapped mean derived from 150 iterations of the above-described computation.

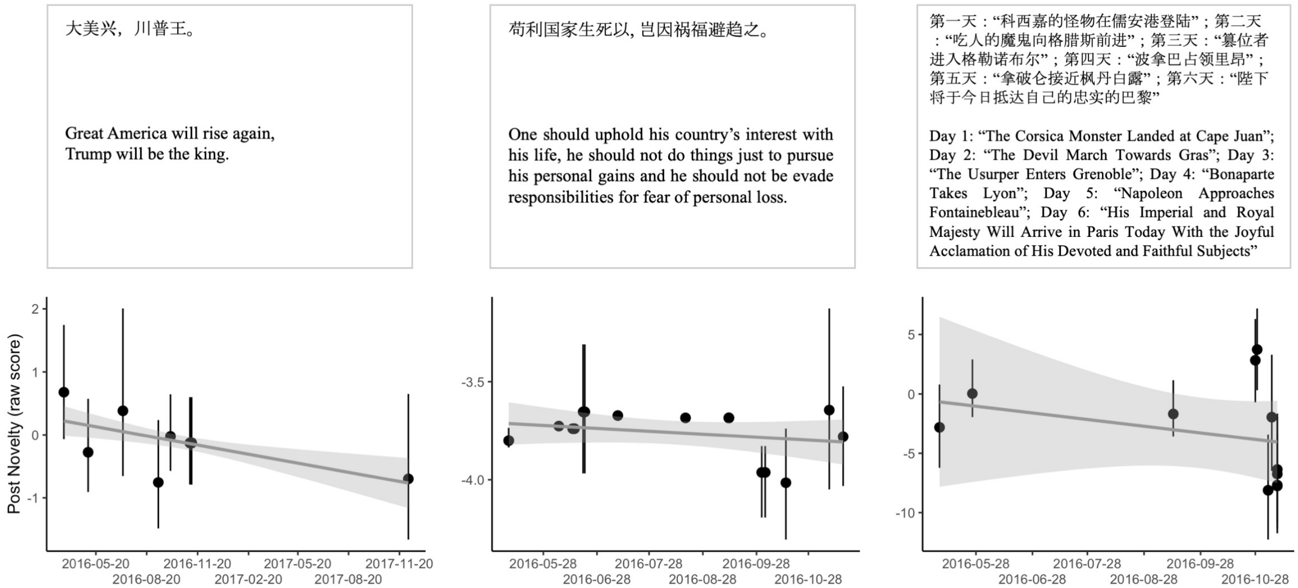

Figure 3 Post Content and Novelty Score Across Time of the Trump King Post (Left), the Chinese Political Motto Post (Middle), and the Napoleon Post (Right)

Note: Error bar displays confidence interval at 5% and 95% using bootstrapping samples. Trend fitted using OLS estimation.

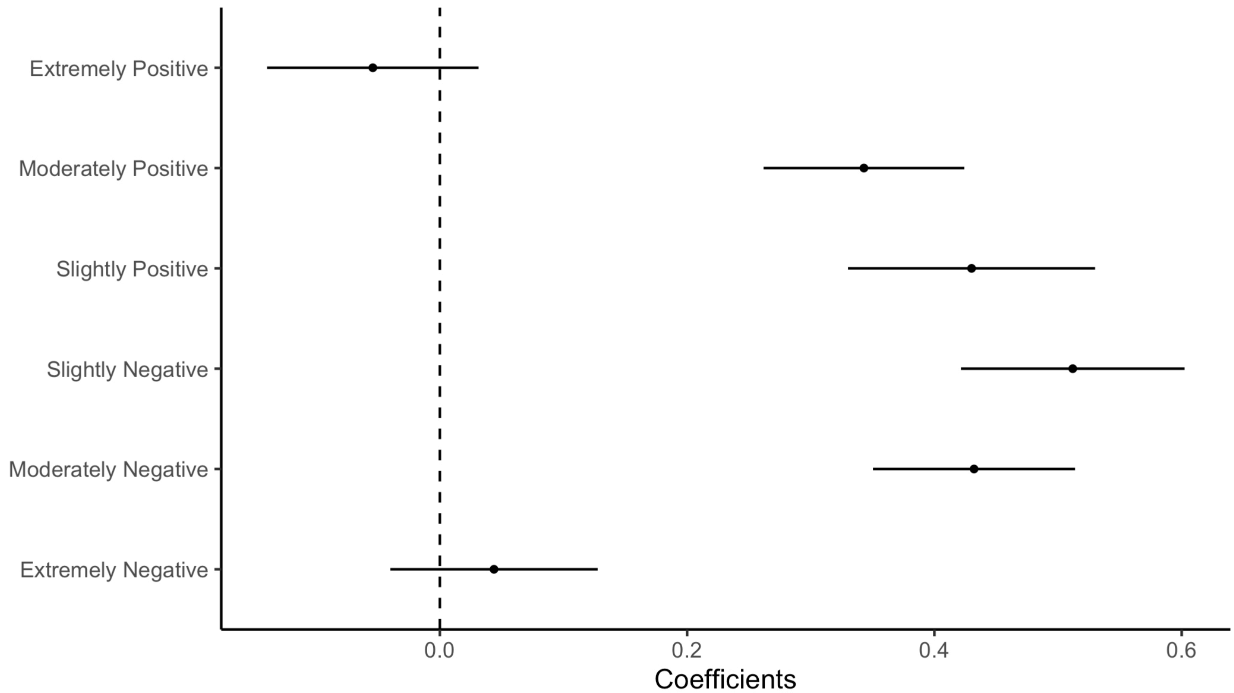

Figure 4 Model 6 Coefficients of Emotionality Dummies

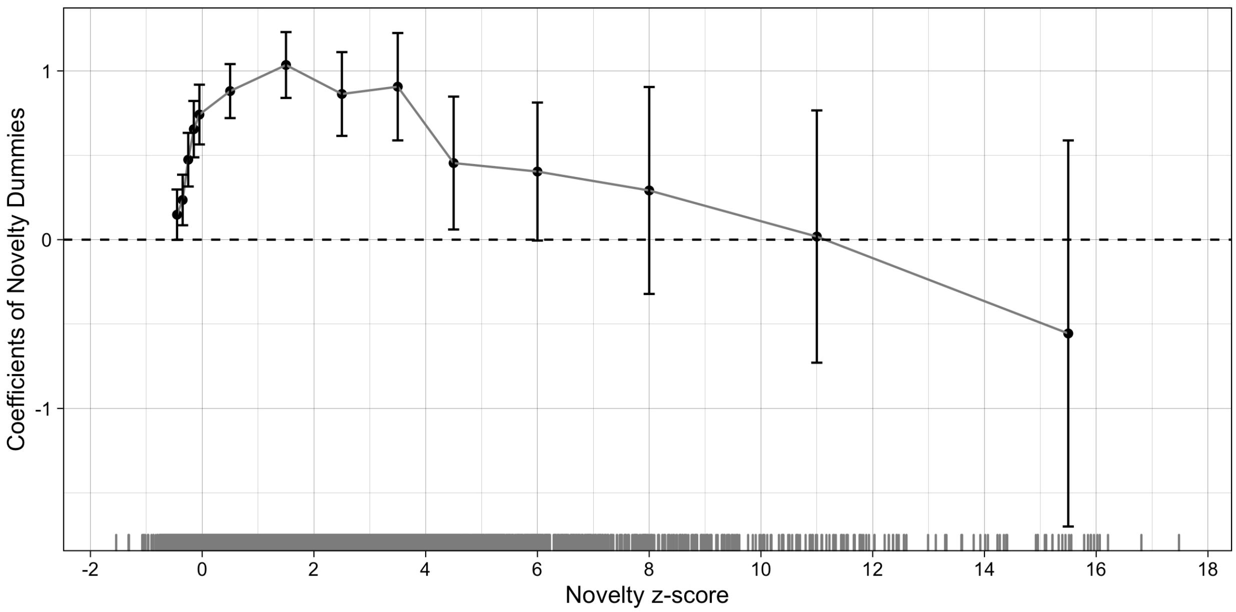

Figure 5 Coefficients of Model 6 Using Novelty Dummies

Note: Dummy variables indicate which score range an observation belongs to. The reference category is the lowest score range (from -2 to -0.5). The x-axis value is the respective dummy's midpoint score. The rug plot shows the observations at each score value.

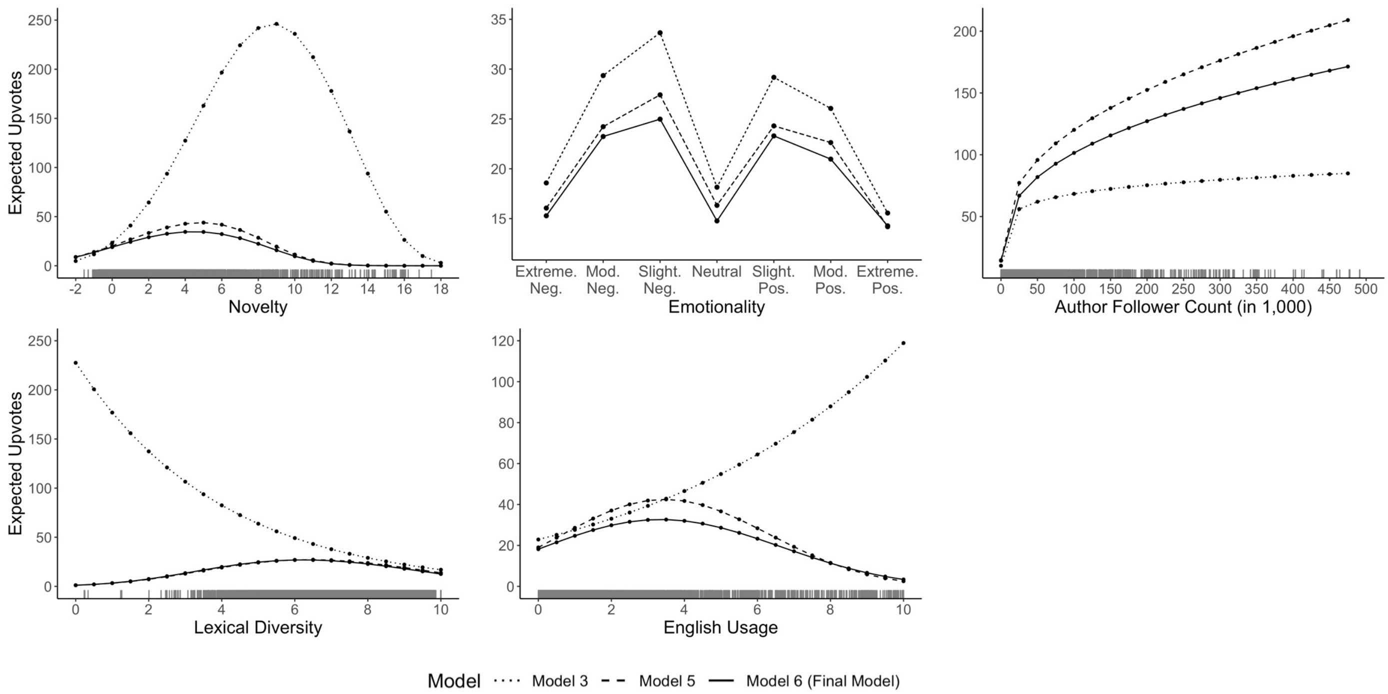

Figure 6 Predicted Number of Upvotes of Key IVs and Controls, by Models

Notes: Model 3 includes all four sets of theoretical predictors but does not control for post length; Model 5 added squared terms for Lexical Diversity and English Usage, and also controlled for post length; Model 6 added all other control variables on top of Model 5.

APPENDIX

A. Distribution of the Dependent Variable (Answer Upvotes)

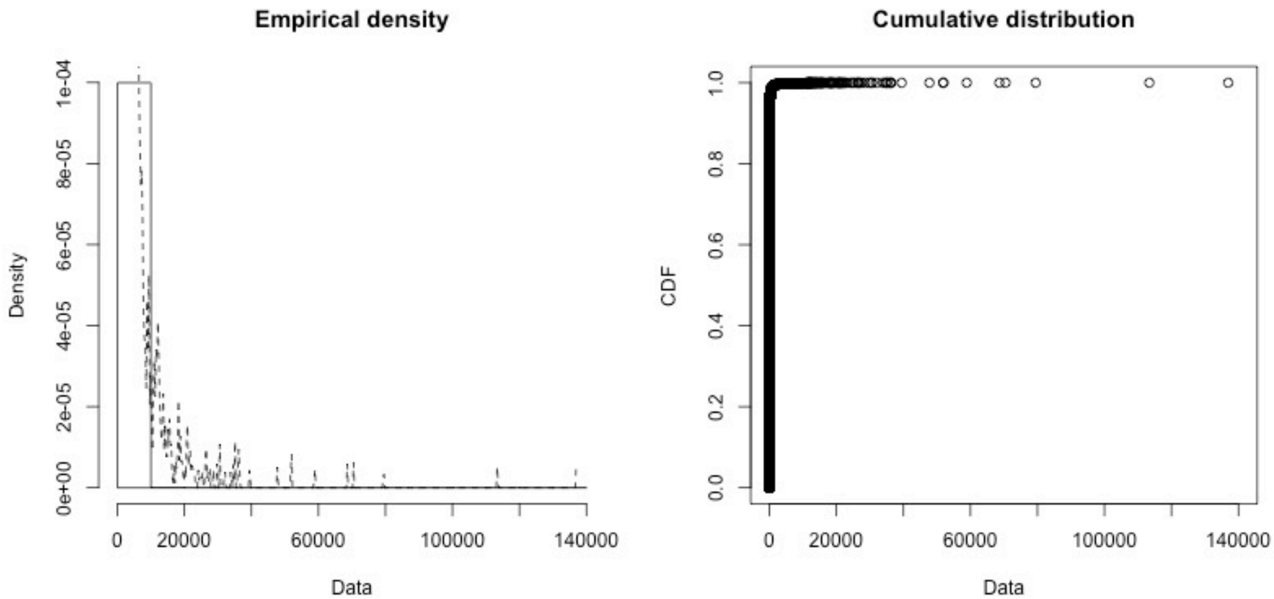

Figure A1 Distribution of the Dependent Variable (Answer Upvotes)

B. Modeling Results with All Variables Displayed

Table B1: Modeling Results with All Variables Displayed

	Dependent variable: Answer Upvote					
	Models					
	(1)	(2)	(3)	(4)	(5)	(6)
Novelty	0.578*** (0.020)	0.775*** (0.024)	0.546*** (0.025)	0.367*** (0.030)	0.311*** (0.030)	0.239*** (0.031)
Novelty^2		−0.042*** (0.002)	−0.030*** (0.002)	−0.028*** (0.002)	−0.026*** (0.002)	−0.024*** (0.002)
Emotionality (Ref: Neutral)						
Extremely Positive	−0.197*** (0.044)	−0.186*** (0.044)	−0.199*** (0.044)	−0.188*** (0.044)	−0.184*** (0.044)	−0.054 (0.044)
Moderately Positive	0.598*** (0.041)	0.525*** (0.041)	0.350*** (0.042)	0.397*** (0.042)	0.321*** (0.042)	0.343*** (0.041)
Slightly Positive	0.841*** (0.049)	0.720*** (0.049)	0.433*** (0.051)	0.446*** (0.051)	0.364*** (0.052)	0.430*** (0.051)
Slightly Negative	0.950*** (0.044)	0.852*** (0.045)	0.598*** (0.046)	0.594*** (0.046)	0.508*** (0.046)	0.512*** (0.046)
Moderately Negative	0.727*** (0.040)	0.667*** (0.040)	0.450*** (0.042)	0.465*** (0.042)	0.363*** (0.042)	0.432*** (0.042)
Extremely Negative	0.004 (0.044)	0.018 (0.043)	0.026 (0.043)	0.030 (0.043)	−0.023 (0.043)	0.044 (0.043)
Author Follower Count (in 1,000 and logged)	0.150*** (0.003)	0.150*** (0.003)	0.145*** (0.003)	0.143*** (0.003)	0.211*** (0.005)	0.198*** (0.005)
Author Follower Count (in 1,000 and logged)^2					0.017*** (0.001)	0.017*** (0.001)
Author is Top-writer (Ref: Not Top-writer)	0.818*** (0.120)	0.795*** (0.120)	0.740*** (0.120)	0.747*** (0.120)	0.110 (0.126)	0.091 (0.125)
Lexical Diversity			−0.272*** (0.013)	−0.203*** (0.014)	0.523*** (0.072)	0.511*** (0.080)
Lexical Diversity^2					−0.044*** (0.005)	−0.045*** (0.005)
English Usage			0.162*** (0.024)	0.102*** (0.024)	0.439*** (0.044)	0.314*** (0.044)
English Usage^2					−0.065*** (0.006)	−0.049*** (0.006)
Answer Length				0.377*** (0.041)	0.401*** (0.039)	0.411*** (0.040)
Author Gender Female (Ref: Male)						−0.095* (0.038)
Author Gender Unknown (Ref: Male)						−0.160*** (0.035)
Question View Count (in million and logged)						0.529*** (0.015)
Question Answer Count (in 100 and logged)						−0.248*** (0.020)
Topic (Ref: U.S. Economy)						
Topic 2016 U.S. Election						0.624*** (0.066)
Topic China-U.S. Comparison						0.191 (0.103)
Topic: U.S. Politics						0.698*** (0.065)
Topic: U.S. Society						−0.314* (0.139)
Time Distance to Election (in days)						−0.001*** (0.0001)
Constant	−9.004 (11.754)	−11.184 (36.945)	−9.401 (53.644)	−11.045 (89.251)	−14.663 (126.223)	−15.122 (201.603)
Observations	75,079	75,079	75,079	75,079	75,079	75,079
Bayesian Inf. Crit.	479,405.800	478,957.500	477,814.300	477,490.000	476,057.300	470,298.100

Note: *p<0.05; **p<0.01; ***p<0.001 (two-tailed tests)
To show coefficients, Lexicon Diversity and English Usage are timed by 10.

C. Descriptive Statistics and Modeling Result Using Continuous Emotionality Measure

In these models, the continuous emotionality measure is the absolute value of the sentiment score, and its value ranges from 0 to 1, with 0 representing least intense emotion and 1 representing most intense emotion.

Table C1: Descriptive Statistics of Continuous Emotionality Measure

	Non-zero upvote (N=49230)	**Zero upvote (N=25849)**	**Overall (N=75079)**
Emotionality (Continuous)			
Mean (SD)	0.398 (0.366)	0.481 (0.414)	0.426 (0.385)
Median [Min, Max]	0.290 [0, 1.00]	0.330 [0, 1.00]	0.330 [0, 1.00]

Table C2: Correlation of Key Variables using Continuous Emotionality Measure

	Answer Upvote	Novelty	Emotionality	Author Follwer (Logged)	Lexical Diversity	Eng Usage	Answer Length
Answer Upvote	1.0000						
Novelty	0.2045	1.0000					
Emotionality	-0.0542	-0.2294	1.0000				
Author Follwer (Logged)	0.1292	0.1400	-0.0706	1.0000			
Lexical Diversity	-0.1443	-0.5373	0.2583	-0.1733	1.0000		
Eng Usage	0.0222	0.0145	-0.0195	0.0277	-0.1471	1.0000	
Answer Length	0.1875	0.6830	-0.1764	0.1395	-0.5312	0.2555	1.0000

Table C3: Modeling Results using Continuous Emotionality Measure

	Dependent variable: Answer Upvote					
	Models					
	(1)	(2)	(3)	(4)	(5)	(6)
Novelty	0.754^{***} (0.022)	0.911^{***} (0.023)	0.594^{***} (0.025)	0.409^{***} (0.030)	0.339^{***} (0.030)	0.270^{***} (0.031)
Novelty^2		-0.050^{***} (0.002)	-0.034^{***} (0.002)	-0.031^{***} (0.002)	-0.028^{***} (0.002)	-0.027^{***} (0.002)
Emotionality	-0.059^{***} (0.004)	0.166^{***} (0.014)	0.113^{***} (0.014)	0.127^{***} (0.014)	0.101^{***} (0.014)	0.107^{***} (0.013)
Emotionality^2		-0.021^{***} (0.001)	-0.014^{***} (0.001)	-0.015^{***} (0.001)	-0.013^{***} (0.001)	-0.012^{***} (0.001)
Author Follower Count (in 1,000 and logged)	0.153^{***} (0.003)	0.153^{***} (0.003)	0.146^{***} (0.003)	0.144^{***} (0.003)	0.214^{***} (0.005)	0.200^{***} (0.005)
Author Follower Count (in 1,000 and logged)^2					0.018^{***} (0.001)	0.017^{***} (0.001)
Author is Top-writer (Ref: Not Top-writer)	0.824^{***} (0.121)	0.781^{***} (0.120)	0.736^{***} (0.120)	0.749^{***} (0.121)	0.088 (0.126)	0.071 (0.125)
Lexical Diversity			-0.310^{***} (0.013)	-0.233^{***} (0.014)	0.638^{***} (0.069)	0.644^{***} (0.076)
Lexical Diversity^2					-0.053^{***} (0.004)	-0.055^{***} (0.005)
English Usage			0.145^{***} (0.024)	0.083^{***} (0.024)	0.425^{***} (0.044)	0.307^{***} (0.044)
English Usage^2					-0.066^{***} (0.006)	-0.050^{***} (0.006)
Control: Answer Length				0.405^{***} (0.043)	0.429^{***} (0.040)	0.443^{***} (0.041)
Other Control Variables	No	No	No	No	No	Yes
Constant	-8.530 (12.663)	-5.735^{*} (2.853)	-5.699 (11.013)	-11.088 (115.129)	-11.604 (24.991)	-15.221 (187.152)
Observations	75,079	75,079	75,079	75,079	75,079	75,079
Bayesian Inf. Crit.	480,745.200	479,466.600	478,053.500	477,695.300	476,166.300	470,421.400

Note: *p<0.05; **p<0.01; ***p<0.001
To show coefficients Emotionality, Lexicon Diversity and English Usage have been multiplied by 10.

D. Sensitivity Test (W2V Minimum Word Frequency = 0 vs. 10)

Table D1: Modeling Result Comparison, W2V using minimum word frequency = 0 vs. = 10

	Dependent variable: Answer Upvote	
	Model	
	(1)	(2)
Novelty (min0win20)	0.239***	
	(0.031)	
Novelty $(\text{min0win20})^2$	−0.024***	
	(0.002)	
Novelty (min10win20)		0.386***
		(0.037)
Novelty $(\text{min10win20})^2$		−0.034***
		(0.002)
Emotionality (Ref: Neutral)		
Extremely Positive	−0.054	−0.050
	(0.044)	(0.044)
Moderately Positive	0.343***	0.336***
	(0.041)	(0.041)
Slightly Positive	0.430***	0.410***
	(0.051)	(0.051)
Slightly Negative	0.512***	0.490***
	(0.046)	(0.046)
Moderately Negative	0.432***	0.416***
	(0.042)	(0.042)
Extremely Negative	0.044	0.050
	(0.043)	(0.043)
Author Follower Count (in 1,000 and logged)	0.198***	0.198***
	(0.005)	(0.005)
Author Follower Count $(\text{in 1,000 and logged})^2$	0.017***	0.017***
	(0.001)	(0.001)
Author is Top-writer (Ref: Not Top-writer)	0.091	0.102
	(0.125)	(0.125)
Lexical Diversity	0.511***	0.440***
	(0.080)	(0.082)
Lexical Diversity^2	−0.045***	−0.040***
	(0.005)	(0.005)
English Usage	0.314***	0.331***
	(0.044)	(0.044)
English Usage^2	−0.049***	−0.049***
	(0.006)	(0.006)
Control: Answer Length	0.411***	0.284***
	(0.040)	(0.043)
Other Controls	Yes	Yes
Constant	−15.122	−14.812
	(201.603)	(198.343)
Observations	75,079	75,079
Bayesian Inf. Crit.	470,298.100	470,223.800
Note:	*p<0.05; **p<0.01; ***p<0.001 (two-tailed tests)	

E. Modeling Results of the Novelty-Dummy Model

Table E1. Novelty-Dummy Modeling Results

	Dependent variable: Answer Upvote
	Novelty Dummies Model
Novelty (Ref: Novelty Score ≤ -0.5)	
Novelty Score(-0.5,-0.4]	0.148
	(0.076)
Novelty Score(-0.4,-0.3]	0.235**
	(0.076)
Novelty Score(-0.3,-0.2]	0.474***
	(0.081)
Novelty Score(-0.2,-0.1]	0.655***
	(0.085)
Novelty Score(-0.1,0]	0.741***
	(0.090)
Novelty Score(0,1]	0.881***
	(0.082)
Novelty Score(1,2]	1.035***
	(0.100)
Novelty Score(2,3]	0.863***
	(0.127)
Novelty Score(3,4]	0.906***
	(0.162)
Novelty Score(4,5]	0.454*
	(0.201)
Novelty Score(5,7]	0.404
	(0.209)
Novelty Score(7,9]	0.292
	(0.313)
Novelty Score(9,13]	0.018
	(0.381)
Novelty Score ≥ 13	-0.556
	(0.584)
Emotionality (Ref: Neutral)	
Extremely Positive	-0.030
	(0.044)
Moderately Positive	0.200***
	(0.042)
Slightly Positive	0.271***
	(0.052)
Slightly Negative	0.340***
	(0.048)
Moderately Negative	0.287***
	(0.043)
Extremely Negative	0.085*
	(0.043)
Author Follower Count (in 1,000 and logged)	0.196***
	(0.005)
Author Follower Count (in 1,000 and logged)^2	0.016***
	(0.001)
Author is Top-writer (Ref: Not Top-writer)	0.114
	(0.125)
Lexical Diversity	0.197*
	(0.096)
Lexical Diversity^2	-0.022***
	(0.006)
English Usage	0.312***
	(0.044)
English Usage^2	-0.046***
	(0.006)
Control: Answer Length	0.433***
	(0.039)
Other Controls	Yes
Constant	-14.038
	(206.711)
Observations	75,079
Bayesian Inf. Crit.	470,053.900
Note:	*p<0.05; **p<0.01; ***p<0.001 (two-tailed tests)

F. Modeling Results Using Only U.S. Politics and 2016 U.S. Election Posts

Table F1: Modeling Results of Posts tagged with "U.S. Politics" or "2016 U.S. Election" Only

	Dependent variable: Answer Upvote					
	Models					
	(1)	(2)	(3)	(4)	(5)	(6)
Novelty	0.573***	0.774***	0.532***	0.336***	0.283***	0.226***
	(0.021)	(0.024)	(0.026)	(0.031)	(0.031)	(0.032)
Novelty^2		−0.042***	−0.030***	−0.028***	−0.025***	−0.024***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Emotionality (Ref: Neutral)						
Extremely Positive	−0.200***	−0.188***	−0.202***	−0.189***	−0.186***	−0.049
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Moderately Positive	0.627***	0.553***	0.371***	0.422***	0.342***	0.383***
	(0.042)	(0.042)	(0.043)	(0.043)	(0.044)	(0.043)
Slightly Positive	0.830***	0.703***	0.421***	0.426***	0.336***	0.429***
	(0.051)	(0.051)	(0.053)	(0.053)	(0.053)	(0.053)
Slightly Negative	0.964***	0.865***	0.602***	0.596***	0.506***	0.549***
	(0.046)	(0.046)	(0.047)	(0.047)	(0.048)	(0.047)
Moderately Negative	0.735***	0.674***	0.445***	0.460***	0.356***	0.447***
	(0.041)	(0.042)	(0.043)	(0.043)	(0.044)	(0.043)
Extremely Negative	0.006	0.021	0.028	0.034	−0.023	0.063
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.044)
Author Follower Count (in 1,000 and logged)	0.149***	0.149***	0.144***	0.142***	0.210***	0.198***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Author Follower Count (in 1,000 and logged)^2					0.017***	0.017***
					(0.001)	(0.001)
Author is Top-writer (Ref: Not Top-writer)	0.860***	0.838***	0.779***	0.788***	0.155	0.106
	(0.126)	(0.126)	(0.126)	(0.126)	(0.132)	(0.131)
Lexical Diversity			−0.286***	−0.207***	0.546***	0.530***
			(0.013)	(0.015)	(0.073)	(0.081)
Lexical Diversity^2					−0.046***	−0.046***
					(0.005)	(0.005)
English Usage			0.146***	0.082***	0.406***	0.296***
			(0.024)	(0.024)	(0.045)	(0.044)
English Usage^2					−0.063***	−0.048***
					(0.006)	(0.006)
Control: Answer Length				0.434***	0.456***	0.444***
				(0.045)	(0.043)	(0.044)
Other Control Variables	No	No	No	No	No	Yes
Constant	−8.685	−13.281	−5.657	−6.033	−14.244	−14.469
	(10.464)	(110.108)	(9.203)	(7.799)	(103.755)	(199.269)
Observations	70,784	70,784	70,784	70,784	70,784	70,784
Bayesian Inf. Crit.	453,985.300	453,563.900	452,439.600	452,092.400	450,758.300	445,570.100

Note: *p<0.05; **p<0.01; ***p<0.001 (two-tailed tests)
To show coefficients Lexicon Diversity and English Usage have been multiplied by 10.

G. Post Length Comparison of the Q&A Forum and Weibo

Table G1 shows the average post length on the Q&A forum and Weibo from December 2019 to February 2020. The Q&A forum data is scraped by the author for this study, which are political discussions about U.S. politics. The Weibo data is drawn from Lu, Pan and Xu's (2021) study on Weibo's discussion about COVID-19 which used the data provided by Fu and Zhu (2020). While these two datasets are not comparable in terms of the topics they engage with, the Weibo data, which contains more than 1 million posts, provides a valid sample that represents the average quality of Weibo posts. In both data, URLs are removed from the text. In addition, hashtags as well as retweeted portion of the content are removed from the Weibo text.

As shown in Table G1, the Q&A forum's posts are consistently longer than those of Weibo. In the January and February 2020, the Q&A forum posts even doubled the length of Weibo posts.

Table G1: Average Post Length Comparison

	Q&A Forum	**Weibo**
2019-12	194.0 (N=2,947)	102.8 (N=14,363)
2020-01	219.2 (N=3,534)	87.8 (N=359,555)
2020-02	242.4 (N=1,502)	93.9 (N=856,435)

Note: table shows mean post length calculated by number of characters. Numbers in the parenthesis are sizes of the sample used to calculate the mean.

H. CGSS (Chinese General Social Survey) 2018 Data on English-speaking Skills

Table H1. Weighted Count: What is the level of your English speaking skill? (N = 12,758)

Highest Education	Cannot Understand	Poor	So-So	Good	Great	Don't Know/Refuse to Answer	Total
Primary school or lower	4,011	164	49	10	1	4	4,238
Middle School	3,086	742	109	5	5	5	3,951
Vocational or technical high school	461	381	107	11	1	0	961
High school	772	581	279	28	3	1	1,663
3-year College	165	377	209	28	4	1	784
4-year University	75	335	457	140	26	0	1,033
Graduate or higher	2	14	53	41	18	0	127
Total	8,570	2,595	1,264	262	57	11	12,758

Source: Chinese General Social Survey (CGSS) 2018

Table H2. Percentage of respondents whose subjective evaluation of English Speaking level is above "poor" (Calculated using weighted count in Table H1)

Highest Education	Percentage
Primary school or lower	1.4%
Middle School	3.0%
Vocational or technical high school	12.4%
High school	18.6%
3-year College	30.7%
4-year University	60.3%
Graduate or higher	87.3%
Overall	12.4%

Source: Chinese General Social Survey (CGSS) 2018