Nigeria: Tracking and Promoting Good Governance

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Executive Summary

In October 2016, the United States Institute of Peace (USIP) convened ten Nigerian governors, numerous NGO leaders, and top US officials in Washington D.C. to discuss long-term governance strategies for Nigeria. These leaders evaluated financial and political corruption at the local, state, and federal levels, violence related to terrorist and ethnic factions, and issues related to internal and external displacement. The symposium illuminated two immediate goals, among others, for the USIP and the Nigerian governors: (1) increase foreign direct investment (FDI) in order to spur economic growth, especially in Northern states, and (2) determine how different types of violence impact constituent opinions on state and federal governments.

The Yale Capstone Team worked closely with the PeaceTech Lab and USIP in order to realize these goals. First, the Yale Capstone Team analyzed the relationship between different types of violence and constituent opinion on different levels of government. The team collected millions of Nigerian social media posts from 2014 and 2016 to proxy for public opinion, filtered for those related to specific actors and locations, and harnessed cutting-edge, US government vetted algorithms to classify the underlying sentiment of each post. By superimposing specific incidents of violence (i.e. riots and protests, Boko Haram attacks, Fulani Herdsmen attacks, and military interventions) on the timeline of posts, the analysis illuminates shifts in public opinion following a given incident. This novel study conclusively shows that Nigerian citizens assign blame to different levels of government depending on which violent actor is involved. The full results of the analysis are included in part one of the report.

Second, the economics team analyzed federal and state initiatives that could reduce common barriers for foreign direct investment, including lack of government transparency and oversight, risks associated with money laundering and unintentional terrorist financing, and inability to track spending and outcomes. Peer country analysis, expert input, and independent research illuminated financial intelligence units (FIU) as a viable strategy to mitigate these issues and thereby spur economic growth. Extended research on best practices for FIU structuring and potential outcomes, as well as public opinion on the value of financial oversight, is included in part two of this report.

This report sheds light on the two central questions asked by Nigerian governors and NGO leaders at the USIP summits, providing preliminary conclusions on how to increase FDI and how to relate violence on public opinion. Further research would look at concrete steps to implementing a robust FIU in Nigeria, as well as creating action items for government institutions held accountable by Nigerian citizens for specific types of violence.

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1 Executive Summary

Currently, over 1.6 billion people in the world use some form of social media. Social media data can offer insights regarding social and political issues in a way that reveals unparalleled ground-up perceptions from civilians. The Yale Global Affairs Senior Capstone project was tasked with harnessing the fire-hose of social media data in order to analyze its link to violent extremism and civil conflict in Nigeria. Our primary research questions focused on how incidents of violence affect public sentiment towards the federal government, military, and state governors. We analyzed public sentiment on these three institutions of governance through social media data.

To obtain social media data that was salient to the issues we wished to study, we developed a lexicon of terms for two broad categories of analysis: posts relating to the federal government and posts relating to the military. Each lexicon was filtered through Crimson Hexagon to produce the social media data relevant to our research questions.

Afterwards, raw social media data was downloaded in bulk from Crimson Hexagon. We then used a Python script employing a sentiment dictionary developed by the National Research Council to parse and analyze the data. For each tweet, relevant sentiments were cumulatively tallied and used to calculate the overall sentiment of each query.

In the following analysis, we examine the correlations between incidents of violence—including attacks by Boko Haram and Fulani herdsmen, military reprisals, and riots and protests—and change in the sentiment of social media discourse relating to the federal government, the military, the state government, and President Buhari specifically. This report details our research methods and findings.

2 Crimson Hexagon and Lexicon

The data used for the following sentiment analysis was taken from the social media data platform Crimson Hexagon. We filtered for Nigerian Twitter posts relating to the federal government, the military, and individual state governors. To identify posts in the federal government and military categories, we created two lexicons consisting of a series of terms relating to the category. We consulted a variety of sources to develop these lexicons, scraping digital newspaper articles, speaking to Nigeria experts at Yale University's Jackson Institute, and conducting independent research. Additionally, the lexicons included both the English terms and the Hausa translations. Using these lexicons, we collected posts on both topics from Nigeria as a whole as well as from three individual Nigerian states.

3 Sentiment Analysis

Once our Twitter data was collected, we used sentiment analysis code to identify positive, negative, and neutral tweets. We used the Word-Emotion Association Lexicon from the NRC (National Research Council) to develop our sentiment analysis code. The NRC's Word-Emotion Association Lexicon consists of a list of words and their associations with eight emotions—anger, fear, anticipation, trust, surprise, sadness, joy, and disgust—as well as three general sentiment descriptors—positive, negative, and neutral. The annotations were manually done through Amazon's Mechanical Turk, a full dictionary of over 14,000 common words commonly associated with each sentiment.

The NRC dictionary can be downloaded at: http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm

The original lexicon has annotations at the word-sense level. On each line of the dictionary, a single word is displayed along with its corresponding sentiments, with a 1 (if the word is that sentiment) or 0 (if it is not) following. The word-level lexicon was created by taking the union of emotions associated with all the senses of a word.

We created a python script to conduct sentiment analysis on Crimson Hexagon data downloaded using our lexicons. For a single dataset, the NRC dictionary was loaded into memory and then used to analyze each tweet, displayed in a CVS format as a single line.

First, the tweet identifiers (date, state, etc.) and then the tweet's contents were loaded into memory. Using the NRC dictionary, we parsed each word within the tweet and searched within the dictionary to see if a match was found. If so, then the word's corresponding sentiment count incremented by 1. The overall sentiment of the tweet was based on a cumulative calculation done of each tweet at the word-sense level.

Formulas for the calculation of sentiments within a single tweet:

$$Positive = joy + positive + trust \tag{1}$$

$$Negative = anger + disgust + fear + negative + sadness \tag{2}$$

$$Neutral = (if positive == negative) \tag{3}$$

A binary (1 or 0) value is assigned based on the cumulative sentiments of each tweet, based on number of sentiments expressed. The final product was an outfile with the dates split into month, day, year format and additional sections added for the corresponding Positive Sentiment, Negative Sentiment, or Neutral Sentiment found within that tweet.

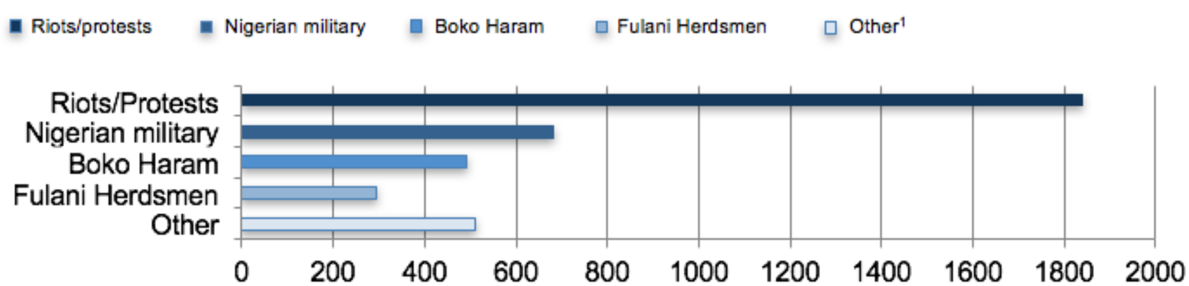
4 Empirical Design

We used these sentiment analysis results to measure public opinion over time. The analysis of our results focuses on public perception of four institutions of governance: the military, the federal government, the state government as represented by the state governor, and President Buhari.

We collected tweets about both Buhari and the state governors from 2015-2016, as neither Buhari nor many state governors were in office before that year. We expanded the timeline for the federal government and military to 2014-2016. We are aware that a change in government happened in 2015 at the federal level, but we include a time trend to account for overarching trends. Additionally, since our regression is run on the day-to-day level, we were more concerned that overall trends might obscure a significant result, not that they would produce a false positive. The two outcome variables are the percentage of positive and negative tweets.

To identify incidents of violence we used the Armed Conflict Location and Event Data Project (ACLED) dataset. ACLED best suited our research needs because it records acts of civil unrest and political violence, both of which are likely to affect public opinion and be publicized and tweeted about. Figure 1 displays the main identifiable actors who committed acts of violence according to the ACLED dataset. Based off of this information, we used any incident or act of violence perpetrated by the top four actors—Rioters/Protesters, Boko Haram, Fulani Herdsman, and the Military—as our regressors.

Figure 1: Incidents of Violence, by Actors



Testing all incidents or attacks by these actors might not generate any effect, as small actions perpetrated by the military or Boko Haram could be common enough that individuals would be unlikely to comment on them on social media. So, we created a second category of regressors for each actor: high-fatality regressors of Boko Haram, Fulani Herdsman, Riots/Protests, and the military.

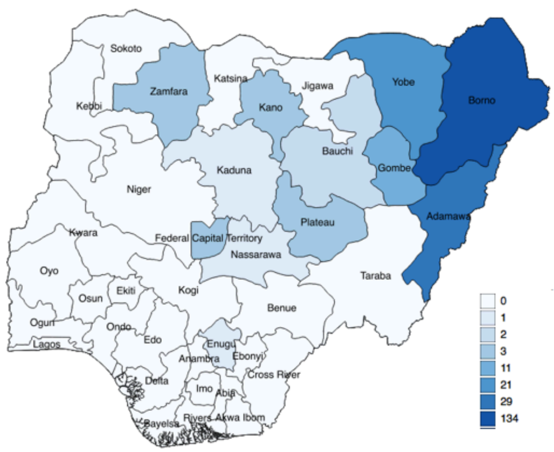
With respect to non-state violent actors, there are three possible hypotheses we tested about their attacks' effect on public opinion. First, that violence causes people to blame the government for failing to keep them safe, causing an increase in negative sentiment and a decrease in positive sentiment. Second, that violence makes people more supportive of the government as a possible provider of security in unstable times. Or third, the public views violence and the government as separate issues and do not link the two.

There are two main hypotheses we tested regarding the military: theories interpreting military as an outcome variable and theories interpreting military as a regressor. As a regressor, given the geographical location of military acts of violence, we assume they are primarily strategic operations the military carried out against Boko Haram. In Borno, then, we tested how operations by the military make people feel about the state and federal government. We first tested if they link operations by the military with the state and federal government. Second, we tested if operations by the military made people feel more positively about their government

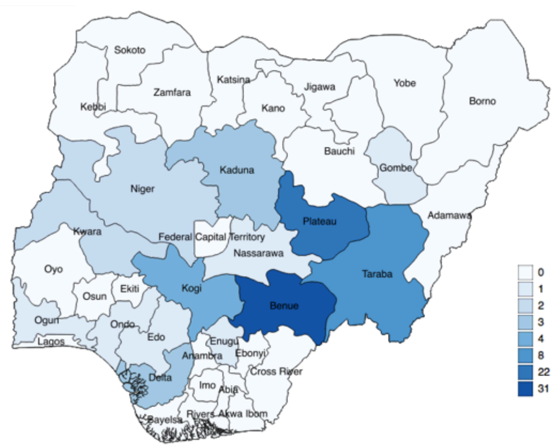
We then had to determine the levels at which we run the regressions. We ran a series of regressions for Nigeria as a whole to test how acts of violence perpetrated by these various actors affect perceptions of the military, the federal Government, and Buhari.

We then developed case studies of individual states to examine how perceptions of state governors change following violent incidents and how perceptions of federal governing institutions or the military specifically change. These case studies also account for the fact that the dispersion of violent incidents is not concentrated in one location. Figure 2 shows the dispersion of violent incidents by actor. Boko Haram is most active in the Northeast, Fulani herdsman are most active in the eastern end of the Middle Belt states, and riots and protests occur most commonly in the southwest part of the country.

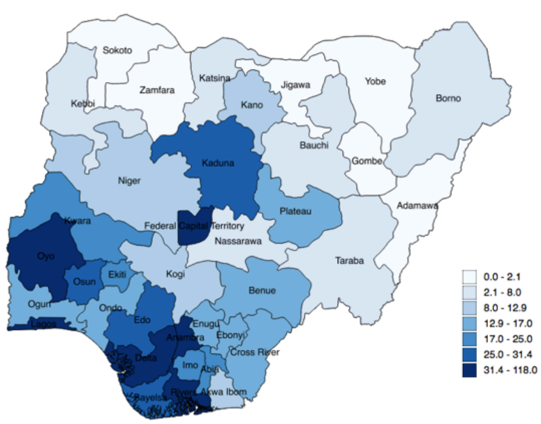
Figure 2: Distribution of Actor Violence and Tweets



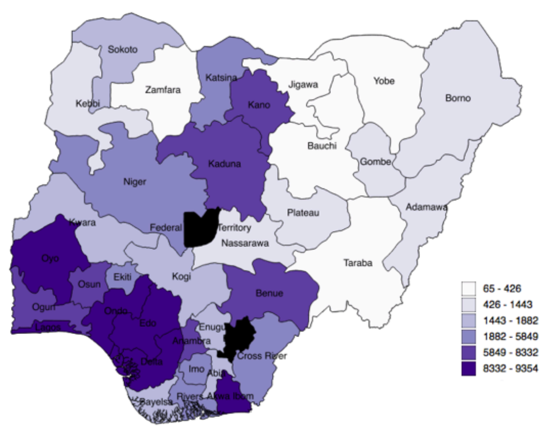
(a) Distribution of Boko Haram Attacks



(b) Distribution of Fulani Herdsman Attacks



(c) Distribution of Riots and Protests



(d) Number of Tweets about Governors

We chose a case study from each of these regions: Borno, Benue, and Lagos. As evidenced in subfigure 2d, Borno has more Boko Haram attacks and a substantively larger sample of tweets than any of its northeastern neighbors. Similarly, in the Middle Belt states most affected by Fulani Herdsman, Benue has the highest number of attacks as well as the largest sample of tweets relative to its neighbors. Finally, in the states most affected by riots and protests, Lagos is one of the states in which riots/protests occur most frequently, has a large sample of relevant tweets, and contains the city of Lagos, the largest city in Nigeria and therefore a major center of urban life.

For each geographical level of data—Nigeria, Lagos, Borno, and Benue—we created a time series dataset that is unique at the date level. For each day, we reported the number of total tweets, positive tweets, negative tweets, and neutral tweets, as well as the percentage of tweets per day that are positive, negative, and neutral. We also created a series of 0-1 dummy variables for if an incident of violent occurred, if a certain actor committed an attack, or if a protest occurred. We then estimated the follow fundamental regression equation:

$$sentiment_t = \beta_0 + \beta_1 x_t + \varepsilon_t \tag{4}$$

This regression is empirically the same as conducting a t-test to see if the means of the outcome variable are significantly different if an attack has occurred or not occurred. The regression coefficient can then be interpreted as the additive increase or decrease in percentage points following an incident of violence. We also estimated an equation where we replaced the regressor with lagged values for the regressor to test if changes in sentiment occur on the day of, day after, or two days after. Additionally, we estimated with the lagged values because we assumed that the news of certain events might not circulate instantaneously and that the dates in the ACLED dataset may be reported with error. We also added in a simple control for time trends.

5 Results

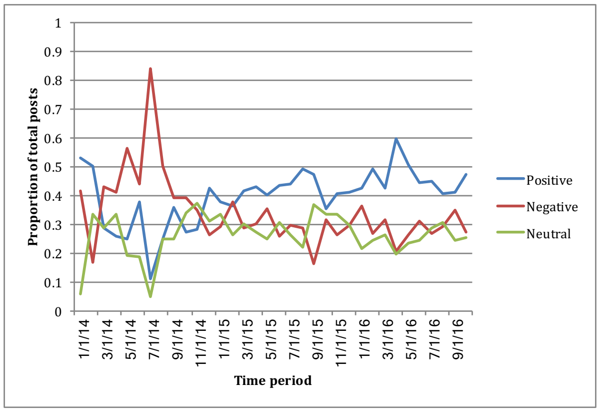
5.1 Borno

Over the 2015-2016 period, Figure 4 shows there is little linkage between the acts of violence and the governor in Borno. The main significant result is that when there is a high-fatality act of violence, there is an 18% point increase in negative tweets about the governor. Actor-specific types of violence do not produce significant results. The only significant result for Boko Haram disappeared when the control for time trends was added. This seems to suggest that the residents of Borno do not strongly link their governor with acts of violence and do not blame him more when violent incidents occur, except when there is a high-fatality count. This may be because violence is common in Borno and seems to largely emanate from an external source. It may also be because people recognize that the state governor has a limited capacity to oppose violent insurgent groups. One possible source of error for the governor results is the limited number of tweets about the state governor, resulting in a smaller data sample. However, for the federal government and military, there were more tweets that were better able to span the period of time.

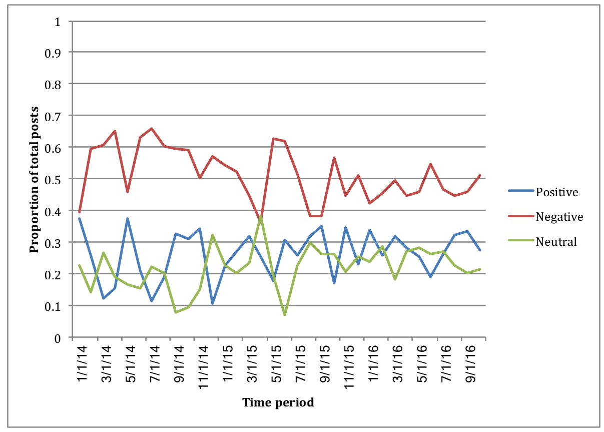
As we can see from figure 5, there is little linkage between occurrences of violent events and the federal government. Actions by the military seem to cause a 4% point decrease in negative sentiment about the federal government, however the significance of the result disappears when the time control is added.

Figure 6 shows more linkage between incidents of violence and public sentiment about the military. Any incident of violence is correlated with approximately a 7% point increase in negative tweets and a 5% point decrease in positive tweets about the military two days after the attack. The size of these coefficients,

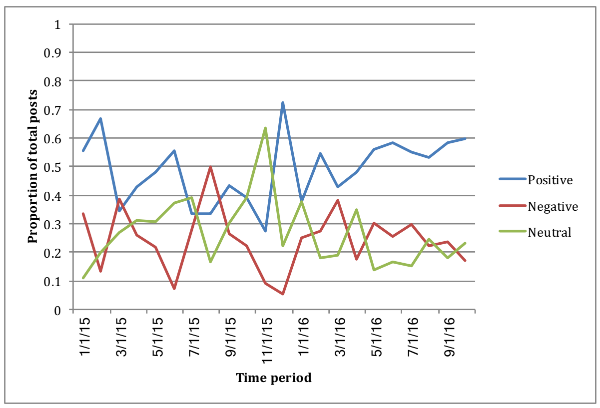
Figure 3: Change in the sentiment of tweets about various actors in Borno



(a) Sentiment towards the Federal Government, 2014-2016



(b) Sentiment towards the Military, 2014-2016



(c) Sentiment towards Governor Shettima, 2015-2016

Figure 4: Regressions Results for Sentiment about Governor Shettima, Borno

	Negative				Positive			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Attack	Boko Haram	Military	Riot/Protest	Attack	Boko Haram	Military	Riot/Protest
Day Of	0.0777	0.0551	0.0350	-0.0933	-0.0533	-0.0904	-0.0254	0.158
	(0.0403)	(0.0520)	(0.0426)	(0.154)	(0.0491)	(0.0629)	(0.0517)	(0.186)
Day After	0.0681	0.0613	0.0766	-0.182	-0.0572	-0.0114	-0.0821	0.271
	(0.0399)	(0.0519)	(0.0423)	(0.130)	(0.0484)	(0.0631)	(0.0514)	(0.157)
2 Days After	-0.0220	0.0796	-0.0634	0.0259	0.0344	0.00398	0.0443	-0.00781
	(0.0403)	(0.0523)	(0.0431)	(0.130)	(0.0488)	(0.0636)	(0.0524)	(0.158)
N	301	301	301	301	301	301	301	301

Standard errors in parentheses

=* p<0.05 ** p<0.01 *** p<0.001

Figure 5: Regressions Results for Sentiment about the Federal Government, Borno

	Negative				Positive			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Attack	Boko Haram	Military	Riot/Protest	Attack	Boko Haram	Military	Riot/Protest
Day Of	-0.0217	-0.00489	-0.0354	0.0426	0.0120	0.00783	0.0280	-0.0400
	(0.0174)	(0.0213)	(0.0193)	(0.0671)	(0.0175)	(0.0214)	(0.0194)	(0.0675)
Day After	0.0135	0.00427	-0.0157	0.104	0.00965	0.0119	0.0320	-0.0941
	(0.0174)	(0.0211)	(0.0192)	(0.0693)	(0.0175)	(0.0213)	(0.0193)	(0.0698)
2 Days After	0.00820	0.0128	-0.0136	0.0402	-0.0123	-0.0149	0.00534	0.0486
	(0.0174)	(0.0212)	(0.0193)	(0.0694)	(0.0175)	(0.0214)	(0.0195)	(0.0699)
N	823	823	823	823	823	823	823	823

Standard errors in parentheses
=* p<0.05 ** p<0.01 *** p<0.001

Figure 6: Regressions Results for Sentiment about the Military, Borno

	Negative				Positive			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Attack	Boko Haram	Military	Riot/Protest	Attack	Boko Haram	Military	Riot/Protest
Day Of	-0.00755	-0.0485	0.0231	-0.0646	-0.0331	-0.0183	-0.0353	0.0104
	(0.0222)	(0.0266)	(0.0248)	(0.0814)	(0.0199)	(0.0240)	(0.0223)	(0.0731)
Day After	0.0361	0.0288	0.0308	-0.0716	-0.000654	-0.00200	-0.00279	0.0532
	(0.0221)	(0.0265)	(0.0249)	(0.0838)	(0.0199)	(0.0238)	(0.0224)	(0.0753)
2 Days After	0.0686**	0.0443	0.0758**	0.0617	-0.0536**	-0.0284	-0.0657**	-0.0608
	(0.0220)	(0.0262)	(0.0248)	(0.0837)	(0.0198)	(0.0236)	(0.0223)	(0.0750)
N	902	902	902	902	902	902	902	902

Standard errors in parentheses
=* p<0.05 ** p<0.01 *** p<0.001

consistency of sentiment shift, and significance level all indicate that an occurrence of violence causes people to feel more negatively about the military.

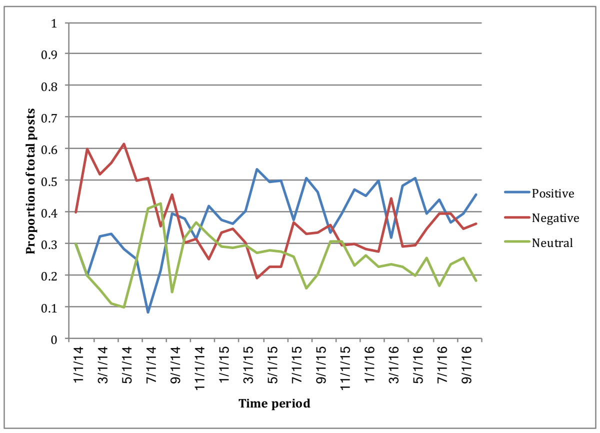
It seems that most of this effect is driven by military actions. Incidents of violence perpetrated by the military are related to a 7% point increase in negative tweets and an approximately 6% point decrease in positive tweets two days after the attack. The size of these coefficients, consistency of sentiment shift, and significance level all seem to indicate that acts of violence from the military cause people to feel more negatively about the military. This might suggest that the residents of Borno view the military as ineffective or perhaps think its methods are too brutal and violate human rights. Whatever the exact cause, it seems that the military has not been effective at winning over the public in the area where it is most active.

Attacks by Boko Haram only seem to shift sentiment about the military when they have high fatalities. A high-fatality attack by Boko Haram is related to an approximately 13% point increase in the negative tweets about the military. This seems to signal that people both blame the military for failing to protect them against large attacks and are simultaneously unhappy with the ways in which the military pursues fighting Boko Haram.

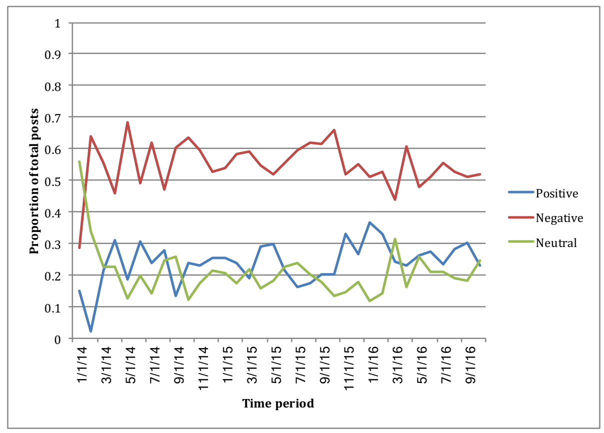
5.2 Benue

In Benue, violent incidents only shift sentiment about the state governor as figure 8 shows. Any incident of violence is related with an approximately 8% point increase in negative tweets both the day of and the day after the incident of violence, and an approximately 6.5% percentage point increase in negative tweets two days after the incident of violence. Following incidents of violence, the percentage of negative tweets about the governor is approximately 8% points higher than it is on average.

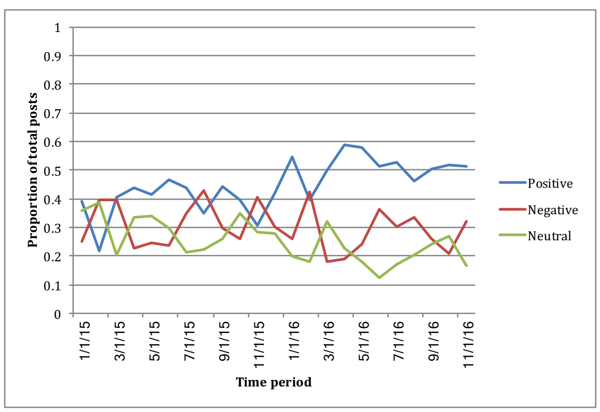
Figure 7: Change in the sentiment of tweets about various actors in Benue



(a) Sentiment towards the Federal Government, 2014-2016



(b) Sentiment towards the Military, 2014-2016



(c) Sentiment towards Governor Ortom, 2015-2016

Attacks by the Fulani herdsman specifically also have an effect on tweets about the governor. These attacks are related to a 9% point increase in negative tweets a day after the attack and an approximately 9% point decrease in positive tweets two days after the attack. The negative sentiment caused by a Fulani attack seems less persistent over time than that caused by incidents of violence in general.

Figure 8: Regressions Results for Sentiment about Governor Ortom, Benue

	Negative			Positive		
	(1)	(2)	(3)	(4)	(5)	(6)
	Attack	Fulani	Riot/Protest	Attack	Fulani	Riot/Protest
Day Of	0.0800**	0.0844	-0.0192	-0.0191	-0.00532	0.0298
	(0.0298)	(0.0443)	(0.0543)	(0.0323)	(0.0478)	(0.0585)
Day After	0.0796**	0.0922*	0.00933	-0.0320	-0.0263	-0.0437
	(0.0302)	(0.0455)	(0.0543)	(0.0327)	(0.0491)	(0.0584)
2 Days After	0.0633*	0.0816	-0.0472	-0.0550	-0.0993*	0.0132
	(0.0299)	(0.0444)	(0.0543)	(0.0322)	(0.0477)	(0.0584)
N	659	659	659	659	659	659

Standard errors in parentheses
=* p<0.05 ** p<0.01 *** p<0.001

Figure 9: Regressions Results for Sentiment about the Federal Government, Benue

	Negative			Positive		
	(1)	(2)	(3)	(4)	(5)	(6)
	Attack	Fulani	Riot/Protest	Attack	Fulani	Riot/Protest
Day Of	-0.0197	-0.0374	-0.0513	0.0117	0.0312	0.0161
	(0.0278)	(0.0394)	(0.0518)	(0.0269)	(0.0382)	(0.0502)
Day After	0.0194	0.0258	-0.00794	0.0204	0.0208	0.0707
	(0.0270)	(0.0376)	(0.0508)	(0.0262)	(0.0365)	(0.0492)
2 Days After	-0.0251	0.0160	-0.0324	0.0223	-0.00446	0.0478
	(0.0274)	(0.0383)	(0.0528)	(0.0266)	(0.0372)	(0.0512)
N	846	846	846	846	846	846

Standard errors in parentheses
=* p<0.05 ** p<0.01 *** p<0.001

Figure 10: Regressions Results for Sentiment about the Military, Benue

	Negative			Positive		
	(1)	(2)	(3)	(4)	(5)	(6)
	Attack	Fulani	Riot/Protest	Attack	Fulani	Riot/Protest
Day Of	0.0370	0.0179	0.0662	-0.0374	-0.0432	-0.0611
	(0.0328)	(0.0456)	(0.0629)	(0.0290)	(0.0402)	(0.0555)
Day After	-0.0146	0.0220	0.00305	0.0148	0.00108	-0.0298
	(0.0322)	(0.0438)	(0.0618)	(0.0284)	(0.0387)	(0.0546)
2 Days After	0.0378	0.0181	0.00400	-0.0215	0.0114	-0.00816
	(0.0331)	(0.0459)	(0.0640)	(0.0293)	(0.0406)	(0.0566)
N	926	926	926	926	926	926

Standard errors in parentheses
=* p<0.05 ** p<0.01 *** p<0.001

These results seem to strongly support the thesis that Benue residents blame the state governor for violent incidents or Fulani herdsmen attacks, perhaps because they feel as though the state government has failed to protect them. However, as figures 9 and 10 show there are no significant relationships between violent incidents of any kind and shift in public sentiment about the federal government or military. Perhaps this is because the violence that confronts residents of Benue, primarily violence by the Fulani herdsman and militias, is dealt with at the state and not the federal level. According to ACLED, the military is not active in Benue.

5.3 Lagos

Riots or protests account for the vast majority of the violent incidents in Lagos. Perhaps due to the frequency of these events, Lagos' citizens do not seem to strongly care about them, as there is no significant relationship between a violent incident and perceptions of any institution of governance. However there are large and significant relationships between public perception and acts of violence by organized non-state actors. Perhaps since these incidents are so rare, when they do occur, they cause dramatic public outcry.

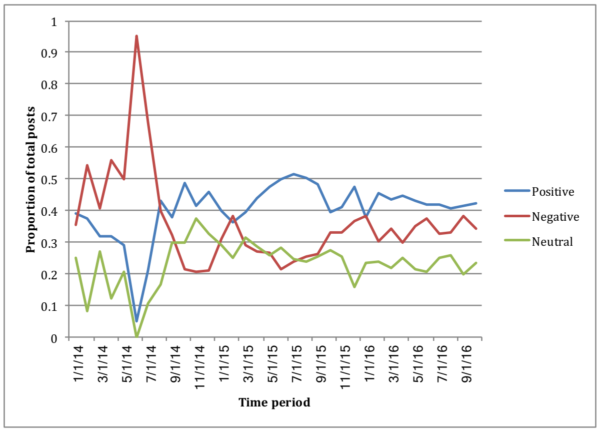
As figure 13 shows there was only one Fulani attack in Lagos during 2015-2016 and the percentage of negative tweets about the state governor increased by 77.5% percentage points while the percentage of positive tweets decreased by approximately 61% percentage points, indicating that people were deeply unhappy that the governor failed to provide security on that one occasion.

There were no Boko Haram attacks in 2015-2016 in Lagos, but in 2014 there was one such attack, and the percentage of negative tweets about the federal government increased by 64.5% percentage points for the two days following this event, once again adding support for the hypothesis that people blame the government for failing to protect them.

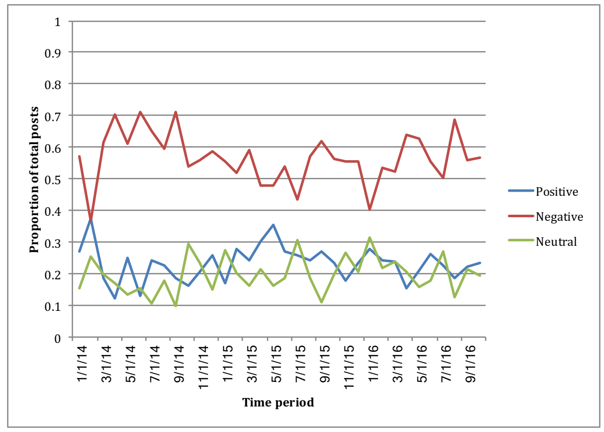
Interestingly, there was no significant relationship between the federal government and Fulani attacks, and the Boko Haram attack occurred before our Twitter sample begins for the current Lagos governor. This could possibly suggest that Lagos mirrors the pattern seen in Borno and Benue—that of people blaming the state government for Fulani attacks and the federal government for Boko Haram attacks. However, given that this hypothesis is based off of only two incidents of violence, we cannot definitively determine if that is the case.

Both military incidents and public opinion on the military are only significant in relationship to each other as figure 14 shows. There have only been six incidents of violence perpetrated by the military in Lagos over the 2014-2016 period, but they are related to a 28% percentage point increase in the percent of negative tweets about the military on the day of the incident of violence. This might indicate that, similar to the people in Borno, the citizens of Lagos, in addition to having a generally negative opinion of the military, become more displeased when they see the military in action. However, there may not enough data to strongly confirm this result.

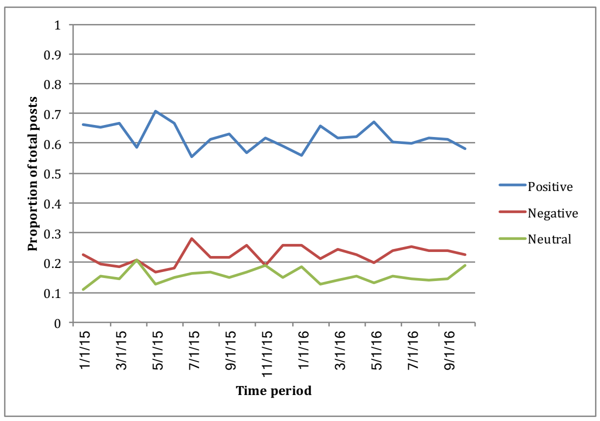
Figure 11: Change in the sentiment of tweets about various actors in Lagos



(a) Sentiment towards the Federal Government, 2014-2016



(b) Sentiment towards the Military, 2014-2016



(c) Sentiment towards Governor Ambode, 2015-2016

Figure 12: Regressions Results for Sentiment about Governor Ambode, Lagos

	Negative				Positive			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Attack	Fulani	Military	Riot/Protest	Attack	Fulani	Military	Riot/Protest
Day Of	-0.0113	0.774***	0.127	-0.00310	0.00774	-0.608***	-0.107	-0.00301
	(0.0138)	(0.153)	(0.0779)	(0.0148)	(0.0157)	(0.176)	(0.0889)	(0.0169)
Day After	-0.00713	0.233	-0.0115	-0.00123	-0.00560	-0.145	0.00568	-0.00747
	(0.0138)	(0.155)	(0.0780)	(0.0148)	(0.0157)	(0.177)	(0.0888)	(0.0169)
2 Days After	-0.000926	0.0438	0.0466	0.00391	0.00538	-0.0609	-0.0238	-0.000883
	(0.0138)	(0.156)	(0.0781)	(0.0148)	(0.0157)	(0.177)	(0.0887)	(0.0169)
N	667	667	667	667	667	667	667	667

Standard errors in parentheses
=* p<0.05 ** p<0.01 *** p<0.001

Figure 13: Regressions Results for Sentiment about the Federal Government, Lagos

	Negative					Positive				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Attack	Fulani	Military	Riot/Protest	Boko Haram	Attack	Fulani	Military	Riot/Protest	Riot/Protest
Day Of	0.00780	-0.0814	0.0441	0.00170	0.634*	-0.0206	-0.00934	-0.0785	-0.0137	-0.388
	(0.0197)	(0.250)	(0.102)	(0.0212)	(0.249)	(0.0193)	(0.245)	(0.100)	(0.0208)	(0.245)
Day After	-0.000890	0.00542	0.0942	0.00214	0.632*	-0.000622	0.00614	-0.0776	0.000258	-0.385
	(0.0196)	(0.250)	(0.125)	(0.0211)	(0.249)	(0.0191)	(0.244)	(0.122)	(0.0206)	(0.244)
2 Days After	0.00211	0.0731	0.0429	0.00204	0	0.0150	0.0447	0.0867	0.0194	0
	(0.0197)	(0.250)	(0.125)	(0.0210)	(.)	(0.0192)	(0.244)	(0.122)	(0.0206)	(.)
N	861	861	861	861	861	861	861	861	861	861

Standard errors in parentheses
=* p<0.05 ** p<0.01 *** p<0.001

Figure 14: Regressions Results for Sentiment about the Military, Lagos

	Negative					Positive				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Attack	Fulani	Military	Riot/Protest	Boko Haram	Attack	Fulani	Military	Riot/Protest	Boko Haram
Day Of	-0.00345	0.457	0.283*	-0.0139	0.410	-0.0295	-0.238	-0.234	-0.0172	-0.228
	(0.0258)	(0.342)	(0.140)	(0.0278)	(0.342)	(0.0221)	(0.293)	(0.120)	(0.0239)	(0.293)
Day After	0.0103	0.291	0.241	-0.0292	0.408	-0.0118	-0.0702	-0.0674	0.0249	-0.229
	(0.0259)	(0.341)	(0.153)	(0.0279)	(0.341)	(0.0223)	(0.293)	(0.131)	(0.0240)	(0.293)
2 Days After	0.000979	0.458	0.0203	-0.0161	0.408	0.00312	-0.237	0.149	0.0194	-0.229
	(0.0260)	(0.341)	(0.140)	(0.0281)	(0.341)	(0.0224)	(0.293)	(0.120)	(0.0241)	(0.293)
N	920	920	920	920	920	920	920	920	920	920

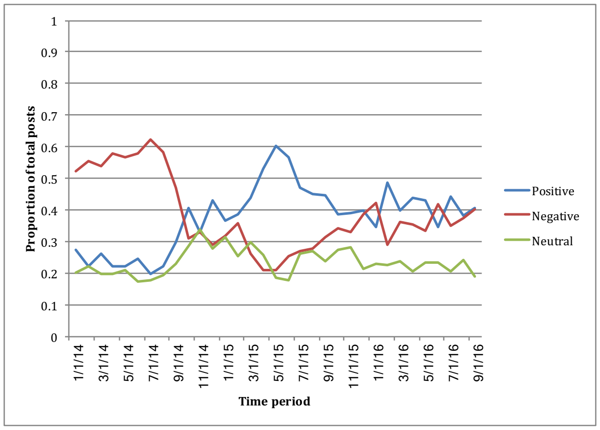
Standard errors in parentheses
=* p<0.05 ** p<0.01 *** p<0.001

5.4 Nigeria

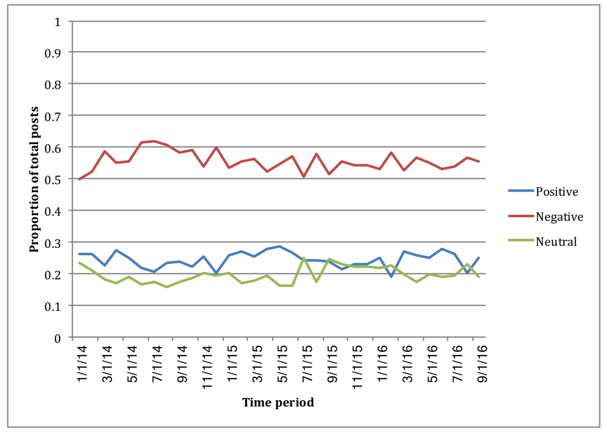
The Nigeria regressions expand outward from the granularity of the state level regressions and capture how Nigerian public opinion moves following incidents of violence. For Buhari, the federal government, and the military, many of the results on the national level have a significant result that disappears when the time control is added. This is probably due to noise and the great quantity of data. Apart from this, there are two consistent patterns of results that emerge.

As shown in figure 16, riots and protests are followed by a significant increase of approximately 3% points in the percent of positive tweets about both Buhari and the federal government. For Buhari, this effect is only significant on the day after the riot or protest, but for the federal government, figure 17 shows it is strongly significant for the day of, the day after, and two days after the protest and is accompanied by a statistically significant decrease of approximately 2.5% points in the percent of negative tweets about the federal government. This seems to confirm that riots and protests are actually followed by people feeling more positive about the federal government and Buhari. Perhaps this is because the riots and protests are cathartic and after airing their grievances people feel more positively. Or, perhaps the civil disorder and unrest that accompanies riots and protests makes all those not rioting and protesting more insecure and so

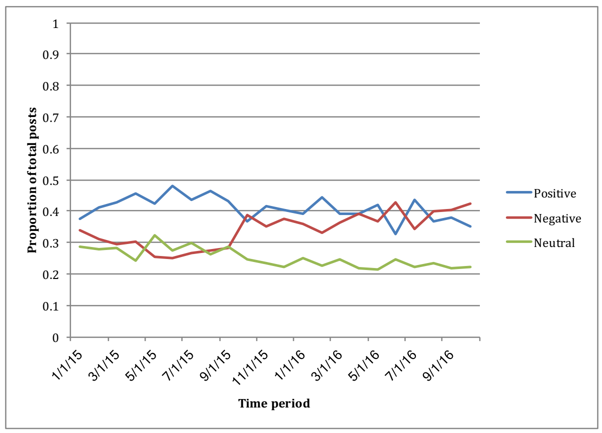
Figure 15: Change in the sentiment of tweets about various actors in Nigeria



(a) Sentiment towards the Federal Government, 2014-2016



(b) Sentiment towards the Military, 2014-2016



(c) Sentiment towards President Buhari, 2015-2016

more likely to support the federal government as a security provider. Alternatively, since there is a direct challenge to the federal government, its defenders may feel a need to be more vocal on Twitter in the days after riots or protests.

The second main pattern is that only high-fatality events tend to have an effect on national sentiment. This makes sense on a national scale, since incidents powerful enough to affect public opinion would most likely be ones that received significant press attention due to high body counts.

Figure 18 shows high-fatality riots and protests were followed by an approximately 3% point increase in the percent of negative tweets about the military the day of the riot, a 2% point increase two days after, and an approximately 2% decrease in the number of positive tweets about the military. High-fatality Boko Haram attacks were followed by a an approximately 3% point increase in the percent of negative tweets about the military the day after the attack and a 2.5% point increase two days after. This suggests that people do link the military with civil unrest on a national level and seem to blame the military for failing to protect them following high-fatality incidents of violence or in the midst of civil unrest.

Figure 16: Regressions Results for Sentiment about President Buhari, Nigeria

	Negative					Positive				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Attack	Fulani	Military	Riot/Protest	Boko Haram	Attack	Fulani	Military	Riot/Protest	Boko Haram
Day Of	0.0103	0.00859	0.00967	-0.0160	0.0109	0.0324	0.00190	-0.00551	0.000529	-0.00896
	(0.0243)	(0.0156)	(0.0119)	(0.0133)	(0.0136)	(0.0250)	(0.0160)	(0.0122)	(0.0137)	(0.0140)
Day After	-0.0109	-0.00756	-0.00384	-0.0133	0.0111	0.0342	0.00697	0.0208	0.0298*	-0.00366
	(0.0244)	(0.0155)	(0.0119)	(0.0133)	(0.0136)	(0.0252)	(0.0160)	(0.0122)	(0.0137)	(0.0140)
2 Days After	-0.00360	0.000181	-0.0101	-0.0338*	-0.00575	0.0200	-0.00374	0.0186	0.0205	0.0185
	(0.0247)	(0.0155)	(0.0119)	(0.0133)	(0.0136)	(0.0254)	(0.0160)	(0.0122)	(0.0137)	(0.0140)
N	668	668	668	668	668	668	668	668	668	668

Standard errors in parentheses
=* p<0.05 ** p<0.01 *** p<0.001

Figure 17: Regressions Results for Sentiment about the Federal Government, Nigeria

	Negative					Positive				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Attack	Fulani	Military	Riot/Protest	Boko Haram	Attack	Fulani	Military	Riot/Protest	Boko Haram
Day Of	-0.00220	0.00840	0.00657	-0.0216*	-0.00178	0.00884	-0.0120	-0.00284	0.0255**	-0.00120
	(0.0258)	(0.0118)	(0.00966)	(0.0104)	(0.0101)	(0.0224)	(0.0103)	(0.00837)	(0.00899)	(0.00879)
Day After	0.00579	0.00267	-0.00903	-0.0171	0.00463	-0.00618	0.00205	0.00233	0.0256**	-0.000929
	(0.0258)	(0.0119)	(0.00966)	(0.0104)	(0.0101)	(0.0224)	(0.0103)	(0.00838)	(0.00899)	(0.00879)
2 Days After	-0.0179	0.00349	-0.00452	-0.0201	-0.00336	0.000382	-0.0104	-0.000919	0.0222*	0.00791
	(0.0258)	(0.0119)	(0.00967)	(0.0104)	(0.0102)	(0.0224)	(0.0103)	(0.00838)	(0.00901)	(0.00879)
N	1002	1002	1002	1002	1002	1002	1002	1002	1002	1002

Standard errors in parentheses
=* p<0.05 ** p<0.01 *** p<0.001

Figure 18: Regressions Results for Sentiment about the Military following high-casualty violence, Nigeria

	Negative					Positive				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Attack	Fulani	Military	Riot/Protest	Boko Haram	Attack	Fulani	Military	Riot/Protest	Boko Haram
Day Of	0.0203*	0.0272	0.0248*	0.0292**	0.0115	-0.0120	-0.0137	-0.0145	-0.0195*	-0.00878
	(0.0102)	(0.0174)	(0.0120)	(0.0112)	(0.0122)	(0.00819)	(0.0140)	(0.00966)	(0.00902)	(0.00983)
Day After	0.0155	0.0163	0.0228	0.0158	0.0293*	-0.00371	0.00154	-0.00761	-0.00286	-0.0149
	(0.0102)	(0.0174)	(0.0120)	(0.0112)	(0.0122)	(0.00820)	(0.0140)	(0.00967)	(0.00905)	(0.00983)
2 Days After	0.0162	0.0253	0.00890	0.0260*	0.0245*	-0.00455	-0.00690	-0.00201	-0.0110	-0.0160
	(0.0102)	(0.0174)	(0.0120)	(0.0112)	(0.0122)	(0.00819)	(0.0140)	(0.00967)	(0.00903)	(0.00981)
N	1002	1002	1002	1002	1002	1002	1002	1002	1002	1002

Standard errors in parentheses
=* p<0.05 ** p<0.01 *** p<0.001

For the military, high-casualty violent incidents of any type were followed by a significant 2% point increase in the percent of negative tweets. High-fatality actions by the military specifically were followed by an approximately 2.5% point increase in the percent of negative tweets about the military. These are likely to be incidents viewed by the public as human rights violations. In short, when fatalities are high, either as a result of military actions or at the hands of violent groups, the military's favorability on social media decreases.

For the federal government, high-fatality violent incidents of any type were followed by a significant 3-5% point decrease in the percent of positive tweets. However, there is no consistent significant effect for more specific attackers. Perhaps the difference between the federal government and the military results suggests that people view them as different entities, seeing the military as the actor responsible for public security and preventing violence and therefore more culpable when violent incidents occur.

6 Conclusion

Based on the above findings, there are several key takeaways worth noting. First, while social media access in Nigeria is not yet pervasive, the significance of many of our findings indicates that social media can still be a useful tool to analyze public opinion, and may even reach segments of the population not typically represented in other traditional survey methods. Second, analysis of public opinion on governance in Nigeria varies dramatically on a state-by-state level, and thus analysis on the national level may miss significant regional or state-specific trends that are worth examining. Thirdly, while the relationships vary from state to state, there are significant correlations between incidents of violence and public opinion on various governing institutions, specifically the federal government, military, president, and state governors. With further research, a more general pattern on an individual state level or on the national level could be identified, and thus Nigerian governing institutions may be able to adjust behavior to improve civilian opinion of governance.

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Sentiment Analysis:

Research Questions and Approach:

Prior studies on issues of financial corruption, intelligence, or regulation have seldom incorporated an analysis on public discourse and/or opinion. The implications of financial regulatory reform is usually assessed through expert opinions of economists and policy makers and so through this limited focus, the opinion of the on-the-ground average individual is lost in understanding the potential implications that financial regulation may have. The distribution of public surveys has the potential to capture aspects of public opinion on the financial regulatory regime and its implications on governance. However, survey-based methods are not only extremely costly to distribute, but are also entrenched in an array of self-reporting biases and methodological issues including small sample sizes and/or confusing/indirect questions. Survey-based approaches would also fail in capturing what issues are actually cause for concern for the average citizen, to what extent different issues exist in public discourse, and to what extent different issues have the capacity to sway public opinion.

Through harnessing the entire social media fire-hose, we can capture the public voice without facing the biases that are associated with survey-based approaches. Once we have access to these differing voices, using a sentiment analytic program, Linguistic Inquiry and Word Count (LIWC), we can examine the sentiment that exists within each tweet. Through this analysis, we hope to answer four questions. First, can social media analytics be used to capture public sentiment on the Nigerian Financial Intelligence Unit? Answering this broad question requires us to examine the second research question, which examines to what extent there exists a strong public discourse surrounding the NFIU? More broadly, does there exist a strong discourse surrounding issues pertaining to financial regulation? And can major events related to financial intelligence and/or corruption cause shifts in public attitudes. Once we have an idea of the broad perceptions on the Nigerian financial regulatory regime, we can examine who Nigerians are more likely to attribute responsibility to with regards to financial regulation.

While financial regulatory reforms are under the jurisdiction of the federal government, our research question sought to examine to what extent this reality is perceived amongst Nigerians. Do Nigerians associate financial corruption issues at the state level? Or do they associate it with the federal government? Although one of the aims of the survey conducted by USIP was to examine how and to what extent Nigerians attributed responsibility/blame on corruption and governance issues across differing government levels, this question remained unanswered. Therefore, given that USIP is working with governors to examine ways through which they can encourage structures that can promote good governance and low corruption, understanding public sentiment at a granular level can allow them to tailor their reforms to the needs of the population. Given that perceptions of financial corruption are closely linked to issues of political stability, understanding the pathways through which these issues are perceived can help reform the image and improve the perception of Nigerian governance.

Crimson Hexagon and Lexicon

Using a similar approach to that of our analysis on the perception of violence in Nigeria, we obtained the data for the sentiment analysis using the social media data platform Crimson Hexagon. Although Crimson Hexagon provides us with publicly available social media data from an array of sources, given that the large majority (99 percent) was derived from Twitter sources, and given the politicization of this specific medium of social media, we narrowed down our focus to running our analysis using only Twitter data.

To filter through all the publicly available Twitter data, we constructed three lexicons. The first lexicon consisted of words only pertaining to the financial regulatory regime. This included all the international and national Nigerian institutions, legislative acts, and terminology linked to the operations of the financial intelligence unit (all of which we henceforth refer to as the 'financial regulatory regime') as they interlinked with a broader financial terminology. We then intersected this financial lexicon with terms pertaining to the federal government and to the state government in order to examine the extent to which Nigerians associate these issues with differing levels of government. We constructed these lexicons through consultation with experts from the Jackson Institute and Professor Richard Gordon (the Director of the Financial Integrity Institute) as well as using a Python script to scrape data from articles and Nigerian blogs. These lexicons were then inputted into Crimson Hexagon to collect raw twitter data from Nigeria as a whole.

Sentiment Analysis:

To translate this raw twitter data into sentiment that we can run regressions on, we use LIWC – a program used by the Secretary of Defense's MINERVA project. LIWC is a "text analysis module [which]... reads written or transcribed verbal texts … compares each word in the text against a user-defined dictionary … [which] identifies which words are associated with which psychologically relevant categories."[1] The psychologically relevant categories were built so as to encompass theories from a variety of fields including linguistics, psychology, business, and medicine. Furthermore, as the literature on the field of sentiment analysis has grown (and continues to grow), dictionaries can be modified in order to take into account differing "behaviors, needs, thinking styles, or other psychological states"[2] and how they may affect the language used for each. The program works similarly to the Python script code written for the violence sentiment analysis. For each tweet, LIWC provides us with a percentage of words associated with positive or negative sentiment. In order to run an analysis on these tweets, a binary (1 or 0) was assigned based on whether the majority of tweets were positive or negative or neutral (if positive sentiment equaled negative sentiment). In addition to these broad buckets of sentiment, LIWC also provides us with a disaggregated view of negative sentiment, allowing us to examine specific subsets of emotions that go past the binary. It also provided us with a time orientation of tweets.

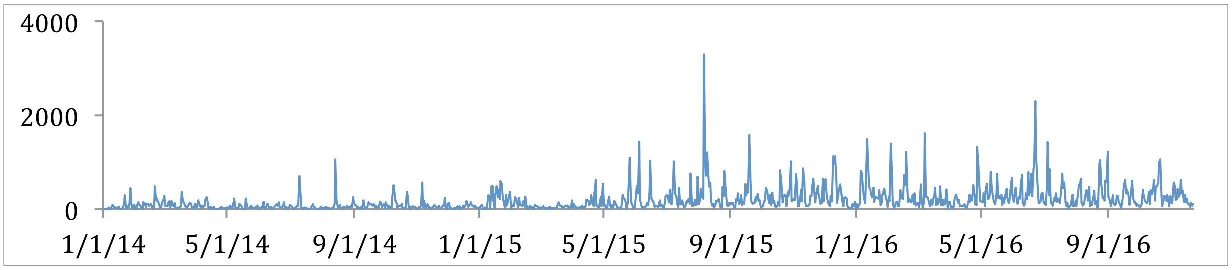
Empirical Design and Findings:

To answer our research questions, we began by examining whether public discourse in Nigeria exists on financial intelligence units. Using a lexicon limited to only the terms "financial intelligence unit" or "FIU" we found over 8,000 posts between 2010 and 2016. Given the obscurity of this financial regulatory body, this is quite a large number of posts, indicating that FIUs exist to some extent in the public discourse. We expand this lexicon to include terms directly associated to FIUs (including international and Nigerian institutions with direct links to the NFIU and legislative acts related to anti-money laundering and countering financing of terrorism efforts) as intersected with a broader lexicon of financial terminology (See Appendix 1). Upon doing so we find over 200,000 posts between 2010 and 2016. Looking specifically between 2014 and 2016, we see that a 73 percent of total posts occurred during Buhari's presidency (this is a weighted measure taking into account the increase in internet penetration and the general upsurge of social media use). One hypothesis for this recent increase in posts on financial intelligence could be that one of Buhari's promises on the campaign was to deliver an autonomous financial intelligence unit that would work towards eliminating corruption in Nigeria. Using Crimson Hexagon we can examine the fluctuation of these posts over time. As

[1] "How it Works." LIWC 2015: How it Works | LIWC. N.p., n.d. Web. 19 Dec. 2016.
[2] Ibid.

Figure 1 shows, the volume of posts fluctuates over time as the topic becomes more salient in public discourse.

Figure 1: Fluctuations in total posts about the financial regulatory regime between 2014 and 2016



Using LIWC we can construct a time series dataset aggregated at the day level containing the proportion of positive, negative, and neutral tweets per day. Once we have the sentiment data, we can examine how the occurrence of events pertaining to financial corruption/intelligence/regulation affects sentiment. Through discussions with experts such as Ambassador Campbell and Professor Richard Gordon, coupled with extensive research using major Nigerian media sources, like Vanguard, we constructed a timeline of major financial regulatory events (See Appendix 2). Figure 2 shows the proportion of negative, positive, and neutral tweets as they fluctuate over time. While we see that the majority of tweets contain neutral sentiment, we hypothesize that this is due to a large proportion of these tweets reporting on financial events rather than offering commentaries. The graph shows spikes over time, with negative sentiment being greater than positive in early 2014 – possible a result of the series of scandals involving the sacking of CBN Governor Sanusi following his announcement that billions of dollars in oil revenues owed to the treasury was missing. Given that foreign investors had viewed Sanusi as an effective regulator of the banking sector, his removal resulted in high fluctuations in financial markets with the value of the Naira dropping to a record low. Public outburst following the deposal of Sanusi was huge given that 90 percent of the economic benefits of oil production are reaped by Nigeria's one percent, therefore when oil money goes missing it "touches a nerve in Nigeria."[3] This again goes to show that issues of financial corruption and regulation affect the public consciousness and resonate within Nigeria.

[3] Nossiter, Adam. "Governor of Nigeria's Central Bank Is Fired After Warning of Missing Oil Revenue." *The New York Times*. The New York Times, 20 Feb. 2014. Web. 1 Dec. 2016.

Figure 3, examines the change in sentiment in the days following the BuhariGate scandal where Colonel Sambo Dasuki was arrested and placed under investigation by the EFCC following his involvement in a $2.2 billion fraudulent arms deal, and it was found that President Buhari was complicit in this fraudulency and had accepted 2 SUVs as gifts from former President Goodluck Jonathan. Figure 3 shows that following the outbreak of the scandal the proportion of negative tweets spiked, representing a shift in sentiment.

Figure 2: Change in sentiment on the financial regulatory regime in Nigeria

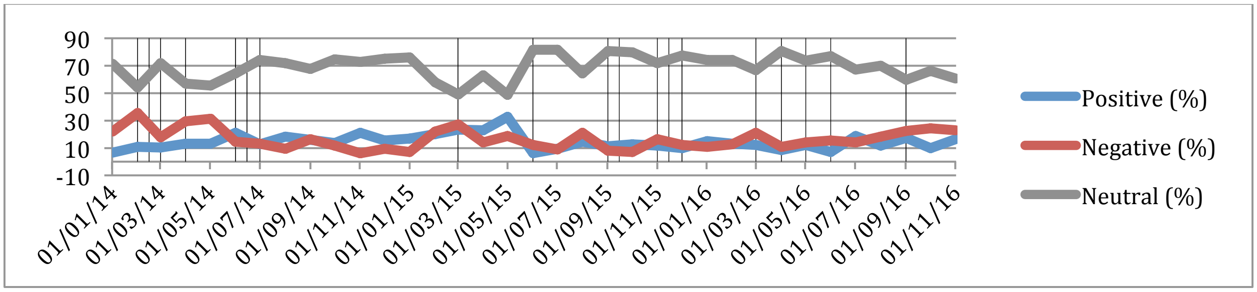
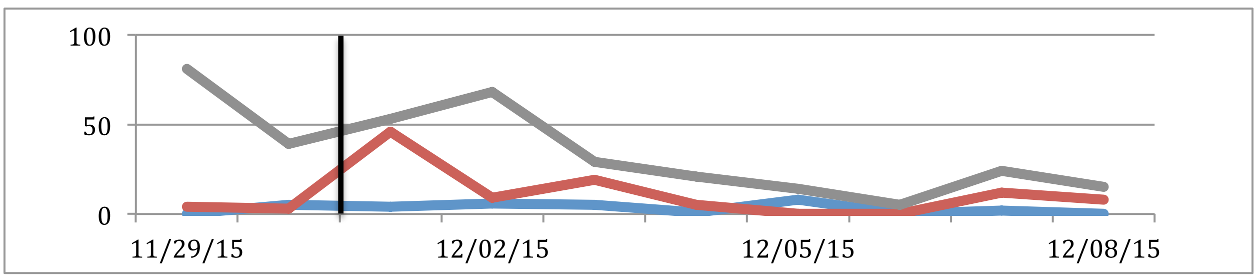


Figure 3: Change in sentiment on the financial regulatory regime using #BuhariGate as a case study



Not every financial regulatory event is the same. Therefore, we break the events down into three categories: positive events (major financial regulatory reforms that would have positive implications), negative events (major scandals or negative reform that brings to light rampant corruption in Nigeria), or neutral events (where public perception could shift in either direction or may have ambiguous implications that benefit different sectors of society in different methods).

After merging the sentiment analysis dataset with the constructed timeline of financial regulatory events, we run the same regression as done for the violence sentiment analysis:

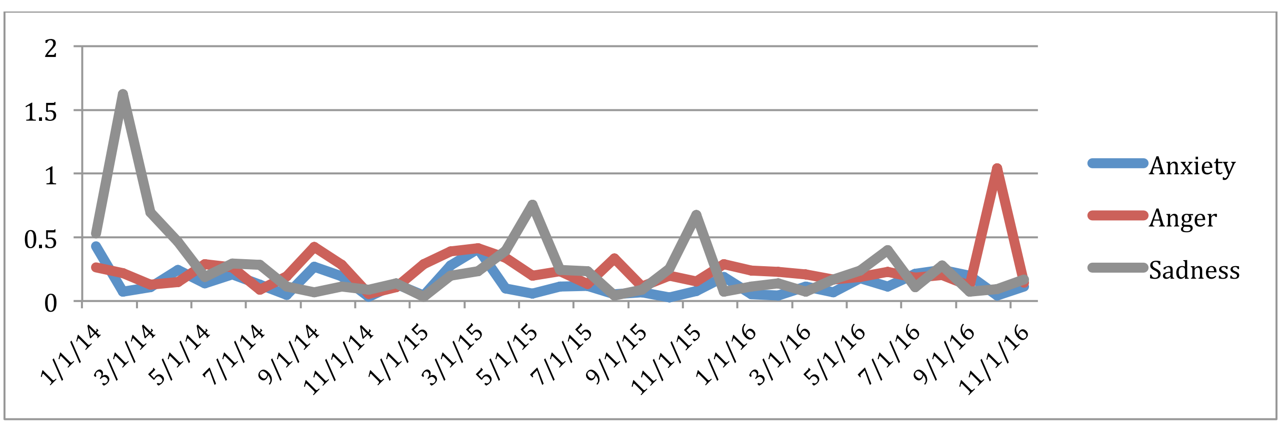
$$sentiment_i = \beta_0 + \beta_1 x_t + \varepsilon_t$$

The influence of events on public sentiment is not immediate. Therefore, we generated lagged variables that capture sentiment the day of the event, two days after, and seven days after.

The results (see Appendix 3) show that events related to the financial system are followed by significant changes in general sentiment. The regression analysis shows that in the seven days following an event we see a statistically significant increase in the proportion of negative tweets by 13 percent and statistically significant decrease in the proportion of neutral tweets. Furthermore, following a negative event, (on the day of) we see a statistically significant decrease in positive tweets by 11 percent and a statistically significant increase in neutral tweets. These results show that even when positive events occur, there is a lack of increase in positive sentiment, which alludes to a general skepticism that exists towards anti-corruption efforts. The significant changes in neutral sentiment can be explained as people reporting events rather than reacting to them.

Furthermore, social media analytics do not have to be binary; they do not have to be examined solely in terms of positive/negative emotions. Instead, we can disentangle the negative emotions and based on the language that people are using determine the exact emotion being portrayed through language. So with regards to negative sentiment associated with the financial regulatory regime: are Nigerians anxious? Are they angry? Are they sad? Through an examination of the data between 2014 and 2016, the results show that the highest proportion of negative sentiment arises from emotions of anger or sadness. Understanding the specific emotions behind negative sentiment could have underlying policy implications and political ramifications. While sadness and anxiety are more passive forms of negative sentiment, anger can be a sign of deeper-rooted frustrations that could be translated into violent action (as evidenced by the huge proportion of riots and protests).

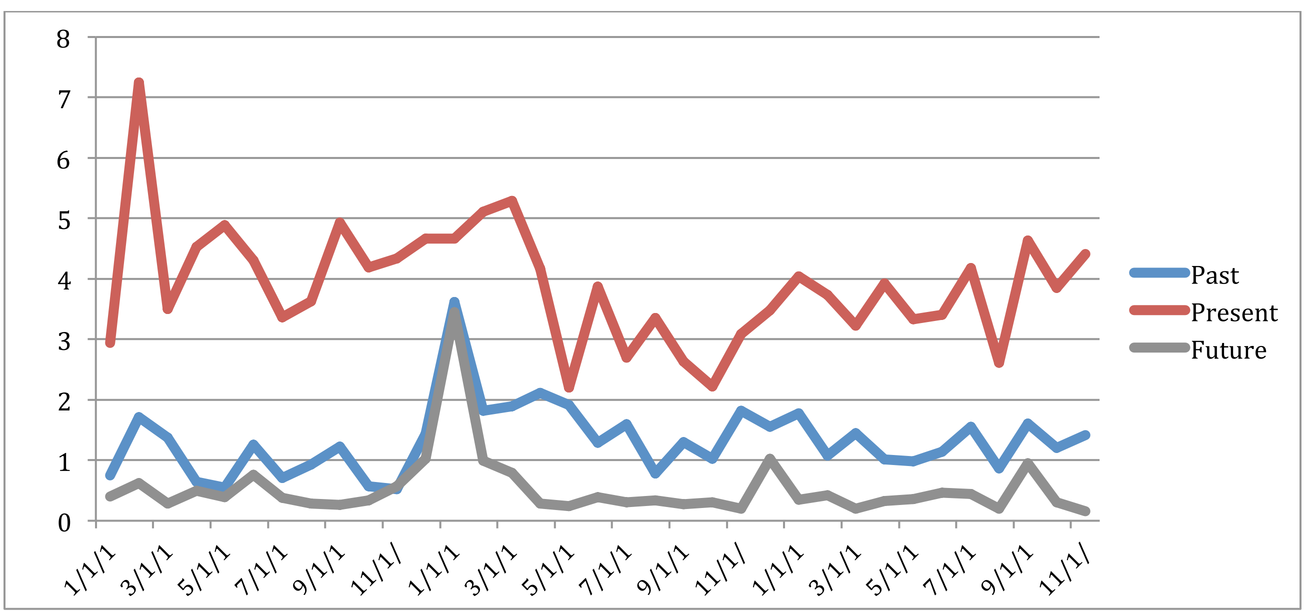
Figure 4: Fluctuation in proportion of negative sentiment between 2014 and 2016



Through an examination of the fluctuations in the proportion of specific forms of negative sentiment, such as anger, governors could harness this data in order to predict where violence could erupt. If such analysis can provide us with when examining a topic like financial regulation that is not the most ‘emotive’ of topics, this methodology can be expanded to examine other issues of concern for Nigerians.

Social media analytics can also show us how Nigerians discuss issues pertaining to financial regulation with regards to their time orientation. Using LIWC, we can examine the tense people use when discussing these issues to understand how Nigerians perceive these issues. Are Nigerians concerned with events of the past? Do they speak about how financial regulation affects their future? Do they solely think of these issues in the present? Figure 5 shows that the majority of tweets examine these issues as related to the present, thus highlighting that Nigerians are focused on immediate pressing concerns, and less concerned with issues of the past and least concerned with issues of the future. While we do see fluctuations over time – namely spikes in posts on the future and past at the New Year and the election period, present remains the highest. This has deep policy implications in terms of how Nigerian governors would phrase different issues pertaining to financial corruption and how they should direct their focus towards examining immediate pressing problems.

Figure 5: Fluctuations in proportions of differing time orientations between 2014 and 2016



Finally, we examine the extent to which Nigerians associate financial corruption issues with different levels of government. Using the lexicons constructed that intersect the terms associated with the financial regulatory regime with that used on the federal government (see Appendix 1), the data gathered from Crimson Hexagon shows that 28,674 tweets were posted between March 2015 and Present. This is only approximately half of the posts of the volume of Tweets posted between March 2015 and Present when intersecting the financial lexicon with terms associated with the state government (see Appendix 1).

Figure 6: Changes in sentiment towards the federal government over time

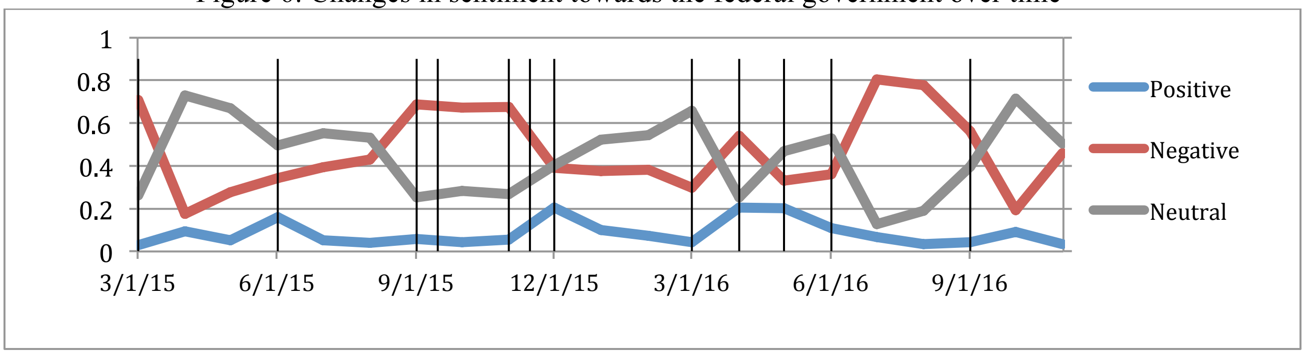
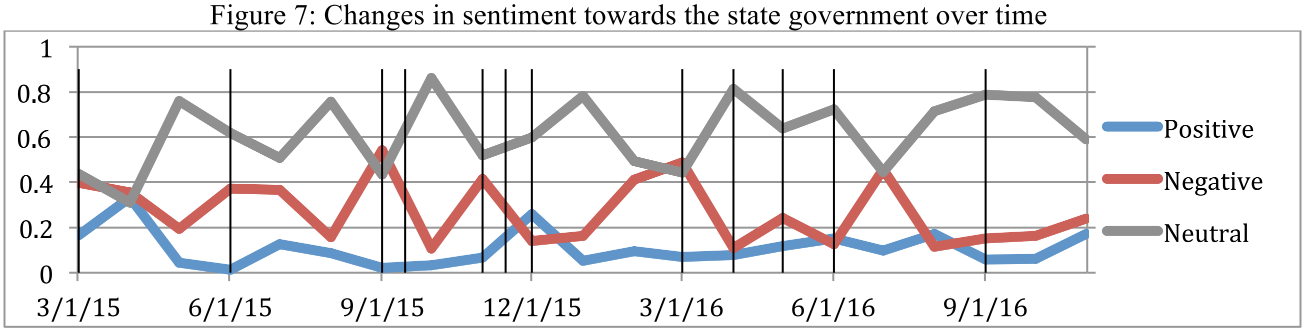


Figure 7: Changes in sentiment towards the state government over time



Examining Figure 6 and 7 shows that positive tweets comprise the lowest proportion, highlighting the low positive sentiment towards both the federal and the state governments with regards to issues pertaining to financial regulation. Around the time of major events as identified by our timeline, we see spikes in negative sentiment. Surprisingly, when we run the regression to examine how financial regulatory events change sentiment towards the federal government (see Appendix 4), we see that following an event there is a statistically significant increase in the proportion of positive tweets by 220 percent. Furthermore, following a negative event, the results show an increase in the percentage positive tweets by 23 percent in the two days after, and 29 percent in the seven days after. The results also show that 7 days following a negative event, the proportion of negative tweets significantly decreases by 41 percent. Given that financial regulation falls under the jurisdiction of the federal government, it is surprising that Nigerian public opinion does not appear to hold the federal government responsible to events pertaining to financial regulation. However, when we run the regression to examine how financial regulatory events change sentiment at the state level (see Appendix 5), we see a statistically significant increase of 72 percent in the proportion of negative tweets following a positive event and a statistically significant decrease in neutral tweets by 65 percent. This trend emphasizes a general skepticism towards anti-corruption efforts as pursued at the state level. Comparing these results with those obtained regarding the federal government could indicate that Nigerians associate blame or praise pertaining to financial corruption with the state level rather than the federal government. Given that financial regulatory bodies such as the Central Bank of Nigeria, the Nigerian Financial Intelligence Unit, or the EFCC, are federal bodies this is an interesting and surprising finding. This finding however, can act as a motivation for governors to lobby the federal government to take steps towards eliminating corruption through major financial regulatory reform such as taking steps towards creating a stronger, more autonomous Financial Intelligence Unit.

Appendix

Appendix 1:

Lexicon for terms associated with the financial regulatory regime:

("Financial Intelligence" OR FIU OR "Financial Intelligence Unit" OR NFIU OR "Nigerian Financial Intelligence Unit" OR EFCC OR "Economic and Financial Crimes Commission" OR "Nigeria Drug Law Enforcement Agency " OR "Special Control Unit against Money Laundering" OR "Central Bank of Nigeria" OR CBN OR "Economics and Financial Crimes Commission Establishment Act" OR HURIWA OR "Human Rights Writers Association of Nigeria" OR "Integrity Group" OR ICPC OR "Independent Corrupt Practices Commission" OR NAICOM OR "National Insurance Commissions" OR "National Treasury" OR NBA OR "Nigerian Bar Association" OR "National Judicial Court" OR "Egmont Group of Financial Intelligence Units" OR Egmont OR FATF OR "Financial Action Task Force" OR "Financial Action Task Force Recommendation" OR GIABA OR "Intergovernmental Action Group Against Money Laundering in West Africa" OR "International Money Laundering Information Network" OR "Eastern and Southern African Anti-Money Laundering Group" OR UN OR "United Nations" OR IMF OR "World Bank" OR "United Nations Convention Against Corruption" OR MPLA OR "Money Laundering Prohibition Act" OR TPA OR "Terrorism Prevention Act" OR AML OR "Anti Money Laundering" OR CFT OR "Combating Financing of Terrorism" OR "Countering Financing of Terrorism" OR "Currency Transaction Reports") AND (FDI OR "Foreign Direct Investment" OR "Foreign Investment" OR "Financial institutions" OR "Commercial Banks" OR "Financial Stability" OR "Financial illiteracy" OR "Illicit Funds Flow" OR "Derisking" OR "Legislation" OR "Money" OR "Cash" OR "Poverty" OR "Financial Autonomy" OR "Financial Fraud" OR "Financial Flows" OR "Cash Flows" OR "Nigeria Factor" OR "Terrorist Financing" OR "Money Laundering" OR "Organised crime" OR Funding OR Funds OR "Campaign Funding")

Lexicon for terms associated with the financial regulatory regime, as pertaining to the federal government:

(Buhari OR "federal government" OR "Government of Nigeria" OR "Nigerian government" OR shugaban OR "shugaban kasa" OR "gwamnatin tarayya" OR gwamnatin OR gwamnati) AND (("Financial Intelligence" OR FIU OR "Financial Intelligence Unit" OR NFIU OR "Nigerian Financial Intelligence Unit" OR EFCC OR "Economic and Financial Crimes Commission" OR "Nigeria Drug Law Enforcement Agency " OR "Special Control Unit against Money Laundering" OR "Central Bank of Nigeria" OR CBN OR "Economics and Financial Crimes Commission Establishment Act" OR HURIWA OR "Human Rights Writers Association of Nigeria" OR "Integrity Group" OR ICPC OR "Independent Corrupt Practices Commission" OR NAICOM OR "National Insurance Commissions" OR "National Treasury" OR NBA OR "Nigerian Bar Association" OR "National Judicial Court" OR FDI OR "Foreign Direct Investment" OR "Foreign Investment" OR "Financial institutions" OR "Commercial Banks" OR "Financial Stability" OR "Financial illiteracy" OR "Illicit Funds Flow" OR "Derisking" OR

“Legislation” OR “Money” OR “Cash” OR “Poverty” OR “Financial Autonomy” OR UNCAC OR “United Nations Convention Against Corruption” OR MPLA OR “Money Laundering Prohibition Act” OR TPA OR “Terrorism Prevention Act” OR AML OR “Anti Money Laundering” OR CFT OR “Combating Financing of Terrorism” OR “Countering Financing of Terrorism” OR “Currency Transaction Reports”) AND (Stealing OR Steal OR Crime OR Criminal OR Fraud OR Justice OR Guilty OR Corruption OR Corrupting OR Corrupt OR Lie OR Liar OR Lying OR Injustice OR Unjust OR Perjury OR Unfair OR Criminal OR Alleged))

Lexicon for terms associated with the financial regulatory regime, as pertaining to the state government:

(Governor OR Governors OR Governorship OR State OR States OR PDP OR "People's Democratic Party" OR APC OR " All Progressives Congress" OR APGA OR " All Progressives Grand Alliance" OR "Jibrilla Bindow" OR Bindow OR "Ahmad Yarima Misau" OR Misau OR "Kashim Shettima" OR Shettima OR "Ibramhim Hassan Dankwambo" OR Dankwambo OR "Darius Ishaku" OR Ishaku OR "Ibrahim Geidam" OR Geidam OR "Badaru Abubakar" OR Abubakar OR "Nasir Ahmed el-Rufai" OR "el-Rufai" OR "Abdullahi Umar Ganduje" OR Ganduje OR "Aminu Bello Masari" OR Masari OR "Abubakar Atiku Bagudu" OR Bagudu OR "Aminu Waziri Tambuwal" OR Tambuwal OR "Abdul-Aziz Yari Abubakar" OR "Samuel Ortom" OR Ortom OR "Yahaya Bello" OR Bello OR "Simon Lalong" OR Lalong OR "Okezie Ikpeazu" OR Ikpeazu OR "Willie Obiano" OR Obiano OR "Dave Umahi" OR Umahi OR "Ifeanyi Ugwuanyi" OR Ugwuanyi OR "Owelle Rochas Okorocha" OR Okorocha OR "Udom Gabriel Emmanuel" OR Emmanuel OR "Henry Dickson" OR Dickson OR "Benedict Ayade" OR Ayade OR "Ifeanyi Okowa" OR Okowa OR "Adams Oshiomhole" OR Oshiomhole OR "Ezenwo Nyesom Wike" OR Wike OR "Ayo Fayose" OR Fayose OR "Akinwunmi Ambode" OR Ambode OR "Ibikunle Oyelaja Amosun" or Amosun OR "Olusegun Mimiko" OR Mimiko OR "Rauf Aregbesola" OR Aregbesola OR "Isiaka Abiola Ajimobi") AND ((“Financial Intelligence” OR FIU OR “Financial Intelligence Unit” OR NFIU OR “Nigerian Financial Intelligence Unit” OR EFCC OR “Economic and Financial Crimes Commission” OR “Nigeria Drug Law Enforcement Agency “ OR “Special Control Unit against Money Laundering” OR “Central Bank of Nigeria” OR CBN OR “Economics and Financial Crimes Commission Establishment Act” OR HURIWA OR “Human Rights Writers Association of Nigeria” OR “Integrity Group” OR ICPC OR “Independent Corrupt Practices Commission” OR NAICOM OR “National Insurance Commissions” OR “National Treasury” OR NBA OR “Nigerian Bar Association” OR “National Judicial Court” OR FDI OR “Foreign Direct Investment” OR “Foreign Investment” OR “Financial institutions” OR “Commercial Banks” OR “Financial Stability” OR “Financial illiteracy” OR “Illicit Funds Flow” OR “Derisking” OR “Legislation” OR “Money” OR “Cash” OR “Poverty” OR “Financial Autonomy” OR UNCAC OR “United Nations Convention Against Corruption” OR MPLA OR “Money Laundering Prohibition Act” OR TPA OR “Terrorism Prevention Act” OR AML OR “Anti Money Laundering” OR CFT OR “Combating Financing of Terrorism” OR “Countering Financing of Terrorism” OR “Currency Transaction Reports”) AND (Stealing OR Steal OR Crime OR Criminal OR Fraud OR Justice OR Guilty OR Corruption OR Corrupting OR Corrupt OR Lie OR Liar OR Lying OR Injustice OR Unjust OR Perjury OR Unfair OR Criminal OR Alleged))

Appendix 2:
Timeline of Major Financial Regulatory Events:

Date	Dummy	Positive	Negative	Description
01-Feb-14	1	1	0	MasterCard-backed biometric ID system launched
20-Feb-14	1	0	1	Goodluck Jonathan sacks Central Bank of Nigeria Governor, Sanusi Lamido Sanusi, after missing oil revenue claims. Put the naira under pressure.
22-Feb-14	1	0	1	Goodluck Jonathan sacks 5 ministers, including:
04-Mar-14	1	1	0	CBN approves liquidation of 83 micro-finance banks
14-Apr-14	1	0	1	276 female students captured (Chibok schoolgirls kidnapping)
08-Jun-14	1	1	0	Sacked Central Bank of Nigeria Governor, Sanusi Lamido Sanusi, named Emir of Kano by the State Secretary to the government
21-Jun-14	1	1	0	Kayode Fayemi is replaced as Governor of Ekiti by Ayo Fayose, who was previously impeached for charges of embezzling money (Fayose was backed by Goodluck Jonathan in this election)
02-Jul-14	1	0	0	CBN bans all loan-defaulters from accessing credit in Nigerian banks
15-Mar-15	1	1	0	Buhari puts forward his contract with the Nigerian people (http://www.vanguardngr.com/2015/03/my-contract-with-nigeria-buhari)
02-Jun-15	1	0	1	Nigerian bankers charged with swapping newspapers for money
04-Sep-15	1	1	0	Buhari publicly declares all his assets
14-Sep-15	1	1	0	New directive from Buhari to make sure state revenue goes into a federal account, instead of private accounts. Suggested that this could lead to huge money outflows from Nigeria
03-Nov-15	1	0	1	Buhari claims that he inherited an empty treasury after GL Jonathan's reign
12-Nov-15	1	0	1	FRC criticizes the CBN for their unwholesome disclosures

01-Dec-15	1	0	1	Sambo Dasuki arrested over $2bn arms fraud. Buhari also somewhat involved. Nigerians take to Twitter with #Buharigate after Buhari received 2 cars from Sambo
23-Mar-16	1	0	0	Nigeria passes highest ever budget, despite low oil prices
22-Apr-16	1	0	1	Former finance minister, Nenadi Usman, is arrested by EFCC for taking money from the central bank.
03-May-16	1	0	1	Nigerian VP, Osinbajo, claims that $15bn was stolen from Nigerian government (dwarfs previous estimate of $5.5bn)
10-Jun-16	1	0	1	MTN, Africa's biggest phone provider, pays $1.7bn to Nigerian government (1/3 of original fine)
01-Sep-16	1	0	1	Minister of Finance admits that Nigeria is in its worst possible time with negative GDP results signalling that Nigeria is in a recession

Appendix 4:

Federal Government Sentiment:

Following a General Event

VARIABLES	posdiff	posdiff2	posdiff7	negdiff	negdiff2	negdiff7	neutdiff	neutdiff2	neutdiff7
dummy	-0.0177	0.215**	0.249***	-0.0852	-0.142	-0.141	0.103	-0.0738	-0.108
	(0.0808)	(0.0877)	(0.0947)	(0.136)	(0.136)	(0.153)	(0.131)	(0.137)	(0.148)
Constant	0.000379	-0.00461	-0.00626	0.000345	0.00175	0.00203	-0.000724	0.00286	0.00423
	(0.0118)	(0.0128)	(0.0139)	(0.0198)	(0.0198)	(0.0225)	(0.0192)	(0.0201)	(0.0217)
Observations	562	561	556	562	561	556	562	561	556
R-squared	0.000	0.011	0.012	0.001	0.002	0.002	0.001	0.001	0.001

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Following a Positive Event

VARIABLES	posdiff	posdiff2	posdiff7	negdiff	negdiff2	negdiff7	neutdiff	neutdiff2	neutdiff7
positivedummy	0.0437	0.210	0.222	0.0610	0.130	0.121	-0.105	-0.340	-0.344
	(0.139)	(0.151)	(0.164)	(0.233)	(0.233)	(0.264)	(0.226)	(0.235)	(0.253)
Constant	-0.000311	-0.00150	-0.00250	-0.00191	-0.00221	-0.00189	0.00222	0.00371	0.00438
	(0.0117)	(0.0128)	(0.0139)	(0.0197)	(0.0197)	(0.0224)	(0.0190)	(0.0199)	(0.0215)
Observations	562	561	556	562	561	556	562	561	556
R-squared	0.000	0.003	0.003	0.000	0.001	0.000	0.000	0.004	0.003

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Following a Negative Event

VARIABLES	posdiff	posdiff2	posdiff7	negdiff	negdiff2	negdiff7	neutdiff	neutdiff2	neutdiff7
negativedummy	-0.0552	0.233**	0.295**	-0.164	-0.267	-0.406**	0.219	0.0341	0.111
	(0.105)	(0.115)	(0.124)	(0.177)	(0.177)	(0.199)	(0.171)	(0.179)	(0.192)
Constant	0.000688	-0.00291	-0.00460	0.000568	0.00206	0.00410	-0.00126	0.000853	0.000508
	(0.0117)	(0.0128)	(0.0139)	(0.0197)	(0.0197)	(0.0224)	(0.0191)	(0.0200)	(0.0216)
Observations	562	561	556	562	561	556	562	561	556
R-squared	0.000	0.007	0.010	0.002	0.004	0.007	0.003	0.000	0.001

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Following a Neutral Event

VARIABLES	posdiff	posdiff2	posdiff7	negdiff	negdiff2	negdiff7	neutdiff	neutdiff2	neutdiff7
neutraldummy	8.18e-11	0.0835	0.000897	-0.110	-0.333	0.669	0.110	0.249	-0.670
	(0.277)	(0.302)	(0.327)	(0.466)	(0.465)	(0.526)	(0.450)	(0.470)	(0.506)
Constant	-8.18e-11	-0.000149	-0.000897	-0.00128	-0.000686	-0.00222	0.00128	0.000835	0.00311
	(0.0117)	(0.0128)	(0.0139)	(0.0196)	(0.0196)	(0.0223)	(0.0190)	(0.0199)	(0.0214)
Observations	562	561	556	562	561	556	562	561	556
R-squared	0.000	0.000	0.000	0.000	0.001	0.003	0.000	0.001	0.003

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix 5:

Governor's Sentiment:

Following a General Event:

VARIABLES	posdiff	posdiff2	posdiff7	negdiff	negdiff2	negdiff7	neutdiff	neutdiff2	neutdiff7
dummy	0.0763	0.144	0.207*	0.000378	0.0790	0.176	-0.0767	-0.223	-0.383**
	(0.100)	(0.105)	(0.107)	(0.128)	(0.140)	(0.147)	(0.136)	(0.150)	(0.152)
Constant	-0.000571	-0.000820	0.000229	-0.00169	-0.00453	-0.00949	0.00226	0.00535	0.00926
	(0.0136)	(0.0143)	(0.0146)	(0.0175)	(0.0191)	(0.0202)	(0.0185)	(0.0204)	(0.0207)
Observations	594	593	588	594	593	588	594	593	588
R-squared	0.001	0.003	0.006	0.000	0.001	0.002	0.001	0.004	0.011

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Following a Positive Event

VARIABLES	posdiff	posdiff2	posdiff7	negdiff	negdiff2	negdiff7	neutdiff	neutdiff2	neutdiff7
positivedummy	0.329	-0.0735	-0.0758	-0.0162	0.487	0.725**	-0.313	-0.413	-0.649*
	(0.233)	(0.244)	(0.250)	(0.299)	(0.326)	(0.342)	(0.317)	(0.349)	(0.354)
Constant	-0.000265	0.00210	0.00436	-0.00163	-0.00471	-0.00867	0.00189	0.00261	0.00431
	(0.0135)	(0.0142)	(0.0146)	(0.0173)	(0.0189)	(0.0200)	(0.0184)	(0.0203)	(0.0206)
Observations	594	593	588	594	593	588	594	593	588
R-squared	0.003	0.000	0.000	0.000	0.004	0.008	0.002	0.002	0.006

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Following a Negative Event

VARIABLES	posdiff	posdiff2	posdiff7	negdiff	negdiff2	negdiff7	neutdiff	neutdiff2	neutdiff7
negativedummy	0.0297	0.104	0.206	0.00150	0.136	0.103	-0.0312	-0.240	-0.310
	(0.125)	(0.131)	(0.134)	(0.160)	(0.175)	(0.184)	(0.170)	(0.187)	(0.190)
Constant	0.000491	0.000626	0.00164	-0.00170	-0.00467	-0.00743	0.00121	0.00404	0.00579
	(0.0136)	(0.0142)	(0.0146)	(0.0174)	(0.0190)	(0.0201)	(0.0185)	(0.0203)	(0.0207)
Observations	594	593	588	594	593	588	594	593	588
R-squared	0.000	0.001	0.004	0.000	0.001	0.001	0.000	0.003	0.005

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Following a Neutral Event

VARIABLES	posdiff	posdiff2	posdiff7	negdiff	negdiff2	negdiff7	neutdiff	neutdiff2	neutdiff7
neutraldummy	-0.000843	1.000***	0.998***	-0.0609	-0.999**	-0.995**	0.0618	-0.00121	-0.00210
	(0.330)	(0.343)	(0.350)	(0.422)	(0.460)	(0.484)	(0.448)	(0.493)	(0.501)
Constant	0.000843	0.000169	0.00240	-0.00158	-0.00138	-0.00451	0.000738	0.00121	0.00210
	(0.0135)	(0.0141)	(0.0144)	(0.0173)	(0.0189)	(0.0199)	(0.0184)	(0.0203)	(0.0207)
Observations	594	593	588	594	593	588	594	593	588
R-squared	0.000	0.014	0.014	0.000	0.008	0.007	0.000	0.000	0.000

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1