

**Three International Studies Computational Social Science Inquiries Examining Large
Corpora of Natural Data**

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Abstract

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Computational methods provide novel and important approaches for social science inquiries. Due to the ever-increasing availability of large sets, or corpora, of mixed qualitative/quantitative data to the social scientist, algorithmic approaches provide effective opportunities to induce findings about social phenomenon. Here, such approaches are used to analyze three diverse areas of inquiry using related methods. First, energy investment from the People's Republic of China in the Islamic Republic of Pakistan is modeled utilizing an open procurement and bidding dataset from within Pakistan. This work posits a series of costly regulatory concessions made by Pakistan to obtain Chinese funding, and suggests an emerging model of Chinese concessionality in foreign lending. Second, propaganda generated on the social media site Twitter by the Russian Federation during the United States' 2016 Presidential Election is inductively modeled and subjected to quantitative sentiment and emotional analysis. This research suggests an information campaign designed to favor several conservative topics, but one that also pushed topic content from across the political spectrum. The Russian disinformation campaign also simultaneously emphasized increased anger within online political discourse. Third, a large original corpus of YouTube comments drawn from

the “QAnon” political movement is analyzed. This research indicates a host of novel conjectural characteristics regarding this movement, including that the largest proportion of discussion within the dataset is concerned with the alleged sexual abuse of underaged minors by US political and media actors. This analysis also highlights as yet unexplored international relations beliefs within the movement, and suggests that such discussion is proportionally most concerned with the People’s Republic of China. Each of these projects raise numerous questions for further research and also ultimately validate the utilization of inductive algorithms like topic models for future scientific inquiries into social phenomena.

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Dedication:

To Anne, the love of my life and the only reason this ever got finished.

The China Pakistan Economic Corridor as a Challenge to Pakistan's Regulatory Sovereignty

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Abstract:

On April 20th, 2015 the governments of China and Pakistan announced a series of project agreements focused on infrastructure and energy development within Pakistan. Total project funding included within the China Pakistan Economic Corridor [CPEC] has reached over 46 billion dollars, at least 35 billion of which is devoted to the energy sector. If all of these investments materialize, CPEC would equal all foreign direct investment inflows into Pakistan from 1970 to 2017. Pakistan's energy deficits and the large energy focus of CPEC makes it important to ascertain the impact of Chinese energy project funding on the country. Through qualitative and text-as-data examination of contracts from National Electric Power Regulatory Authority (NEPRA) several conclusions regarding these contracts become evident: 1. Atypical lobbying campaigns to NEPRA accompanied CPEC. 2. CPEC funding is associated with the adoption of Chinese state-owned insurance for new energy projects. 3. CPEC funding is causally connected to concessions for Chinese actors in regards to tariffing, taxation and project implementation. These factors indicate CPEC is associated with shifts in the regulatory sovereignty of Pakistan's energy system. This paper posits that such changes represent broader preferences in Chinese foreign lending within the One Belt One Road policy.

Key Words: China Pakistan Economic Corridor, One Belt One Road, Chinese investment, energy investment, regulatory control.

In memory of my friend, Greg Shtraks

Introduction and Research Question:

The first decade-plus of the twenty first century has seen remarkable changes in the international political economy of foreign investment. Large development projects and project funding choices represent key strategic indicators of what regimes prioritize, particularly regimes with closely-tied economic and political structures. Project selection, imposed conditions, and resulting institutional changes caused by investment all convey important strategic information. For example, western lenders often impose good governance conditions that indicate underlying political, economic and moral interests, and these conditions can substantially change the institutions of a given recipient state.

The entrance of the People's Republic of China into the international project financing picture necessitates viewing PRC lending with a similar critical lens. Both the PRC's overall investment strategy as well as the impacts of this strategy on Global South states should be assessed by social scientists. However, reliability problems with Chinese economic and financial data are well established. Many researchers believe these data are at best unverifiable and at worst inaccurate (Plekhanov, 2017 and Koch-Weser, 2013). Work comparing GDP to energy utilization suggests key national statistics are fabricated (Yu, 2014), while research into outward-bound investment data is problematized by the role of state-owned enterprises and the generally opaque nature of investments.

In the face of these data challenges, Pakistani regulators provide an unexpected solution. The National Electric Power Regulatory Authority (NEPRA) data analyzed here originates from a regulator influenced by both decades of open procurement rule building as well as (more recently) Chinese investment. NEPRA's data availability is complemented by the growing relationship between China and Pakistan through One-Belt-One-Road's China Pakistan Economic Corridor (CPEC). On April 20th, 2015 China and Pakistan announced a series of project agreements focused on

infrastructure and energy development within Pakistan totaling over 46 billion dollars, with at least 35 billion devoted to the energy sector. If all of these investments materialize, CPEC would equal all the foreign direct investment inflows into the country from 1970 to the present. Critically, the requirements, conditions, payment structures, insurance information and environmental/social remediation details for all energy projects within CPEC are available through NEPRA archives, presenting a data-acquisition “end around” through which Chinese development lending goals can be ascertained.

Examining NEPRA files regarding CPEC projects provides important conclusions regarding both OBOR/CPEC and China’s broader outward development lending policy. First, CPEC is associated with an extensive lobbying effort to influence regulatory decision making within Pakistan. Second, CPEC appears *causally associated* with mandatory adoption of Chinese state-owned project insurance for development projects, a substantial change from previous open bidding requirements. Third, CPEC funding is causally connected to concessions given to Chinese actors for pricing, tariffing, taxation and project implementation. These conclusions are apparent both through case study review and through repeatable text-as-data tools like topic modeling. These data suggest Pakistan ceded controls over regulatory decision-making regarding its own energy and infrastructure spending. Explaining why Pakistan would take this extremely unusual step to cede key regulatory controls requires further investigation.

Hypotheses:

To address the question of variance in Pakistan’s regulatory landscape, several hypotheses present themselves as both feasible and informative. The null hypothesis in regards to Pakistan’s regulatory capacity must be that China’s foreign investment in Pakistan has a random relationship with Pakistan’s domestic regulatory control. Any research program must begin by assuming no relationship between these two variables.

Building on the available literature on China's domestic development model¹ several hypotheses present themselves:

1. If CPEC/Chinese funding is present for projects, then regulatory and procurement process impacts and captures are more likely to occur.²
2. If lending exists in a "best case" bilateral scenario (where China and the recipient state have strong relationships/dependencies), regulatory and procurement impacts could be more evident.

Such a debate also necessitates a clear rubric for what constitutes procurement process impacts/captures. I propose a three-part delineation:

1. It denotes an abandonment of internationally agreed upon, IMF supported standards for open bidding and procurement (if these standards were in place previously).³
2. It signifies other financial contractual elements moving from more open/optional to closed/mandatory forms.
3. Increasingly the regulatory system will de-prioritize Pakistan's preferences, needs and desires for preferences of actors within the Chinese international project funding regime. This will be visible through tariff, project, and project insurance pricing that favors viability and long term ROI for Chinese actors.

Research Design, Data Collection, and Methodology:

This case study treats Pakistan's project bidding/procurement regulatory regime, and specifically the regulatory control of Pakistan's National Electric Power Regulatory Authority (NEPRA), as the dependent variable, and China's foreign development investment (specifically CPEC funding) as an independent variable. Concretely, the dependent variable here is Pakistan's most important electricity regulatory body. Abstractly, it is Pakistan's sovereignty regarding infrastructure decision making.

Both case study/temporal treatment effect and inductive topic model approaches are used.

¹ Key literature here includes, Hsueh, Roselyn. *China's Regulatory State, A New Strategy for Globalization*. Cornell University Press. 2011.

² This paper treats FAGIA/OFDI/ODI and other types of grant/non-grant funding as fungible for several reasons. Most important is the reality that these metrics were developed to describe OECD/"Western" lending, and do not suit Chinese government-sponsored investment particularly well. It is increasingly clear China does not conform to OECD standards for development flows (indeed, this is one of the larger motivations for this paper).

³ I refer frequently to such standards throughout this piece. It should be noted a reference to such a system is not a blanket endorsement of the morality or effectiveness of these processes.

For the purposes of CPEC’s impacts on Pakistan’s regulatory regime, causal conditions can be demonstrated by examining qualitative data in a chronological manner (figure 1). Data indicates that the causal condition of CPEC’s announcement is found only with specific regulatory outcomes. Additionally, such regulatory changes are not found without CPEC funding. Changes in the regulatory petition landscape can also be replicably discovered from the data using topic model analysis.



Fig 1: Diagram of time-series document analysis approach.

Traditional qualitative case study methods are particularly strong at indicating causal flows. However, it is increasingly important to supplement these designs with other quantitative methods so that inherent reproducibility problems can be addressed. Case approaches can paint a convincing case of X causing Y but such analysis (particularly in relation to large corpora of text data), invariably leads to research that over-relies on author area expertise. Fortunately, tools like topic models hold potential to reproducibly “discover topics from the data, rather than assume them” (Roberts et al. 2014). These methods inductively construct topics based on the co-occurrence of words within documents, and are often classified as *quantitative analysis of qualitative data*. These mixed measures allow for assessment of the impact of Chinese funding on Pakistan’s regulatory regime through large-n narrative/text data (“corpora”). Here, data collection process for both case study and topic model work revolves around the NEPRA tariff petition dataset hosted in PDF/JPEG format (publicly available at <https://www.nepra.org.pk/petitions.htm>). The NEPRA database begins in 2007 and currently consists of 321 documents at 1.01 GB of disk space. While the total number of documents here is moderate, the size of the corpus indicates complexity (many of the NEPRA documents are hundreds

of pages in length).

To utilize this data for topic model analysis, limit arbitrary topic number setting, lessen the impact of researcher bias, and to increase replicability, several standard pre-processing steps were undertaken. First, the NEPRA PDF's were converted into a computer-legible format (OCR). This process was optimized to minimize artifacts. OCR data can be characterized as “dirty” as these documents are full of signatures, stamps, seals, and printer marks. Data of this type needs to undergo extensive preparation before it can be fed into a topic model algorithm (Müller et al. 2018). This cleaning occurred in R using the Readtext/Quanteda packages. This process allows metadata to be read by R and for standard “preprocessing” measures to be taken (Welbers et al. 2017). Stopwords/symbols/hyperlink syntax were removed at this stage. Then, data was converted into a Document Frequency Matrix (DFM), allowing for data analysis with matrix/vector algebra (Welbers et al. 2017). Tokens were created using the SnowballC package (Bastin and Bouchet-Valat, 2014) through Quanteda. Finally, topic model analysis was done with the STM package.

Several technical choices are required for modeling and may be of interest to practitioners. K levels (total topics) were chosen to reflect current topic number ranges/means in the literature (Müller et al. 2018 and Roberts et al. 2018). The final models used here were informed by the STM package's defaults, using Lee and Mimno's (2014) *t*-SNE/anchor words algorithm. This algorithm, along with a “spectral” initialization, constructs plausible k values for data size (the STM package and Lee and Mimno both note this is not the “correct” k initialization, merely one that is well fitted to the data space). Visualizations of these estimates can be found in the appendix.

Literature Review

Area Studies Literature:

Recent scholarship notes a gap in the study of China-to-Global-South lending: “Curiously, analysis of China's role in facilitating or hindering development in the Global South (or even the effect

of the changing global context on China's own development) has not been a topic that SCID [*Studies in Comparative International Development*] authors have explored.” (Stallings and Evans 2016). There is a clear need to fully understand the impact of China's foreign investment policy on developing countries. The nature of this research topic also means it is critical to inform inquiry with a diverse combination of area and methods literatures.

China's domestic development policy has been the focus of extensive inquiry. Kroeber (2016) provides an overview of China's political economy of development that stresses “regulatory control”, but notes substantial regulatory work is given to state-owned firms. Other scholars (Helleiner and Kirshner, 2014 and Bell and Feng, 2013) have focused on the unique domestic political economy of the PRC. Works like these provide critical background in the levers of monetary and fiscal control within the Chinese system and also highlight the need for actors to go abroad for new projects.

In international development Whittaker (2010) notes that progression through economic development stages has changed in drastic ways, and contend “compressed development” is the new reality. All stages of development now occur simultaneously and states no longer move from one to the next, a trend evident in both China and Pakistan. Analysis of China's role in the international investment system is still in its infancy, but Kato et al. (2016) spend considerable time unpacking China's use of the “going out strategy” as support for domestic firms, as well as China's preference for bilateral loans. Commodities focused work like Economy and Levi's *By All Means Necessary* (2016) and Dollar's (2016) explorations of Chinese resource extraction in Africa differ from this inquiry in sectoral and geographic focus but are important for context building.

Other work on Chinese international development investment include Derek Scissors' policy analyst work at the American Enterprise Institute (Scissors, 2016). Work by Charles Wolf, Xiao Wang and Eric Warner at RAND attempts to compare Chinese lending and grants to more “traditional” sources of funding (Wolf, 2015). A related study bridging domestic and international foci is Sanderson

and Forsyth's look at the China Development Bank (Sanderson and Forsythe, 2013). Chinese outward investment is also analyzed in Gallagher and Irwin's *Exporting National Champions* (Gallagher and Irwin, 2014). These authors focus on China's role in the international lending economy, compare this role to other late developing states in East Asia, and problematize categorizing Chinese outward investment/development investment/OFDI in traditional ways. Increased PRC policy focus on (and SOE involvement in) outbound investment has necessitated a shift from traditional categories of aid and lending towards a broader *grant/non-grant style* funding conceptualization. Scholars have convincingly argued that separation of economic and political decision making (and thus the usage of investment categories) in this outward bound investment is impossible in the case of the PRC (Walter and Howie, 2011). The examination of the PRC's investment decisions in Pakistan conducted in this paper supports this conclusion.

Pakistan has seen an explosion of growth in non-grant style project funding, and such investment does not occur in a vacuum. A host of Pakistan-centric literature is necessary to incorporate into any study of Chinese investment in that country. Specific area studies literatures frame the development state case study of Pakistan. Naseemullah and Arnold (2013) claim that Pakistan already deals with "indirect" or "hybrid" oversight. USAID reports on focus specifically on Pakistan's government procurement apparatus (*USAID Trade Project*, 2014), while reports from Pakistan's Public Procurement Regulatory Authority and from the IMF also provide regulatory background (*IMF Report on the Observance of Standards and Codes*, 2000 and, *The National Procurement Strategy 2013-2016*, 2016). These sources detail a move from nationalized energy utilities to privatization to incremental reforms in procurement. Since the early 2000's Pakistan's federal government has emphasized improving procurement/bidding processes, working extensively with the IMF/WTO to undertake structural reforms (Mehra, 2016). In 2015 Pakistan even attained observer status in the WTO's Government Procurement Agreement (GPA). These reforms promote a regulatory structure that emphasizes

contracts, “value for money”, efficiency, accountability, and transparency (“Public Procurement Rules 2004”, 2004).

Computational Social Science Literature:

It is possible that the lack of rigorous description of the impacts of Chinese investment on developing states is an underdeveloped literature is in part due to the data and inference challenges inherent in the question. Causal conclusions are unlikely to emerge purely from statistical analysis of the datasets aggregating Chinese outward investments for both methodological and data-quality reasons. At the same time, simply interpreting qualitative case study information leaves much to be desired in terms of reproducible conclusions.

Increasingly, metrics from Psychology and Computer Science are available that help researchers split the difference between these approaches. Müller et al. (2018) note that topic modeling lies between “measurement-centric quantitative” and “interpretation-centric qualitative” methods. They note the potential for building new constructs identified from within large datasets and claim topic modeling represents “a new and complementary approach” to existing methods. This approach makes it possible to study inductively what occurs within the data, combining benefits of quantitative/qualitative approaches (Berente and Seidel, 2014; Tonidandel et al. 2016).

Rehurek and Sojka (2010) note that “The idea behind topical modelling is that texts in natural languages can be expressed in terms of a limited number of underlying concepts (or topics), a process which both improves efficiency [...] and eliminates noise [...].” As large corpora are becoming increasingly available these tools are also increasingly attractive to researchers who wish to make sense of large datasets.

Properly utilizing such models requires a brief aside. We build on Boumans and Trilling’s (2016) methodological approach that establishes “counting/dictionary”, “supervised

machine learning”, and “unsupervised machine learning” as the current schemes for text analysis. They order these approaches from most deductive to most inductive, respectively, and this paper uses unsupervised topic models for analysis. Topic models are generative probabilistic models which can be used to extract topics from collections of documents. These models investigate latent structures within texts without manual coding, thus reducing time and cost (Blei et al. 2003). Topic models assume observed words (“bags of words”) are generated by a joint-probability of two mixtures. Documents are a mixture of topics and topics are a mixture of words. Each topic is defined as a unique distribution of words, creating a word-topic matrix. This word-topic matrix provides a conditional probability for every word (row) given each latent topic (column). These probability distributions allow an observer to rank-order words by topic and to determine the most common words per topic and the most common topics per corpus (Wesslen, 2018). Topic models have been used to analyze academic material (Hall et al. 2008), climate change coverage (Jiang et al. 2017), online communities (Martin, 2017), country-level conflict data (Mueller and Rauh 2017), Congressional speeches (Quinn et al. 2010), and central bank documents (Hansen et al. 2014).⁴

Given the increasing availability of narrative data online, the China-to-Global South development research gap can be approached with replicable methods. Pakistan provides an excellent case study for new types of textual data analysis because of its (relative) historical emphasis on openness and transparency. Pakistan’s regulatory archives provide a space in which to dive into trends

⁴ For an in depth overview of this review/interpretation process see: Chang et al. 2009.

surrounding Chinese development lending, and the size of the dataset necessitates methods that reduce complexity into succinct outputs.

Project Insurance Case Study:

It should not come as a surprise that China's development investment policy goals are well-demonstrated in Pakistan. China and Pakistan have a long modern history of contact, beginning with Pakistan's recognition of the PRC in 1950 (Afridi and Bajoria, 2010). Following this, Chinese military assistance to Pakistan began in 1966 and economic cooperation was initiated in 1979. This relationship has intensified in recent decades as both states have recognized the strategic value and shared interests of the other. Xi Jinping's first visit to Islamabad in 2015 saw him compare visiting Pakistan to visiting the home of a brother. Chinese development investment in Pakistan thus provides a useful case study of what the PRC's international investment policy looks like with close partners. Chinese development investment in Pakistan demonstrates Chinese investment policy goals when political, historical, and social realities between host and recipient are most favorable.

What then does the PRC/Pakistan project finance relationship look like? By examining petitions from private, Chinese SOE and Government of Pakistan actors to NEPRA, novel conclusions about CPEC and Chinese funding in Pakistan begin to emerge. By collecting data on either side of the announcement of CPEC on the 20th of April, 2015, the relationship between CPEC and Pakistani regulatory oversight can be examined. Research into NEPRA archives indicates that in July of 2015 (CPEC start: April 2015) there were a large number of petitions for inclusion of particular insurance fees in wind power projects filed consecutively. This phenomenon is unmatched in NEPRA's history and does not occur for other issues. The following case study will examine these petitions to determine support for the null hypothesis that there is no relationship between Pakistan's regulatory capacity and an increase in China's investment. To determine if evidence supports this claim, this paper will proceed by setting the regulatory scene through a brief history. The influx of

petitions will then be examined with logical approaches. Following this, the same data will be examined with topic models.

Pakistan's energy regulatory structure features NEPRA as a key player. NEPRA's mission is to "[...] develop and pursue a Regulatory Framework, which ensures the provision of safe, reliable, efficient and affordable electric power to the electricity consumers of Pakistan; we shall facilitate the transition from a protected monopoly service structure to a competitive environment where several power sector entities function in an efficiency oriented or market driven environment and shall maintain a balance between the interests of the consumers and service providers [...]" (NEPRA Web Portal: "Mission"). The organization conducts energy project rulemaking and the transition from state-controlled energy provision to open/competitive systems (NEPRA stresses the need to transition from "*political to commercial priority* in economic decision making", NEPRA Web Portal: "NEPRA"). NEPRA's main powers to achieve these goals are electricity licensing, safety standard establishment/enforcement, and power provision to consumers. NEPRA also approves investment/acquisition programs for utilities and determines tariffing for power projects (NEPRA Web Portal: "NEPRA"). NEPRA has set up a system in which it receives a variety of petitions regarding insurance rates/providers, licenses, tariffs, cost adjustments, and interest rates. It acts through determinations of these cases to create statutory rulings. Attracting international investment, promoting competitive structures for industry, protecting the interests of investors/consumers, and demonstrating a dedication to "objectivity and impartiality" are key goals for the organization (NEPRA Web Portal: "NEPRA"). In project investment and tariff setting NEPRA is a critical lynchpin in the regulatory system.

NEPRA makes available online substantial records for public scrutiny. In a given year these petitions generally take the form of unrelated, stand-alone requests from public/private actors for specific project changes. Many of these petitions aim to create or revise energy tariffs. For example,

in 2014 all 20 of the petitions to NEPRA from private actors concerned tariff awards, negotiations, applications, petitions, EPC (Engineering, Procurement, Construction) contracts and consumer-end or pass-through tariffs (NEPRA Website, Petitions). In 2014, as in every other year outside of 2015, it is extremely unusual for one petition to match another in any important organizing details. Energy projects, regardless of sector, usually differ drastically as they deal with a variety of one-off construction/operation issues. As such, NEPRA's random catalogue of documents makes sense as there are simply few cross-cutting issues for multiple projects. *Outside of 2015, there are no instances of more than 5 sequential petitions to NEPRA that relate to the same subject, and even these document sets are always from either 1.] the same company filing multiple related petitions focused on one project, or 2.] regional government electricity suppliers filing regular updates.*

While the 2007-2014 and 2014-2019 periods of the NEPRA data show little coordinated content, data from 2015 changes starkly. Here, private, public, Chinese SOE and Pakistani provincial actors begin petitioning NEPRA on wind power generation. In June-July of 2015, sixteen consecutive petitions to NEPRA from sixteen different actors all push for accepting Chinese state-owned insurance provider Sinosure (China Export and Credit Insurance Corporation/中国出口信用保险公司) as the insurer for wind power projects. The NEPRA database shows a large uptick in requests that the Government capitulate to Chinese requirements to utilize insurance through this state-owned firm. Sinosure is China's main insurer of export financing and provides protection for SOE's and other firms against political, commercial and/or credit risks operating or exporting abroad. Critically, these petition documents all occur within a several days of one another, many of them share verbatim language, and all fall within a short temporal window immediately following CPEC's announcement (figure 2).

Adjustment in K-ELECTRIC schedule of Tariff on account of Fuel Price and Power purchase cost variation for Quarter Ended June 2015	View
Petition for the Determination of Consumer End Tariff for FY 2015-16 to 2019-20 under multiyear tariff regime in respect of Peshawar Electric Supply Company Limited (PESCO)	View
Petition for the Determination of Consumer End Tariff for FY 2015-16 to 2019-20 under multiyear tariff regime in respect of Faisalabad Electric Supply Company Limited (FESCO)	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by Indus Wind Energy Ltd.	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by Lakeside Energy Pvt. Ltd.	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by Master Green Energy	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by Mr. Arooj Asghar	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by NASDA Energy Pvt. Ltd.	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by Triconboston Consulting Corporation Pvt. Ltd.	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by Western Energy Pvt. Ltd.	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by Wind Eagle Ltd.	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by Bridge Factor Pvt. Ltd.	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by Din Energy Ltd.	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by Emerald Energy Ltd.	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by Energy Deptt Govt of Sindh	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by Frontier Renewable Energy Pvt. Ltd.	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by Green Power Ltd.	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by Harbin Electric International Company Ltd.	View
Review Petition - Upfront Tariff for Wind Power Generation Tariff filed by Hartford Alternative Energy Pvt. Ltd.	View
Tariff Petition filed by K-Electric regarding Monthly Fuel Cost Adjustment (FCA) due to variation in Fuel and Power Purchase Price for the Month of April 2015	View
Tariff Petition filed by K-Electric regarding Monthly Fuel Cost Adjustment (FCA) due to variation in Fuel and Power Purchase Price for the Month of May 2015	View
Tariff Petition on behalf of Central Power Generation Company Limited (CPGCL) GENCO-II	View
Petition filed by Wapda Hydro Electric for revision of Tariff for FY 2015-16 for Bulk Supply of Power from Wapda Hydel Power Stations	View

Fig 2: NEPRA Petitions Related to Wind Energy/Sinosure.
From NEPRA Web Portal: “Petitions”.

In contrast to previous years of diverse NEPRA petition data, the Sinosure related documents demonstrate topical similarity. They are *unanimous* in noting that Chinese state-owned insurance for project funding is required for Chinese capital. Five separate petitions from firms note: “[...] Sinosure Insurance is a contingent requirement of Debt from China. It is approved by NEPRA for other Projects (Coal etc.). It is a mandatory cost for Chinese Debt and should be incorporated as a pass-through cost by NEPRA.” (Indus Wind Energy Limited, 2015, Lakeside Energy Limited, 2015, Nasda Energy Limited, 2015, Din Group, 2015, Emerald Energy Limited, 2015). Highly similar language is also found in a petition from the Government of Sindh Energy Department, signifying possible coordinated inter-governmental and private sector pressure (Government of Sindh, 2015).

Furthermore, Harbin Electric International, a subsidiary of Chinese state owned enterprise Harbin Electric, filed its own petition pressuring for Sinosure fees (Harbin Electric International Company Limited, 2015). All these petitions include similar language pushing for Sinosure adoption.

Another petition from 2015, mirrored closely by several others with similar language, notes that “Sinosure is a compulsory requirement and having Sinosure or not is becoming a Go—No Go situation at the moment” (Wind Eagle Limited, 2015 and Frontier Renewable Energy 2015). This language strongly argues NEPRA must capitulate to what amounts to a large consumer fee for project funding. Sinosure’s rates, set at a maximum of 7% of the total loan benchmark or Chinese-originating debt (whichever comes in at a lower level), often exceed the interest rate on a project that might only reach 5.5%.

Other petitions to NEPRA during this influx period note Pakistan’s overall dire energy situation. These documents view Sinosure inclusion in project costs/tariffs as an key provision for the government. One firm notes:

Exclusion of Sino Shore [sic] premium will effectively shut the door for project financing from China which on account of its Foreign Exchange Reserves is fast emerging as the single most important source of capital. The appetite for ‘Pakistan Risk’ amongst the Western financial institutions is limited. This decision alone substantially reduces the potential capital sources as available to projects located in Pakistan. [...] almost all of the wind projects under development in Pakistan has [sic] signed up for wind turbines manufactured in China [...]. In absence of Sino Shore [sic] premium, it will be extremely difficult to tap the Chinese ECA [Export Credit Agency] funding [...] (Green Power Limited, 2015).

This document highlights the quid pro quo circularity of CPEC, essentially loaning capital to buy Chinese manufactured energy products to be installed and potentially operated by Chinese firms (possibly SOE’s). It appears Chinese funding was also predicated on state-owned Sinosure insurance as well. Development financing from western lenders was painted as unavailable due to geopolitical/financial risk intolerance. *In this way Sinosure represents a comparative advantage for Chinese-led development investment to address risk.*

These concerted and organized pleas to NEPRA from companies, Chinese SOE's and from within the Pakistani government itself are equally adamant that to Sinosure requirements are inherently (and causally) connected to CPEC itself:

[...] due to the recent launch of the China Pakistan Economic Corridor, a number of local projects would be funded and/or set-up by Chinese companies and financial institutions and there would be a huge influx of Chinese investment into Pakistan, in particular into the power sector. Therefore, *it is crucial that as part of the development and implementation of the China Pakistan Economic Corridor, the upfront tariff for wind power projects allows the cost of Sinosure insurance as part of the project costs* — as the same would encourage Chinese investment (Master Green Energy Limited, 2015, Western Energy Private Limited, 2015, Bridge Factor Private Limited, 2015, Frontier Renewable Energy, 2015, Hartford Alternative Energy Limited, 2015).

Paying for Sinosure through pass-through tariffs thus represents a regulatory modification originating with the Corridor itself. The NEPRA petition landscape pre and post CPEC gives a clear picture of the pressures facing the government.

This causal association between CPEC and petitions for including Sinosure costs in tariffs demonstrate significant increases in external pressure on NEPRA to capitulate to Chinese requirements. Importantly, this flood of petitions *proved extremely effective in securing this concession*. Prior to 2015 there were four upfront tariff decisions issued by NEPRA for wind power projects, but none of these decisions spanning the 2011 to 2014 time period mentions Sinosure. *Only after the announcement of CPEC on the 20th of April 2015 does the issue emerge in NEPRA's records*.

Closely following the announcement of CPEC we find the first mention of Sinosure in the context of NEPRA's oversight. Sinosure appears in a determination (not a petition) document regarding tariffs on wind projects. This June 24th 2015 document comes *two months after CPEC is announced and succinctly rejects specialized insurance being included as a pass-through item in tariffs*:

The Authority has considered the issue in detail and has noted that although Sinosure/other agencies fees were not allowed in the upfront tariff [...] however, in spite of that, many projects were able to achieve financial close [...]. *The Authority after due deliberation has decided to continue the decision taken in the upfront tariff, 2013 in this regard. Accordingly Sinosure/other agencies fees is not allowed as a separate cost head/pass through item in this upfront tariff* (Determination of National Electric Power Regulatory Authority,

2015).

In June of 2015 NEPRA saw no reason to extend pass-through status to Sinosure fees. The regulator notes that lack of Sinosure fees in upfront project tariffs has not prevented success in the past and it saw no reason to extend this privilege to current projects. *Within only a few weeks NEPRA would be petitioned with the sixteen petitions.*

Following the sixteen petitions clustered in late June/early July of 2015, NEPRA reversed its earlier determination: “Accordingly, the Authority after due consideration has decided that for wind power projects having foreign financing, an appropriate adjustment in the benchmark project cost will be allowed on account of Sinosure or other credit insurance fees.” (Decision of the Authority in the Matter of Motions for Leave for Review, 2015). The contrast in regulatory direction is stark. In April of 2015, CPEC is announced as a multi-billion dollar deal with a plurality of funds in energy projects. Shortly thereafter NEPRA receives early inquiries regarding CPEC projects. In mid-June NEPRA announces it will not revise pass-through tariffs to include default funding for Sinosure. In late June and early July NEPRA receives the flood of petitions to include Sinosure. Finally, in October, NEPRA capitulates and includes up to 7% pass-through tariff inclusion for Sinosure (figure 3). The Sinosure fee revision *is the only element of the pre-CPEC NEPRA determination that changed* in between decisions, despite critical per-megawatt project cost adjustments also being heavily contested during this period (Decision of the Authority in the Matter of Motions for Leave for Review, 2015).



Fig 3: Diagram of NEPRA/CPEC decisions over time.

Thus, the petition effort to NEPRA is defined by several characteristics. 1.] The petition effort was an unprecedented lobbying effort for a China-friendly policy outcome. 2.] The effort was unusually coordinated in both timing and content. 3.] The effort was entirely successful. These fees amount to significant costs (typically 1.5% on equity/1.5% on debt, though sometimes up to at least 5.28%), and stand out all the more due to Pakistan's lack of international funding access, overall development level, and massive energy infrastructure needs.

CPEC also appears to be having a broader impact on regulatory control, with the program exposing changes in the relationship between Pakistan's executive government and other regulatory actors. The Corridor worsened schisms between the Executive and the Public Procurement Regulatory Authority (PPRA)⁵ as decisions by Pakistan's Economic Coordination Committee (an executive committee responsible for economic security decisions) to approve an earlier ruling that the ECC could overrule the PPRA Ordinance in relation to Chinese funded projects (Rana, 2016).⁶ The ECC override *specifically stresses CPEC is the cause of this procurement change and notes bids will be conducted in China and be limited to Chinese firms.*⁷

Moreover, it appears Chinese-funded projects will be provided unique legal moats to limit exposure to structural "circular debt" energy payment problems. February of 2016 saw ECC approval

⁵ "[...] an autonomous body endowed with the responsibility of prescribing regulations and procedures for public procurements by Federal Government owned public sector organizations with a view to improve governance, management, transparency, accountability and quality of public procurement of goods, works and services." PPRA Web Portal, <http://www.ppra.org.pk/>

⁶ There are additional project case studies detailing CPEC's rollback of open procurement *outside* the energy sector, including ECC tax exemptions for the completion of the Karakoram Highway and Karachi-Lahore Motorway projects (Sial, 2016). The ECC approved exempting construction material for CPEC National Highway Authority infrastructure projects of import taxes ("NHA's CPEC projects exempted from import duties" 2016, and "ECC allows tax exemptions for CPEC development projects", 2017). Tax exemptions for all CPEC rail projects has been discussed ("ECC allows tax exemptions for CPEC development projects", 2017). ECC concessions/PPRA exemptions do not extend to funds from other countries (Rana, 2019).

⁷ NEPRA also challenged the Prime Minister's directives, noting that CPEC project security costs would be placed within power tariffs. The Authority asserted that allowing security costs to the CPEC projects would "create legal complexities and discrimination among other power projects" (Kazmi, 2016).

for a “revolving fund” (equal to 22% of monthly power provider payments) *backed by sovereign guarantees* to supply uninterrupted payments to Chinese backers of CPEC energy projects (“ECC approves plan”, 2016). Thus, instead of guaranteeing solutions to energy provision issues for consumers (as might happen in an open-bid system), CPEC projects have found legal pathways and (astonishingly) sovereign guarantees to protect investments. Importantly, this was another hard-line requirement lobbied for and imposed by China (Mustafa, 2018). While this fund appears to be slow to implementation, there are no plans to create such options for domestic firms (Pal, 2016).

Pakistan’s Regulatory Data from a Computational Social Science Perspective:

The analysis conducted previously indicates CPEC has had a substantial and detrimental impact on Pakistan’s regulatory control. This analysis, like all qualitative case studies, can be strengthened by introducing repeatable methods. This section uses topic models to reproducibly assess how CPEC may have changed Pakistan’s official regulatory discourse (analysis will be divided into “results” and “interpretations” sections for clarity). The results section will model the data before and after CPEC, then model the entire corpus to ascertain the topical characteristics of the NEPRA documents. Then “topics over time” analysis via a regression tool within the STM package will be conducted. Finally, interpretation of topics will allow examination of corpus topics in relation to the time-treatment structure explained earlier.

Topic Models: Results

Conducting a pre/post CPEC split on topics within the NEPRA corpus demonstrates several important changes in the discussion around regulatory issues in Pakistan. This section presents the results of topic modeling of the NEPRA data (full topic labels are available in the online appendix). This section is constructed as an impartial presentation of these results with model interpretations being conducted in the following section.

Prior to CPEC's announcement the topics that occurred in highest proportion in NEPRA documents are listed below in "Pre CPEC Topics". When the data includes only pre-CPEC documents the five most proportionally important topics are 1, 16, 8, 2 and 13. Topic 1, which at around .17 (17%) has the highest proportion by a wide margin, primarily revolves around the Korangi industrialized area of Karachi. Topic 16, the second most important pre CPEC topic, is concerned with the Quetta Electric Supply Company (QESCO), Hyderabad Electric Supply Company (HESCO), and the Multan Electric Supply Company (MEPCO). These large electric power generators regularly petition and report to NEPRA for various project reasons and to comply with regulatory oversight rules. Petitions from these groups make up a regular and repetitive component of the NEPRA database. Rounding out the top 3 topics, topic 8 seems to primarily revolve around EPC issues. Topic 2 contains information relating to hydropower projects in several areas of the country, and topic 13 revolves around peak/off peak charges for energy, "time-of-day" production issues, and the Peshawar Electric Supply Company (PESCO) and Tribal Electric Supply Company (TESCO). These energy generators follow a regular petition pattern like QESCO/HESCO/MEPCO. All told, the pre CPEC corpus shows what one might expect: a regulatory database dominated by requests made by government-owned electricity distribution companies (DISCOs) that buy electricity from producers and sell it to consumers. The pre CPEC topic model demonstrates reporting generated by large state actors. As one might expect, the pre CPEC model also demonstrates the economic prominence of Karachi. Importantly, while less prominent topics like topic 18 demonstrate a focus on wind/renewable energy, upfront tariffing/insurance/Sinosure are absent (figure 4).

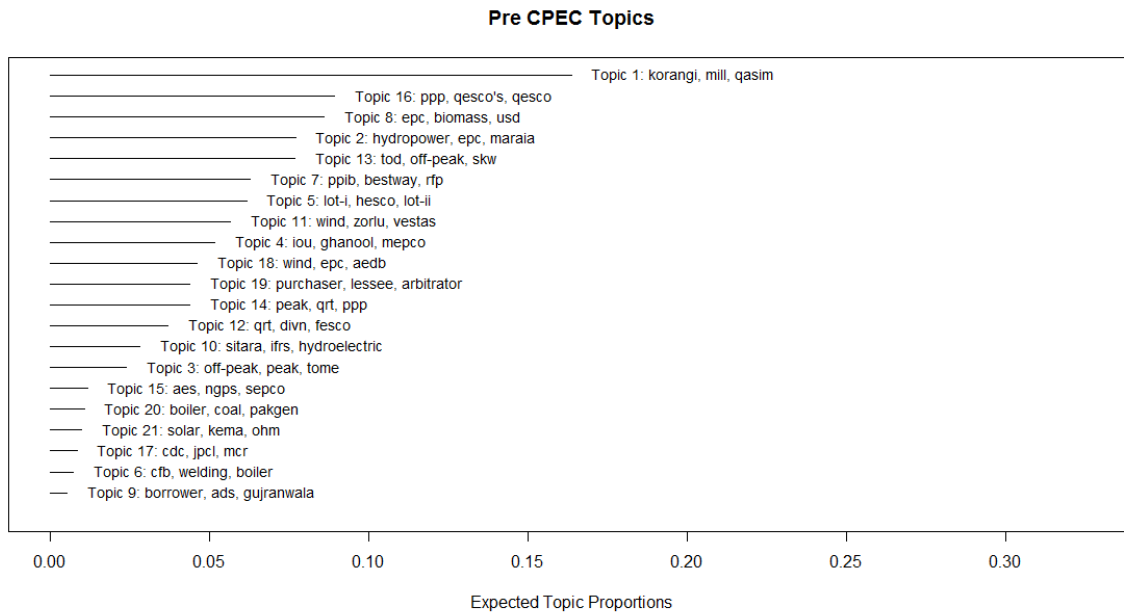


Fig 4: Pre CPEC Topics, NEPRA Petition Data
“Score” Topic Model Output (April 9th 2019)

Topic models of the NEPRA corpus following CPEC are markedly different. The most prominent topic is topic 5, which like topic 1 in the pre CPEC model is far and away the outlier in terms of prominence (around .15% of the corpus). Topic 5 is largely concentrated on language regarding the Lakhra Power Generation Company Limited (LPGCL), along with a series of terms related to petitioning, tariffing, upfront tariffing, and unsolicited bidding/ bidding competitiveness. LPGCL owns the Lakhra Power Plant (LPP), a coal-fired facility in Sindh that has received investment from the China Development Bank (CDB) and the Industrial and Commercial Bank of China (ICBC), has EPC operations insured by Sinasure, and uses coal fields partially owned by a Chinese company.⁸ This topic appears to be in part related to a challenged petition regarding various pleas LPGCL had made to NEPRA to help LPP maintain operation through recent operational difficulties. LPGCL aside, the remainder of this topic relates to the other topics within the Sinasure

⁸ See: Final Report for the Preparatory Survey on Lakhra Coal Fired Thermal Power Plant Construction Project in Pakistan, October 2016.

subset documents (tariffing/upfront tariffs, unsolicited/competitive bids, renewable energy and a Sinosure subset petitioner/wind energy firm). Chinese involvement in the LPGCL project presents a topic for further research, but for now it is enough to note the salience of the topic to the bidding, tariffing and competitiveness elements of this study.

Topic 18, the second most prominent topic post CPEC, centers on renewable projects in the wind sector, participating EPC firms, onshore and offshore wind projects, bidding, a wind firm, petitioning processes, and several energy firms from the Middle East and China. While Sinosure is not mentioned directly, the topic is still heavily focused on bidding and related energy sectors. Topic 17 comes in as the third most prominent topic in the post CPEC corpus, and contains the words *upfront, wind, sinosure, aedb, renewable, hartford, chinese, stakeholders, motion, turbines*, etc. Topic 17 has an overwhelming emphasis on Sinosure petition related terms, and continues the trends of the pre CPEC corpus with some modifications (figure 5).⁹

⁹The model shown here was generated in March of 2019, several years after the announcement of CPEC and the Sinosure wind petitions that followed. A model generated from NEPRA data in the summer of 2018 is available in Appendix II at the end of this paper. This model contains topics with relatively higher amounts of topics pertaining to Sinosure and related tariffing issues due to its closer temporal association with those petitions (and fewer documents generated at a later date with less similar content).

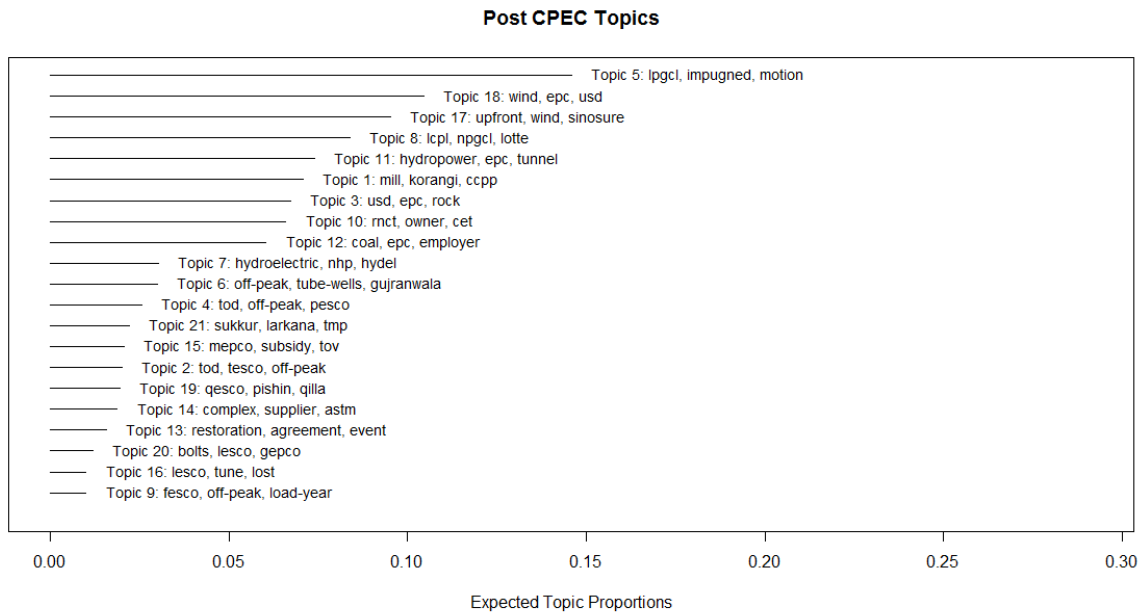


Fig 5: Post CPEC Topics, NEPRA Petition Data
“Score” Topic Model Output (April 9th 2019)

The total corpus “score” output clearly shows an overall change in regulatory discourse. The full topic labels list shows topics 13 (1st in proportional prominence) and 21 (6th in proportional prominence) directly reference words related to Sinosure, wind energy, China, lending/lending rates, LIBOR rates, upfront tariffing, renewable energy and wind energy firms and components. Despite several years elapsing between the date this model was generated and the announcement of CPEC (and the influx of Sinosure/wind power/tariffing related petitions), NEPRA’s official regulatory discourse shows Sinosure related topics remain the first and sixth most proportionally prominent topics in the data. Topic models indicate these terms play a central and dominant role in the NEPRA regulatory corpus.

The most important topics in the corpus show the major discursive variance in the NEPRA documents pertains to the changes lobbied for within the Sinosure subset of sixteen documents examined in the prior case study section. Indeed, the other prominent topics are the same, or highly

similar, pre and post CPEC (figure 6).¹⁰

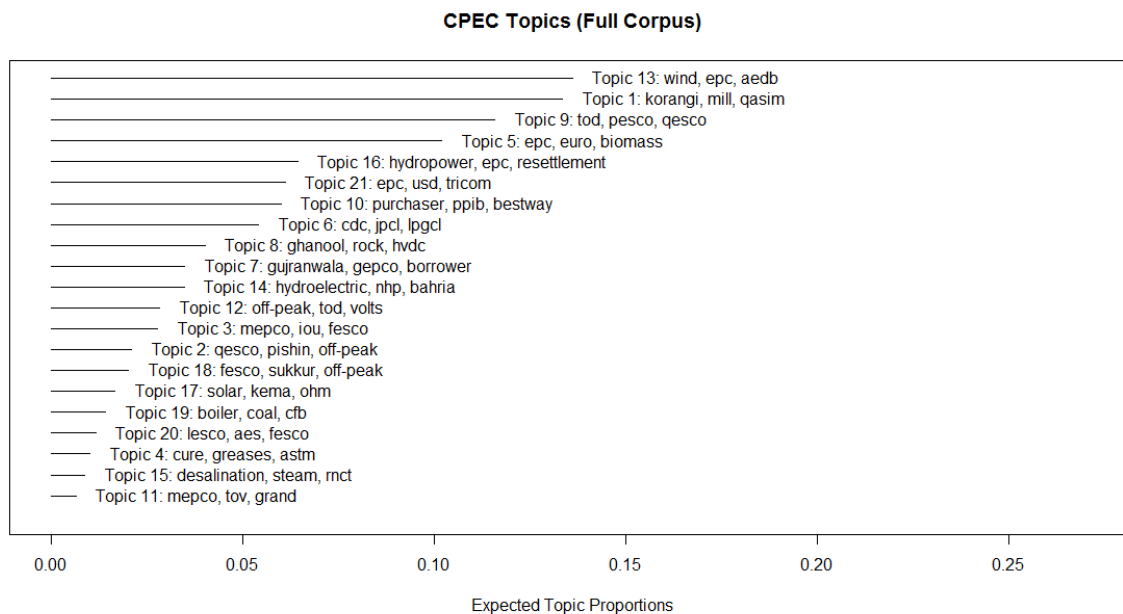


Fig 6: CPEC Topics, NEPRA Petition Data
“Score” Topic Model Output (April 9th 2019).

Utilizing the “estimateEffect” function within the STM package allows for the estimation of a model (without arbitrary date cutoffs) where the documents in a corpus become units for a regression and the proportion of each topic in the corpus the outcome. Covariates can be assigned to meta-data, including a variable created from the year of document publication. This estimate also incorporates a confidence interval measure for uncertainty in the topic proportion. Here, the model is run on a topics with “year” as a predictor variable. As the figure below demonstrates, topic 13 increases to over 20% of the corpus proportionally by the end of the archive period, while topic 21 remains steady around 6% of the corpus (figure 7).

¹⁰ The stm package makes available several different types of word weightings for topic models. Score is a metric previously used effectively in the lda package by Jonathan Chang. Due to the “dirty” nature of the NEPRA documents (many of these PDFs contain signatures, irregular tables, stains, etc.) the NEPRA corpus was examined with stm’s score outputs as this algorithm displayed the most consistently sensible topics to a human observer (topics were less frequently constructed from non word units that resulted from the OCR process). This topic-supervision process is one detailed at length in Chang *et al.*, 2009.

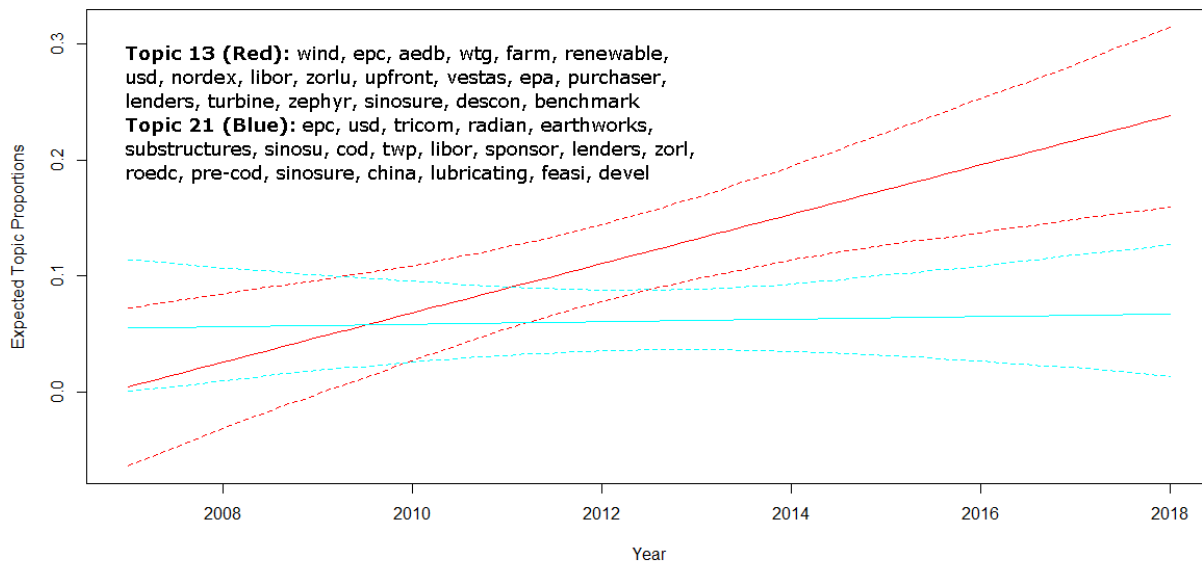


Fig 7: Sinosure/tariffing topics over time (April 9th 2019).

Topic Models: Interpretations

Prior to CPEC, topic models demonstrate a regulatory oversight process defined primarily by repetitive government-to-government documents. The overwhelming content type of this pre CPEC corpus appears generated for routine updates to regulators. Following the announcement of CPEC terms related to our research questions became prominent topical elements. Topics 13 and 21 in the full corpus and topic 17 in the post CPEC corpus are notable for their direct reference to Sinosure, but several other smaller topics also merit discussion. In the post CPEC corpus topic 3 (7th in prominence) contains terms related to currencies, wind energy, a wind firm with a petition in the 16 Sinosure related documents, as well as LIBOR lending rates. Topic 5 (1st in prominence) mentions the LPGCL project and its impugned petition (which used Sinosure), but also notes the leave for review tariff process, unsolicited (project bids), uncompetitive (bids), upfront (tariffing), renewable energy, and a wind firm that participated in the Sinosure subset petitions. Topic 18 (2nd in prominence) contains the words wind, epc, renewable, purchaser (likely WAPDA), another Sinosure subset wind firm, bidders, and the Chinese state-owned firm Hydrochina. These topic content terms

indicate a digression of NEPRA's regulatory discourse following CPEC, and replicably corroborate the previous case study.

Moving to analysis of the the full corpus, the first and sixth most prominent topics (13 and 21, respectively) appear to contain the entirety of words coinciding with Sinosure subset document language. These topics contain frequent reference to words that demonstrate the importance of lobbying efforts to the regulatory discourse. In topics 13 and 21 firm's that made Sinosure petitions are evident, demonstrating the extensive petitioning by these and other actors. Topic 13 also contains references to wind energy, the AEDB (Alternative Energy Development Board), technical wind energy terms, as well as renewables in general.

These findings corroborate the importance of renewable/wind energy generation to CPEC/OBOR, Chinese-backed energy firms, and Pakistan itself. Prominence for such terms should be considered when examining China's overall policy preferences with CPEC and OBOR in general. These results also demonstrate what sectors were most discussed during the rollout of CPEC. From the findings of this modeling, wind energy appears to be a priority for both CPEC firms and Pakistan itself. Retrofitting a notoriously underperforming coal energy plant, as well as several large hydropower projects, are also important points of energy related discussion. However, it can be stated that wind energy is perhaps the most prominent energy related topic.

The similarity of many other prominent topics in the pre CPEC and full corpus models also demonstrates an important take away. While these topics are not identical pre and post CPEC, it does appear that the Sinosure/upfront tariffing terms constitute the primary new prominent topics in the full corpus. Examining the most important topics in the full corpus (post-CPEC) shows the major discursive change in the NEPRA documents pertains to words contained within the sixteen Sinosure documents.

Finally, "Sinosure topics" 13 and 21 show important changes in prominence over time.

Topic 21 appeared remarkably stable throughout the observation period, signifying a baseline level of discussion of topics related to Sinosure and China that hovers around 7% of the corpus. This result indicates the SOE is a stable and long-lasting topic for NEPRA (and China did have energy investments in Pakistan before CPEC). However, this baseline is complimented by a sharp increase in prominence for topic 21 over the same period. This increase replicably corroborates the case study work in the previous section by demonstrating that a nexus of terms regarding tariffing, upfront tariff inclusion, wind energy, Sinosure, renewables, etc., increased over the course of the study period and in a manner coinciding with CPEC.

Conclusion, CPEC in Pakistan and CPEC as an Indicator:

It is prudent to return to this paper's hypotheses to help structure the preceding observations:

1.] If CPEC/Chinese funding is present for projects, then regulatory and procurement process impacts and captures are more likely to occur.

Adoption of mandatory Chinese project insurance as part of a pass-through tariff is associated with NEPRA petitions stressing this outcome immediately following CPEC's initialization. This flood of petitions is a departure from normal, and is tied conclusively to CPEC through repeated petition content. This regulatory change represents a substantial loss of agency/sovereignty over the procurement system by the government of Pakistan and represents support of hypotheses 1.

Mandatory Sinosure premiums are an example of the type of "coordination" frequently referenced regarding Chinese international investment policy. The flood of NEPRA petitions followed a long history of Chinese state owned enterprise contracts in Pakistan (as well as imports of SOE-produced energy equipment), and Sinosure was conveyed as a strategic inevitability required to secure CPEC funds. Chinese Policy Banks and SOE's often work in concert on infrastructure investment, at times overlooking risks and/or outstripping real demand. However, Sinosure is

ultimately an insurance provider interested in capitalist risk hedging with “Chinese characteristics” that supports hybridized Chinese investments.

Mandated Sinosure premiums represent substantial challenges to the sovereignty of the government of Pakistan over its energy infrastructure. Insuring large energy projects is a fundamental and standard element of international finance. However, the form and process of the mandatory Sinosure/pass-through tariff decision for Chinese wind projects (and energy projects in general) are departures from international norms. While requiring insurance on projects is typical for international corporations, channeling this insurance through a state-owned enterprise is not. For example, German firms require insurance from Euler Hermes for its foreign project financing. The large distinction here is that Euler Hermes is not capitalized and directed by the German-government. Selecting a competitive premium from this publicly traded company does not involve German government policy priorities. Pakistan is allowing a foreign government to dictate key elements of project financing as well as outcomes in the event of project disruptions. The monopolistic nature of Sinosure premiums needs further examination. How these rates compare to global norms, and if Sinosure rates are impacted by lack of competition, are compelling further questions.

The evidence presented here indicates the removal of open bidding and procurement and the capitulation to Chinese demands on insurance costs were the direct result of massive Chinese financing as well as extensive lobbying by a variety of actors. Topic model approaches bolster these conclusions with repeatable evidence of a concerted lobbying campaign to alter Pakistan’s regulatory oversight. These models demonstrate that the official regulatory discussion in Pakistan was altered markedly in favor of passing the cost of Chinese state owned insurance onto Pakistan’s consumers. The taxing/tariffing, procurement oversight, and Chinese state-owned project insurance concessions discussed here demonstrate that tens of billions of dollars of project development are strong enough to warrant sacrifices in Pakistan’s oversight capacity. These data also show a broader challenge to

international development lending norms that are more substantial than simply a heavy emphasis on debt-driven projects. More research is needed, but such findings suggest a new form of development lending is occurring in the world system.

2.] If lending exists in a “best case” bilateral scenario (where China and the recipient state have strong relationships/dependencies), regulatory and procurement impacts could be more evident.

An open, international and transparent bidding process for large scale energy projects is a key responsibility for sovereign states in the current global order. How a country chooses to spend money on energy for its citizens is a core component of government agency. The implications of CPEC funding being tied to regulatory changes are enormous for Pakistan, but should also be considered in the wider context of China’s outbound investment policy. Decades of work to mandate a global order characterized by open and competitive bidding/procurement for development projects could be in danger. Open and competitive bidding/procurement has been the focus of Western-led development reforms, so it is notable that China’s premier funding program with a close ally does not conform to this paradigm. Due to the increasing size of China’s global economic role further research is needed to understand if this finding is generalizable.

The NEPRA case should be considered in the context of government regulatory sovereignty. Pakistan has tremendous growing pains that in some ways resemble China’s earlier challenges. However, in other demographic, financial and infrastructural aspects the country is more like its South Asian neighbors or regions of quickly-developing Africa. An astonishing two-thirds of Pakistanis are under the age of 30, a fact all the more troubling considering the myriad challenges the country will face in the coming years (Lord, 2016). There is an understandable motivation for the government to invest in energy development at all costs, but this approach appears to have enormous consequences for state control. Whatever CPEC’s underlying motives, the NEPRA case study makes clear what the costs of large scale Chinese investment can look like for recipient state

regulatory capacity. The susceptibility of NEPRA to outside lobbying efforts also supports the conclusion that Pakistan is one example of possible outcomes for OBOR recipient states when China has maximum sway.

It remains to be seen how revisionist this energy investment policy will be for the international political economy of development investment. Does CPEC represent a broader challenge to investment standards, or simply a one-off conducted in a relatively sympathetic polity? Did the OECD-based rules for transparent investment ever really result in positive changes on the ground (as common sense would suggest they might), and thus could the Chinese model of investment be detrimental? There is no way to definitively answer these questions at this relatively early point in the collaborative relationship between the PRC and Pakistan. However, it is clear Chinese financing comes with new energy regulatory standards and requirements that are tied intimately to the Chinese state apparatus. Increasingly, case studies suggest some of these standards come at the cost of indigenous regulatory capacity for recipients of Chinese funds.

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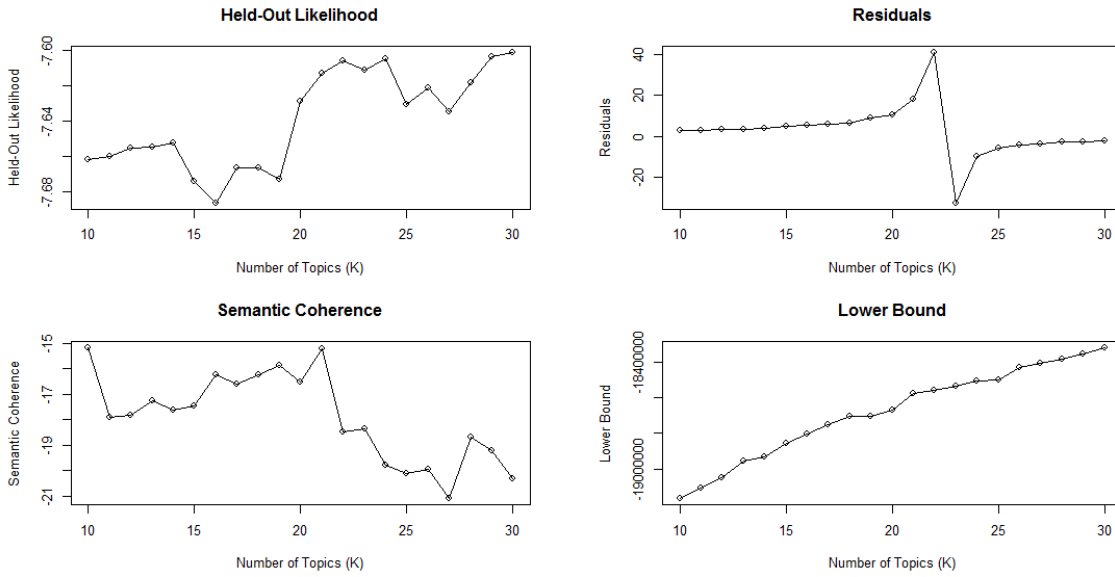
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Appendix:

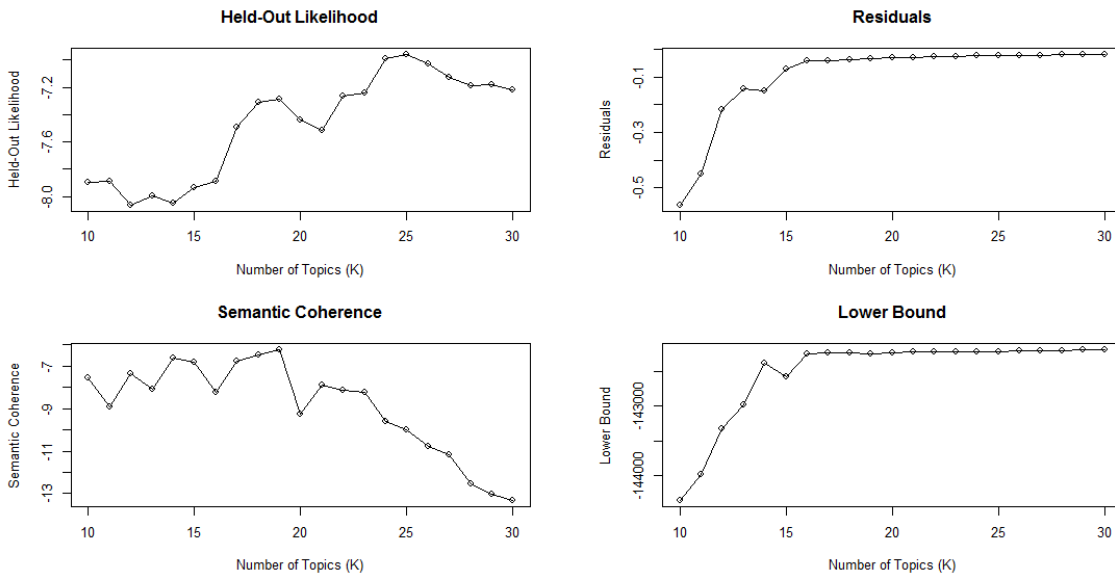
Total Topic Number Estimates:

Diagnostic Values by Number of Topics

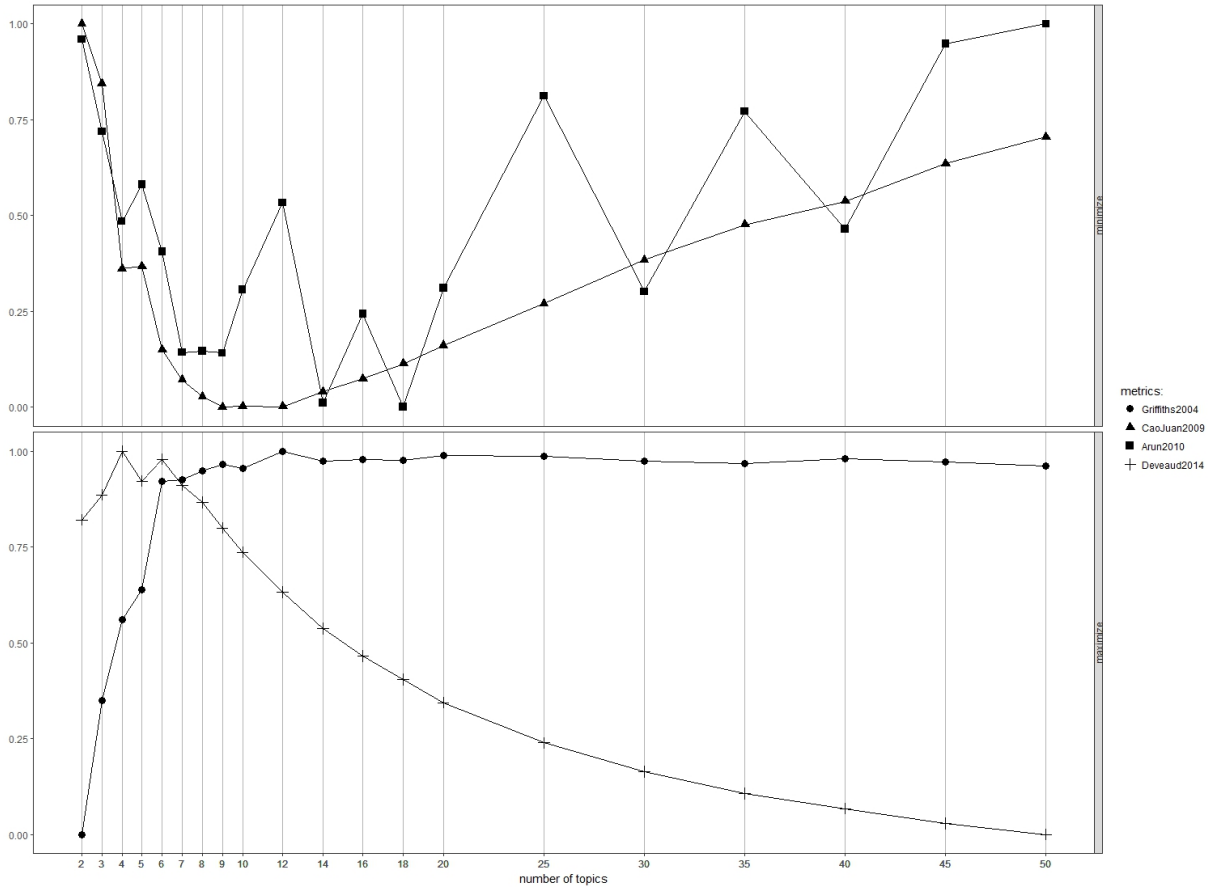


“Finding K” Estimate for full NEPRA corpus

Diagnostic Values by Number of Topics



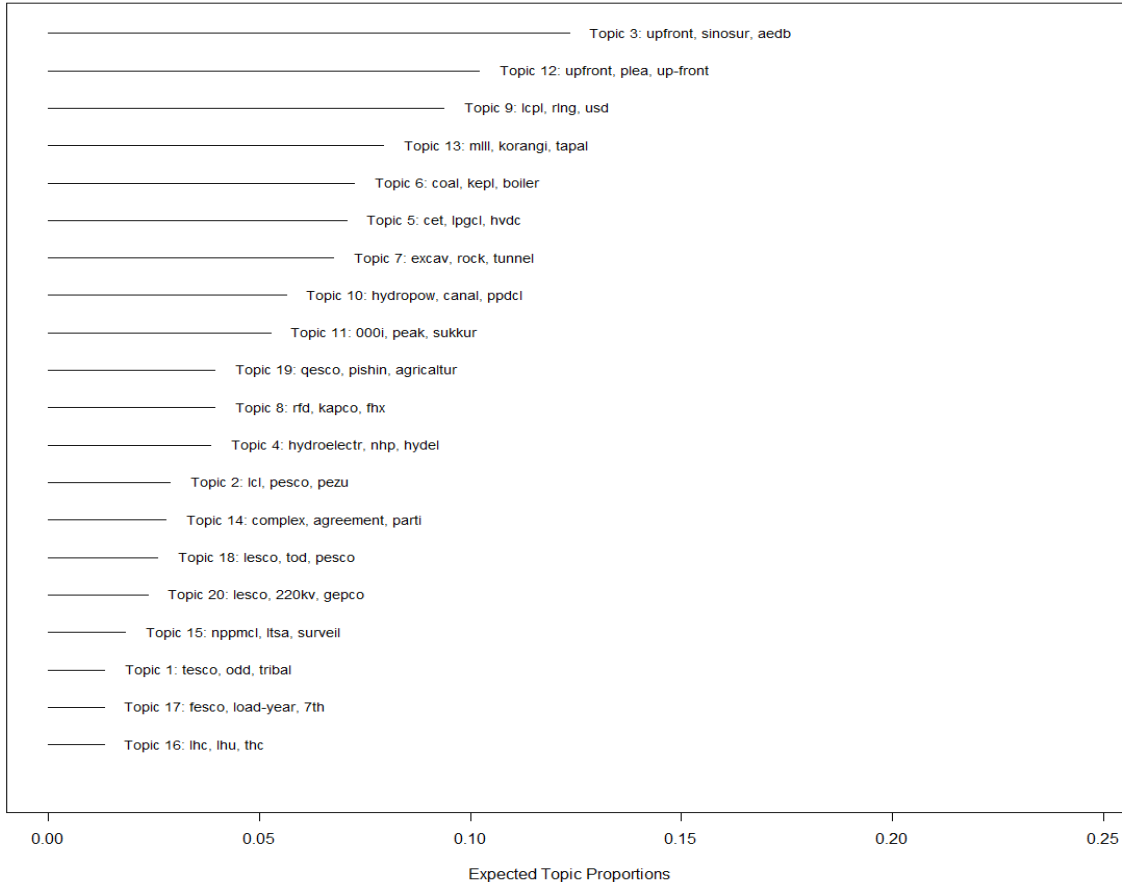
“Finding K” Estimate for “Sinosure Subset” sub-corpus



Optimal topic number estimates for Sinosure petition subset
(estimate from “LDA” package)

Post CPEC NEPRA Topic Model (June 2018):

Post CPEC Topics



Topics and Emotions in Russian Twitter Propaganda

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Abstract:

The increasing importance of social media to political communication means the study of government-sponsored social media activity deserves further exploration. In particular, text-as-data techniques like topic models and emotional lexicons provide potential for new types of content analysis of large collections of government-backed social media discourse. Applying text-as-data methods to a corpus of Russian-sponsored Twitter data generated before, during and after the 2016 US Presidential election shows Tweets containing a diverse set of policy-related topics as well as levels of angry and fearful emotional language that peaks in close association to the election. Text-as-data techniques show Russian sponsored Tweets mentioned candidate Clinton overwhelmingly negatively and referenced candidate Trump in a positive but less consistent manner. The Tweets contained large minorities of apolitical topics, and also saw higher levels of conservative hashtags than progressive ones. Topics within the Tweet data show a contradictory set of topics on all “sides” of the political spectrum alongside increases in fearful and angry language in temporal association with the US election. The findings of this inquiry provide evidence that the Tweets were sent to heighten existing tensions through topically heterogeneous propaganda. They also caution against an overly black and white interpretation of Russian disinformation efforts online.

Key Words: online propaganda, election interference, social media, 2016 Presidential Election, topic models, text as data, cyberwar, Russian Federation.

To Anne and my parents,
for giving me the courage to always change direction if it needed changing

“In all chaos there is a cosmos, in all disorder a secret order” Carl Jung

Introduction

Social Media and Electoral Democracy:

Social media venues are increasingly recognized as central discursive elements of the electoral processes of democracies. The 2016 US Presidential Election demonstrates this clearly, as election day 2016 saw Twitter as the largest source of breaking news in the country with 40+ million Tweets generated (Isaac and Ember 2016). Worldwide, Twitter has been adopted by politicians across a wide swath of cultural and social backgrounds as an effective way to communicate with constituents.⁹ Social media venues like Twitter are also increasingly recognized as platforms for nation states to produce and distribute disinformation, particularly during election periods.

Unsurprisingly, social media discourse during election periods has received increased study related to political participation and to the “traction” between social media support and electoral success (Adamic and Glance, 2005; Diakopoulos and Shamma, 2010; Bekafigo and McBride, 2013; Carlisle and Patton, 2013; DiGrazia, *et al.*, 2013). Some studies have noted that social media may influence political participation and engagement in both online and offline contexts (Dimitrova *et al.*, 2011, Johnson *et al.*, 2010, and Zhang *et al.*, 2013). Academics have used social media to predict election outcomes with error terms close to traditional polls (Tumasjan *et al.*, 2011) and social media may also hold the power to influence individual choices and preferences (Aral and Walker, 2010). Importantly, researchers have also raised concerns that the popularity and effectiveness of social media as political arena may allow for the spreading of propaganda and the manipulation of public opinion (Howard, 2006; El-Khalili, 2013; Woolley and Howard, 2016; Shorey and Howard, 2016). Automated or semi-automated social media accounts are beginning to be studied for their relationship to democratic discourse, and the potential they hold for disruptive impacts on

discussion in open societies (Bessi and Ferrara, 2016). Scholars have demonstrated not only the potential power of such agents in the social media system but also the need for additional methodological tools to analyze these large qualitative datasets in repeatable ways.

While other studies interrogate social media data to discover general public communication by citizens (Larsson and Moe in Weller *et al*, 2014), the extent and characteristics of bot communications and the diffusion of information between bots and humans (Bessi and Ferrara, 2016), or to analyze the “soft influence” potential of online forums for cross-national political actors (Zelenkauskaitė and Balduccini, 2017), this paper concerns itself with a policy-centric study of social media data and reaches new conclusions about the topical and emotional composition of Russian Federation agents’ discussion on Twitter during the 2016 US Presidential Election.

If, as research suggests, political actors increasingly view digital platforms as a *primary* form of policy communication as they provide traction for policies (Stieglitz and Dang-Xuan 2012), it holds that policy preferences can be induced from social media messaging. The primary role of social media for campaigns and governments means this data can be utilized as an inductive lens to understand the policy objectives of state actors. *This approach is particularly useful when state policy objectives are obfuscated and/or clandestine in nature, and when datasets associated with one political actor present themselves.* If political actors, including nation states, are treating social media as a platform for policy dissemination, analysis of the content (here, individual Tweets) produced by state actors on online platforms can be helpful in understanding what state actor’s desired policy outcomes would be. Such efforts are facilitated by advances in computational methods capable of replicably analyzing the large-n corpora of qualitative online data generated by nation state participation in social media.

Russian Disinformation Policy and Social Media:

Twitter data regarding the 2016 US presidential election provides an excellent case study for this kind of state-affiliated social media analysis. The 2016 campaign was not only remarkable for the

popularity of Twitter as a discursive political arena, but also because of the degree to which this arena (and indeed the election itself) was compromised by state-backed actors. Indeed, the current consensus of the US intelligence community now suggests Russian “meddling” in the election unequivocally occurred (United States Department of Justice Press Release 18 - 198, 2018).

Twitter and NBC news have also publicly, and in testimony to Congress, tied Russian interventions on the platform to the Russian Federation. Specifically, Twitter has presented research tying Tweets on the platform to the Russia-based and state-affiliated Internet Research Agency (Testimony of Sean J. Edgett, United States Senate, 2017 and Popken, 2018). The Internet Research Agency (IRA) has been assessed by the US intelligence community (here, the Federal Bureau of Investigation, the Central Intelligence Agency and the National Security Agency) as an organization of “professional trolls located in Saint Petersburg” (“Intelligence Community Assessment” 2017). The overall assessment of the U.S. intelligence community is that the IRA is tied to the Russian President through its financier who is “a close Putin ally with ties to Russian intelligence” (“Intelligence Community Assessment” 2017). A Special Counsel indictment notes “The organization (the IRA) sought, in part, to conduct what it called *‘information warfare against the United States of America’* through fictitious U.S. personas on social media platforms and other Internet-based media” [emphasis mine] (“Indictment Document” 2018). U.S. intelligence community reports note the Russian influence campaign was ordered *directly by the President of the Russian Federation*, and was also in part focused on undermining public faith in the democratic process (“Intelligence Community Assessment” 2017). For their part, former IRA employees who have spoken on the record note their confidence that the organization is “absolutely” connected to the Russian state (Popken and Cobiella, 2017). The March 2018 Twitter/NBC News corpus of over 200,000 tweets analyzed here demonstrates one element of this cohesive program on the part of the Russian Federation to interfere in the US electoral debate.

This paper presents a data inquiry that resulted in new conclusions about the topical and emotional composition of Russian Federation agents' discussion on Twitter during the 2016 US Presidential Election. The inquiry described here uses topic models to inductively view latent topics based on the co-occurrence patterns of words within documents. This allows the researcher to “discover topics from the data, rather than assume them” (Roberts *et al.*, 2014). Topic modeling to understand underlying concepts also “both improves efficiency (new representation takes up less space) and eliminates noise (transformation into topics can be viewed as noise reduction)” (Rehurek and Sojka, 2010). This feature of the method is demonstrated in various literatures to date, including analysis of climate change media coverage (Jiang *et al.*, 2017), as a predictor of country level conflict (Mueller and Rauh 2017), for the categorization of speeches in the US congress (Quinn *et al.*, 2010), and to quantify discussions in the central bank committee of the Bank of England (Hansen, McMahon, and Pratt 2014).

Applying topic modeling methods to the Twitter corpus indicates Russian-backed Twitter intervention from 2014-2017 had relatively high proportions of anti-Clinton/pro-Trump topics, though it should be noted that topics related to Clinton can be interpreted as more consistently negative than those regarding Trump are positive. Complicating matters, the corpus is also concerned with discussing both conservative policy objectives as well as progressive policy objectives, though hashtag use is proportionally overwhelmingly conservative-focused. Topic models indicate a high degree of topical heterogeneity and suggest Russian efforts sought to simultaneously provide support for discussion of a wide variety of contradictory political topics while also prioritizing goals around the candidates in the race. In other words, the Russian-backed Twitter corpus is not only topically diverse but also displays concrete foci or goals relating to language around candidates Clinton and Trump.

This inquiry also includes the application of emotional lexicons to the corpus to allow for comparison of the emotional value of word choice within Tweets against a time period coinciding with the 2016 presidential election. This paper uses the English Regressive Imagery Dictionary (RID) designed by Martindale (1975, 1990), which consists of roughly 3,150 words and roots “assigned to 29 categories of primary process cognition, 7 categories of secondary process cognition, and 7 categories of emotions” (Martindale 1975). These emotions include “positive affect”, “anxiety”, “sadness”, “affection”, “aggression”, “expressive behavior” and “glory”. Evidence supporting the Martindale Lexicon can be found in Martindale, (1975, 1990), Martindale & Dailey (1996), Reynes, Martindale & Dahl (1984), Martindale and Fischer (1977), West *et al.*, (1983), West, Martindale, and Sutton-Smith (1985) and West & Martindale (1988). This paper also utilizes the National Research Council Canada (NRC) Emotion Lexicon. The NRC lexicon is a list of English words and their associations with the eight emotions of anger, fear, anticipation, trust, surprise, sadness, joy, and disgust (Mohammad and Turney, 2013). The NRC Emotion Lexicon annotations were manually coded via crowdsourcing through Amazon's Mechanical Turk. This coding process was developed to help reduce variance between coders for word-emotion associations. Further usage of the lexicon can be found in Mohammad and Yang (2011), Mohammad (2011) and Mohammad and Turney (2010).

What follows is a brief overview of our research questions, data, and methods. After establishing research questions, this paper presents two topic model output results for the Twitter corpus. Following this, the results of the model are interpreted. Next, several emotional lexicons are used to provide further information on the data. Finally, the paper concludes with a discussion of possible explanations for the topic model and emotional lexicon outputs.

Research Questions:

- What topics make up the largest proportions of the Russian-backed Twitter corpus? What policies, individuals and social movements were most discussed in the Tweets?
- What, if any, emotional and/or semantic trends are evident in the Russian-backed Twitter corpus over time?
- Taken together, what do the topics and emotional/semantic themes of IRA/Russian Tweets say about the policy goals of the actor(s) that supported their creation?

To address these research questions an inductive analysis of the Tweets within this corpus has been conducted here for a simple reason: the aim of this paper is to provide insight into the topical and emotional content and characteristics of Russian-backed Twitter data which was unknown at the initiation of this inquiry. As such, this paper forgoes formal hypotheses to a.] better represent a naive starting point with the data, and b.] to avoid *post hoc* theorizing. In the interest of research transparency it should be noted there were no formal expectations of specific topics or emotional content patterns when this analysis began.

Data:

Data collection for this inquiry consisted of obtaining the publicly available Twitter/NBC News corpus of IRA/Russian Federation associated Tweets from July of 2014 to September of 2017. The Russian-backed IRA Tweets, and not the account handles themselves, are the primary level of analysis in this inquiry. This data was made publicly available by NBC news in collaboration with three unnamed sources familiar with Twitter’s development system on March of 2018, and consists of some 200,000 Tweets from 3,814 Twitter accounts associated by Twitter with the Russia-based Internet Research Agency.¹¹ The same underlying Twitter accounts, originating from several

¹¹ To clarify, the list presented to Congress by Twitter originally included 2,752 Twitter accounts linked by Twitter to the IRA. Later, Twitter would amend this number to the 3,814 number used in this inquiry. More information on this can be found in a Twitter blog post at “Update on Twitter’s review of the 2016 US election”, 2018.

third parties as well as Twitter's internal analysis of Russia-linked accounts, were also presented in Twitter testimony to the US Congress in October and November of 2017 (Testimony of Sean J. Edgett, United States Senate, 2017).

The third parties that originally alerted Twitter to the IRA linkage are not named specifically in the Congressional testimony, but Twitter's counsel notes "The IRA tips we got were from news organizations in 2015 and then also a third-party company we used to do deep web monitoring to give us threat information" (Russia Investigative Task Force Hearing With Social Media Companies, U.S. House of Representatives, 2017). Twitter's counsel also notes "[...] we've been fighting these types of issues for a while. We saw, in 2015, IRA activity and took large scale action against those accounts and shared that information with other companies at the time."

Twitter does note its investigators have traced Russia-linked accounts in the past through detection of "unusual activity" including patterns of Tweets, "likes", and "follows" (Testimony of Sean J. Edgett, United States Senate, 2017). Twitter also notes they employ internal, manual reviews conducted by employees. This proprietary process also incorporates user reports to "calibrate" detection tools to identify spam. Twitter notes specifically that they "rely on objective, measurable signals" like the timing of Tweets to classify a given action as automated (Testimony of Sean J. Edgett, United States Senate, 2017).

As no single characteristic can reliably determine geographic origin of a Tweet, Twitter utilized several criteria ranging from origin of account creation, user registration tying the account to a Russian phone carrier or a Russian email address, user display names showing Cyrillic characters, frequency of user Tweets in the Russian language, and/or whether the user has ever logged in from any Russian IP address (Testimony of Sean J. Edgett, United States Senate, 2017). As such, Twitter assumed an account to be Russian-linked if the account had a Russian email address/mobile number/credit card/login IP; or, the Russian Federation was the declared country on the account;

or, Russian language or Cyrillic characters appeared in the account information or name. The 3,814 user accounts whose Tweets are examined here were linked to the IRA through this information, through the aforementioned deep web monitoring, through press/journalist tips to Twitter, and through analyzing specific purchases of promoted tweets during the election period (Testimony of Sean J. Edgett, United States Senate, 2017, and Russia Investigative Task Force Hearing With Social Media Companies, U.S. House of Representatives, 2017).

The author is not aware of any speculation that the data used here is unreliable. However, prior to engaging in this inquiry it is important to address whether the Twitter data represents IRA-linked content to bolster concept validity. Indeed, no dataset is perfect, a thorough understanding of underlying information is key to any research project, and there are several caveats to be made with the NBC/Twitter Corpus. In particular, it should be noted that Twitter lacks complete transparency in releasing full data sets related to controversial issues like Russian interference. Twitter did not itself release the Tweet content related to IRA activity (only a list of user names), as the firm has a policy of deleting controversial posts entirely. As such, the Twitter/NBC News corpus, like many other Twitter corpora, rely on third parties to access the information and/or re-attach Twitter ID's to actual Tweets. Twitter's Terms of Service (TOS) does not allow full datasets of Tweets to be given to a third party, but the TOS does allow datasets of Tweet IDs to be shared. From this the data, full Tweet content can be re-attached to the appropriate account. Twitter also does not provide full code or detailed metrics for their identification process, nor do they appear to disclose the names of their subcontractors.

In this context researchers must unfortunately also do without additional corroborating evidence that may be either classified by the Federal Government, kept private by Twitter itself, and/or protected by NBC News (who are also understandably keen to protect sources). For example, the individuals who connected the Twitter user names to actual Tweet data are

anonymous, and the practice of connecting user names to user data is a common enough practice in journalism and academic research to make further identification impossible. Ultimately, the NBC/Twitter dataset used in this inquiry represents not only Twitter’s public efforts to disclose Russian meddling on the site but also the work of others to connect user names to underlying Tweets.

With the above data sourcing realities in mind, there are several important logical corroborators for the dataset. First, the underlying user names in this corpus were presented in testimony to the US Congress by a legal professional. Second, organizations and researchers ranging from the Atlantic Council to academic researchers at Clemson University have utilized this data or related datasets for analysis. The Digital Forensics Lab at the Atlantic Council notes Twitter “maintains high confidence [the data are] associated with the Russian Internet Research Agency [...]” (Digital Forensics Lab, Medium.com, 2018). Third, follow up coverage of this dataset indicates very few of the accounts in question were real/human US accounts misidentified as Russian-backed. Analysis by researchers suggest perhaps only 20 accounts out the data were actually real US individuals.¹²

Finally, concept validity is also supported by Twitter’s Congressional testimony, stating 9% of the original 2,752 Tweets were “election-related”, with roughly 47% being automated (Testimony of Sean J. Edgett, United States Senate, 2017). As such, we can also be confident the Tweet data

¹² Drs. Darren Linvill and Patrick Warren cite this count in several *Wired.com* articles covering their research on Russian disinformation campaigns. The claims of Linvill and Warren are in reference to their research on the Twitter data, but underlying peer reviewed articles containing these claims were not publicly available at time of writing. References to the 20 person value found by Drs. Darren Linvill and Patrick Warren can be found in, Martineau, Paris. “Twitter’s Dated Data Dump Doesn’t Tell Us About Future Meddling.” *Wired.com*. 2018. <https://www.wired.com/story/twitters-dated-data-dump-doesnt-tell-us-about-future-meddling/> And, Calderwood, Alex; Riglin, Erin; Vaidyanathan, Shreya. “How Americans Wound Up on Twitter’s List of Russian Bots.” *Wired.com*. 2018. <https://www.wired.com/story/how-americans-wound-up-on-twitters-list-of-russian-bots/>

examined here was not simply selected by Twitter because of content relationships or matches to the US election itself.

Methodology:

To utilize these Tweets for topic model and emotional lexicon analysis several standard steps had to be undertaken in R. Data cleaning was an initial requirement as this textual data (and Twitter data in particular) was characterized by high proportions of non-word content and typos. As noted elsewhere, data of this type typically needs to undergo extensive preparation before it can be fed into a topic model algorithm (Müller, Schmiedel, vom Brocke, 2018).

This said, one of the major advantages of performing text analysis in R is the ability to combine different analytics packages and streamline data cleaning. Additionally, the analysis conducted is inherently replicable. This paper utilizes the *Quanteda* and *STM* packages, along with several emotional lexicons, to produce analysis of the data. To prepare the tweet data it first must be imported from the .csv file into R (R natively supports reading flat text files such as .csv). After confirming the data was properly encoded, the Tweets were converted from the .csv file into a *Quanteda* corpus using the *Quanteda* package. This allowed for metadata to be read by R as separate variables and is also one opportunity for standard “preprocessing” measures to be taken (Welbers, Kasper, Van Atteveldt, Wouter, and Benoit, Kenneth, 2017). This corpus was then converted into a Document Frequency Matrix, *Quanteda*’s version of a Document Feature Matrix. This step allows for data analysis with matrix and vector algebra and moves the data character text to numeric values (Welbers, Kasper, Van Atteveldt, Wouter, and Benoit, Kenneth, 2017).

A DTM/DFM was created from a *Quanteda* corpus because this allowed the associated metadata and document-level variables (including Tweet-specific year-month-day/hour:minute:second time values) to be preserved in the DFM. Subsequently, R packages could then determine how often a given term is used in each document, data/time values for each

document, etc. Common stopwords were also removed during the DFM conversion process. The resulting DFM also removed punctuation and converted all letters to a lower-case form. Symbols and hyperlink related syntax were also removed for clarity. Tokens (originally words) were stemmed using the SnowballC package (Bastin and Bouchet-Valat, 2014) through Quanteda. Additionally, additional topic model analysis using only the STM package (forgoing Quanteda) was conducted to utilize additional estimators for k (topic number) values.

This analysis then diverges into two data approaches that build on Boumans and Trilling's (2016) characterization establishing "counting/and dictionary", "supervised machine learning", and "unsupervised machine learning" as the three current methodological schemes for text analysis. Their study orders these three approaches from most deductive to most inductive, respectively. They convincingly argue dictionary/lexicon analysis employs the use of *a priori* coding schemes (words to emotions) while unsupervised learning tools use algorithms to induce meaningful from text data. Here, topic models are used to draw patterns from the co-occurrence of words in the Twitter data,¹³ while emotional lexicons are deployed as pre-established patterns to sit on top of the Twitter data.¹⁴

Topic model-based research generally refers to the number of topics within the analysis as a value of k . This k value is the only element of the unsupervised method set by the user, and

¹³ More accurately, when using topic models the user assumes observed words (in a "bag of words" model that ignores word order) are generated by a joint-probability of two mixtures. Documents are a mixture of topics and topics are a mixture of words. Each topic is a discrete distribution of words, creating a word-topic matrix. This word-topic matrix provides a conditional probability for every word (row) given each latent topic (column). These probability distributions allow an observer to order and rank words by topics and thus to determine the most common word used when referring to each topic. For more details, see: Wesslen, Ryan. Computer-Assisted Text Analysis for Social Science: Topic Models and Beyond. arXiv preprint arXiv:1803.11045. 2018.

¹⁴ These patterns are invariably subject to critiques of intercoder reliability. However, it should be noted: 1. *Human* sentiment coding agreement is never 100 percent, and at least one study shows sentiment agreement between human coders at around 82 percent (Wilson, Wiebe, and Hoffmann, 2005). This work also shows lexicon analysis can match or nearly match this kind of reliability. 2. One of the emotional lexicons used here is crowd sourced, and thus makes attempts to address inter-coder reliability inherently. The other has been deployed in multiple studies and has a long peer reviewed track record.

represents the total number of topics requested by the user to summarize the corpus. This inquiry began by using a series of k values (in a variety of initializations and labeling outputs), examining $k=5$, $k=10$, $k=20$, $k=50$, $k=56$, $k=60$ and $k=100$ models in the exploratory stage of research. These k levels were chosen to reflect current topic number ranges listed in relevant literature to assess the overall topical content at different topic number levels (Müller, Schmiedel, vom Brocke, 2018; Roberts, Stewart, Tingley, 2018).¹⁵ Producing multiple k value models was also done to assist in reading and establishing the topical characteristics of the corpus for the researcher. After initial modeling and comparison, the author chose to exclusively use the “spectral” initialization recommended by the STM package vignette as it (in general) outperforms both Latent Dirichlet Allocation via collapsed Gibbs sampling as well as random initialization (Roberts, Stewart, Tingley, 2018).

Obviously, including summaries of all the topic models listed above in this paper would produce a final report of both great length and high repetition. As such, the $k=56$ model was chosen to summarise this corpus for a variety of reasons explained briefly below. First, the $k=56$ model fits well within the already referenced best practices in topic modeling literature for a corpus of this size. Second, this model was informed by STM’s “ $k=0$ ” functionality that uses Lee and Mimno’s (2014) t -SNE/anchor words algorithm, along with the spectral initialization, to construct plausible k values for a given data space size (note however the STM package stresses this is not a “correct” k initialization, merely one that is well-fitted to the data space). This initialization process is not deterministic, and thus will not necessarily produce the same number of topics/content within topics in each run. As such, the author ran multiple $k=0$ /spectral models, noting the resulting range

¹⁵ One aggregation of topic model studies notes 10-50 topics ($\bar{x}=35$), while the STM package references $k=60$ -100 as a “good starting point” for larger corpora. The overall takeaway is that there is no perfect or “correct” k value, and that the subsequent models are replicable tools to assist in research, not immutable, “pure” or otherwise indefectible summarizations of data.

of models to be centered roughly around the k value chosen here. In other words, 56 topics was a value that fell within a range of multiple similar estimates made by the package to fit the data well. Third, a $k=56$ model also corresponds well to estimates for this dataset resulting from metrics developed by both Arun *et al.* (2010) and Griffith and Steyvers (2004). For these reasons utilizing the $k=56$ model is well-supported in this application.

This paper presents the $k=56$ model using the “highest probability” and “score” labeling algorithms. The highest probability labeling algorithm is inferred directly from the topic-word distribution parameter, β . The score labeling algorithm is a matrix containing the log probabilities of seeing word v conditional on topic k . Highest probability and score labeling algorithms were used here as they routinely generated only non-junk topics for all topics in the model. In other words, these configurations were least prone to constructing topics with non-word data remaining in the corpus despite preprocessing. This inquiry structures analysis of both labeling outputs in two ways. First, we present the results of the models. Second, we provide subject matter expert interpretation of the models in keeping with the literature of topic models (Müller, Schmiedel, vom Brocke, 2018).¹⁶ Both results and interpretation sections also include description and interpretation of words and hashtags included in the topic labels generated by the models.

The second element of this analysis focuses on the use of emotional lexicons with the Tweet data to discern potential emotional and semantic trends over the July of 2014 to September of 2017 time period. This analysis concerns the emotional and semantic values of the language within the IRA Tweets as measured by the Martindale and NRC lexicons (Martindale, 1975 and 1990, and Mohammad and Turney 2013). Emotional lexicons were used with the same data as the topic model analysis and was also conducted by first running the Tweets through Quanteda’s Document

¹⁶ For one *conceptual* question regarding the interpretation of these models coders unfamiliar with the corpus were also utilized to rate topics.

Frequency Matrix function with one of the lexicons set as a dictionary. This step coded the Tweets to the respective emotions and sentiments contained in each of the lexicons. This DFM was then converted to a conventional data frame, and a string value variable indicating Tweet creation time was converted into a “Date” format. Proportions of emotions and sentiments could then be measured over time. Tweets remain the primary level of analysis in the emotion lexicon section as well.

Topics Models, Results:

What are the most important topics within the Russian-backed Twitter corpus coinciding with the 2016 US Presidential election? To help answer this question several visualizations of the $k=56$ model are useful [Figures 1 and 2, below]. Figure 1 shows the model in the “highest probability” labeling algorithm format (inferred directly from the topic-word distribution parameter, β), while Figure 2 shows the model in the “score” format (a k by v matrix containing the log probabilities of seeing word v conditional on topic k).

Topic models of the data reveal several general observations. On the whole this is a corpus with a majority of topics referencing political concepts, with the highest probability labeling algorithm having 75 percent and the score labeling outputs having 73.2 percent of topics containing political language as judged by the author.¹⁷ Using the spectral initialization at $k=56$ the highest probability labeling algorithm shows 42 of 56 topics (75 percent) contain political language (fig. 1 and appendix 1). At the $k=56$ level the score labeling algorithm shows 41 out of 56 topics (73.2 percent) contain political language (see fig. 2 and appendix II).¹⁸

¹⁷ The author defined political language simply as words associated with prominent politicians, social movements, political campaigns, government policies, political hashtags, nation states, religions, foreign leaders and political concepts like patriotism. This definition also included US political slang like “snowflake” or “woke”. Such a definition was also presented to the coders unfamiliar with the corpus prior to their assistance.

¹⁸ Full topic label lists are available in appendix I and II for the highest probability and score models, respectively. Readers concerned with the interpretation given here can refer to the full model outputs.

Assessment of political/apolitical language by three coding assistants unfamiliar with the corpus contents actually rated the corpus significantly less political in content, with the highest probability label seeing a mean of 31 (55.4 percent) and the score label seeing a mean of 33 (58.9 percent) of topics as containing political wording.¹⁹ More discussion of this disparity can be found in the Topic Models Interpretation section that follows.

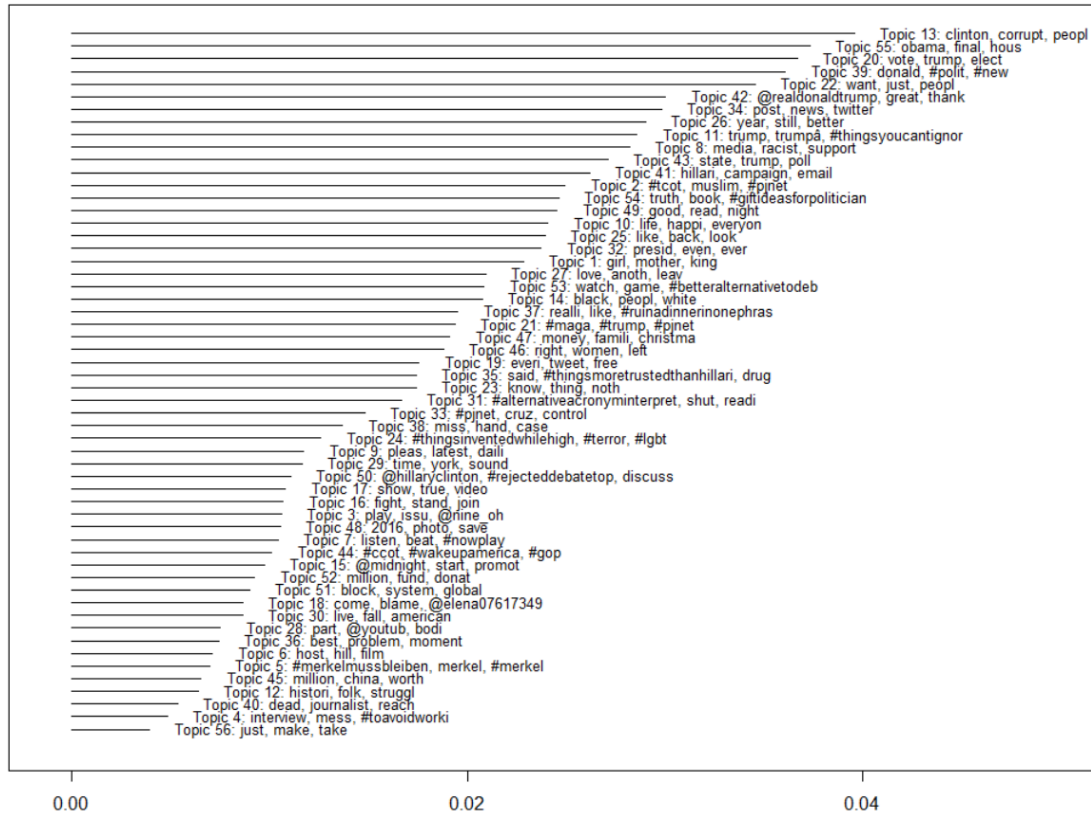


Figure 1: Expected Topic Proportions (highest probability labeling algorithm) for Internet Research Agency sponsored Tweets, k=56.

¹⁹ Krippendorff's alpha (Ka) reliability coefficient values, as well as simple agreement percentages, were calculated for coder's political/apolitical ratings. For the highest probability output the Ka coefficient was .734, while the score output rating value was .587. The simple agreement percentages were 80.4 and 69.6 for the highest probability and score outputs, respectively. Neither of the Ka values here is particularly strong, indicating a relative lack of agreement between coders. Due to the inductive structure of this inquiry (and thus the limited coaching/instructions for coders), as well as the highly esoteric nature of the Twitter data (hashtags, slang, etc.), such low Ka scores are not necessarily surprising.

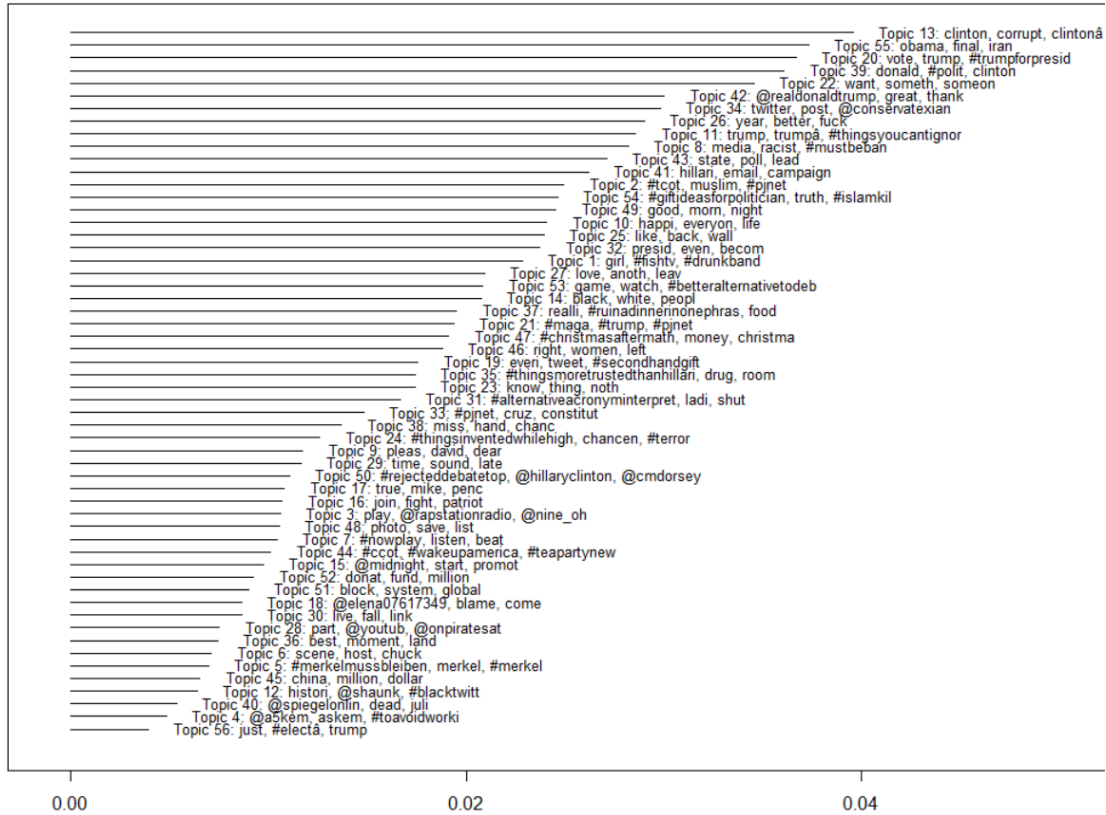


Figure 2: Expected Topic Proportions (score labeling algorithm) for Internet Research Agency sponsored Tweets, k=56.

Several characteristics of the corpus are relevant in relation of the research questions of this paper. The k=56/highest probability model contains 10 topics (17 percent of the topics) referencing candidate Trump, of which 4 were identified by the author as being supportive of Trump/the campaign via topic content.²⁰ The role of the Clinton campaign and Hillary Clinton herself in the corpus in the k=56/highest probability topic model is both prominent and negative. This model contains 7 topics (12.5 percent of the topics) referencing candidate Clinton, of which all 7 can be identified as being anti-Clinton via topic content.

²⁰ Review from coders unfamiliar with the data was not conducted for the more specific topics present in this inquiry. The author chose to forgo this review because topic content for these topics was self-evident (as in the case of the “Clinton/Trump” coding). Topics either mention Obama, Trump, Black Lives Matter, etc., or they do not. Whether a topic is “political” or “apolitical” is a subjective assessment judged to be improved by repeat coder validation. As always, readers are encouraged to review the topics themselves in appendix I and II.

In the highest probability model, 6 topics (10.7 percent of the topics) were judged by the author to contain language referring to refugees and border issues, and 2 of 6 had negative context. In contrast to the Clinton topics, of the 5 topics (8.9 percent) referencing President Obama, only 1 topic was identified as being overtly negative in topic content. 3 topics (5.3 percent of the corpus) involve the Black Lives Matter movement and/or Black Power movements, 2 of which appeared to have positive language context. 7 topics (12.5 percent of the corpus) contain Christian language, with 2 of 7 having positive context. The highest probability model also has 2 topics (3.5 percent of the corpus) featuring Russia and/or President Putin, though no positive/negative context was clear in topics featuring Russian and/or Putin.

Finally, 14 (25 percent) of the topics in the highest probability output were judged by the author to be apolitical and contain no overtly political language. As noted previously, coders unfamiliar with the data scored this output as 44.6 percent apolitical. This is a pattern closely mirrored in the score output.

The k=56/score configuration shows similar topical distributions, with several subtle but important differences. The k=56/score model contains 9 topics (16.07 percent of the topics) judged by the author to refer to candidate Trump, of which 4 can be identified as being explicitly pro-Trump via topic content. The Clinton campaign/Hillary Clinton in the k=56/score model are also referenced in 9 topics (16.07 percent), of which 7 were identified as being anti-Clinton via topic content (one of the two topics identifying Clinton that is not explicitly anti-Clinton or pro-Trump appears to reference the Clinton Foundation, a popular negative talking point among some conservative media outlets during the 2016 campaign). In the score output there are an equal number of topics containing language opposing Clinton as there are containing language supporting Trump. In the score configuration candidate Clinton and candidate Trump were also featured in equal numbers of topics proportionally. Notably, the single most prominent topic in each output

both contain language focused on the Clinton campaign and/or Hillary Clinton, and both of the most proportionally prominent topics contain context/language that is negative towards the Clinton campaign.

The k=56/score output shows 4 topics (7.14 percent of the topics) featuring language referencing refugees and border issues with 2 of 4 identified by the author as negative in content. In contrast to the Clinton topics, of the 3 topics (5.3 percent of the corpus) referencing President Obama, only 1 topic was identified as being negative towards President Obama in topic content. Again, 3 topics (5.3 percent) involve the Black Lives Matter (BLM) movement and/or Black Power movements, 2 of which were coded by the author as positive references to the BLM movement. The score model shows 4 topics (7 percent) contain Christian language, all without positive or negative context. 2 topics (3.5 percent) concern Russia and or President Putin, though no context could be discerned.

Like with the previous output, a large proportion of the score model contains apolitical topics. In the score output, 15 topics (26.7 percent) appeared to the author to be apolitical or contain no overtly political language. Observers unfamiliar with the corpus judged it to be composed of 41.1 percent apolitical topics.

Hashtags within the topics show the Tweets more likely to feature conservative and/or Republican content. Conservative hashtags like “#maga”, “#trump”, “#pjnet”,²¹ and “#tcot”²², “#trumpforpresident”, “#ccot”²³, “#lntyhbt”,²⁴ “#trumptrain” and “#neverhillary” appear at least

²¹ PJNET, or the Patriot Journalist Network, is a conservative information network and associated Twitter account (some potentially bots) currently banned from Twitter. PJNET has been tied to disinformation campaigns related to education politics. See, Mak, Aaron. “Twitter Is Shutting Down a Conservative Group’s Automated Tweets.” Slate.com, 2017. http://www.slate.com/blogs/future_tense/2017/10/17/twitter_has_labeled_a_conservative_group_s_automated_tweets_as_spam.html

²² “TCOT” is an abbreviation for “Top Conservatives on Twitter”.

²³ “CCOT” is an abbreviation for Christian Conservatives on Twitter.

²⁴ “Let not your heart be troubled” (“LNYHBT”) is a phrase associated with conservative television personality Sean Hannity.

37 times in the highest probability output and 52 times in the score output. In contrast, the highest probability output had at least 8 progressive associated hashtags, while the score output had at least 9 such hashtags. Coding for hashtags was conducted only by the author as hashtags identification requires subject matter expertise and research for accurate identification.

As a segue into the next portion of this paper it should also be noted that potentially violent language, including terms like “kill”, “hate”, “attack” and “protest”, are present in several topics in both topic model outputs. Several racial slurs targeting African Americans are also included in various topics generated from the data.

Topic Models, Interpretation:

One of the values of topic models is that they allow subject matter expert review of replicable and transparent building blocks (here, the topic outputs). This section concerns itself with an SME review of the topic model results described above.

First, it is notable that both model outputs contain many topics containing no discernible references to political phenomena. SME review of the outputs finds 25 and 26.7 percent of topics as apolitical for the highest probability and score outputs respectively. Review from coders unfamiliar with the corpus show even higher levels of apolitical topical content, with ratings of 44.6 and 41.1 percent apolitical for the highest probability and score outputs respectively. Readers should note the obscure hashtags, slang, and individuals referenced in the corpus may help explain this difference. For example, this corpus contains references to Trump supporter and pundit Sheriff David Clarke, as well as to the hashtag “#BB4SP” (Barracuda Brigade for Sarah Palin), representing an obscure political personality and a difficult to interpret hashtag, respectively. Such complex language may help explain the relatively weak Krippendorff’s alpha coefficients and simple agreement percentages between the coders. As obscure abbreviated references and hashtags are contained in many of topics in both outputs, low inter rater reliability (IRR) may indicate that topic models benefit from subject

matter expert review and interpretation (Müller, Schmiedel, vom Brocke, 2018). These IRR scores may also indicate more extensive pre-coding training would be advisable for future similar studies. The esoteric language within the topics, as well as the relatively low IRR scores, do indicate variance between a subject matter expert and interpreters unfamiliar with the data is not necessarily surprising. It is nonetheless interesting to note this corpus is if anything *less political* in language content than the author's assessment.

Topic models showing 25-26.7 percent of topics (SME review) being non-political may be partially explained by the fact that managers of artificial networks of Twitter profiles are likely interested in not appearing to be artificial. Such an interest in appearing human may help partially explain the absence of a binary and unified narrative from the IRA-associated accounts containing only political information. The apolitical content and topics within the IRA Twitter data provides a fruitful further avenue of research and a modulation of our understanding of Russian-linked online interference. As we discuss in the final section of this paper, the IRA's role as something of an outside contractor for the Russian state may also explain some of this content (the IRA may have been experimenting with multiple strategies to win government approval and funding, and/or may have had multiple contracts or projects underway at a given time).

In terms of political topics, topic models generate several key findings. While intelligence community investigators of Russian disinformation are likely unsurprised to find President Trump and his campaign featured heavily in this data, it remains noteworthy a corpus of this provenance appears to feature then-candidate Trump as one of the most prominent topics. Interestingly, Trump does not appear in the majority of topics here, indicating the common perspective that Russian meddling was purely or primarily pro-Trump is oversimplified. The topic model analysis included here both replicably corroborates intelligence community accounts and anecdotal social media

opinions claiming Russian support for the Trump campaign while at the same time adding nuance and complexity.

Indeed, in the score label output, Donald Trump and the Trump campaign do not exclusively hold the most prominent topical position in the Russian Twitter data. In this output the number of topics featuring Clinton and Trump are equal. If we combine frequency of candidate name/hashtag inclusion into a topic with frequency of negative context of a topic, the role of the Clinton campaign and candidate Clinton stands on its own as a feature of the data. It is notable that while there is seemingly a more ambiguous treatment of the Trump campaign and Donald Trump himself in the data, the topics generated by Russian agents regarding Clinton are overwhelmingly negative in word content. Upon SME qualitative review, both labeling algorithm outputs Russian-backed Twitter topics about Hillary Clinton were more likely to be negative than Russian-backed Twitter topics regarding Donald Trump were to be positive. When judging by the language context of each topic the score output appears to show a corpus at least as focused on negative language in association with the Clinton campaign than on positive language around the Trump campaign.

The findings of this inquiry also complicate analysis of Russian-sponsored online propaganda by indicating the Tweet corpus contains a host of both conservative and progressive political topics. An SME qualitative summarization of the top five most proportional topics in each label output helps point this out. The top 5 most prominent topics by proportion of the total corpus in the highest probability output shows a diverse mix of language content. An SME labeling of these topics based on their content might be stated as: Topic #1 (Topic 13) “Corrupt Clinton and Never Hillary”, Topic #2 (Topic 55) “The Obama Administration and International Relations”, Topic #3 (Topic 20) “Vote Trump, MAGA, fraud and Hillary for Prison”, Topic #4 (Topic 39) “Trump/Clinton, Immigration and Russia”, Topic #5 (Topic 22) “Change the World, ‘Donald’, and

Refugees”. The top 5 topics in this output demonstrate this corpus has multiple overarching policy goals and does not focus exclusively on supporting the Trump campaign.

An SME qualitative labeling of the score topics shows quite a similar picture to the highest probability output. Based on content, SME labeling might be stated as: Topic #1 (Topic 13) “Corrupt Clinton and Never Hillary”, Topic #2 (Topic 55) “The Obama Administration, Congress and International Relations”, Topic #3 (Topic 20) “Vote Trump, Get out the Vote, and Hillary for Prison”, Topic #4 (Topic 39) “Trump/Clinton, Rallies, Immigration and Russia”, and Topic #5 (Topic 22) “Change the World, ‘Donald’, Anti-Islam and Refugees”.

Topics in both the highest probability and score labeling outputs contain language referencing a variety of contradictory political positions. Immigration, refugees, and border issues are all included in topics in both outputs. At the same time, race politics/identity movements, in particular the Black Lives Matter Movement, plays a prominent policy role in the corpus. Beyond the two “primary” candidate-centered topics, topic models indicate Russian-backed Twitter intervention also supported a topical heterogeneity that must be recognized. Contextually, the host of differing topics in the models make positing a monolithic progressive or conservative policy preference within the data difficult. Both the highest probability and score topic model outputs demonstrate this disinformation effort was both complex and nuanced. For example, while then-candidate Trump is one of the central topics in the Russian Tweet corpus, the data also demonstrates negative conversation regarding the Clinton campaign was in some ways as important a topic to the creators of the Tweets as positive conversation regarding the Trump campaign.

An important caveat to this assessment is that hashtag usage in the Tweets appears to indicate topics in the Russian Twitter data include much higher levels of conservative hashtag use than liberal/progressive hashtag use. Further exploration of variance in policy topics and hashtag utilization are one interesting avenue for future research opened up by this data.

As a segue into the next portion of this paper it should also be noted that potentially aggressive language, including terms like “kill”, “hate”, “attack” and “protest”, are present in several topics in the topic models. Several racial slurs targeting African Americans are also included in various topics generated from the data. Discussion of increases in angry and fearful language in this corpus will make up the next section of this paper.

Emotional Lexicon Analysis Results:

The IRA-linked Tweets also contain trends in terms of emotional language content and sentiment analysis. The Twitter data contains a year-month-day/hour:minute:second (“Y-M-D/H:M:S”) format time value for each document (Tweet), making temporal analysis possible. Using several emotional lexicons on the Tweets shows the IRA used increasingly aggressive language on social media during and immediately preceding the 2016 election. Cross referencing all the IRA-tied tweets with a peer-reviewed dictionary containing lists of words associated with particular emotions makes it clear that during September, October and November of 2016 the overall number of aggressive words in the corpus increased in quantity. Using the Martindale lexicon it is apparent the number of anger-associated words in the corpus was highly concentrated around the temporal window of the election (Martindale 1975, 1990) [Figure 3].

The Martindale findings are also corroborated with the more recently created crowdsourced NRC dictionary developed by Mohammad and Turney (Mohammad, and Turney 2013). Using the NRC lexicon, measures of fear and anger see proportional increases somewhat earlier than the Martindale configuration [Figure 4, 5, 6], as well as smaller increases in this type of language coinciding with the election period. Both of the increases in proportion of fearful and angry words occur in the 2016 calendar year. Additionally, both emotional word usage increases fall within the election cycle and come well after the IRA was already confirmed to be closely monitoring/discussing interfering in the 2016 election.

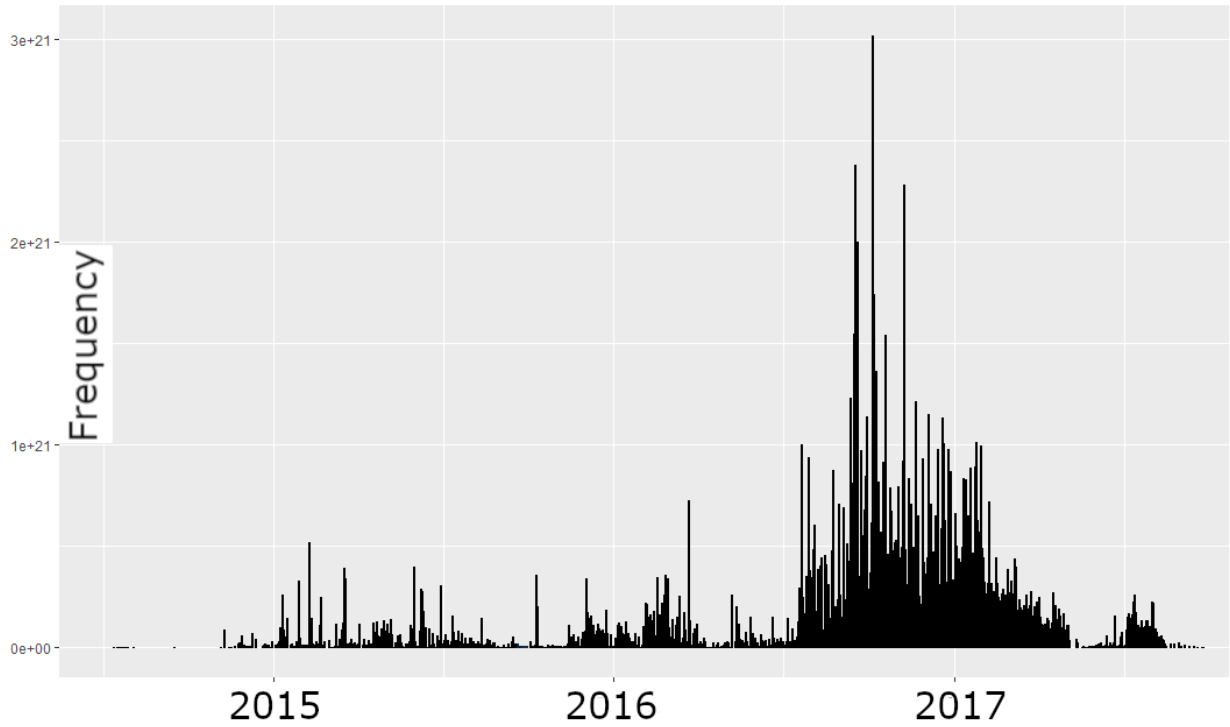


Figure 3: Number of aggression-associated words over time (Martindale 1975). X Axis from the Y-M-D/H:M:S value of each Tweet document.

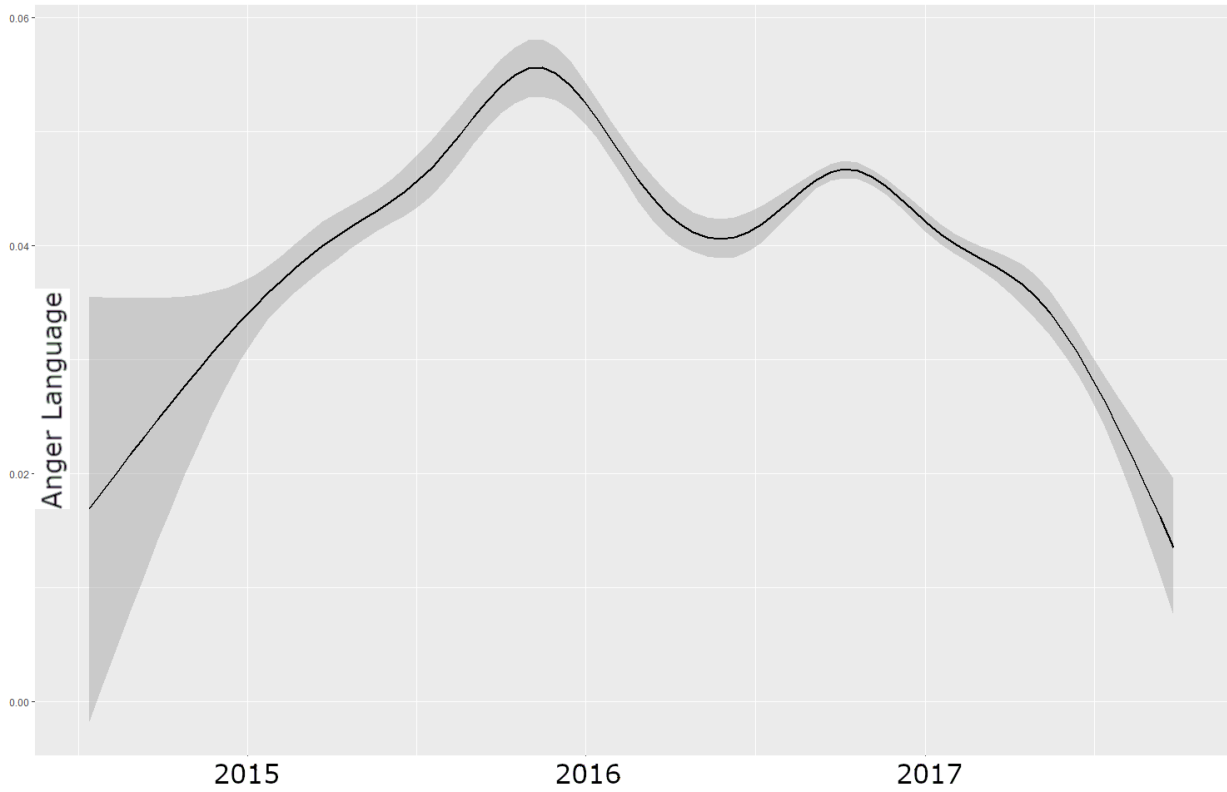


Figure 4: Proportion of anger-associated language tweets over time (Mohammad, Turney 2013). X Axis from the Y-M-D/H:M:S value of each Tweet document.

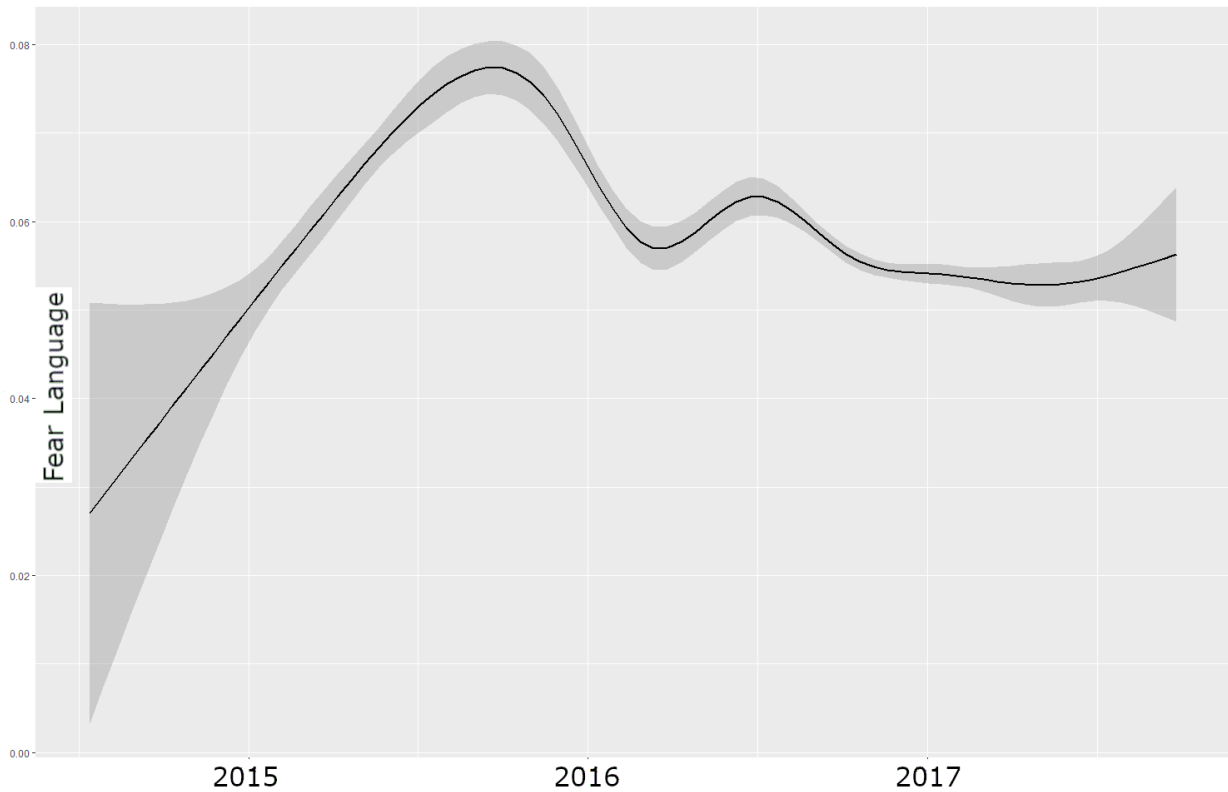


Figure 5: Proportion of fear-associated language tweets over time (Mohammad, Turney 2013). X Axis from the Y-M-D/H:M:S value of each Tweet document.

Discussion:

What topics make up the largest proportions of the Russian-backed Twitter corpus? What policies, individuals and social movements were most discussed in the Tweets? What, if any, emotional and/or semantic trends are evident in the Russian-backed Twitter corpus over time?

The findings detailed here necessitate a more nuanced conceptualization of Russian Twitter interference than as a singularly pro-Trump project. First, topic models indicate many of the prominent topics in the data may be better articulated as “anti-Hillary” than “pro-Trump”. Second, topic models show us the data is topically heterogeneous and contradictory, addresses a variety of political positions and issues, and has a relatively high proportion of apolitical topic content.

Anecdotal Twitter-user and US Intelligence Community information lends credibility to the claims

of pro-Trump Russian interference, and indeed the findings of this inquiry support such a conclusion. However, topic model analysis modifies such a perspective in important ways.

Topics generated by Russia-backed accounts on Twitter before and during the 2016 election do feature then-candidate Trump heavily. Hashtag use in Russian-backed discourse is also overwhelmingly focused on politically conservative issues, talking points, organizations and beliefs. However, topic models paint a more complex picture that shows the Clinton campaign as in some ways an equal target of Russian efforts online. Contextually speaking, Russian Twitter propaganda was by some measures more negative towards Clinton than it was positive towards Trump, and in the score label output Clinton's campaign was an equally important topic in the data. This corpus also contains too high a degree of topical heterogeneity and contradiction to categorize it as simply "pro-Trump" (or for that matter "anti-Clinton").

It is noteworthy that in conjunction with this topical complexity there are also distinct emotional word usage patterns in the Twitter corpus. This is important because it is entirely reasonable to expect *a priori* that a corpus allegedly *supportive* of conservative US politics (attacking Democrats and supporting Republicans being held equal for the moment) *would not* display spikes of fearful and angry emotional content during the election period. Indeed, because this is a corpus at least somewhat concerned with candidate Trump winning, it is interesting one method used to achieve this goal would include peaked levels of angry/fearful emotional wording. A corpus heavily featuring conservative political hashtags and topics, while also being increasingly fearful and angry, raises further questions. Additional research should be conducted to interrogate possible associations between conservative/progressive topics and particular emotions and sentiments in Russian-backed online messaging.

The Twitter data also suggests an IRA/Russian policy aimed at negatively impacting US political consensus. Such a policy is displayed here through the angry/fearful, topically diverse, and

topically contradictory nature of the topics within the data. The Russian/IRA²⁵ efforts seem to prioritize several favored outcomes while pushing all sides of a debate and encouraging multiple different political viewpoints. The Russian tweets also appear to model unbiased human users, instead of automated or semi-automated accounts, to facilitate this attack on consensus. Such acting may be an important element to the “bot” and/or “troll” Twitter farm operational model in that it allows for covert infiltration of real human networks (Ferrara *et al.*, 2016). This is further supported by assertions elsewhere claiming accounts presented by Twitter to the US Senate are likely actually “cyborg” accounts at least partially operated by human users (Chu *et al.*, 2012b). These factors help explain the prevalence of apolitical and “small-talk” topics in the corpus; the topics could have been promoted to garner trust from human Twitter users and obfuscate the true origin of the Tweets.

While topic models demonstrate a diversity of topics within the corpus and thus suggests a contradictory flow of information, policy and public perception management are of course not just about topics but also about emotions and sentiments. Russian policy frameworks set on confusion and heightened “political intensity” (“Indictment Document” 2018) are supported and expounded upon through observations of increased angry and fearful wording in the Tweets. While this data is limited in several important ways (can a reference distribution of human Twitter users be obtained during this time period and compared to the Russian accounts? Would this distribution show statistically significant differences in such emotions to the Russian distribution? Can we ever be sure a reference distribution is not corrupted by Russian troll/”cyborg” accounts?), it is still important to observe Russian-sponsored Tweets containing angry and fearful words increasing in frequency in close proximity to a US election. Previous work has demonstrated political parties exploit online

²⁵ Logistically, major operations within the Russian Federation are sometimes coordinated through the presidential administration, but many are carried out by an array of “political entrepreneurs” hoping that their success will “win them the Kremlin’s favor” (Galeotti 2018). This may also help explain the host of topics within this corpus. Of course, it also provides plausible deniability for the Kremlin as the IRA is not officially a structural element of the state and is more of a favored sub-contractor receiving state funding.

campaigning in a “stop-start” structure centered on election cycles (Gibson, 2004 and Larsson and Moe in Weller *et al*, 2014). In this sense increases in overall Twitter activity should not necessarily surprise us. However, this inquiry a.] makes clear the Russia-backed Tweets examined here show a similar “stop-start” characteristic *within the temporal context of a domestic US election*, b.] demonstrate such election-centric cycles of Russia-backed messaging may be characterized by increased levels of anger, fear, etc., and c.] increases in certain types of emotional word usage may be a component of online Russian propaganda activity more broadly.

Taken together, what do the topics and emotional/semantic themes of IRA/Russian Tweets say about the policy goals of the actor(s) that supported their creation?

The topically diverse, politically conflicted, and fearful/angry nature of the data also necessitates a more nuanced theoretical explanation than simply “Russian Twitter misinformation was pro-Trump”. The IRA/Russian efforts on Twitter in 2015-2017 are in many ways best explained as part of a broader policy of Russian Federation propaganda emphasizing demoralization, division, and distraction while targeting democratic polities using opportunistic, fragmented, and contradictory messaging. Similar articulations have been convincingly offered, without the social media data context, by scholars like Paul and Matthews (2016). Others have noted Russian Federation policy operates through a series of semi-formal organizing strategies to guide disinformation campaigns, and include the “Firehose of Falsehood” (Paul and Matthews, 2016), “Gerasimov” (Galeotti, 2018), and “Aleksandr Dugin” (Dunlop, 2004) models of intelligence operations.

Aleksandr Dugin, a Russian academic and political advisor whose work “The Foundations of Geopolitics” is seen as a “textbook” for the Academy of the General Staff of the Russian military believes the Russian State should encourage separatism and unrest in the United States, in particular along racial lines (Dunlop 2004). Similarly, a “hybrid war” and/or a “Gerasimov Doctrine” approach to conflict aims to “destabilise societies and create ambiguity to hinder decision-making.”

(“European Commission Press Release”, 2016). These approaches often emphasize social media as a powerful medium of distribution that plays a central element in disinformation operations.

Moreover, digital information and communication issues also appear to be key risks mentioned in Russia’s 2014 military doctrine (Military Doctrine of the Russian Federation, 2014).

Internal memos from the IRA itself note that the organization should “use any opportunity to criticize Hillary and the rest (except Sanders and Trump—we support them)” and that “it is imperative to intensify criticizing Hillary Clinton” (“Indictment Document” 2018). This analysis suggests anti-Clinton topical emphasis was proportionally one of the more dominant elements of the Twitter campaign. One of the topic models demonstrates the Russian efforts were more anti-Clinton than they were Pro-Trump, and both models show negative discourse around the Clinton campaign as one of the two most prominent topics. This presents an important if subtle difference from current scholarly and popular assessments of Russian intervention in US social media.

Numerous topics connected to Candidate Trump, along with President Obama and a host of domestic and international policy issues, appear in both topic model outputs from all sides of the political spectrum. Meanwhile, the IRA itself noting a bias towards both Sanders and Trump suggests a deeply pragmatic policy focused on disinformation that does not easily conform to domestic US “left/right” paradigms and supports viewing such social media efforts from a Russian policy/Russian geopolitical interests’ perspective. Stepping back from specific candidate support or immigration policy debates, the Russian effort here has candidate preferences but is also highly concerned with discursive chaos. The corpus examined here lends replicable, social media centered support to the idea that the Russian disinformation approach may not necessarily be most concerned with pushing a particular policy outcome, but instead with the promotion of a host of contradictory outcomes.

The findings of this inquiry are also in dialogue with a growing body of literature in the computational social sciences related to online propaganda, manipulation, and discussion setting. The findings of this paper help establish that similar types of conversation manipulation outlined in previous scholarship is not limited to so-called “young democracies” and can be found even in highly developed representative systems (Zelenkauskaite and Balduccini, 2017). The findings of this inquiry are also important in light of recent scholarship demonstrating automated efforts on Twitter are likely larger and more pervasive manipulations of discourse than previously identified (Bessi and Ferrara, 2016). Woolley and Howard (2016) identify a fundamental need to understand how the data of the individual is used for “political applications”, and the author hopes this study helps add to such an understanding through an exploration of nested Russian policy objectives in social media data.

Further research is certainly needed to attempt to find a reference distribution with which to compare the data used here. Perhaps further research could incorporate causality tests of emotional interactions between the Russian accounts and human users. Interesting work has also been done to use topic models alongside regression analysis for predictive purposes (Mueller and Rauh 2017), an avenue of research this author is currently pursuing as well. All the same, the spike in IRA-sponsored angry/fearful language, along with the topic content shown here, provides a specific discursive preference within Russian-state associated Tweets.

A pervasive electoral communications platform being utilized by a foreign state for its own policy objectives is worthy of a deep, inductive and repeatable analysis. The research conducted here was not concerned with measuring the impact of Russian interference on American citizens, but in fact what the form of the interference may indicate about underlying Russian policy objectives. The IRA has a “stated goal of “spread[ing] distrust towards the candidates and the political system in general” (“Indictment Document” 2018), and the underlying Twitter data examined here affirms this

goal while also adding to it in important ways. This type of biased, contradictory, angry, and fearful discourse, as articulated through topic models and emotional lexicons, helps to define Russian social media disinformation and propaganda campaigns.

Data Availability:

The Twitter data set is publicly available. It can be accessed at: <https://www.nbcnews.com/tech/social-media/now-available-more-200-000-deleted-russian-troll-tweets-n844731>

Software Information:

R was used for the analysis conducted in this paper. The “stm” and “quanteda” packages were particularly relied upon.

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Appendix:

Appendix I: Topic label content (highest probability labeling algorithm)for Internet Research Agency sponsored Tweets, k=56.

Topic 1: girl, mother, king, blue, green, street, @gamiliel, dude, #fishtv, beer, catch, #drunkband, ball, dark, robert, #redneckamovi, door, brother, harri, #dogsong

Topic 2: #tcot, muslim, #pjnet, islam, attack, terrorist, terror, christian, #teaparti, refuge, radic, kill, obama, peac, @guntrust, must, america, europ, #isi, legaci

Topic 3: play, issu, @nine_oh, @rapstationradio, emx9jgtv3v, #nowplay, @1063atl, featur, radio, magazin, artist, feat, ichlwqg0i, #music, #listen2, #rap, #hiphop, digit, print, @indieradioplay

Topic 4: interview, mess, #toavoidworki, guest, @a5kem, #busi, channel, matthew, #vulnerabilityin5word, @ospatriot, steve, #podernfamili, @emenogu_phil, askem, segment, furious, scream, subscrib, jimmi, @wyzechef

Topic 5: #merkelmussbleiben, merkel, #merkel, frau, #girlstalkselfi, nicht, deutschland, wird, unser, sich, dass, amtszeit, immer, schaffen, kein, kanzlerin, angela, viel, bleibt, auto

Topic 6: host, hill, film, scene, #addabandtoatvshow, warren, chuck, behind, chao, knock, elizabeth, schumer, till, @blicqer, introduc, premier, effect, transform, flash, #artyoucanhear

Topic 7: listen, beat, #nowplay, track, @boogsmalon, soldier, produc, tune, dirti, music, avail, hook, grand, rapper, live, london, @nine_oh, dope, gang, prod

Topic 8: media, racist, support, protest, liber, polit, #mustbeban, call, #trumpsfavoriteheadlin, racism, video, outsid, report, govern, #blacklivesmatt, realiti, violenc, nazi, educ, white

Topic 9: pleas, latest, daili, dear, bless, david, mark, thank, share, sheriff, clark, @kattfunni, @tlcprincess, lewi, barri, chicken, @trivagod, duke, @jstines3, castro

Topic 10: life, happi, everyon, littl, make, wish, fear, deserv, nice, @breitbartnew, celebr, @deray, beauti, birthday, @tycashh, monday, thank, friday, other, gotta

Topic 11: trump, trumpâ, #thingsyoucantignor, order, just, rock, video, #obamaswishlist, front, @blicqer, presid, step, take, execut, call, ignor, woman, name, talk, inaugur

Topic 12: histori, folk, struggl, @shaunk, @blicqer, cultur, #blacktwitt, africa, upset, @khankne, @em2wic, hidden, hypocrit, buri, @jojokejohn, cycl, histor, @trueblackpow, contribut, inform

Topic 13: clinton, corrupt, peopl, american, #debat, hillari, media, #neverhillari, clintonâ, call, sick, @hillaryclinton, crimin, said, just, question, trump, prison, #debatenight, support

Topic 14: black, peopl, white, kill, polic, woman, matter, children, power, hous, #blacklivesmatt, live, student, amaz, arrest, murder, young, crime, @blicqer, shot

Topic 15: @midnight, start, promot, detail, @jayceodpromot, head, @chicagoildaili, career, click, quick, just, #chicago, #mondaymotiv, drag, #break, #addcartoonstohistori, woke, lieben, mein, @independ

Topic 16: fight, stand, join, patriot, freedom, armi, enlist, america, @abninfvet, veteran, dare, today, click, rrrzgbccxbo, grow, sign, fellow, american, speech, socialist

Topic 17: show, true, video, stori, penc, mike, sexual, victim, view, assault, silenc, abort, plane, @realalexjon, includ, onlin, #dnc, toler, watch, spot

Topic 18: come, blame, @elena07617349, suspect, known, enjoy, polic, theyâ, #idontneedacostumebecaus, repeat, hope, dalla, favor, anti, revolut, pure, spell, snowflak, band, forgotten

Topic 19: everi, tweet, free, anyth, #secondhandgift, phone, minut, half, futur, kick, gift, cool, card, album, kiss, babi, player, gave, tree, appl

Topic 20: vote, trump, elect, democrat, voter, #trumpforpresid, anyon, today, #trumppence16,

#maga, support, #trump, fraud, parti, #electionday, #trump2016, senat, earli, #hillaryforprison2016, candid

Topic 21: #maga, #trump, #pjnet, #trump2016, #cruzcrew, #hillari, #trumptrain, #prayers4california, #neverhillari, #wakeupamerica, cartoon, #obama, #uniteblu, #tedcruz, exact, @christichat, @amrightnow, agre, #cosproject, #lnyhbt

Topic 22: want, just, peopl, chang, world, someth, work, someon, mani, feel, hear, like, make, donâ, place, stop, refuge, think, perfect, countri

Topic 23: know, thing, noth, need, mean, happen, never, #thingspeopleontwitterlik, #gopdeb, everyth, #vegasgopdeb, y'all, @jadedbypolit, gold, @lupash7, cours, research, peopl, well, #liberallog

Topic 24: #thingsinventedwhilehigh, #terror, #lgbt, @ohhsocialmedia, Chancen, @agendaofevil, sigh, real, @drc_19, bruh, @amerpatriot1, @justicewillett, hahahah, para, @az_valentin, @quinnqueen, @bleuishbleu, @questlov, @trusselis, franã

Topic 25: like, back, look, without, bring, wall, around, build, border, just, #makemehateyouinonephras, take, #2017survivaltip, avoid, come, street, hold, keep, season, talk

Topic 26: year, still, better, look, fuck, wait, russian, word, done, lost, death, already, 2017, shit, welcom, hour, damn, well, drink, long

Topic 27: love, anoth, leav, heart, hell, creat, singl, just, dream, expect, wife, #valentinesdayin3word, alon, short, soon, husband, much, seat, publish, pizza

Topic 28: part, @youtub, bodi, except, establish, #sport, @activistpost, tour, video, main, @onpiratesat, #myolympicsportwouldeb, process, pick, playlist, tale, robot, anniversari, @nyc_everyday, measur

Topic 29: time, york, sound, late, crazi, sing, wast, @shutupamanda, excit, stuff, @jarmadillo, cold, like, butt, just, @charissemsrd, legend, @chris_1791, mobil, awar

Topic 30: live, fall, american, link, intern, danger, learn, stream, plant, baltimor, injur, #phosphorusdisast, apart, everyday, #thingsdonebymistak, octob, water, updat, market, protest

Topic 31: #alternativeacronyminterpret, shut, readi, ladi, bitch, direct, idiot, organ, drive, fool, attent, pari, definit, dumb, self, studi, conspiraci, anim, femal, terribl

Topic 32: presid, even, ever, next, becom, first, thought, think, #idrunforpresidentif, trump, might, unit, never, #igetdepressedwhen, worst, obama, potus, elect, make, though

Topic 33: #pjnet, cruz, control, constitut, lord, govt, conserv, amend, defeat, militari, liberti, american, #rednationris, jesus, republ, @tedcruz, reagan, disgrac, @ggeett37aaa, govern

Topic 34: post, news, twitter, follow, @conservatexian, hate, open, fact, check, parti, move, clear, account, facebook, joke, fake, choic, #2016electionin3word, #thingsthatshouldbecensor, make

Topic 35: said, #thingsmoretrustedthanhillari, drug, room, bank, pull, #nocybercensorship, hollywood, agenda, info, tear, high, safe, lack, homeless, cheat, west, cancer, internet, bulli

Topic 36: best, problem, moment, land, industri, altern, integr, modern, gegen, afghanistan, #brexit, sich, jetzt, sind, #cdu, fundament, mehr, rent, mein, nicht

Topic 37: realli, like, #ruinadinnerinonephras, #survivalguidetothanksgiv, food, guess, huge, pray, tonight, sorri, awesom, hair, wanna, make, invit, marri, dress, just, finish, sister

Topic 38: miss, hand, case, chanc, strong, sell, small, song, univers, enter, origin, doubt, gonna, found, opportun, music, blood, easi, just, contest

Topic 39: donald, #polit, #new, clinton, support, ralli, speech, immigr, republican, plan, debat, call, russia, comment, meet, campaign, endors, putin, accus, presid

Topic 40: dead, journalist, reach, #local, 2015, juli, @spiegelonlin, truck, offens, sweden, wind, leagu, @phoenixnewsaz, 2013, slow, @camboviet, effort, region, villag, provid

Topic 41: hillari, campaign, email, bill, investig, foundat, wikileak, releas, leak, health, @wikileak, reveal, hack, camp, donor, scandal, sander, birther, comey, privat

Topic 42: @realdonaldtrump, great, thank, america, @hillaryclinton, @potus, @foxnew, @cnn, make, #maga, proud, honor, american, need, #makeamericagreatagain, @seanhann, @kellyannepol, countri, @jenn_abram, #trumpbecaus

Topic 43: state, trump, poll, nation, lead, point, secur, break, #2016in4word, news, report, ahead, race, show, depart, secretari, #new, north, among, dept

Topic 44: #ccot, #wakeupamerica, #gop, #usa, #teapartynew, #america, michael, @gop, kelli, #conserv, #nra, #polit, #theteaparti, sweet, @dmashak, simpli, bigger, @thedemocrat, #wethepeopl, #tgdn

Topic 45: million, china, worth, dollar, @zerohedg, googl, explos, complain, smith, #oscarssowhit, #oscarhasnocolor, capit, normal, imag, @screamymonkey, affair, @welt, chart, loan, label

Topic 46: right, women, left, protect, human, wrong, seem, march, #ihavearighttoknow, @talibkw, yeah, session, @feministajon, civil, respect, equal, defend, #guns4ni, anti-trump, marriag

Topic 47: money, famili, christma, full, #christmasaftermath, #todolistbeforechristma, whole, spend, realiz, complet, #my2017resolut, away, take, broke, propos, present, taken, georg, santa, credit

Topic 48: 2016, photo, save, john, list, servic, energi, @hashtagroundup, rose, sunday, #makemusicreligi, secret, @blicqer, spoke, decemb, show, februari, april, week, make

Topic 49: good, read, night, friend, morn, enough, idea, last, pretti, #myfarewellwordswouldb, ain't, make, feel, actor, #whatiwouldtella15yearoldm, @politweec, #myemynominationwouldb, ever, @keshatedd, intent

Topic 50: @hillaryclinton, #rejecteddebatetop, discuss, star, @cmdorsey, @realjameswood, prefer, @berniesand, wear, crap, wave, wood, behavior, toward, @jamesokeefeiii, regard, #imnotwithh, less, sock, brief

Topic 51: block, system, global, massiv, union, germani, german, websit, ring, island, allen, sport, migrant, #athleticstvshow, partner, auch, pool, sind, haben, heut

Topic 52: million, fund, donat, went, #clinton, spent, launch, #election2016, grant, budget, chariti, percent, pretend, billion, foundat, paid, 2014, #clintonfound, @blaviti, firm

Topic 53: watch, game, #betteralternativetodeb, hashtag, @giselleevn, #thingsnottaughtatschool, movi, sleep, special, receiv, rape, mass, light, flag, #reallifemagicspel, grab, #tofeelbetteri, @worldofhashtag, danc, clean

Topic 54: truth, book, #giftideasforpolitician, #islamkil, target, water, sens, shoot, common, #prayforbrussel, #brussel, smoke, limit, #isi, ticket, soul, increas, brain, term, account

Topic 55: obama, final, hous, deal, offic, iran, congress, presid, barack, michell, american, administr, court, refuge, syria, israel, obamaâ, climat, #new, syrian

Topic 56: just, make, take, trump, think, call, keep, peopl, real, need, stop, give, never, tell, show, talk, come, help, much, must

Appendix II: Topic label content (score labeling algorithm)for Internet Research Agency sponsored Tweets, k=56.

Topic 1: girl, #fishtv, #drunkband, #dogsong, #redneckamovi, @gamiliel, #sexysport, #summeramovi, blue, mother, #maketvshowscanadian, #dickflick, dude, #addamovieruinamovi, king, beer, #maketvsexi, #onewordoffbook, green, #stonedcomicbook

Topic 2: #tcot, muslim, #pjnet, islam, terrorist, #teaparti, terror, attack, christian, @guntrust, radic, #renewus, #isi, refuge, @petefrt, @fallenangelmovi, #islam, legaci, #ccot, kill

Topic 3: play, @rapstationradio, @nine_oh, emx9jgtv3v, @1063atl, #nowplay, issu, feat, ichlzwqg0i, #listen2, #music, magazin, @indieradioplay, #rapstationradio, @stopbeefinradio, #rap, #hiphop, radio, featur, @dagr8fm

Topic 4: @a5kem, askem, #toavoidworki, mess, interview, guest, #vulnerabilityin5word, #busi, matthew, @emenogu_phil, @ospatriot, channel, @slobodarskasrbi, segment, #podernfamili, subscrib, @wyzechef, furious, @sarahkendzior, @coasttocoastam

Topic 5: #merkelmussbleiben, merkel, #merkel, frau, #girlstalkselfi, nicht, deutschland, wird, amtszeit, unser, schaffen, sich, dass, immer, kein, kanzlerin, bleibt, viel, tagebuch, ganz

Topic 6: scene, host, chuck, #addabandtoatvshow, #artyoucanhear, hill, premier, chao, schumer, warren, elizabeth, flash, knock, film, mama, davi, introduc, #art, till, daddi

Topic 7: #nowplay, listen, beat, @boogsmalon, tune, produc, track, soldier, prod, dirti, 1js42r66si, @nine_oh, feat, hook, rapper, @dagr8fm, grand, #dagr8fm, london, t-shirt

Topic 8: media, racist, #mustbeban, protest, #trumpsfavoriteheadlin, support, racism, nazi, liber, outsid, #blacklivesmatt, #rncincl, mainstream, polit, nigga, realiti, @danageezus, correct, ivanka, educ

Topic 9: pleas, david, dear, daili, bless, latest, mark, sheriff, clark, @tlcprincess, thank, chicken, @kattfunni, lewi, @trivagod, @rappersiq, barri, @jstines3, castro, #famouscreatur

Topic 10: happi, everyon, life, birthday, littl, wish, @tycashh, deserv, fear, @deray, @annogalact, gotta, @breitbartnew, monday, #god, friday, nice, smile, #happybirthdayharrytruman, #supremesacrificeday

Topic 11: trump, trumpâ, #thingsyoucantignor, #obamaswishlist, rock, front, order, execut, presid, breath, @gloed_up, inaugur, step, pipelin, @tgjones_62, repli, just, loud, @bizpacreview, ignor

Topic 12: histori, @shaunk, #blacktwitt, @em2wic, @trueblackpow, folk, struggl, @moorbey, @khankne, @fresh_flames1, africa, @angelaw676, @blackmoses2015, cultur, @3rdeyeplug, @jojokejohn, belov, @historyhero, cycl, contribut

Topic 13: clinton, corrupt, clintonâ, #debat, hillari, #neverhillari, #debatenight, crook, sick, @hillaryclinton, #demdeb, #birther, prison, #hillaryshealth, crimin, american, #benghazi, peopl, media, @cernovich

Topic 14: black, white, peopl, kill, polic, matter, children, woman, #blacklivesmatt, amaz, power, student, hous, color, male, murder, arrest, young, chicago, live

Topic 15: @midnight, start, promot, @jayceodpromot, lieben, detail, #mondaymotiv, click, mein, @chicagoildaili, drag, nacht, euch, #addcartoonstohistori, #chicago, nsche, woke, #morgen, career, guten

Topic 16: join, fight, patriot, stand, enlist, freedom, @abninfvet, armi, rrzgbccxbo, rrzgbcu8tm, dare, usfa, click, @usfreedomarmi, #usfa, #bb4sp, veteran, fellow, america, central

Topic 17: true, mike, penc, show, sexual, view, assault, stori, silenc, victim, video, plane, abort, @realalexjon, toler, #dnc, #ilove__butihate__, interrupt, writer, loui

Topic 18: @elena07617349, blame, come, dalla, suspect, known, #idontneedacostumebecaus, theyâ, band, enjoy, revolut, #media, pure, anti, snowflak, spell, favor, @ashleywarrior, @italians4trump, repeat

Topic 19: everi, tweet, #secondhandgift, phone, free, anyth, album, minut, gift, kick, card, player, half, cool, tree, kiss, appl, shirt, bone, futur

Topic 20: vote, trump, #trumpforpresid, voter, elect, democrat, anyon, #electionday, #trump Pence16, #hillaryforprison2016, #maga, fraud, elector, #trump2016, earli, #lostin3word, #trumptrain, #trump, ballot, popular

Topic 21: #maga, #trump, #pjnet, #cruzcrew, #trump2016, #trumptrain, @amrightnow, #tedcruz, #uniteblu, @dbargen, #wakeupamerica, #lnyhbt, #hillari, #cosproject, #prayers4california, #realdonaldtrump, cartoon, #veteran, @christichat, @robhoey

Topic 22: want, someth, someone, chang, donâ, just, hear, peopl, world, #potuslasttweet, work, refuge, #islamkil, feel, #sometimesitsokto, nobodi, place, perfect, mani, @abusedtaxpay

Topic 23: know, thing, noth, mean, need, @lupash7, #vegasgopdeb, @jadedbypolit, happen,

#gopdeb, @mikerz, #thingspeopleontwitterlik, @jhwalz32, @sarcatstyx, @kcarlin, never, @geraldyak420, #liberallog, @shariromin, gold

Topic 24: #thingsinventedwhilehigh, Chancen, #terror, #lgbt, @ohhsocialmedia, @quinnqueen, @drc_19, #justiceforbenghazi4, @agendaofevil, hahahah, @bleuishbleu, frauen, #whytepanth, @whytepantherrn, @chuca_85, @diosmisalva, @lauranestor4, @mariaguenzani, @silviarn19, @vivaciousstar2

Topic 25: like, back, wall, without, build, around, bring, look, border, #makemehateyouinonephras, #2017survivaltip, avoid, season, street, #istartcryingwhen, goal, #unlikelythingsheardatwalmart, @blackgirlnerd, walk, hold

Topic 26: year, better, fuck, wait, still, russian, done, 2017, lost, already, death, look, welcome, drink, word, damn, shit, music, hour, berni

Topic 27: love, another, leave, heart, single, #valentinesdayin3word, dream, expect, hell, alone, wife, create, short, husband, pizza, seat, dinner, publish, chocolate, ugly

Topic 28: part, @youtub, @onpiratesat, except, #sport, body, establish, tale, tour, main, @activistpost, playlist, #snrtg, #myolympicsportwouldb, anniversary, #mrrobot, robot, #tvseri, pursue, #usanetwork

Topic 29: time, sound, late, sing, york, waste, @jarmadillo, @shutupamanda, excited, @charissemsrd, crazy, butt, mobile, legend, stuff, cold, curse, #twittercanbeabit, freeze, technology

Topic 30: live, fall, link, stream, intern, #phosphorusdisast, american, injure, phosphorus, apart, plant, #hamburg, halt, october, baltimore, everyday, #thingsdonebymistak, asleep, @todaypittsburgh, danger

Topic 31: #alternativeacronyminterpret, lady, shut, bitch, direct, idiot, party, fool, ready, drive, organ, self, attent, conspiracy, dumb, terrible, anime, driver, dump, design

Topic 32: president, even, become, thought, ever, next, #idrnforsidentif, #igetdepressedwhen, unit, first, might, worst, though, prayer, #probabletrumpstweet, think, obama, trump, potus, vice

Topic 33: #pjnet, cruz, constituent, lord, control, amend, #rednationris, @ggeett37aaa, liberty, govt, defeat, #trust, republic, #syria, jesus, @peddoc63, @tedcruz, disgrace, #wakeupamerica, #climatechang

Topic 34: twitter, post, @conservatexian, news, follow, hate, open, #2016electionin3word, fact, account, facebook, clear, #thingsthatshouldbecensor, joke, move, check, choice, troll, party, suspend

Topic 35: #thingsmoretrustedthanhillari, drug, room, #nocybercensorship, bank, agenda, info, said, tear, lack, pull, homeless, hollywood, cancer, cheat, pressure, taco, bulli, chinese, jone

Topic 36: best, moment, land, problem, industry, #cdu, altern, gegen, sich, jetzt, integr, sind, mehr, #brexit, deutschland, afghanistan, modern, mein, sehr, kein

Topic 37: really, #ruinadinonephras, food, pray, #survivalguidetothanksgiv, awesome, huge, marry, guess, sorry, invite, hair, cook, dress, wanna, sister, @johnfplan, like, finish, suppose

Topic 38: miss, hand, chance, case, strong, enter, small, opportunist, @musicjunkypush, sell, song, @powermusicteam, indie, doubt, univers, @braziliangirl32, contest, @cherimus, blood, @yaboymiko

Topic 39: donald, #polit, clinton, #new, rally, support, immigr, speech, republican, campaign, debat, comment, ohio, russia, endorses, convent, putin, accus, melania, @zaibatsunew

Topic 40: @spiegelonlin, dead, juli, journalist, #local, reach, 2015, truck, leben, leagu, erdogan, @phoenixnewsaz, wieder, sweden, offens, region, 2013, wind, @camboviet, @millcitynew

Topic 41: hillari, email, campaign, bill, foundat, investig, wikileaks, leak, @wikileaks, donor, comey, release, birther, server, camp, scandal, health, probe, chelsea, sander

Topic 42: @realdonaldtrump, great, thank, @hillaryclinton, @potus, @foxnew, america, @cnn, @seanhann, #maga, #makeamericagreatagain, @kellyannepol, proud, #trumpbecause, @loudobb, honor, @jenn_abram, #fakenew, @carmineszozora, #americafirst

Topic 43: state, poll, lead, point, nation, trump, #2016in4word, secur, depart, secretari, dept, ahead, break, among, north, carolina, unit, source, swing, news

Topic 44: #ccot, #wakeupamerica, #teapartynew, #conserv, #gop, #usa, #america, #theteaparti, @gop, #nra, kelli, @dmashak, michael, sweet, #wethepeopl, #tgdn, #makedclisten, @thedemocrat, #patriot, #republican

Topic 45: china, million, dollar, worth, googl, #oscarssowhit, @zerohedg, complain, capit, explos, smith, @welt, #oscarhasnocolor, @tagesschau, @screamymonkey, hier, normal, warum, affair, #flã

Topic 46: right, women, left, human, @talibkw, yeah, march, protect, seem, #ihavearighttoknow, @feministajon, session, wrong, civil, equal, #guns4ni, marriag, wing, #womensmarch, jeff

Topic 47: #christmasaftermath, money, christma, full, #todolistbeforechristma, famili, whole, realiz, #my2017resolut, santa, complet, broke, spend, propos, present, @batshake1, credit, stick, thereâ, wrap

Topic 48: photo, save, list, 2016, john, servic, @hashtagroundup, rose, #makemusicreligi, energi, 3qdisjyh9, sunday, @zenrand, decemb, @500px, februari, spoke, @thehashtaggam, @hashtagzoo, upbuild

Topic 49: good, morn, night, read, friend, idea, enough, #myfarewellwordswouldb, pretti, ain't, @politweec, #whatiwouldtella15yearoldm, last, @keshatedd, luck, #myemmynominationwouldb, felt, advic, actor, @ilovemywife0007

Topic 50: #rejecteddebatetop, @hillaryclinton, @cmdorsey, discuss, star, @realjameswood, @berniesand, @jamesokeefeiii, wave, prefer, whisper, hail, wood, sock, @flotus, behavior, @timkain, #imnotwithh, crap, @billclinton

Topic 51: block, system, global, germani, german, massiv, websit, union, auch, sind, haben, heut, #athleticstvshow, schã, einen, allen, nach, ring, morgen, island

Topic 52: donat, fund, million, went, #clinton, #election2016, spent, budget, chariti, launch, grant, percent, foundat, firm, #clintonfound, @blaviti, 2014, 2011, #hurricanematthew, #fbi

Topic 53: game, watch, #betteralternativetodeb, @giselleevn, hashtag, sleep, #thingsnottaughtatschool, movi, receiv, @worldofhashtag, danc, rape, special, mass, light, clown, #tofeelbetteri, #reallifemagicspel, shoe, weather

Topic 54: #giftideasforpolitician, truth, #islamkil, #iceisi, #opiceisi, #target, @ctrlsec, book, #prayforbrussel, target, sens, #brussel, soul, smoke, common, #isi, water, ticket, limit, increas

Topic 55: obama, final, iran, barack, michell, administr, congress, hous, deal, presid, bb4sp, syria, approv, syrian, offic, climat, sentenc, admin, @gerfingerpoken, court

Topic 56: just, #electâ, trump, @romaacorn, make, #imwithchickenavocadosubwaydressedwithsweetonionanddoublehoney mustard, #imwithhumusmarshmallowspeanutbuttersteakribey, take, think, call, peopl, keep, real, give, never, stop, need, tell, show, much

Characterizing QAnon: Analysis of YouTube Comments Presents New Conclusions About A Popular Conservative Conspiracy.

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Abstract:

QAnon has become an important phenomenon in American politics due to both its popularity with some individuals as well as its adoption/endorsement by prominent political elites. However, this conspiracy theory/social movement has received sparse investigation in the social sciences. This gap is particularly noticeable in regards to a.] QAnon’s overall conjectural worldview, or what the movement says it believes, and, b.] QAnon’s international relations worldview, or what the movement says it believes about global affairs. This piece addresses these research gaps by using repeatable inductive computational social science methods to analyze a sample of comments from an online media platform popular with QAnon believers. This investigation produced several novel conclusions regarding the QAnon phenomenon, including that 1.] QAnon comments contain a continuation and modification of previous “far right” conjectures that posit a wide-ranging, internationalized connection between the US government (particularly prominent Democrats) and sexual violence against children, 2.] QAnon comments contain prominent topics dominated by both anti-semitic language as well as Christian theology and imagery (and this Christian language is tied closely to President Trump), 3.] QAnon comments do in fact contain substantial discussion of international affairs, 4.] The international political discussion within QAnon primarily revolves around China, Russia and Israel, in that order of prominence. 5.] Discussion of China in the QAnon comments received more “likes” than other international topics, and these comments are dominated by a nexus of conjectures tying former Presidential candidate, Senator, and Secretary of State Hillary Clinton to the Chinese party-state. Aside from these novel conclusions regarding QAnon itself, this paper also seeks to make a contribution to repeatable social science analysis of YouTube comments more generally.

Key Words: QAnon, conspiracies, alt-right, President Donald Trump, China, YouTube, topic models.

For Ty

Introduction:

“History forgets the moderates” - Andrew Bird

QAnon is an influential but little studied political phenomenon. In 2018-2019 the conspiracy theory/social movement has been mentioned by President Donald Trump as well as numerous high-profile individuals in several areas of American public life (Elfrink, 2019 and Coaston, 2019). QAnon has gained traction in the “Alt Right”, white nationalist, and broader American conservative movements, with some of its conjectures and sub-theories being mentioned and supported by prominent political and media figures (Coaston, 2018 and Carter, 2018). There is some evidence that terrorists and attempted-terrorists on the far right have also found inspiration in the movement’s tenants, particularly the “deep state”, anti-Democratic Party, “Jewish World Order”, and anti-Muslim/anti-immigrant narratives imbedded within QAnon (Kelley, 2019). While rigorous academic research on the phenomenon is scarce, observers have noted that QAnon “has been able to attract mass attention and help start a kind of social movement (called by some the “Trumpenproletariat”)” (Dragoš, 2019).

The general lack of inductive research regarding this movement could potentially be influenced by the upsetting and offensive nature of much of the discourse within the QAnon phenomenon, which can be racist, sexist, violent and deeply offensive. Additionally, because minimal inductive work into QAnon-related content has occurred, there is little consensus on what believers of the theory discuss, how they discuss it, what topics within the community are popular/unpopular, and what broad political conjectures define the movement. Accordingly, the international political/social worldview of QAnon is entirely under-described and under-explored. Repeatable, transparent and rigorous analysis of the content of this conspiracy theory community is needed.

Simultaneous to both the emergence of QAnon and the lack of rigorous analysis of the conspiracy theory, the YouTube platform has become an important forum of communication for QAnon and related “alt right”/far right groups. Broadly, YouTube also represents a popular venue for general political communication/discussion and affirms Fluck’s (2015) argument that “Global governance increasingly depends on practices through which large amounts of data are created and circulated”. As digital platforms like YouTube play an increasingly key role in understanding communication surrounding domestic and international politics, utilizing the YouTube comment space for social science research is warranted. Conveniently, comments on the site are accessible for repeatable computational analysis. As such, this paper uses a research methodology built on inductive and repeatable analysis of QAnon-related comment content on YouTube (treating the YouTube QAnon comment corpus as a proxy for the wider QAnon community) to inform both a conspiracy theory studies and an international studies social science conversation. This inquiry adopts the premise that inductively understanding and defining *what QAnon is*, in a replicable way, represents an important undertaking since (despite the prominent role of QAnon in American political discourse) there has been comparatively little social science research done on the phenomenon. What analysis has been done typically falls into either: A:] network/”node” analysis concerned with which online actors are communicating with each other, and/or B:] Limited/“small-n”/non-repeatable content analysis. This paper addresses these research gaps by offering a robust and repeatable qualitative/quantitative examination of QAnon-related discussion on a prominent digital media platform using digital methods approaches.

As this study will demonstrate, QAnon is somewhat unique as a conspiracy theory/social movement not only because it combines elements of both of these political phenomena (and has seen adoption by some political elites), but also (and more importantly) because of its novel conjectural narratives about US and international politics. Aistrophe and Bleiker (2018) inform us that

conspiracy narratives “[...] are intrinsically linked to power relations *and the production of foreign policy knowledge* [emphasis mine].” This paper adopts such an understanding of conspiracies as potentially informative to both foreign policy and international studies as a discipline. It is with this key foreign policy/international studies context that this paper offers the first rigorous and repeatable analysis (that the author is aware of) of what QAnon believers believe. Accordingly, this inquiry advances several novel conclusions, induced from the YouTube comments sample, about the worldview of QAnon in both domestic (US) and international contexts.

Research Questions:

1. What topics constitute the QAnon YouTube comments corpus? What concepts, policies, individuals, and social movements were most discussed in the comments?

2. What comments on QAnon YouTube videos are the most popular (as measured by “likes”)? What do these popular comments tell us about what ideas “gain traction” in the social movement/conspiracy theory?

3. What, if any, international relations topics or themes stand out in the comment data?

4. Taken together, how do the topics and popular comments within the QAnon comments corpus help to characterize the conspiracy theory/social movement?

To address these research questions an inductive analysis of the comments within this corpus has been conducted here for a simple reason: the aim of this paper is to provide insight into the overarching topical characteristics of QAnon, which were largely unknown at the initiation of this inquiry. As such, this paper forgoes formal hypotheses to better represent a naive starting point with the data and to avoid *post hoc* theorizing. Besides general suspicions on the part of the researcher (due to the public reputation of QAnon), there were no formal expectations of specific topical comment content patterns when this analysis began. This approach, paired with computational social science methods, allows the researcher to “discover topics from the data, rather than assume them” (Roberts *et al.*, 2014).

Data Collection:

YouTube comments were obtained using the utilizing YouTube Data Tools' (YTDT) Video Info and Comments Module (Rieder, 2015).²⁶ This tool collects comments from the YouTube API, unneests them, and records the comments along with a host of meta-data (e.g., “likes”, “replies”, and “YYYY-MM-DD/HH:MM:SS” time variables). The comment query process involved selecting video ID's from YouTube videos, querying the comment stream using the Video Info and Comments Module, and exporting the corresponding files. These files were then modified slightly by the author prior to being read into R by adding a “channel” variable for all comments. Following this the files were combined into a master spreadsheet that can be read into R. Caution was taken not to generate duplicate files, and missing data was removed.

Elements of this paper's channel and video selection were both purposive and random, so some explanation is warranted (somewhat similar selection methods, minus the unsupervised digital methods used here, can be found in Lingam and Aripin, 2017 and Murthy and Sharma, 2019).²⁷ Channel selection was conducted utilizing previous literature on popular QAnon channels, primarily being informed by Briones *et al.*, (2019). This research team qualitatively compiled a list of popular QAnon YouTube channels by 1.] searching for QAnon on YouTube and exploring the recommended channels, 2.] Retrieving YouTube channels from high-scoring QAnon Reddit posts in the subreddits r/CBTS, r/the_great_awakening and r/The_Donald. This work resulted in a team-curated list of QAnon-salient YouTube channels, some of which were utilized in this paper. The channels “Lionel Nation” (~202,000 subscribers), “Destroying the Illusion” (~136,000 subscribers), “JustInformed Talk” (~108,000 subscribers), “Prayingmedic” (~107,000 subscribers), “Lift The

²⁶ YTDT was written and is maintained by Dr. Bernhard Rieder, Associate Professor of the University of Amsterdam and a researcher at the Digital Methods Initiative (DMI). The full suite of tools is available at <https://tools.digitalmethods.net/netvizz/youtube/index.php>, “Video Info and Comments.” Source code for YTDT can be found at: <https://github.com/bernorieder/YouTube-Data-Tools>

²⁷ Examples of typical ethnographic methods being utilized on YouTube comments can be found in Lange (2007).

Veil” (~53,000 subscribers), and “Bill Smith” (~45,000 subscribers) were included in comment querying for this paper. “TracyBeanz” (~106,000 subscribers) and “SphereBeing Alliance” (~94,000 subscribers), channels originally included in Briones *et al.*, (2019), were excluded by the author for this inquiry as they were judged to contain too much unrelated content on a per-channel and per-video basis.

Following this purposive sampling (necessary for the obvious reason that most of the YouTube “population” of videos/comments does not involve QAnon), the author used the website <https://www.random.org/> to generate random numbers to inform video selection. Five randomly selected videos were chosen from each channel according to the value generated using the random number generator (random.org allows for a number range to be set that can correspond to the total number of QAnon related videos for each channel), and comments were collected from these videos. This resulted in a data frame containing 26,821 comments generated in response to videos that featured/focused on QAnon.

In terms of data collection ethics, Reilly (2014) argues that maximally ethical best practices for the analysis of YouTube comments should remove usernames and avoid comment paraphrasing unless exact reproduction is necessary to “illustrate key themes from the dataset”. While we agree broadly with assessments arguing exact comment reproduction should be avoided if not necessary²⁸ to “illustrate key themes from the dataset” (Reilly, 2014), some analysis included here does include direct (anonymized) reproduction of YouTube comments. This was done specifically because the topic modeling method used here does not produce direct quotes, and instead relies on co-occurrence of words to create a generalized summarization of latent topics within a corpus. These model outputs effectively demonstrate topics, but can be less specific at times concerning the underlying semantics of word associations. For example, as we will see later topic models of this

²⁸ A strict/maximal ethical stance noted by Reilly to go “far beyond conventional approaches.”

corpus exhibit frequent co-occurrences of Hillary Clinton and the People’s Republic of China. In some topics, the semantic meaning of these associations is clear (with “Hillary”, “spy”, “traitor” and “China” all occur in close association in the same topic), while in other topics a semantic meaning may be less explicit. For this reason it can be helpful to think of these models less as objective truths about the corpus and more as tools for reading very large collections of texts. In such a conceptualization, once the broader topical themes of the discourse space are (quickly/conveniently) established with topic models, the researcher can query specific words/groups of words *that are informed by these models* to more directly confirm/disconfirm semantic meaning. This is the approach taken here, and as such properly anonymized direct quotations have great utility in illustrating key themes.

Methods:

Once the tabular data was combined it underwent cleaning/“preprocessing” (Welbers, et al., 2017), was converted into a corpus object, and finally into a Quanteda document frequency matrix (DFM). This preprocessing included removing stopwords, as well as several words (generally names) related to the YouTuber responsible for making the original video. This was necessary to avoid having some prominent topics devoted simply to replies from YouTubers thanking the channel creator (names that might plausibly also refer to other prominent political/cultural figures were not removed). Conversion into a DFM allows for matrix algebra techniques to be deployed, and moves the character data to numeric values (Welbers et al., 2017). This process preserved associated metadata and document-level variables, including comment-specific time values, while removing punctuation, and converted all letters to lower-case format. Symbols and hyperlink related syntax were also removed. Tokens (originally words) were stemmed using the SnowballC package (Bastin and Bouchet-Valat, 2014) through Quanteda.

For topic models, setting the number of topics (represented as a value k) is an important task. This k value is the only element of the unsupervised method set by the user, and represents the total number of topics requested by the user to summarize the corpus. This inquiry began by using a series of k values (in a variety of initializations²⁹ and labeling outputs), examining $k=5$, $k=10$, $k=14$, $k=50$, $k=55$, and $k=65$ models in the exploratory stage of research. These k levels were chosen to reflect current topic number ranges listed in relevant literature to assess the overall topical content at different topic number levels (Schmiedel, *et al.*, 2018; Roberts, *et al.*, 2018). Producing multiple k value models was also done to assist in reading and establishing the topical characteristics of the corpus for the researcher. Topic model k value estimation was then conducted using the “FindTopicsNumber” function within the LDA package (appendix Figure 1), and the “searchK” function in the STM package (appendix Figure 2). These estimators indicated a k value of 14 was well-fitted for the full data. Several k estimates (suggesting $k=7$ was well fitted) were run for smaller subsets of the data, and these are also available in the appendix.

Including summaries of all the topic models listed above in this paper would produce a final report of both great length and high repetitiveness. As such, the recommended $k=14/k=7$ models were chosen to summarise this corpus/corpus subsets, along with the “highest probability” labeling algorithm. The highest probability labeling algorithm is inferred directly from the topic-word distribution parameter, β . This labeling algorithm was used here as it routinely generated only non-junk topics for all topics in the model. In other words, this configuration was least prone to constructing topics that included non-word data that remained in the corpus despite preprocessing.

²⁹ These models were informed by STM’s “ $k=0$ ” functionality that uses Lee and Mimno’s (2014) t-SNE/anchor words algorithm, along with the spectral initialization, to construct plausible k values for a given data space size (note however the STM package stresses this is not a “correct” k initialization, merely one that is well-fitted to the data space). After initial modeling and comparison, the author chose to exclusively use the “spectral” initialization recommended by the STM package vignette as it (in general) outperforms both Latent Dirichlet Allocation via collapsed Gibbs sampling as well as random initialization (Roberts, *et al.*, 2018).

The results of the topic models are then presented in two ways. First, this paper presents the visualization results of the models (and references to full model word labels in the appendix). Second, this paper provides subject matter expert (SME) interpretation of the models in keeping with the literature of topic models (Schmiedel, *et al.*, 2018). This division was judged to be appropriate to prevent conflation of results with SME interpretation decisions on the part of the reader.

The second element of this paper is similar in that it is composed of topic modeling. However, this second inquiry focuses on “popular” and “hyper-popular” comments within the YouTube comments corpus. The cutoff for popular comments is drawn (admittedly somewhat arbitrarily³⁰) at 10 “likes” or above. The cutoff for hyper-popular comments is drawn at 70 “likes” or above (the “popular” category thus also including the “hyper-popular” category). These selections of “popular” and “hyper-popular” comments make up .055 percent and .006 percent of the corpus, respectively. These selections were made to inform take-aways about what opinions and comments *resonated* the most within the QAnon YouTube comments. Inquiry is again structured and presented in independent results and interpretation sections for these models.

One of the unexpected outcomes of this unsupervised examination of the comment data was the emergence of China as an important international relations topic within the comment data. As such, for reasons that will become more clear as this paper progresses, the third element of this analysis focuses on the use of topic models to examine the role of this specific topic cluster within the QAnon data. Comments remain the primary level of analysis in the China-centric section as well, and the presentation format also remains the same.

³⁰ While numerous papers, particularly in the medical sciences, have dealt with the popularity of YouTube *videos* as measured by “likes”, the author is unaware of such work using “likes” as a metric for YouTube *comments*. For research that has incorporated “likes” as a measure of video popularity, see: Oksanen *et al.*, 2015 and Kelly-Hedrick *et al.*, 2018.

Finally, the last section of this paper (“Analysis of International Comments”) utilizes a complementary but entirely different computational social science tool for analysis. This section further explores the China-related comments, but does so utilizing the key words in context (KWIC) tool present in the Quanteda package in the R programming environment. This package allows for something like a contextualized “Ctrl F” search to be deployed on a given corpus, and for the resulting comments to be explored by the SME. The final section of this paper conducts such an analysis to explore the international perspective/worldview of QAnon and specifically comments referencing the People’s Republic of China.

Broadly, this topic model and KWIC analysis is informed by Boumans and Trilling’s (2016) conceptualization establishing “counting/and dictionary”, “supervised machine learning”, and “unsupervised machine learning” as the three current methodological schemes for text analysis. They convincingly argue that these approaches should be ordered from most deductive to most inductive, respectively. This inquiry is also informed by Krippendorff’s (2004) content analysis methodology in that it attempts to ask “Which data are analyzed?”/“How are the data defined?”/“From what population are data drawn?”/“What is the relevant context?”/“What are the boundaries of the analysis?”/“What is to be measured?” Additionally, this paper’s structure was partially informed by Holsti (1969) in that it aims to describe/make inferences about the “characteristics of communications” through identifying content trend patterns, analyzing information flows, and assessing responses to communications (here through popularity/“likes”).

Literature Review:

This paper is first and foremost in conversation with the small amount of previous computational social science research that deals with QAnon. In their work on the topic of “normification” of fringe movements from digital to conventional media spaces, Briones *et al.*, (2019) call for more content analysis on QAnon while establishing a list of QAnon-related YouTube

channels. Regarding YouTube-based research programs in general, Murthy and Sharma (2019) note the general “dearth of literature exploring YouTube’s comment space”. Veletsianos *et al.*, (2018), also note the limited current research agenda on the platform during their analysis on comment sentiment as a function of presenter/presentation characteristics on YouTube. These inquiries represent the current state of the field, but also serve as a call for increased investigative work on QAnon (in Briones *et al.* 2019), as well as YouTube comments more generally (Murthy and Sharma, 2019 and Veletsianos *et al.* 2018).

In part due to this small cluster of academic literature specific to QAnon/YouTube, research on the QAnon phenomenon should also be informed by broader conspiracy theory social and behavioral science literature.³¹ Scholars have defined conspiracy theories as “a proposed plot by powerful people or organizations working together in secret to accomplish some (usually sinister) goal” (Coady, 2006; Douglas & Sutton, 2008; Goertzel, 1994). Others have studied the related concept of conspiracist ideation, positing it can be “described as a belief in the existence of a ‘vast, insidious, preternaturally effective international conspiratorial network designed to perpetrate acts of the most fiendish character’” (Hofstadter, 1966). Importantly, such theories are not necessarily false, and real information (like a former US President being involved in a political burglary) has at times confirmed beliefs previously considered fringe (Bale, 2007). Neither do such theories’ marginalized place in public discourse indicate a lack of real world impact. Jolley (2014) notes for example that belief in anti-vaccine conspiracies by parents likely has a significant negative relationship with real rates of vaccination for children.

³¹ Conspiracy theory studies also produce another more mundane/methodological grounding for this inquiry in that there is a call in that literature for qualitative study of such theories. Swami *et al.*, (2011) suggest “The main limitations of the two [quantitative] studies reported here (Swami *et al.*, 2011) are the *correlational design, which means that causal relations cannot be clarified and the non-randomized samples, which means that results can only be generalized with caution.* [...] Future research would also do well to more explicitly understand the context in which conspiracy theories arise; a task that may be more suited to qualitative research methods. Doing so will undoubtedly provide a more rounded picture of the functions that conspiracy theories serve as well as their effects [emphasis mine].”

Regardless of underlying accuracy or actual impacts on behavior, conspiracy belief systems are “notoriously resistant to falsification”, presenting what have been called “degenerating research programs” (Lakatos, 1970 and Clarke, 2002). In such a belief system, new information often does not result in reassessment/disconfirmation of previous beliefs (as one might expect), but instead new layers of conspiracy are added to rationalize new problematic evidence. Goertzel (1994) argues for something similar, noting that conspiracy beliefs form part of a ‘monological belief system’ in which a conspiratorial idea serves as evidence for other conspiracist ideation and afford believers relatively tidy explanations for contingent phenomena that are difficult to explain or that threaten existing belief systems. These concepts may help explain why conspiracy theories like QAnon often seem to hold contradictory positions.

Conspiracy theories may also emerge in social groups experiencing a loss (or perceived loss) of values and social position. Laruelle (2012) writes that the Soviet middle class intelligentsia, whose social status had “fallen apart” in the dissolution of the USSR, found a “form of symbolic compensation for their loss of values, of status, and of *Weltanschauung* [...]” in a variety of conspiracy theories. Conspiracy theories often appear to offer a voice to individuals who feel powerless. Such theories find traction during crises, and when media accounts are discovered to be in error or unreliable (Leman, 2007 and Whitson & Galinsky, 2008). Zarefsky (1984) similarly contends that conspiracy theories “provide a convenient alternative to living with uncertainty”. Many conceptualizations of conspiracy theories generally concur that such theories are rational (or for Hofstadter, “coherent”) attempts to understand complex phenomena and deal with associated feelings of powerlessness (also see Sanders and West, 2003). Debord (2002) notes “every major political event inevitably becomes associated with secrecy and competing attempts to explain the

seemingly inexplicable.”³² These explanations may also help contextualize the often unorthodox assertions in QAnon comments.

The reality that conspiracist beliefs may be associated with a higher authoritarian tendency in the individual (Abalakina-Paap *et al.*, 1999; McHoskey, 1995) may also have utility in understanding the QAnon phenomenon. This association may be in part a function of the tendency among conspiracy theorists to blame outgroups for problems or crises experienced by the ingroup. Relatedly, Altemeyer (2006) argues that right wing authoritarian individuals “have mainly copied the beliefs of the authorities in their lives” and that “Fundamentalists/authoritarians do not always think illogically, [...], hold starkly contradictory ideas, act without integrity, respond dogmatically, and so on. *But it is easy to find situations in which they do, compared with others [...]*” (Altemeyer, 2006). Relatedly, Hofstadter (1964) saw conspiracy theories as potentially dangerous elements of populism, presenting an interesting potential cause for a populist theory/movement adhered to by American conservatives. Indeed, much of QAnon’s discourse seems informed by the perceived threats of rapid technological and demographic change, and the movement adopts an obvious and nearly ubiquitous conservative perspective on such changes. The movement is of course also closely associated with and supportive of President Trump, an admittedly/allegedly conservative populist politician.

These insights are helpful, but other elements of conspiracy theory literature seem inappropriate or incorrect when applied to the QAnon phenomenon. Graumann’s (1987) assertion that antisemitic conspiracy theories typically revolve around a Jewish minority attempting to seize power for itself (instead of preexisting elites abusing power) seems perhaps ill-suited to QAnon (as the movement is both highly antisemitic and also often contends Jewish forces and elites are closely associated/one and the same). More substantively, Clarke’s (2002, 2007) assertions that the

³² Further analysis of the QAnon topic might also explore whether or not this desire to “explain the inexplicable” is related to the voluminous evidence suggesting that the Trump candidacy/administration cooperated with the United States’ traditional geopolitical rival state.

“hyper-critical atmosphere” of the Internet will retard the development of conspiracy theories also appear to be in danger given the empirically detailed (if spurious) content of the Internet-generated and sustained QAnon worldview. Laclau’s (2005b) division of conspiracy theory models into a dialectic between “the power” and “the underdog” is also problematized by QAnon as the ultimate representative of the movement is the most powerful human being on the planet (the President of the United States of America). QAnon would at least complicate such an understanding by displaying novel adaptations within the theory (the so called “deep state”) to accommodate the reality that the heroic locus of the conspiracy is at once victim and all-powerful.³³

Further questions may arise as to what international studies/international relations has to say about conspiracies, or indeed what QAnon has to say about international studies. Here, Aistrophe and Bleiker’s (2018) call for a conceptualization of conspiracies as narratives that “[...] are intrinsically linked to power relations and the production of foreign policy knowledge” is instructive. Aistrophe and Bleiker point out that both the fabricated/legitimized/“successful” *casus belli* for the US war in Iraq, as well as the subsequent delegitimized conspiracies that arose in the Middle East concerning the war, are excellent case studies for the utility and importance of conspiracy theories for foreign policy decision making and decision justifying. They note that conspiracy theory narratives that spring up around political events are “a particularly useful way of understanding how foreign policy knowledge is produced.” This is important because such knowledge is often part of the basis/justification for foreign policy decision making. Mark Fenster (2008), suggests a similar power-perspective of conspiracy theories, noting they can become important tools for the reallocation of power between different political actors, an effective element in political strategies, and can expose latent inequities in political-economic systems. While such altruistic and positive

³³ This paradox reminds the author of Umberto Eco’s essay *Eternal Fascism*, where he succinctly states that Fascist states produce “by a continuous shifting of rhetorical focus” enemies that are “at the same time too strong and too weak” (Eco, 1995).

goals may or may not apply to this particular movement, the overall point regarding the importance for such ideas in international relations and foreign policy contexts remains.

As such, this inquiry (constructed as it is by a scholar of international studies) seeks in part to confirm/disconfirm Aistrophe and Bleiker's (2018) articulation of conspiracies *vis a vis* QAnon by examining the extent to which Trump administration policy objectives/language appears within the QAnon comment data. More simply, this work seeks to understand what the international policy priorities for QAnon might be. It follows that if insufficient rigorous study of QAnon is an overarching "gap", sub-issues such as the international relations components/beliefs of the movement would also be lacking in research focus. Overall, while conspiracy theories have been studied in depth by psychologists/political psychologists, less work has been devoted to such theories from a policy or international studies perspective, even when the underlying conspiracy theory is 1.] internationalized in concepts and subjects, and 2.] increasingly utilized by political actors to push policy goals (including international ones).

Perhaps most importantly, almost no peer-reviewed work has been done to inductively study the Internet QAnon movement *on the Internet*, despite the prominence of the theory in current affairs, *the birth of the conspiracy on the Internet*, and the strong indications that digital venues are critical to the dispersion of ideas within the community. This paper hopes to address this gap while operating under the assumption that the internet is inherently international by nature.

Topic Models, Full Corpus Results:

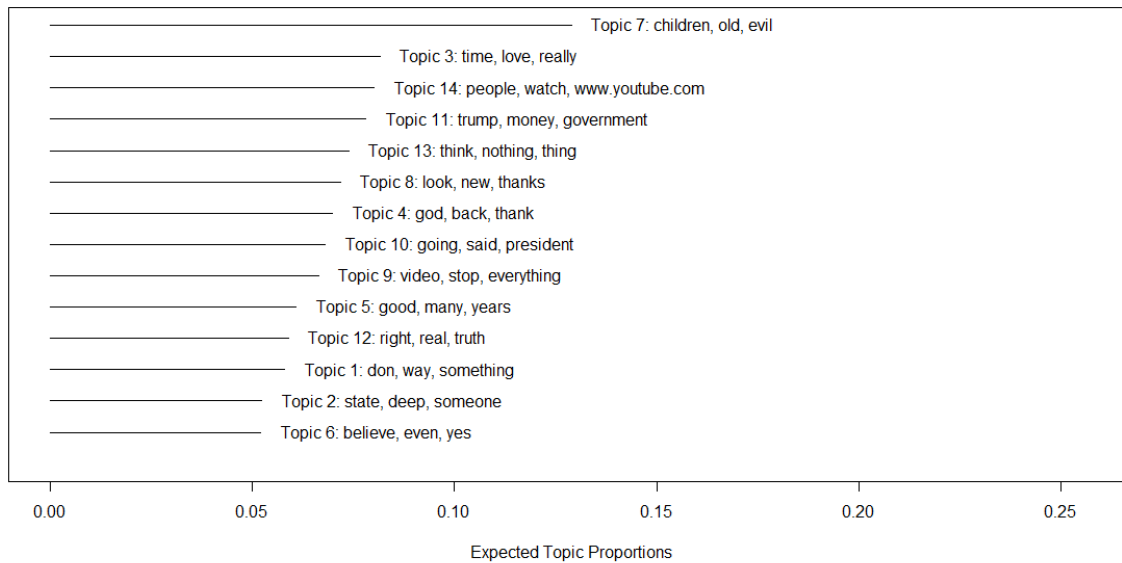


Fig 1: Topic model for all comments in the corpus (Full topic label lists can be found in the appendix)

Full Corpus Interpretations:

The full comments corpus (n=26,821) demonstrates several interesting conclusions about the content of QAnon discussion on YouTube. For brevity, this model can be sufficiently summarized by examining its top five topics, though full topic word label lists are available in the appendix. Topic 7 (1st in prominence) is centered on words referring to children, women, sex, jews, evil, Justice Ruth Bader Ginsburg, the Supreme Court, kids and gay marriage. This topic sets the stage for an overarching emphasis on similar ideas in the overall comment corpus. In particular, it is striking how often women/children/sex, women/sickness/evil, and Jews/Justice Ginsburg occur in close proximity. These themes also occur in other selections based on comment popularity. At around 13 percent prominence this topic also far outweighs any other topic in the full corpus selection (the next most prominent topic coming in around 8 percent of the corpus).

Topic 3 (2nd in prominence) is somewhat esoteric in that there are many abstract words concerning time, love, greatness, hope, etc., but it is apparent that QAnon's "wwg1wga" ("where we

go 1, we go all”) mantra is here as well. Perhaps this topic represents the generally supportive nature of many of the comments towards the QAnon theory/community and YouTubers therein. Topic 14 (3rd in prominence by a slim margin) introduces another prominent theme in the data by featuring Christian symbolism such as god, jesus, evil, christ, lord, word, bible, etc., but also referring to the act of watch[ing] and to YouTube itself. Rounding out a fascinating topic, the concepts of power and history are also central here. Overall, Topic 14 introduces not only the religious fervor and identity of the comments, but also the close association of these beliefs and the YouTube platform.

Topic 11 (4th in prominence) is far more secular and political. Here, Trump, money, government, results, America, whiteness and country all fall together. Alongside these terms are words about war and the military. Meanwhile, blackness, democrats, pay and corrupt(ion) see mention in close proximity. Topic 13 (5th in prominence) is again quite esoteric and full of abstract concepts like thought, agreement, difference, nothing/anything, but we do see the founder of Wikileaks Julian Assange mentioned here.

“Popular”/“Hyper Popular” Selection Results:

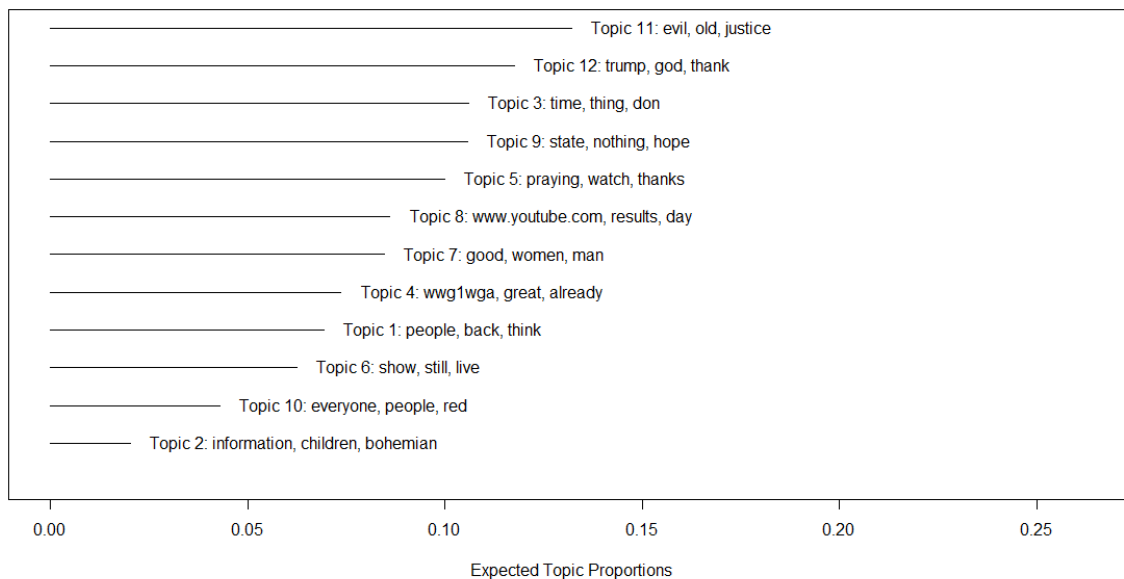


Fig 2: Topic model for all comments with 10 or more total “likes”
(Full topic label lists can be found in the appendix)

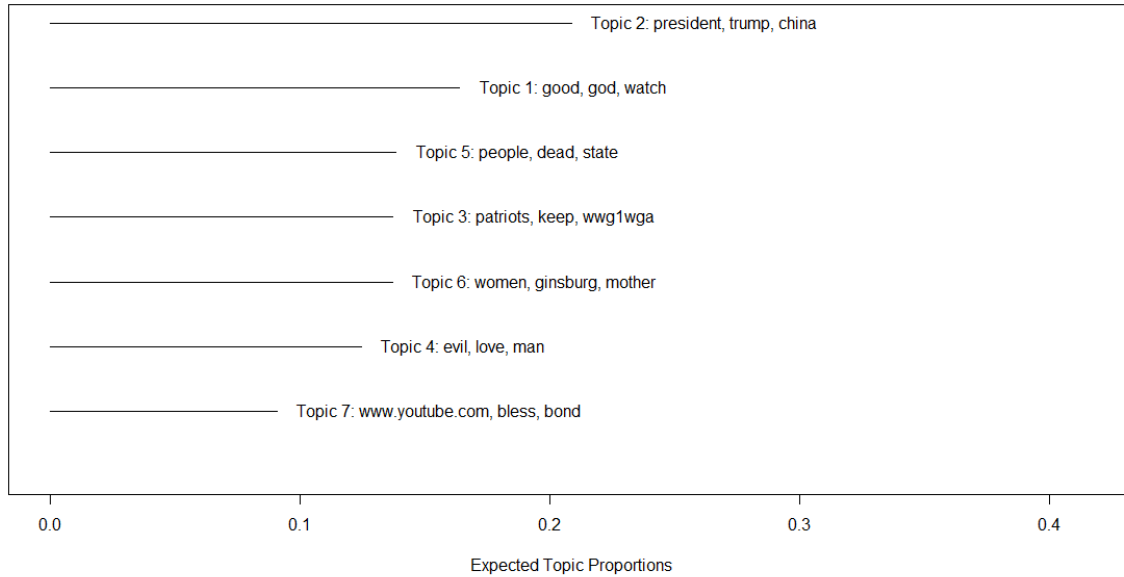


Fig 3: Topic model for all comments with 70 or more total “likes”
(Full topic label lists can be found in the appendix)

“Popular”/“Hyper Popular” Selection Interpretations:

The “popular” comments (those with 10 or more likes, n=1492) within the corpus differ from the full comment topics in several interesting ways. Like the full corpus, for brevity this model can be sufficiently summarized by examining the top five topics, though full topic label lists for all the topics are available in the appendix.

The “popular” comments model is lead off with topic 11 (1st in prominence) which focuses on words related to evil, justice/court (likely Supreme Court Justice), Ginsburg/Ginsberg (sic)/Ruth/Bader, women, sickness, children/child, Clinton, and Jews. This topic reaffirms the importance of the “sexual abuse of children by evil prominent Democratic political figures”

narrative in QAnon. In particular, Supreme Court Ruth Bader Ginsburg appears most connected by the comments to these issues in this corpus/corpus selection. This topic also includes a reference to China, the only international topic to appear in this sub-selection.

Topic 12 (2nd in prominence) heavily emphasizes President Trump, god, blessings, truth, family, and patriots/patriotism/country. This topic's vocabulary again indicates the Christian religious worldview of the comments, as well as the close association between President Trump and religion/god. Topic 3 (3rd in prominence) is esoteric, with little in the way of discernable "big picture" vocabulary outside what is likely a reference to Donald Trump ("don").³⁴

Topic 9 (4th in prominence, but essentially tied for 3rd with topic 3) references words like state, deep, patriots, and white, along with other words seemingly related to discussion like said, talk, info, agree, news, joke, etc. This topic reinforces our understanding of substantial discussion within the QAnon believer community of the "Deep State" and associated issues, though this time notably in "popular" comments. This topic may also indicate a reference to white (caucasian) ethnicity. Topic 5 (5th in prominence) is also interesting in that it seems to contain vocabulary focused on praying/prayer, watch/watching (presumably YouTube), encouragement to keep up the work (presumably on the part of QAnon YouTubers), while also mentioning the President of the United States and the media. Again, we see the nexus of Christian identity and prayer alongside political actors, along with a tension between media sources and information.

Other notable topic contents within the "popular" selection are further references to: Christian concepts and American politics (Topic 7, 7th in prominence); war, history, "maga", "wwg1wga", the mainstream media, fake news/"drops" (QAnon slang for information releases from "Q"), Hillary Clinton and the mainstream media (Topic 4, 8th in prominence); a nexus of terms

³⁴ While words like "really", "said" and "made" are all possible candidates for exclusion from the corpus as stopwords, this paper opted for as conservative a word removal procedure as possible to preserve the underlying data.

connection satan, the Democrats, and the concepts of home, a wall, and god (Topic 6, 10th in prominence); gay/straight sexuality, children and sex (Topic 10, 11th in prominence); and the Bohemian Grove, Hollywood, children, pedophiles, and what is likely former Supreme Court Justice Antonin Scalia (Topic 2, 12th in prominence). These less prominent topics clearly still provide value in supporting an understanding of QAnon (and “popular” comments within that online community) that emphasizes/supports Christianity, President Trump, non-traditional media, a belief in an organized conspiracy to sexually assault children at the highest levels of the government and media, and perhaps conservative/anti immigrant views of the home/the nation. Likewise, “popular” comments in this corpus also indicate a distrust of Democrats/Democratic actors, as well as the so-called mainstream media.

A marked difference between the “hyper popular” comments (70+ “likes”, n=179) and other corpus selections is the increased focus on vocabulary related to international politics. In particular a focus on Donald Trump’s interactions with the People’s Republic of China is evident in topic 2 (1st in prominence), while Israelis are mentioned in topic 5 (3rd in prominence). It would appear that the most popular comments (those with more than 70 “likes”) reference international affairs, particularly related to China, more than less popular comments (China does of course also appear as a term in the most prominent topic of the 10+ “likes” corpus selection as well).

Similar to other topics in previous selections, Topic 1 (2nd in prominence) has vocabulary largely centered on christianity, religion, country/patriotism, and security. Other words without obvious semantic significance (e.g., “watch”, “thanks”, “soon”, “late”) are also fairly common in this topic. This topic again demonstrates the nexus between Christian faith/values and patriotic American identity in the comments. Topic 5 (3rd in prominence) is more esoteric and hard to interpret. Death, the state, israel, democrats, control, welfare, (political?) parties, and the media all make an appearance here.

Topic 3 (4th in prominence, but essentially tied for 3rd) contains words related to patriotism/patriots, QAnon's "wmg1wga" ("where we go 1, we go all") slogan, Supreme Court Justice Ruth Bader Ginsburg, the Supreme Court itself, disgust, and references "old" and "woman" and "children" and "ruth" in close proximity. This topic appears to reinforce the connection between Ginsburg, the Supreme Court, and child abuse mentioned in other topics from previous corpus selections. Topic 6 (5th in prominence, but essentially tied for 3rd) is seemingly similar to topic 3, with Ruth Bader Ginsburg and "women"/"mothers" occurring alongside references to witches, communism, rats, satan and democrats. Words from these two topics carry an obvious animus, distrust and disgust related to several prominent political figures and parties.

Topic 4 (6th in prominence) is somewhat similar to topic 5 in that it is slightly more esoteric and difficult to interpret. This may derive from the fact that some of the core words in the topic are more devoted to broad world-ordering concepts and emotions like "evil", "love", "group", "hate" and "world". However, it is important to note that "don", "children" and "parents" are all included in this topic, providing connection to both the overarching politician of preference for the movement as well as its core conjecture regarding the safety and importance of children and perhaps families. Topic 7 rounds out the topics with a relatively uninteresting collection of words regarding YouTube, religious blessing, and apparently economics.

International Topics in the QAnon Comments Corpus, Topic Models:

The sample of QAnon YouTube comments analyzed contains several topical surprises. While less explicit than some of the other topics in the corpus, the several mid-tier (8th-9th in prominence) international relations topics in the comments stand out. QAnon is not typically understood as a movement/conspiracy theory featuring international relations. That several of these international terms, in particular references to China, stand out as prominent topics in the 10+ and

70+ “likes” categories is also notable. It is curious that China and, to a lesser extent Israel, are more prominent topics/more prominent “popular” topics in the corpus than Russia, despite connections between the Russian Federation and the Trump Administration constituting a headline-dominating political scandal in the United States. Topics in the comments regarding faith, child sexual abuse, and fringe theories about prominent Democratic government officials are surprising and disturbing, but have perhaps been more documented in QAnon and related communities more than beliefs about international relations topics. Indeed, in a corpus of comments derived from a domestic US conspiracy theory/social movement, topic model results stressing actors in the international system is worth further exploration as the international relations perspective of QAnon is both unanticipated and unexplored.

By utilizing the full topic labels for the full corpus model (fig.1) we can see that topic 10 (8th in prominence) and topic 9 (9th in prominence) contain references to states in the international system (full topic labels are available in the appendix). These references constitute the only inclusion of international states, events, or actors in any of the full topic labels in the corpus (and serve as the only topical departure in a dataset otherwise entirely focused on domestic US concepts, individuals, parties, etc). Within these topics we can see Israel falling as word 9 in topic 9, Russia falling as word 18 in topic 10, and China falling as word 11 in topic 10. In the overall corpus references to China/Chinese, Russia/Russians, and Israel/Israeli/Israelis/Israelites occur in distinct comments 285, 255 and 239 times, respectively. Despite the large role antisemitic comments appear to have in the YouTube comments, as well as the well-publicized and long-running media coverage of Trump campaign/Trump administration connections with the Russian Federation, for QAnon China appears to be a more prominent topic of discussion.

When looking at a model of only the comments receiving 10 or more “likes” (n=1492), China stands as a much more prominent element in topic models of the corpus. Here (fig. 2), China

is the 10th word in topic 11 (first in prominence), and co-occurs alongside words related to Supreme Court Justice Ruth Bader Ginsburg, the concepts of evil/old age/sickness, as well as references to jews, children, and the Clinton surname. In the “hyper popular” selection of comments (70 or more “likes”) we see China emerges as the third word in the most prominent topic in the topic model (fig. 3). In this topic (topic 2) China/Chinese co-occur alongside references to President Trump and Hillary Clinton (subject matter expert review of this selection of comments suggests some in the QAnon movement believe Clinton to be a Chinese spy, or have employed Chinese spies in the past). In these sub-selections of only “popular”/“hyper popular” comments from the full corpus, references to Israel and Russia disappear entirely and are not components of any topics in the popular/hyperpopular selection.

Topic models can also be run on selected comments that feature China to explore themes within the QAnon discourse related to that country. These models are specifically *not run* on the full corpus, but instead are conducted on a sub-selection of the YouTube comments that reference China/Chinese people. When comments in the YouTube corpus refer to China, several distinct topical associations emerge as features of the model.

China Comments Selection Results:

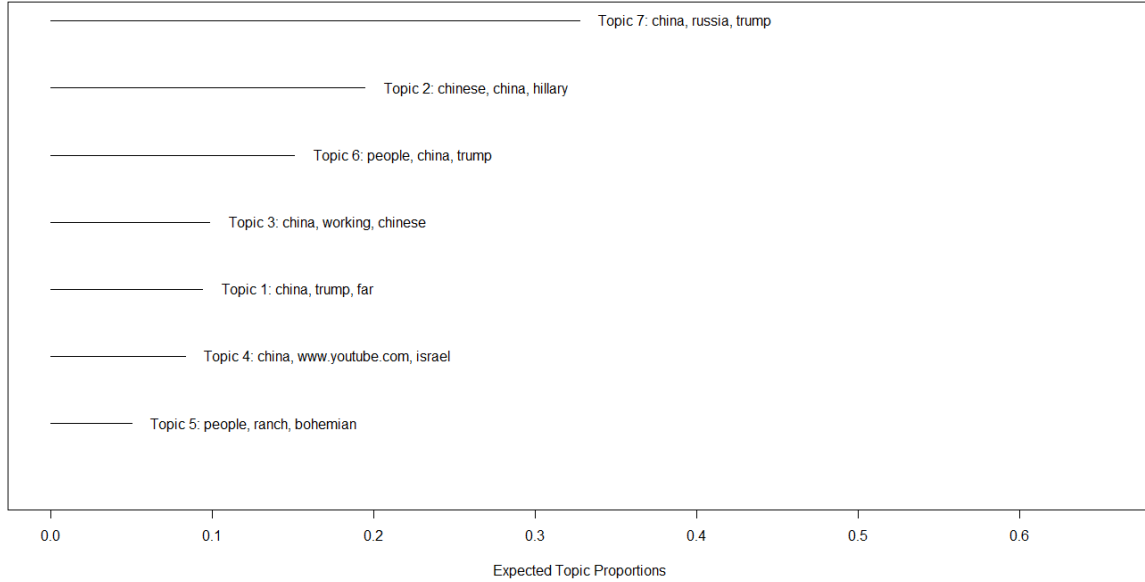


Fig 4: Topic model for all comments referencing China
(Full topic label lists can be found in the appendix)

China Comments Selection Interpretations:

Perhaps the most striking repeated feature of this model is the appearance of references to Hillary Clinton in 4 out of 7 of the topics. Hillary, hilary (sic), “hilderbeast”, and “hrc” are all terms that feature in this output. References to Donald Trump appear to be the only terms featured in this selection more than Clinton (excluding references to China, for obvious reasons). Topic 7 (1st in prominence, and far and away the most important topic in this model) demonstrates co-occurrence patterns between Hillary Clinton, secrets, the military, money, servers and emails. Topic 2 (2nd in prominence) shows similar but perhaps more explicit co-occurrence associations between Hillary Clinton and China/Chinese, agents, spies, computers/hacking and Diane Feinstein. Topic 3 (4th in prominence) features China/Chinese, Google, emails, (Ted?) Lieu, traitors and “hrc” (Hillary Clinton). Finally, topic 4 (6th in prominence) features both China and Israel, as well as America, Russia, Jews, god, country, south/black (potentially a reference to African Americans in the US South), “hilderbeast” and death. Clinton, along with prominent Democratic leaders Lieu and

Feinstein, are heavily connected to China in this model of comments that include references to China. Moreover, these topics paint a picture of a nexus of beliefs about Clinton, China, spying/espionage, hacking, money, servers/emails, the military, and possibly traitorous behavior (presumably towards the United States).

Analysis of International Comments:

While topic models can elucidate broad trends in large corpora, it is also instructive to examine the data at the comment level (and thus use the topic models as tools for reading large collections of text). This qualitative examination can lend/detract support or modify conclusions presented in the unsupervised models. The previous full-corpus models demonstrate we should focus our comment survey on President Trump, Hillary Clinton, server/email related words, secrets/spying/intelligence related words, discussion of China/Russia/the US, the concept of evil, and discussion of Jews and/or African Americans in connection with China/Russia/the US/Ted Lieu/Diane Feinstein/Hillary Clinton. However, further topic modeling of popular comments shows the largest proportion of international relations topics in this corpus reference the People's Republic of China. Indeed, China's role in the corpus as a function of positive feedback and "traction" is quite large. After adjusting for the popularity of comments by subsetting the corpus based on number of "likes", the significant role of China in discussions within the corpus emerges. Comments with 10+ "likes" featured "China"/"Chinese" 23 unique times, while "Israel"/"Israeli"/"Israelis"/"Israelites" and "Russia"/"Russians" were included in only 9 comments with 10+ "likes", respectively. Comments with 70+ "likes" featured "China"/"Chinese" 9 unique times, while "Israel"/"Israeli"/"Israelis"/"Israelites" and "Russia"/"Russians" were included in only 1 comment each. It would appear that China was referenced more often in comments that gained "traction" within this sample, while Israel and Russia occupied a more marginal place in the corpus when adjusting for popularity.

Since topic models and comment counts indicate the PRC is the most prominent international topic in the corpus, and since the presence of this (and any international topic) in this corpus is unexpected, this final analytical section will utilize the key words in context (KWIC³⁵) analysis tool native to the *Quanteda* package in R (Benoit *et al.*, 2018), to view the comment context “window” around usages of the word “China”/“Chinese” in the data. This “window” can be set by the researcher to any number of characters, including a limit large enough to include entire comments. As such, KWIC functions as something akin to a “Ctrl-F” feature, but it produces an html output that can be saved by the user, reviewed and hosted for third party review. Using KWIC we can see a more detailed picture of the nexus of beliefs surrounding China in the QAnon discourse.

KWIC analysis perhaps unsurprisingly shows Donald Trump occupies a prominent place in QAnon discussion involving China. This is largely to be expected as QAnon and Trump have been closely associated in the public sphere for some time, and because the movement emerged in part to defend the actions of the President as part of a greater plan. Additionally, Trump’s “trade war” with the PRC has been continually in the news for much of his administration. Interestingly however, neither the “trade war” nor “tariffs” appear to be substantial topics of discussion in the data, with the former appearing four times and the latter appearing just once in China-related comments. More nuanced elements of the relationship between the US and the PRC are however much discussed, with a relatively heavy focus on 5G technology presenting itself. Of the 289 comments referencing China include 5G 18 times, often referencing President Trump’s interest in the technology, China’s advanced level of 5G, and speculative dangers of the technology. Bizarrely, some comments also connect Christian theology to Chinese and American 5G technology.

³⁵ KWIC is similar to a much older concept credited to Hans Peter Luhn. See, Manning, C. D., Schütze, H. (1999) "Foundations of Statistical Natural Language Processing", The MIT Press.

Trump is going to use what is called God's frequency . That is why he wants to develop 5G here in the United states . The frequency that China wants to use is what is called Satan's 5G frequency . There is a difference between the two. [Comment 1.0]

It is also worth noting that a small number of the comments featuring both Trump and China appear critical of the President. Of the 62 China-related comments that feature "Trump", 6 feature language that is critical of him. Many of these comments derive their criticism from conjecture that Trump is compromised by a number of powerful Jewish/Israeli actors.

Trump is doing for Israel , Trump saves 3 Black kids from China . . . what has Trump done for the genocided WHite farmers of SOuth Africa ? He can address the situation . Nothing . This Trump is a god damned FRAUD ! Less evil than Obama and Valerie Jarrett perhaps but just as dangerous because he is part of ZOG . SO is Britain ! Ran by ZOG.³⁶ [Comment 1.1]

While such comments do not constitute a large proportion of the comments corpus, they do represent a proportionally larger share of the comments than those on the "trade war".

The concept of moral evil appears multiple times in comments that also reference China. As with comment 1.1, many of these comments seem to refer to a cabal of various actors, typically Jewish/Israeli, who are working/have worked to undermine the United States. Many of these comments also refer to some variation of "the evils of Communism" and decry the growing power of the PRC. Several comments note a number of prominent Democrats as evil, including President Obama and Hillary Clinton. QAnon commenters are also concerned that Clinton's email server hack represents an evil/nefarious connection with China.

The nexus of topics connecting China and Hillary Clinton in QAnon YouTube comments starkly dominates the China comments, a fact somewhat reflected by the previous topic model outputs shown in this paper. However, exploring this connection further using KWICs reveals that comments featuring China within the corpus demonstrate a propensity to connect Clinton's political

³⁶ "ZOG" is a white supremacist abbreviation for "Zionist occupation government", "Zionist occupational government", or "Zionist-occupied government". The term is generally used to describe governments (outside of Israel) that have been "taken over" by a supposed global group of powerful Jewish individuals.

past, her email server, and potential treasonous behavior involving US military secrets, while also directly calling for her death. Several examples below provide support for the topic models and indicate that many QAnon commenters believe Clinton to be a Chinese spy:

Yes Hillary is a Chinese spy !! It will be proven !! [Comment 1.2]³⁷

The difference is that Hillary actually does work for China . Trump doesn't work for Russia . That's what makes one instance a joke and the other serious . [Comment 1.3]

Also as first lady Hillary and Bill gave China MFNS . Irrevocable . Gave them military hardware blueprints and top secret intelligence all awhile dumping all cia field agents causing many to be murdered and imprisoned worldwide . I remember the 90s . They are traitors . The media was so bs covering their deeds. [Comment 1.4]

Interestingly, these comments suggest that QAnon appears to posit a mirror image of allegations of corruption against the Trump campaign onto Hillary Clinton/President Bill Clinton/Hillary Clinton's Presidential campaign, while substituting the Russia Federation for the People's Republic of China. Attacks against "the media" are also drawn into this comment type, which also contains elements of so-called "whataboutism" (Kurtzleben, 2017 and Sullivan, 2017). These conjectures of corruption, spying and betrayal of the United States are reflected by the China-specific topic modeling previously described.

Previous topic models also appear to capture both heavy emphasis on Christian theology in the full corpus, as well as strong topical representation of both China and Hillary Clinton (in both full and selected corpora). However, less explicit in the previous models is the nexus of beliefs connecting Clinton, China and Christian theological concepts to one another.

So what if Hillary is the women riding the beast in revelations the one the kings of the world get involved with and has to drink her cup. (if I could remember how to spell right now this would be worded different) now what does it mean come out of her my people and who is the great deceiver ? If Hillary is the the Harlot ? And what is the dragon / beast ? ? ? China ? ? ? I am not sure but some things are adding up some !! [Comment 1.5]

³⁷ Comments are included with original grammatical and spelling errors. Comments have been included here with a proprietary coding system to preserve anonymity.

Hillary is a pedophile a child Trafficker a Terrorist . . . She and Bill gave away shit to China Sold stuff to RUSSIA . . . Hillary and billy drug dealers . . . oh but people play her OPINIONS like she is someone In thye name of JESUS . . . STOP STOP Feeding this evil witch [Comment 1.6]

Of course Hitlary is in the bag for CHINA !! She IS the DEVILS best bitch !!!! Make her Swing !!! Make her Swing !! [Comment 1.7]

These comments demonstrate a clear nexus between biblical millennialism and both Clinton and China (as well as Russia in comment 1.5). Moreover, our topic model outputs also find support in more emphasis on sexual violence against children, though specific comment analysis expands this to specifically include Hillary Clinton as a perpetrator of such activity (other comments suggest Clinton have been involved in organ harvesting in the PRC as well).

Finally, specific comments are valuable in that they confirm the seemingly violent nature of the topics contained in the earlier models shown in this paper. Numerous comments referencing China suggest Hillary Clinton should be assassinated and/or executed without trial.

Hillary is really out of options to avoid military execution for child trafficking and such and such . . . She got no friends left but maybe China . . . Listen to HRC China , she's got a good idea for you . But is Hillary saying that hacking the DOJ is possible ? ? ? Or that it is desirable and legal ? ? ? She once had security clearance ? ? ? WOW . . . Really Q is right . . . These people are stupid !!! Thank God an outsider got to kick them out !!! Retarded . . . [Comment 1.8]

poetic justice . . . hang Hillary with rope Made in China [Comment 1.9]

[...] WILL SOMEONE PLEASE ASSASSINATE HITLERY [Comment 2.0]

She sold access to her tech and more , to China ! Still does I would bet ! THIS SATANIC WITCH MUST BE SHOT IN FRONT OF A FIRING SQUAD FOR HER CRIMES AGAINST CHILDREN , AND THE TORTURE AND MURDER OF CHILDREN ! [Comment 2.1]

These KWIC outputs demonstrate fine-grained support for our topic model conclusions, but also more accurately convey the violence and anger of many of the QAnon comments. QAnon YouTube comments in this sample demonstrate a series of beliefs connecting Hillary Clinton to various treasonous activities involving China, as well as biblical connotations and conjectures that

she is involved in sexual violence against children. They also demonstrate a general animus to Clinton personally, calling for her death on numerous occasions. *Overall, 131 of 289 comments that feature China also featured a reference to Hillary Clinton (in one form or another).* These comments frequently reference various types of traitorous behavior to the US and/or noted that there was a connection between her email server and China.

QAnon Conjectural Characteristics:

Utilizing these topics and topic interpretations, we can observe several characteristic conjectures within the QAnon movement:

1. A worldview that posits the US Government and/or media establishment is compromised by a diverse host of nefarious and/or evil actors.
2. A worldview that posits high level individuals within the US Government (including Supreme Court Justices) and the media (including “Hollywood”) are involved in sexual violence, likely against children. An overall focus on the Supreme Court is also apparent (with similar undertones).
3. A worldview inclusive of Christian theology, imagery and symbolism. A close association between Christian concepts and patriotism. A close association between Christian concepts and the YouTube platform.
4. A worldview incorporating anti semitism, especially in regards to government and media elites.
5. Political support for President Donald Trump, and an association between Trump and both American identity and Christianity.
6. An emphasis on unity and in-group cohesion on the road to the truth.³⁸
7. An apparent emphasis on vaccines and possible (international?) political conspiracies around vaccinations.

³⁸ Exemplified by the movement’s rallying phrase “wwg1wga” or “where we go 1 we go all”. There is speculation this phrase was adopted from either a speech by John F. Kennedy, or was adopted from the movie *White Squall*. See: Rothschild, M. (2018, July 03). Your guide to understanding the QAnon conspiracy. <https://www.dailydot.com/layer8/q-anon-jargon-explained/> and, Quotes from "White Squall". (n.d.). <https://www.imdb.com/title/tt0118158/quotes>

8. Topic models and comment word counts indicate the People's Republic of China is a very prominent international topic for QAnon. This topic is closely paired with discussion of Hillary Clinton, and is often framed in Christian terms. Hillary Clinton's alleged ties with China likely outrank both the "trade war" and Trump Administration tariffs on China in importance for QAnon.

Concluding Discussion:

Several conclusions related to conspiracy theory studies present themselves from examination of the QAnon data. The corpus analyzed here does not provide evidence that the oppositional, strident, and often verbally violent content within the QAnon community has matured, adding nuance to Laclau's (2005b) assessment that conspiracies revolve around divisions between "the underdog" and the community "in power". Given the reality that QAnon as a movement has emerged/become popular *during the presidency of the politician it supports*, the movement's continued animus and anger at "the powers that be"/"the deep state" can be interpreted as an example of what happens when a conspiracy movement finds its focal point in the halls of political power. Instead of adapting or evolving into an understanding of President Trump as a powerful person, QAnon commenters seem more inclined to create new reasons for why he remains an underdog. As such, the popular demand within a conspiracy theory to challenge the social order and gain power seems durable to actual gains in that political power (Yablokov, 2015). This corpus indicates that the demand for challenge/power acquisition has not been mediated in this case by gaining immense, and for several years essentially unrivaled, structural power in the US government. *All of this is to say that a "Laclauian" conceptualization of power vis a vis conspiracies is durable or agnostic to actual power gained. Even when power gain is immense, little may change in the ideation of the conspiracy theory.*

QAnon suggests the continual search for clandestine actors to blame for social/political ills is best conceptualized as a *moving the goalposts* characteristic, as it still occurs when all available scapegoats are out of political power. While much more research is needed to suggest a generalizable trend that might apply outside of QAnon, we theorize several things may be occurring at once. First,

previous literature reviewed in this work (e.g., Altemeyer) suggests there may be some connection between conservative/authoritarian mindsets and identity movements that predisposes individuals to such conceptual *moving of the goalposts*, since these individuals simply look to receive new beliefs from authorities (no matter the content). *An addendum to this is that some of these individuals may have come to rely on YouTubers/YouTube channel hosts as such authorities.* Second, the peculiarities of information on the Internet may also be partly to blame, as individuals are/may perceive they are under a more constant bombardment of facts, events, personalities, etc. Such a phenomenon would align with Fluck's (2015) view that the highly contingent and uncertain global system, often presented to people via online platforms, makes a monologic conspiracy both appealing and comforting to some people.

Whatever the underlying cause of this iterative *moving of the goalposts* in search of a new all-powerful enemy (despite political allies holding power), other elements of conspiracy theory literature seem inappropriate or incorrect after an examination of the QAnon phenomenon. Graumann (1987) notes that “[...] instead of alleging abuse of power by elites, historical theories of Jewish conspiracy usually detailed supposed attempts by a minority to seize power for themselves.” However, the analysis conducted here indicates QAnon followers simultaneously claim that both these phenomena (elite abuse and Jewish seizure of power) are occurring at once, while some commenters have constructed elaborate syncretisms to combine these ideas. In particular, QAnon comments show a high degree of syncretism between anti-Democratic, anti-China, anti-Hillary Clinton, anti-semitic and pro-Christian language. Hard and fast cleavages between these different prejudices are difficult to establish, at least at this stage.

Perhaps more importantly, QAnon comments also appear to strongly counter Clarke's (2002, 2007) assertions that the “hyper-critical atmosphere” of the internet will retard the development of conspiracy theories through discouraging believers from articulating explicit

details/evidence. The empirically inaccurate but fervent/deep evidentiary detail of the QAnon comments examined here strongly suggests this concept is mistaken. Indeed, the evidence examined here suggests the opposite trend has occurred, at least regarding QAnon, as it is thriving in an online space. The QAnon research program may indeed be “non-falsifiable” and somewhat immune to self-contradiction, but the Internet is likely *increasing* the speed at which such a “degenerating research program” can be constructed/maintained/modified, (thus making Clarke half correct).

QAnon’s thriving and popular YouTube community further problematizes Clarke’s idea that:

“As long as there are ways in which the received view is less than perfect, this activity can proceed and internet conspiracy theorists can remain active. However, in and of itself this activity cannot be sufficient to overthrow a received view in favour of a conspiracy theory. The most it can do is cause people to suspend judgement. Before we can reasonably expect a conspiracy theory to replace a received view, that conspiracy theory must be judged to provide a superior explanation of the relevant phenomena than the received view.”

First, the comments and models examined above indicate that QAnon commenters are not merely “suspending judgement”. There is far too much (empirically baseless) theory building to reduce QAnon ideation to this. Second, QAnon makes supporting this perspective difficult as the conspiracy *fully replacing* orthodox political or international relations views for the majority of society is not the only issue at hand. Obviously, the evidence for much all of what QAnon commenter’s posit is lacking, and for this reason many people will reject it. Nonetheless, QAnon's popularity does contribute to the political discussion, as it produces an extreme-right wing perspective with its own internally coherent empiricism and epistemology. One is struck reading QAnon YouTube comments at the fervor and belief commenters give these YouTube videos, and it is important to note that if YouTube view counts are any indication, such beliefs are subscribed to by at least hundreds of thousands (likely millions) of people. As such, QAnon shifts the conversation, or the “Overton Window” of what is possible, real, and politically viable (Lehman, 2012). *Simply put, its mass adoption,*

or lack thereof, is not necessary for it to have a substantial polarizing effect on the spectrum of American political thought.

As such, this paper supports an opinion more akin to Drezner's (2010) view that "[...] it's not that the Internet creates paranoid or conspiratorial views. The world wide web simply allows like-minded extremists separated by geography to form their own online cocoon." As indicated by our analysis of popular comments, the forum of YouTube allows for a normalization of fringe ideas into a countervailing, non-empirical worldview that must be accounted for. If culture is indeed an "aggregate of beliefs and ideologies that stimulate action" (Adams and Roscigno, 2005), and not a first-past-the-post, winner-take-all scenario, the fervor, detail and internal coherence of QAnon's belief system must be a great concern to policymakers and the general American public. *Given the fecundity of the YouTube QAnon content creation environment, the theory does not need to "win over" a majority or plurality of Americans to create a distinct political community with its own news sources, beliefs about politics/international politics, concepts of patriotism, etc.*

The analysis of this paper also informs a conversation of conspiracy theories in relation to international studies/international relations. We agree with Aistrophe and Bleiker (2018) that "In addition to viewing conspiracy as an act, we should also see perceptions of conspiracies as narratives that are intrinsically linked to power relations and the production of foreign policy knowledge." However, other elements of their theoretical approach seem inappropriate in the face of QAnon's relationship with the Trump administration and US political power more broadly. For example, Aistrophe and Bleiker posit that "[...] those who have the power to describe certain positions with the language of conspiracy possess the power to discredit these positions." They note that conspiracies regarding Iraq/Saddam Hussein's regime endorsed by the Bush Administration were believed, and became the basis for important foreign policy decisions, while similarly fringe conspiracies from communities in the Middle East during this period remained relegated to a marginal position.

QAnon is of course both clearly aligned with massive political power and yet remains entirely a fringe American political perspective. QAnon foreign policy/international relations beliefs may be even more marginalized, as this author (someone hopefully relatively highly informed regarding QAnon) was unaware the conspiracy had international relations beliefs at all before this study began. As such, while in some ways QAnon believers can be conceptualized as *the most “pro-Trump”* individuals in the country (and thus highly proximal to political power, at least ideologically), they/their ideas are also 1.] either largely unknown to the general public and/or, 2.] almost entirely ostracized from legitimacy due to the extreme nature of their beliefs. In this circumstance, ideological proximity to power is not a source for legitimacy for the QAnon movement, perhaps particularly in regards to foreign policy. Indeed, despite descriptions and references from the White House *using the language of QAnon*, this credibility gap persists.

Such a credibility gap seems even more acute in relation to international issues. Topic models and comment word counts indicate the People’s Republic of China is the most prominent international topic in the corpus, and connect former Senator, Secretary of State, and Democratic Presidential candidate Hillary Clinton (as well as her husband) intimately to various real/imagined foreign policy disasters related to the PRC. Here again we see Aistrophe and Bleiker are half correct as this corpus indicates a substantial amount of “narratives” and “modes of knowledge production” related to international affairs. However, the legitimization that is theorized to follow such narrative building (thanks to proximity/alignment with political power) is lacking.

Beyond the window of QAnon’s conjectures and patterns of belief, this case study also produces wider take-aways regarding the global system. In particular, QAnon demonstrates that while the global order is increasingly dependent on “big data” generation and utilization, some subset of individuals are less inclined to find rational utility in either the breadth or availability of such information. The international relations topics within this corpus demonstrate that many

popular conjectures within the movement/theory are concerned with foreign affairs and apply the same type of “monological” or “non-falsifiable” thinking to such subjects as they might to domestic affairs. This deeply agrees with Fluck’s (2015) assessment that “At the level of the existential dimension of modernity, conspiracy theorising serves the same consoling function as does technical knowledge [...]; *a world free from contingency and uncertainty is an appealing one to modern individuals, who are increasingly at the mercy of distant and obscure structures* [emphasis mine].” QAnon commenter’s focus on a posited nexus of beliefs connecting Hillary Clinton and the People’s Republic of China, along with a host of other political phenomena, demonstrates just such an appeal. QAnon may indicate that issues of an international nature may be particularly prone to monological conspiracization as people feel such a vulnerability to outside foreign actors. There are a host of future research questions in this vein, as European/American views of China have both a longstanding tradition of orientalized “othering” in regards to this region of the world and many also blame China for more recent economic and social damage.

Of course, this paper also has a host of limitations, primarily due to theal and budgetary limit structurations of the researcher. First and foremost, with additional time and funding, a larger sample of QAnon comments could easily be aggregated. While there is little in the way of a best practices sample for this kind of comment-based research, in general larger samples are always better. Methodologically, further exploration is also needed into the degree that YouTube QAnon comments are produced by bots and/or state sponsored accounts. State support for right-wing comments on Twitter has been detailed elsewhere (Miller, 2019, and Woolley and Howard, 2016), and Al-Rawi *et al.*, (2019) note that QAnon has been in the past a popular topic of discussion for bots. Al-Rawi *et al.*, found that QAnon was a prominent hashtag used by bots on the platform. Such exploration of automated comments related to QAnon’s actual footprint on YouTube in terms of

real human commenters, and also provides an area of further exploration regarding popularity metrics (e.g., “likes” for human-generated content versus bot-generated content).

Setting aside “big picture” academic conversations, as well as inherent methodological limitations, this study presents several relatively straightforward conclusions about QAnon’s conjectural characteristics. QAnon comments contain a continuation and modification of previous “far right” conjectures that posit a wide-ranging, internationalized connection between an evil US government (particularly prominent Democrats) and sexual violence against children. QAnon comments contain prominent topics dominated by both anti-semitic language as well as Christian theology and imagery, and this Christian language is tied closely to President Trump and American patriotism. QAnon comments do in fact contain substantial discussion of international affairs, and this international discussion revolves heavily around China, Russia and Israel, in that order of prominence. Discussion of China in the QAnon comments received more “likes” than other international topics, and these comments are dominated by a nexus of conjectures tying Hillary Clinton to the Chinese party-state (with the “trade war” and Trump Administration tariffs on China taking a “backseat” to Clinton in importance). for QAnon. These characteristics modify our understanding of QAnon and that movement’s presence online, and open up a host of new important research questions for social scientists interested in conspiracies, the role of religion in American political life, the current political paradigm of extreme partisanship, the interaction between the internet and ideas of truth, the role of conspiracies in international affairs, and those interested more simply in the study of QAnon itself.

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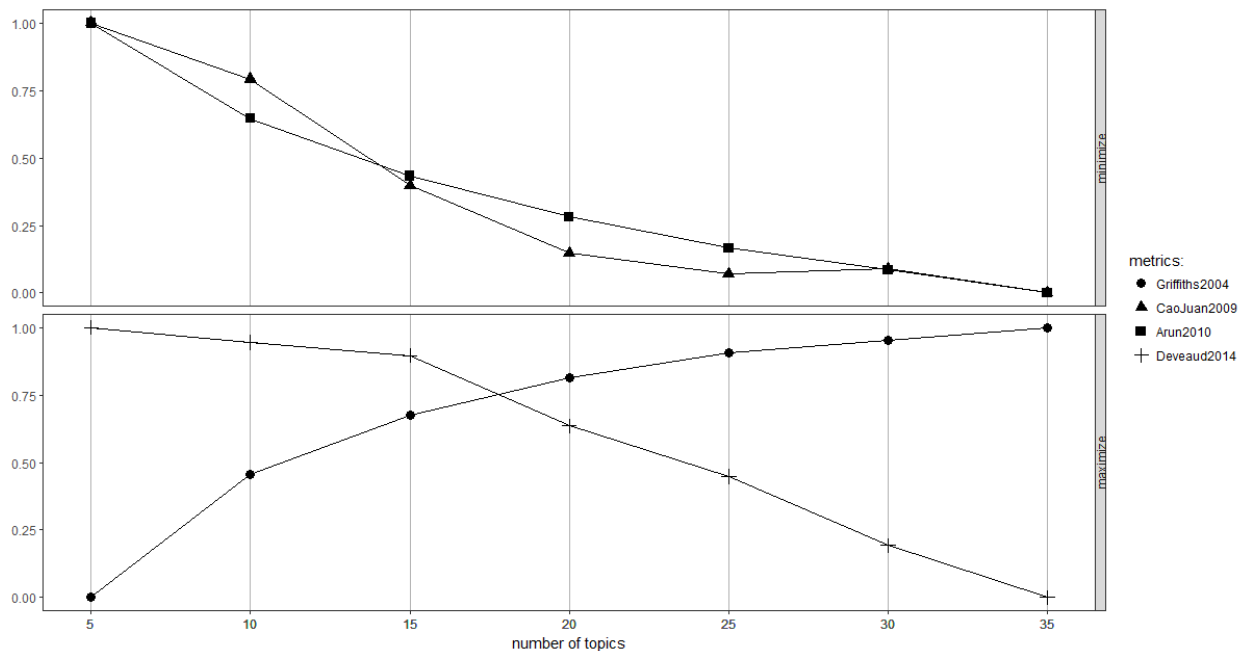
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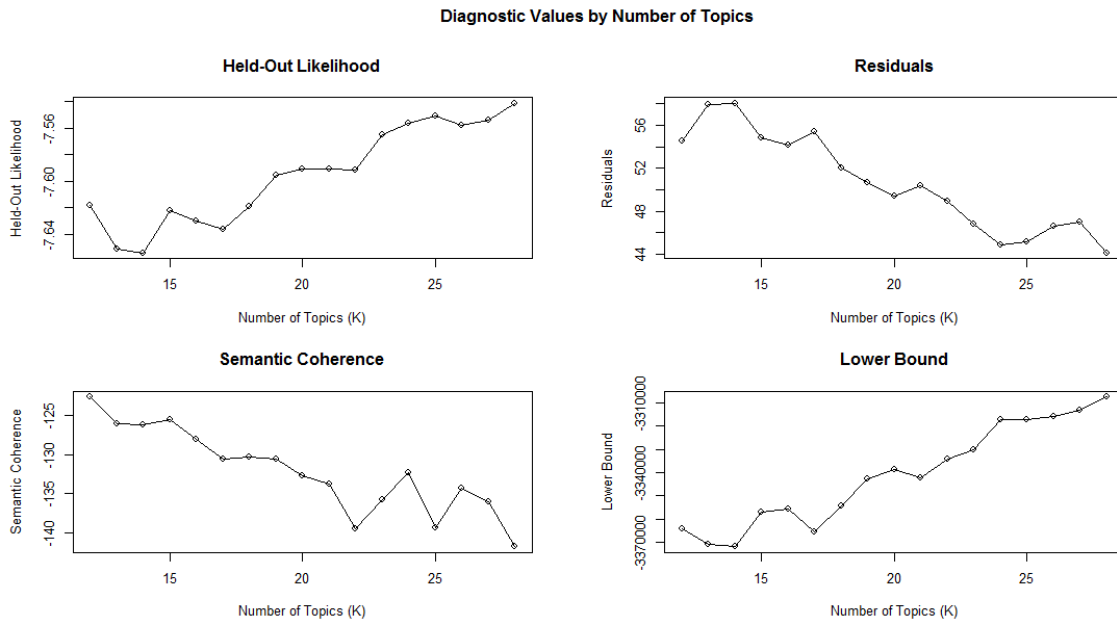
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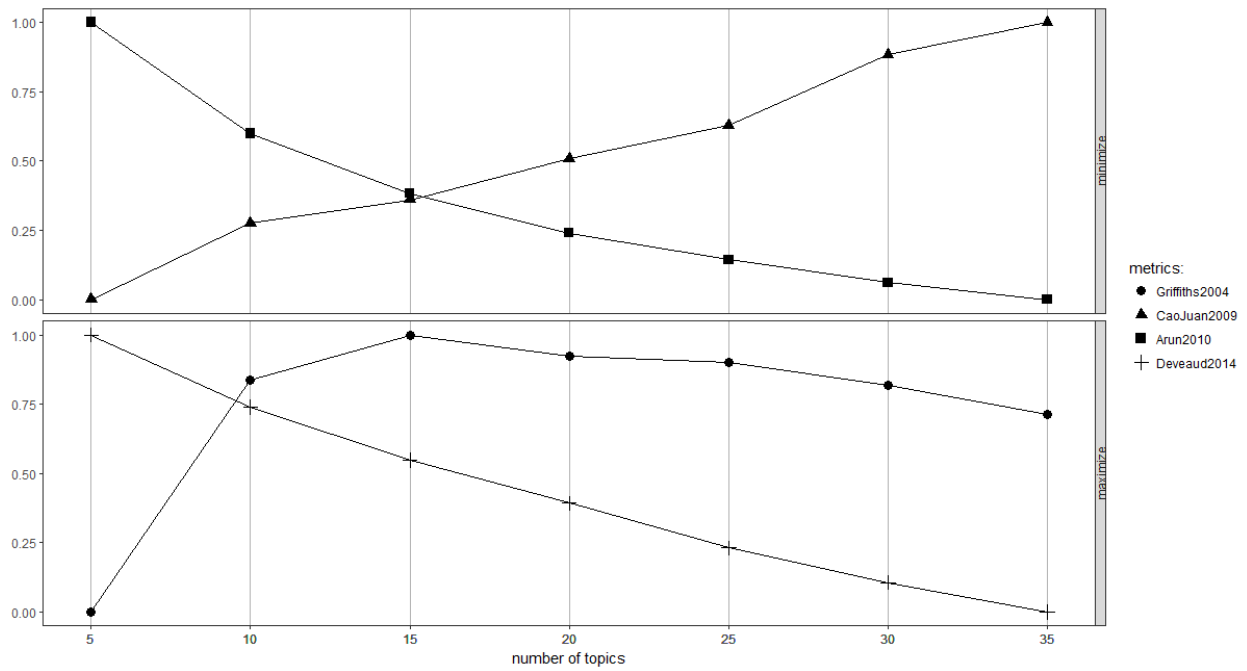
Appendix:



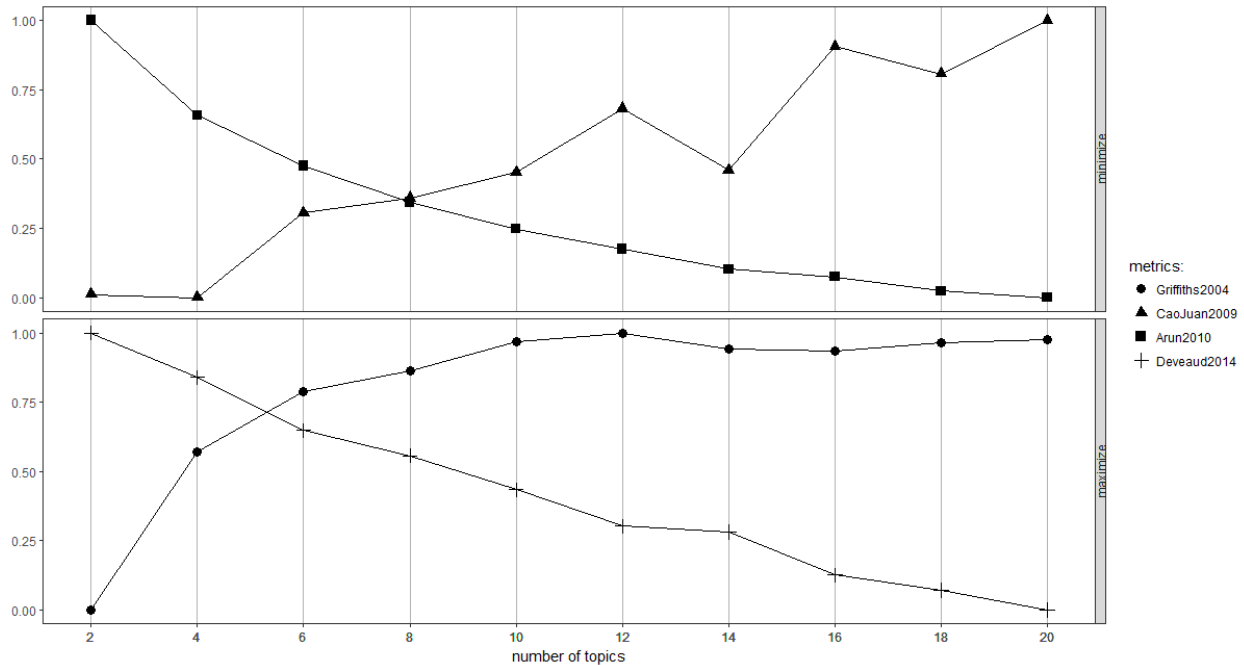
Appendix fig 1: “FindTopicsNumber” estimate for total topic number



Appendix fig 2: “searchK” estimate for total topic number



Appendix fig 3: “FindTopicsNumber” topic number estimate for comments with 10+ “likes”



Appendix fig 4: "FindTopicsNumber" topic number estimate for comments with 70+ "likes"

Appendix Topic Model Label List 1 (Full Corpus):

Topic 1:

don, way, something, lot, trust, understand, call, channel, support, potus, feel, check, praying, care, seen, either, mind, wow, listen, crazy

Topic 2:

state, deep, someone, media, saying, last, talk, question, evidence, times, comment, etc, ask, lost, people, telling, won, ready, march, opinion

Topic 3:

time, love, really, great, bill, work, keep, hope, never, getting, jordan, videos, smith, wwg1wga, hard, tell, best, stuff, better, job

Topic 4:

god, back, thank, bless, please, name, patriots, book, pray, glad, soon, stay, family, help, wonder, home, bush, safe, red, gone

Topic 5:

good, many, years, day, long, trying, happen, post, information, ago, talking, year, dont, next, enough, end, knows, days, watching, use

Topic 6:

believe, even, yes, big, find, everyone, read, already, put, give, guy, heard,youtu.be, research, try, start, sorry, reason, looking, follow

Topic 7:

children, old, evil, sick, women, child, woman, sex, age, jews, ginsburg, men, court, man, kids, gay, hate, marriage, ruth, supreme

Topic 8:

look, new, thanks, always, news, anyone, coming, let, plan, bad, info, hear, youtube, around, another, making, exactly, since, posts, qanon

Topic 9:

video, stop, everything, maybe, control, lionel, point, else, israel, part, free, behind, msm, fact, person, dead, proof, movement, run, public

Topic 10:

going, said, president, still, hillary, clinton, obama, remember, justice, happened, china, guys, never, went, cia, office, time, russia, since, arrested

Topic 11:

trump, money, government, results, america, country, american, white, military, house, war, law, vote, family, black, democrats, pay, corrupt, usa, states

Topic 12:

right, real, truth, fake, show, true, jones, says, alex, wrong, stupid, shit, little, wake, left, false, made, following, space, message

Topic 13:

think, nothing, thing, lol, anything, things, ever, done, thought, actually, man, away, mean, today, agree, might, different, assange, full, wait

Topic 14:

people, watch, www.youtube.com, world, god, jesus, every, must, evil, life, live, power, problem, human, history, christ, lord, word, cause, bible

Appendix Topic Model Label List 2 (Comments with 10+ “Likes”):

Topic 1:

people, back, think, hillary, remember, believe, cnn, thought, real, fake, anything, anyone, death, msnbc, tried, really, john, whole, full, drops

Topic 2:

information, children, bohemian, ranch, order, hollywood, grove, pedophiles, society, creek, poindexter, rent, texas, others, cibolo, guests, hubertus, saint, scalia, parties

Topic 3:

time, thing, don, really, big, said, look, please, something, right, jones, think, never, last, long, made, away, enough, everything, ever

Topic 4:

wwg1wga, great, already, msm, getting, plan, light, times, maga, welcome, watching, always, says, actually, war, bad, true, history, deal, conspiracy

Topic 5:

praying, watch, thanks, love, keep, work, pray, potus, post, left, media, today, listen, days, coming, together, soon, speak, awesome, dave

Topic 6:

show, still, live, laws, care, vote, democrats, dead, man, work, trust, satan, party, oyvey, prison, wall, god, home, never, parents

Topic 7:

good, women, man, love, right, hard, hate, jesus, men, lot, book, america, wrong, stand, bad, many, life, angels, mean, father

Topic 8:

www.youtube.com, results, day, don, must, job, hear, heard, boom, better, never, either, public, controlled, else, correct, feel, end, #wwg1wga, security

Topic 9:

state, nothing, hope, patriots, deep, think, glad, yes, lol, agree, news, someone, white, behind, talk, info, since, joke, wait, said

Topic 10:

everyone, people, red, gay, straight, help, right, anyone, others, around, lives, things, less, opinion, community, especially, brought, children, sex, actually

Topic 11:

evil, old, justice, sick, ginsburg, children, child, court, age, china, supreme, clinton, ruth, woman, looks, jews, years, bader, ginsberg, kids

Topic 12:

trump, god, thank, president, bless, truth, always, many, family, world, craig, video, said, patriot, country, every, ever, patriots, best, brother

Appendix Topic Model Label List 3 (Comments with 70+ “Likes”):

Topic 1:

good, god, watch, work, thank, country, thanks, hard, praying, hear, craig, late, security, patriot, soon, actually, someone, sick, told, money

Topic 2:

president, trump, china, potus, back, behind, brother, working, left, clinton, hillary, times, truth, long, asking, ago, almost, chinese, gave, hang

Topic 3:

patriots, keep, wwg1wga, ginsberg, saying, trying, court, supreme, disgusting, enough, old, woman, american, children, ruth, since, says, views, done, lie

Topic 4:

evil, love, man, sick, right, age, agree, group, world, believe, don, change, kids, stay, crazy, hate, absolutely, head, stand, parents

Topic 5:

people, dead, state, think, always, democrats, point, good, stop, anyone, controlled, door, israeli, list, media, speak, welfare, still, party, years

Topic 6:

women, ginsburg, mother, nothing, looks, bader, ruth, really, away, witch, great, working, system, communist, child, days, funny, rats, satan, democratic

Topic 7:

www.youtube.com, bless, bond, results, year, economy, another, sell, end, boom, interest, let, many, dave, everyone, owe, best, bing, check, private

Appendix Topic Model Label List 4 (Comments referencing China):

Topic 1:

china, trump, far, left, people, really, world, said, anti, president, system, evil, security, america, made, government, bad, right, american, schools

Topic 2:

chinese, china, hillary, agent, spy, years, clinton, trump, hilary, think, tax, don, believe, trumps, dung, feinstein, computer, pray, hack, world

Topic 3:

china, working, chinese, sick, google, emails, many, cover, information, aluminium, lieu, senator, linked, traitor, email, hrc, everything, system, world, white

Topic 4:

china, www.youtube.com, israel, results, america, people, russia, jews, time, nothing, god, country, many, south, black, communication, hillderbeast, run, death, mean

Topic 5:

people, ranch, bohemian, order, creek, poindexter, cibolo, guests, hubertus, rent, saint, keep, china, society, grove, many, trump, believe, news, children

Topic 6:

people, china, trump, remember, many, world, great, america, chinese, country, president, lord, evil, new, right, says, years, look, russia, nations

Topic 7:

china, russia, trump, sold, chinese, clinton, server, yes, hillary, president, back, real, secrets, hrc, military, money, said, asking, access, emails

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