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WHAT GOES UP MUST NOT COME DOWN: THE TWEET RETRACTION PROCESS OF POLITICIANS

A Capstone Experience/Thesis Project

Presented in Partial Fulfillment of the Requirements for the Bachelor of Arts Degree with Honors College Graduate Distinction at Western Kentucky University

By

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Western Kentucky University 2016

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ABSTRACT

In 2011, Congressman Anthony Weiner demonstrated the risks politicians face when utilizing Twitter. While past scholarship regarding Twitter has focused on the impact of the tweets candidates share with their voters, academic attention has not been afforded to the tweets candidates delete. This thesis seeks to delve further into the analysis of Twitter as a political campaign tool by examining the practice of tweet retraction. To achieve this end, this research presents two studies. The first analyzes the deleted tweets of members of the 112th Congress between May and November of 2012 in terms of quantity of retractions and the elapsed time before retraction. Quantitative analysis suggests that age and party ID are not strong predictors of the quantity of deleted tweets, but gender may have a relationship. The second study examines the deleted tweets of 2014 gubernatorial candidates, finding that Democrats tend to delete tweets more quickly than Republicans, while other demographic traits seem to have no effect. This analysis highlights an unexplored area of social media research that could prove extremely valuable in determining the processes politicians follow throughout the course of an election cycle.

Keywords: Twitter, tweet retraction, electoral politics, elections, Congress, gubernatorial

Dedicated to my parents for their unending support, my teachers and professors for
encouraging me to constantly be learning, and the WKU Forensics Team for teaching me
how to critically analyze and question the world around me.

ACKNOWLEDGEMENTS

I would like to thank the people whose support was instrumental to this project. First, thank you to former WKU Forensics Coach Blake Longfellow who introduced me to Politwoops when he pitched it as a topic for my rhetorical criticism speech. I never would have discovered this amazing topic area without his guidance.

Additionally, I offer a sincere round of thanks to Western Kentucky University, the Honors College, and the Political Science Department for providing resources to help students like myself complete theses. I also owe a deep amount of gratitude to the Faculty-Undergraduate Student Engagement (FUSE) program at Western Kentucky University for financially supporting this project and providing me the opportunity to travel to numerous conferences to present this work and learn from other scholars.

Finally, I am sincerely grateful for the support of my thesis committee. I owe many thanks to Dr. Jenni Redifer and Dr. Scott Lasley for their feedback and time. I cannot thank Dr. Timothy Rich enough for the amount of time, effort, and support he has invested in not only this project but in me as a student. He helped me develop this project from its infancy to the very end of the process. He introduced me to the world of academic conferences, and was relentless in his willingness to assist me in achieving my goals. I will never forget the impact he has had on me as a student.

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CHAPTER 1

INTRODUCTION

Since Howard Dean pioneered the use of the internet in his 2004 presidential run, new media has become the centerpiece of American political campaigns. As this trend has evolved, political campaigns have continuously expanded their use of the internet and social media in an attempt to broaden their social appeal to voters. Increasingly, they have turned to Twitter as a mechanism for quickly disseminating small, yet vital bits of information to campaign supporters and potential voters. The shift to social media has become an overwhelming trend in American electoral politics since President Obama demonstrated its effectiveness in his 2008 presidential campaign. However, the true boom in use of Twitter as a campaign tool has been a result of its utility to races of all levels. Twitter, in particular, provides a means of quickly, cheaply, and efficiently campaigning to a targeted group. While well-funded candidates on both sides of the aisle often utilize costly web platforms and high-end consultants, Twitter remains a free resource. Its cost-free status renders it appealing to those who need a free mechanism of disseminating campaign information. In fact, Twitter's draw to political insurgents has been largely due to its cost effectiveness, which is a key advantage (Evans & Cordova, 2013). Despite Twitter's numerous benefits to candidates, it also holds limitations and pitfalls. Candidates once felt comfortable posting campaign information on social media

sites like Twitter because of the reassurance that they could be deleted at any time. Indeed, prior to 2012, candidates were able to retract any tweet they chose for a plethora of reasons including typographical errors, misspeaking, fear of backlash, or incurred backlash. In 2012 it was this mentality that led the Sunlight Foundation to create Politwoops, a searchable database of the deleted tweets of politicians (Macomber, 2012). With this database in existence, politicians are under closer online scrutiny than ever before. In addition to media monitoring of publicly available campaign messages, Politwoops has made politicians vulnerable to a new avenue of analysis: their deleted tweets.

Some tweets published by Politwoops demonstrate an immediately clear purpose for why they were deleted. Some candidates accidentally post personal tweets to their professional account; others have linked their Facebook and Twitter accounts, which often means Facebook posts are truncated when transferred to Twitter due to the 140 character limit for tweets; still more candidates find it prudent to delete typographical errors, broken links to outside websites, tweets posted multiple times, messages from hackers, and statements that could create political backlash. Examples of tweets deleted for clear reasons include Representative Bill Posy, who deleted seven links to a spam weight loss website from his Twitter account in 2012. Also in 2012, Representative Bill Huizenga deleted, "Zombie theme park planned for #Detroit http://t.co/OVVU8ihZ #HellYeah", assumingly because "#HellYeah" might not appear professional or appropriate to colleagues and constituents. During the 2014 gubernatorial cycle, Florida Governor Charlie Crist tweeted, "This race is coming down to the wire. Click here to look up where to vote on Tuesday – it's your civic duty

https://t.co/DJVD8OmXiF" seven times and understandably deleted six of them. While the above instances are mostly harmless examples of hacking, typos, or technological ineptitude, many tweets are deleted due to their larger possibility of incurring political damage. In 2014, Texas gubernatorial candidate Wendy Davis deleted an accidentally retweeted tweet from an Anti-Wendy Davis activist, "RT @JRogerDriscoll: Glad to know @WendyDavisTexas has the support of "HoesOverEmbryos" classy bunch there! http://t.co/PCoaXJAELn". In 2012, Senator David Vitter even deleted a tweet that he 'mistakenly' sent to a supposed prostitute.

When Politwoops was first launched in 2012 there was even a group of politicians that purposely posted and subsequently deleted a series of tweets intended to use Politwoops for their own political gain. On such politician was Representative David Schweikert, who posted and deleted, "#politwoops saves lost tweets, now if we can just get President Obama to save lost jobs…" as well as "Wish #politwoops would hold Obama and Holder accountable for their missing facts on #FastandFurious just as it does missing tweets". Representative Danny Rehberg was not one to miss out on the fun, posting and deleting, "Scary thought: Many of the same pols that messed up 140 characters on #politwoops also wrote and voted for the 2,300 page Obamacare law".

While the above examples of deleted tweets demonstrate clear reasons for retraction, many candidates and officials retract tweets that do not reveal any immediate error. For instance, in 2012 Representative Pete Visclosky deleted, "Congratulations @steelworkers celebrating #70years of protecting workers' rights.", which has no glaring spelling or grammatical errors, no possible non-functioning links, and seems uncontroversial. Similarly Indiana Governor Mike Pence retracted, "#tbt to last year's

pumpkin patch benefiting @MW_FoodBank – stop by this year on Oct. 14, 11:30-1 at the Statehouse! http://t.co/R0gZr2II3k" in 2014, which shows no major errors to the naked eye. Perhaps these tweets were double posted, posted on the wrong day, or needed clarification. Nevertheless, the above examples demonstrate that tweets retracted for both clear and inexplicable reasons provide an interesting field of analysis for any wishing to understand the campaign practices of America's state and federal politicians.

However, because Politwoops was not created until 2012, most of the literature on Twitter use still focuses on political mobilization and the campaign effects of social media use. Virtually no scholarship addresses the idea of retracting a previously tweeted message. Consequently, as previous scholarship has only been able to examine the tweets politicians *choose* to share with the world, a window into the tweets they would rather *remove* from public view could prove valuable to electoral and academic analysis alike. Because Twitter has shown the potential to predict electoral outcomes (Lamarre and Suzuki-Lambrecht, 2013), it is worth examining tweet retraction as a potential predictor of electoral success. Therefore, examining the factors that influence tweet retraction is a vital endeavor for political scholarship.

This analysis contributes to the existing literature in several key ways, most notably by extending the growing quantitative base of work on Twitter use to the realm of tweet retraction. This paper uses two studies, each employing the Politwoops database, to examine the patterns behind candidates' and officials' deleted tweets. The first study examines the deleted tweets of members of the House of Representatives during the 112th Congress in the months leading up to the 2012 general election both in terms of frequency of retractions and the time elapsed until retraction. Core findings suggest that

female members of Congress tend to retract higher numbers of tweets than male members, and older members of Congress tend to take longer to retract tweets than younger members. The second study uses the same database to examine the patterns of tweet retraction amongst sitting governors and gubernatorial challengers during the 2014 general election. This study is particularly of interest because 2014 was the first major election cycle in which the Politwoops database included both incumbents and challengers. Further, while very little academic attention has been afforded to tweet retraction, any existing research appears to be geared toward Congressional tweet retraction; gubernatorial tweet retraction is an area in which research is still necessary. Thus, this second study seeks to expand the existing body of work on political Twitter research by focusing specifically on tweet retraction of gubernatorial candidates in the 2014 election. So to fully examine the elements of tweet retraction, this analysis will first review the existing literature, next examine tweet retraction on a Congressional basis, then expand the analysis to include gubernatorial retraction, before finally exploring the conclusions of these findings.

CHAPTER 2

LITERATURE REVIEW

Twitter primarily functions as a microblogging and social networking site, allowing users to post public messages of 140 characters or less (Golbeck, Grimes & Rogers, 2010). While the site was initially used for personal and social purposes, a growing market is emerging for Twitter as a campaign tool because of its ability to quickly disseminate small pieces of information to a large audience. As Twitter has become an increasingly popular mechanism for campaigning, its use and effects have been examined more frequently. Existing scholarship suggests politicians in countries such as Germany, Australia, South Korea, Scotland, Israel, and the UK all use Twitter extensively (Tumasjan, Sprenger, Sandner, & Welpe, 2010; Grant, Grant, & Moon, 2010; Lee & Oh, 2010; Baxter, Marcella, & Varfis, 2011; Aharony, 2012). However, the United States has emerged as the preeminent political user of this medium (Aharony, 2012). Twitter use in the United States has manifested itself primarily through Congressional and Presidential campaigns. This social networking tool has played important roles in political campaigns, has sparked examination of the factors that influence Tweeting, and has changed the nature of a candidate's relationship to his or her public statements. These findings become clearer in further examination of the literature. Spiliotes (2012) details that Twitter has changed the nature of retail politics, especially within primary elections. Whereas candidates previously had to depend upon

Republican Primary were able to reach voters and garner votes, candidates in the 2012 Republican Primary were able to reach voters and garner credibility through their use of technological advancements that included social media websites, such as Twitter (Spiliotes, 2012). Pew (2012) echoes this idea by analyzing the 2012 US presidential general election. Pew finds that President Obama tweeted 404 times to Governor Romney's 16 times during a 14 day period. With the decisive outcome of the election, this raises questions as to whether President Obama's substantially greater use of Twitter was related to his electoral victory. In fact, of all social media platforms, Twitter showed the largest difference in usage between the two candidates, suggesting that frequency of Twitter use may play a role in the outcome of presidential elections (Pew, 2012).

Lamarre and Suzuki-Lambrecht (2013) explored this same idea by studying all US House races in the 2010 cycle to compare Twitter use with electoral outcomes. They found that successful use of Twitter led to a greater chance of electoral victory (Lamarre and Suzuki-Lambrecht, 2013). This finding suggests that electoral victory may provide candidates with an increased incentive to create a clean and clear Twitter image. This could impact the way candidates and campaigns interact with Twitter. These studies and others have provided significant evidence that Twitter could potentially be used to predict the outcome of elections (Choy, Cheong, Ma, & Koo, 2012; Conover, Goncalves, Rakiewicz, Flammini, & Menczer, 2011; Tumasjan, et al., 2010). Tumasjan, et al. (2010) found that the sheer number of mentions a candidate or party receives can correlate with the result of an election. Similarly, Choy et. al (2012) found that the sentiment of political tweets can be examined to roughly predict the outcome of elections, though problems do exist. Conover, et al (2011) theorize that Twitter can be used as a public opinion monitor

and provide a window into the processes that lead to political alignment. However, further studies have attempted to refute the claim that Twitter has a predictive function (Gayo-Avello, 2012; Metaxas, Mustafaraj, Gayo-Avello, 2011; Gayo-Avello, 2012). Despite Gayo-Avello's refutations, the significant evidence that Twitter could play a role in the outcome of elections has sparked significant need to further analyze candidates' use of this medium.

Scholars have also begun to delve into the reasoning behind candidate's uses of Twitter. While candidates across the globe tweet to expand transparency and outreach (Aharony, 2012; Chi & Yang, 2010), candidates are still motivated by self-preservation and prioritize outreach purposes over those for transparency (Chi & Yang, 2010).

Though research on general Twitter use by politicians and their campaigns has increased in recent years, a related avenue of research that has not been explored is that of Tweet retraction. Terblanche (2011) cautions that social media can be dangerous for a politician's electoral outcomes if used ineffectively or if not controlled by the campaign. A particular message can spread across the internet in a short amount of time, which often negatively affects a candidate's image (Terblanche, 2011). Spiliotes (2012) suggests that a significant social media presence is key to electoral success, giving politicians reason to protect that image by ridding themselves of unpopular posts.

Moreover, Marwick and Boyd explain that the nature of Twitter means "a user has multiple audiences for their tweets and the user may not be aware of who is in those audiences" (as cited in Black, Mascaro, Gallagher, and Goggins, 2012). Due to the diverse nature of political audiences and the desire of the campaign to protect its social media image, if the message causing the embarrassment is circulated by the campaign,

the campaign's natural instinct would be to retract that message. Politicians have frequently done so across various mediums to preserve their own image (Lewandowsky, et al., 2012). However, virtually nothing has been written on the specific practice of tweet retraction.

Previous retractions have traditionally been public, but retracting a message via Twitter has previously not been captured or recorded in a systematic manner. The Sunlight Foundation, an organization dedicated to political transparency, has developed a database called Politwoops that aims to change that. Because Politwoops now captures and publicizes the deleted tweets of almost all federal level American politicians, it is more efficient than ever before to disseminate, analyze, and criticize the tweets politicians have retracted (Macomber, 2012). Existing scholarship has analyzed the impacts of political tweeting and the demographics associated with it, but has failed to examine the factors associated with political tweet retraction, creating a significant need for expanded research.

Significant political research has focused on Twitter use in all political races in general, or to Congressional and Presidential races. Less attention has been afforded to the realm of gubernatorial races and the use of social media. This makes it important to examine not only the existing scholarship on gubernatorial use of social media, but also the realm of gubernatorial races as a whole. Examining patterns in past gubernatorial elections can help shed light on how Twitter may be used in gubernatorial races, despite little scholarship that specifically addresses Twitter use in these instances. Because gubernatorial and Congressional races often face different electorates and occur in

different cycles, they tend to face different electoral factors. Consequently, it is worth examining Twitter trends as they apply to these two types of races separately.

Research has primarily looked at the factors that create success in gubernatorial elections, which can provide insight into which factors in gubernatorial contests are worthy of academic examination. Piereson posits, "Partisanship plays a more central role in elections for governor than it does in Congressional races" (1977, p. 941).

Additionally, Schlesinger contends that politicians are less likely to see governorship as a career, which may reduce electoral effects of incumbency in gubernatorial races (Schlesinger, 1966 as cited in Piereson, 1977). This suggests that incumbency may be an important factor to study when examining gubernatorial races, especially when partisan identification is considered.

More recently, Barth and Ferguson have argued that governors embroiled in scandals, unsurprisingly, lose political approval (Barth & Ferguson, 2002). King confirms this notion, stating that some gubernatorial challengers may win election due to poorly performing or scandal-ridden incumbents, rather than because of enthusiasm for the challenger (King, 2001). Thus, any mechanism which could produce or exacerbate gubernatorial scandals, such as Twitter, warrants examination.

The sum of existing literature surrounding social media demonstrates that there is strong evidence to suggest social media matters in elections, that demographics may influence social media usage, and that it is important to study social media use on a variety of electoral levels. This review highlights significant gaps in the existing literature, as no studies have previously examined tweet retraction, and few studies have

specifically examined gubernatorial Twitter use in depth. As a result, it is important to continue expanding the body of work on these important topics.

CHAPTER 3

STUDY ONE: 2012 CONGRESSIONAL ELECTION

Introduction

The driving question behind this study is whether demographic factors affect the patterns of tweet retraction for members of Congress, and if they do, how that influence manifests itself. To answer, it is important to identify the demographic factors typically involved in Twitter research. Evidence suggests a key factor associated with political tweeting is simply the status of being a politician. Grant, Grant, and Moon (2010) found that politicians tweet significantly more frequently than average citizens. In particular, demographics such as gender and party ID may influence frequency of Twitter use. Evans and Cordova (2013) found little difference between tweet frequency for Republicans and Democrats. In the final months of the 2012 Congressional race, Democrats tweeted an average of 84 times while Republicans tweeted an average of 81times. The same could not be said for the impact of gender on tweet frequency. Women on average tweeted 107 times during the last two months of the campaign while men only tweeted 82 tweets on average during the same time frame (Evans & Cordova, 2013). This suggests that the frequency of tweeting may be influenced by the gender of the member of Congress.

Based on the existing literature, this analysis focuses on three particular demographic variables: age, partisan identification, and gender. The combination of these variables' public availability and their relation to typical debates in electoral politics make them ideal facets for analysis. In an effort to examine both of these dependent variables in relation to the three independent variables, I developed the following four hypotheses:

H₁: Older members of Congress are likely to have fewer tweet retractions than younger members of Congress

H₂: Female members of Congress are likely to have more tweet retractions than male members of Congress.

H₃: Older members of Congress are likely to take longer to retract than younger members of Congress.

H₄: Female members of Congress are likely to take less time to retract than male members of Congress.

Causal relationships in each of these cases are determined by observed patterns in domestic politics. In the cases of H₁ and H₃, older members are typically less inclined to use new technology. This gives merit to the expectation that older members are less inclined to use newer technologies, and when using these technologies they are less aware of when or how to retract. In the case of H₂ and H₄, we can draw upon the findings of Evans and Cordova (2013), who noted that females tweet more than males in general. The greater frequency of published tweets suggests that women may be more concerned with their Twitter presence than men, thus warranting the expectation that they will

retract more frequently and more quickly than their male counterparts. These conventional parameters provide the basis for scientific examination.

I limited my data collection within the Politwoops database to Congressional representatives. I then began to archive and code all tweets in this category from May 17, 2012 until November 6, 2012. The reasoning behind the choice of this particular time period was rooted in two factors: practicality and context. First, the database did not become fully operational until May 17, 2012. Thus, collecting data from before this date would have been logistically challenging and wholly ineffective. A six month time frame created a manageable data set free from additional issues, such as primaries. The contextual reasoning behind the timeframe was to create a picture of what Congressional tweeting looks like specifically in the months leading up to an election. Beginning during a month in which many primary elections take place and ending on election day itself gave a clear picture of what general election retraction looks like for most candidates and what retraction looks like for all candidates in the approximately six months prior to the election.

After selecting the time frame, the data coding process included copying the content of the tweets and coding them based upon age, party ID, and gender. Party ID and gender were variables included in the Politwoops database. For the age of each member, I examined each of their online biographies and calculated their age on the date of the November 6th election to ensure consistency and relevance. This set of data yielded 1050 total tweets for analysis, with an average of 8.56 retractions per candidate.

Because many members in the data set had only one deletion, but some had upwards of 20, an analysis of the data at the member level seemed prudent. After coding the data for each tweet, I created a separate dataset focused solely on the candidates themselves. In this dataset I only examined four factors: number of tweets retracted during the six month period, age of the member, gender, and party ID. This dataset allowed for full causal analysis of each factor in relation to the full picture of each member's retraction activity rather than each individual instance of retraction, which was the only data provided by Politwoops. This second set of data yielded 244 members of Congress to analyze.

Once data coding was complete, I conducted frequency analysis, bivariate correlation analysis, and multivariate regressions to examine the relationship between age and frequency of deletion, while controlling for gender and party ID. In addition to frequency analysis, I analyzed a second pattern of retraction: the timing of retraction. The amount of time between the publication and retraction of a tweet was coded into 6 variables: deletion time in seconds, deletion time in minutes, deletion time in hours, deletion time in log of seconds, deletions that took more than one hour, and deletions that took more than one day.

I then conducted OLS regressions using log of seconds until retraction as the dependent variable. The previous variables of age, gender, and partisan identification were utilized as independent variables. In model one, I included the date of retraction as a control variable. This variable was included in order to control for members who deleted large amount of tweets close to the election or large amounts of tweets further from the election. By controlling for this, it makes it easier to discern patters of timing without a

skew. In model two, I used the date of deletion as a control. By starting at the first day of the dataset and increasing until Election Day, as the number in the date variable increases, the tweet was deleted closer to the election. I also added variables to control for word count as well as the negative tone of tweets based on content analysis¹.

Results

Table 1 analyzes the demographics of individual retracted tweets. The total number of tweets analyzed was 1050. Of these, 788 tweets (75%) were deleted by males, compared to 262 tweets (25%) by females. At the candidate level, 244 candidates retracted tweets. Of these, 190 (77.9%) were male, compared to 54 (22.1%) female. In terms of partisan identification, 533 tweets were deleted by Republicans (50.8%), compared to 517 (49.2%) by Democrats. At the candidate level, 129 were Republicans (52.9%) versus 115 Democrats (47.1%). In terms of age, the mean age of a candidate retracting tweets was 56.57, with a minimum of 31 and maximum of 86.

Table 1: Descriptive Statistics of Congressional Tweets

		Male	Female	Democrat	Republican
Total Tweets	N= 1050	788(75%)	262(25%)	517 (49.2%)	533 (50.8%)
Candidate Level	N=244	190(77.9%)	54(22.1%)	115(47.1%)	129 (52.9%)

Table 2 shows the Pearson correlation for each of the independent variables examined in this study. The negative correlation between member age and frequency of

¹ Content analysis was done using WordStat through Provalis and negative tones were determined using a sentiment analysis dictionary also available through Provalis. Negative tone is measured in the number of negative words.

tweet deletion, fails to reach statistical significance. Similarly, the positive correlation between member gender and frequency of deletion cannot be considered reasonably significant either. Finally, the positive correlation between party ID and frequency of deletion also lacks statistical significance. Therefore, there is no significant evidence to support a bivariate relationship between frequency of deletion with age, gender, or party ID.

Table 2: Pearson Correlation of Retracted Congressional Tweets

Variables	Correlation	Sig.
Age	-0.011	0.863
Gender (Female)	0.147	0.068
Party (Democrat)	0.312	0.522

Table 3 depicts the results of OLS regression analysis. The overall strength of the regression is low, as the adjusted r square of .003 means only 0.3% of the variation in results is explained by the model. The coefficient for the relationship between age and frequency of deletion is -.016. The coefficient for the relationship between gender and frequency of deletion is 1.32. This substantively means that being a female member as opposed to a male member increases the frequency of tweets deleted by 1.32 tweets on average. The coefficient for the relationship between the control of party ID and frequency of deletion is .24 Thus, the conclusion to be taken from the unstandardized coefficients of this regression would be that older members, males, and Republicans, tweet less than younger members, females, and Democrats.

However, when examining the statistical significance for each variable, there is no support for this conclusion. For none of these variables does the correlation reach

statistical significance; therefore, it is clear that none of these relationships can actually be determined to have a causal effect on frequency of deletion.

Table 3: OLS Regression on Retracted Congressional Tweets

	Coeff.	SE	Sig.
Age	-0.016	0.0294	0.592
Female	1.322	0.7485	0.079
Democrat	0.2434	0.648	0.707
Constant	4.784	1.619	0.003
N	244		
Adjusted R2	0.003		

Table 4 depicts the results of Poisson regression analysis. Since tweets are count data and not normally distributed, OLS models may not be appropriate, therefore a Poisson regression provides a more accurate representation of the dataset, accounting for the skew of count data. The overall strength of the model is stronger than the OLS regression at .011. The coefficient for the relationship between age and frequency of deletion is -.004. The coefficient for the relationship between gender and frequency of deletion is .285. The coefficient for the relationship between party ID and frequency of deletion is .057. Thus, the conclusion to be taken from the unstandardized coefficients of this regression would be that older members, males, and Republicans, tweet less than younger members, females, and Democrats. This is the same broad conclusion reached by the OLS regression, at different magnitudes.

When examining the statistical significance for each variable, the differences between the OLS model and the Poisson model are widened. The statistical significance for the relationship between age and frequency of deletion is .222. The statistical

significance for the relationship between gender and frequency of deletion is .000. The statistical significance for the relationship between party ID and frequency of deletion is .393. Each of the levels of statistical significance are stronger in the Poisson model than in the OLS model, suggesting that the conclusions of the Poisson model should be taken more seriously than the conclusions of the OLS model. Further, one of the three variables has measurable statistical significance. The relationship between gender and frequency of deletion is statistically significant at the .001 level. This indicates a high level of statistical significance for the assertion that being a female member will increase the deletion of tweets by .285 tweets on average. Thus, the Poisson model concludes that there is reasonable evidence to suggest a relationship between gender and tweet retraction.

Table 4: Poisson Regression on Retracted Congressional Tweets

	Coeff.	SE	Sig.
Age	-0.004	0.003	0.222
Female	0.285	0.072	0.000
Democrat	0.057	0.066	0.393
Constant	1.570	0.166	0.000
N	244		
Pseudo R2	0.011		

Frequency analysis therefore supported the conclusion about gender, but not age. It is important to examine these relationships in relation to timing as well. Part 2 of the dataset, examining time between publication and retraction also uses the same independent variables, but yields different results.

Table 5 shows crosstabs of the gender of the member retracting the tweet alongside the amount of time until retraction. Here, the amount of time until retraction is shown through a binary categorical variable, simply detailing whether or not the member took more than one hour to retract the tweet. The table illustrates that of the 788 tweets deleted by male members, 577 of them, or 73.2%, were deleted in one hour or less.

Conversely, 211 of the tweets deleted by male members, or 26.8%, were deleted over an hour after they were originally published. In the case of female members, 187, or 71.4%, of the total 262 tweets deleted by females were deleted in one hour or less. Conversely, 75 of the tweets deleted by female members, or 28.6%, were deleted over an hour after their original publication. Of the four sets of crosstabs, however, this is the one set that did not reveal statistical significance, with a Pearson Chi² significance level of only .560. Therefore, these findings are negligible at best.

Table 5: Crosstabs on Gender and retraction timing by hour

			Female1		
			0	1	Total
More than an hour1	Count	0	577	187	764
	%within Female1		73.2%	71.4%	72.8%
	Count	1	211	75	286
	%within Female1		26.8%	28.6%	27.2%
Total	Count		788	262	1050
	%within Female1		100%	100%	100%
Pearson Sig:	.560				

Table 6 examines the same concept as Table 5, but while Table 5 examines retraction timing through the categorical 'more than an hour' variable, Table 6 applies this principle to a similar 'more than a day' variable, by analyzing the counts and

percentages of tweets that were deleted less than and more than one day after their publication.

Table 6: Crosstabs on Partisan ID and retraction timing by hour

			Dems1		
			0	1	Total
More than an hour1	Count	0	407	357	764
	%within Dems1		76.4%	69.1%	72.8%
	Count	1	126	160	286
	%within Dems1		23.6%	30.9%	27.2%
Total	Count		533	517	1050
	%within Dems1		100%	100%	100%
Pearson sig: .008					

Table 7 shows crosstabs of the gender of the member retracting the tweet alongside the amount of time until retraction. Here, the amount of time until retraction is shown through a different binary categorical variable than in Table 5. This variable details whether or not the member took more than one day to retract the tweet. The table illustrates that of the 788 tweets deleted by males, 714 of them, or 90.6%, were deleted in one day or less. Conversely, 74 of the tweets deleted by males, or 9.4% were deleted more than one day after their original publication. In the case of female representatives, 219, or 83.6% of the 262 total tweets deleted by females were deleted within one day. Meanwhile, 43 of the tweets deleted by females, or 16.4% were deleted more than one day after the time of publication. These findings yield a Pearson Chi² significance score of .002, making them significant at a .01 level.

Table 7: Crosstabs on Gender and retraction timing by day

			Female1		
			0	1	Total
More than a day1	Count	0	714	219	933
	%within Female1		90.6%	83.6%	88.9%
	Count	1	74	43	117
	%within Female1		9.4%	16.4%	11.1%
Total	Count		788	262	1050
	%within Female1		100%	100%	100%
Pearson sig: .002					

Table 8 presents OLS regressions, using the elapsed time until retraction as the dependent variable. Since the individual observations are not independent, I use OLS clustered by the individual legislator. Table 9 displays OLS regression of model 1. The model yields an adjusted R square of .117, which means 11.7% of the variation in the data can be explained by the model. The regression uses log of seconds as the dependent variable in order to simplify the results, which otherwise would have an impractically high range and coefficient. Log of seconds is shown compared to the previously utilized variables as well as the control variable of the date of retraction.

The table notes a coefficient of .041 for the relationship between age and time until deletion, statistically significant at the .05 level. Put simply, older legislators are likely to take longer to retract. Table 7 depicts a .118 coefficient for the relationship between partisan identification and the time it takes to delete a tweet. While this finding produces a significance score of .777 and does not come close to reaching statistical significance, it is important to note this is in conflict with later findings. This particular variable relationship, despite its lack of statistical significance, may warrant more extensive examination.

The same is true of the gender variable. Table 8 notes a .073 coefficient for the relationship between gender and the amount of time it takes to delete a tweet. While this finding, much like the partisan identification variable, only produces a statistical significance score of .873 and does not reach statistical significance, it could indicate that future models may be able to point to a statistically significant relationship between being female and taking longer to delete.

The control variable of date yielded interesting results. The variable displayed statistical significance at the .000 level, and yielded a coefficient of .006. This means that there is a positive relationship between a later date and longer time to retraction. Put simply, the closer to the election, the longer it took for a tweet to be deleted.

Table 8: OLS Regression on Timing of Tweet Retraction [Model 1]

	Coef.	SE	Sig
Age	0.041	0.021	0.046
Democrat	-0.118	0.417	0.777
Female	0.073	0.467	0.873
Date	0.006	0.001	0.000
Constant	-0.086	1.472	0.954
N	1046		
R2	0.117		

Table 9 displays OLS regression of model 2. Model 2 differs from model 1 by including 2 additional control variables. These are the level of negative words and the total word count. It is important to note that neither of these two variables displayed statistical significance, which is a likely indicator of why model 1 and 2 yielded similar results.

As is the case in model 1, model 2 shows a lack of statistical significance for the variables of partisan identification and gender. Date remained a pertinent control variable in model 2, showing the same level of statistical significance at the .000 level and the same coefficient of .006. Therefore, both models conclude that the control variable of date does have a relationship with timing until deletion. The nearer the election, the longer it will take a member to retract a tweet. The word count control variable does not appear to have a statistically significant relationship to time between publication and deletion. The level of negative words, however, was slightly significant in the model's results. The positive correlation between negative words and time until deletion is only significant at the .1 level, but seems to suggest that negative tweets are retracted faster, which could lead to significant future results.

Table 9: OLS Regression on Timing of Tweet Retraction [Model 2]

	Coef.	SE	Sig
Age	0.041	0.020	0.043
Democrat	-0.098	0.410	0.811
Female	0.073	0.459	0.873
Date	0.006	0.001	0
Negative Words	-0.225	0.117	0.055
Word Count	0.028	0.018	0.121
Constant	-0.574	1.586	0.718
N	1046		
R2	0.122		

Gender did demonstrate a causal relationship with frequency of deletion through Poisson regression, meaning that while H_1 must be rejected because there is no statistically significant evidence to support it, H_2 may be accepted with statistically

significant Poisson regression results that demonstrate a relationship between gender and frequency of deletion.

In regards to timing of retraction, H₃ may be accepted because two models of OLS regression demonstrate a statistically significant relationship between age and time until retraction. This leads to the conclusion that older members of Congress likely take longer to retract tweets than younger members of Congress. H₄, however, must be rejected because there is no statistically significant evidence within either OLS regression model to support the claim that gender relates to the timing of retraction.

The results of study one suggest that on a Congressional level, patterns exist between age and speed of retraction as well as between gender and frequency of deletion. This analysis suggests that older members retract more slowly than younger members and that female members retract more frequently than male members. These results provide the foundation and grounds for future study of tweet retraction trends.

CHAPTER 4

STUDY TWO: 2014 GUBERNATORIAL ELECTION

Introduction

Similar to the first study, this analysis seeks to determine whether demographic factors affect the frequency and timing of tweet retraction for gubernatorial candidates, and if they do, is this influence similar to the way these variables function for members of Congress. While some existing and in-progress scholarship has addressed this new area of research, the area of gubernatorial tweet retraction has not been addressed. Thus, in analyzing both previous patterns of political and gubernatorial Twitter use as well as past research on tweet retraction, a clear need presents itself for further analysis: how tweet retraction functions at the gubernatorial level. If past research on political Twitter use and tweet retraction holds true, gubernatorial tweet retraction may follow similar patterns as Congressional tweet retraction, or may forge its own path. Thus, it becomes important to examine gubernatorial tweet retraction in order to discern its place in and contribution to this new and emerging field of deleted tweet research.

Because previous literature has shown gender, partisan identification, and age to be relevant in both social media and electoral contexts, these will all be independent variables of this study. Moreover, because Piereson (1977) indicates the importance of

considering the relative strength of parties in an electoral district, competitiveness of the states involved in each gubernatorial election is also a key variable for consideration.

H₁: Female candidates will retract more frequently than male candidates, but will take longer to do so than male candidates.

H₂: Democratic candidates will retract more frequently and more quickly than Republican candidates.

H₃: Older candidates will retract more frequently than younger candidates, but will take longer to do so than younger candidates.

H₄: Candidates in more competitive races will retract more frequently and more quickly than candidates in less competitive races.

The dataset I utilize for this paper contains 250 deleted tweets from both sitting governors and 2014 gubernatorial challengers. The dataset contains governors seeking reelection in the 2014 election cycle as well as those stepping down or seeking reelection in a later cycle. It solely analyzes general election candidates from the Democratic Party and Republican Party and does include bested primary challengers or independent candidates. I collected tweets from these candidates during the time period beginning August 1, 2014 and ending on November 4, 2012 (Election Day) because this is the height of the general election cycle and most primaries have taken place by August 1st. In states whose primaries had not yet taken place on August 1st, the unsuccessful primary candidates' tweets were removed from the dataset and the successful primary candidates' pre-primary election tweets remained as though they were a part of the general election to create a similar size dataset for comparison with those candidates already campaigning for the

general election. This compilation process was designed to create a comprehensive image of gubernatorial tweeting in the months leading up to the general election.

To analyze the dataset, I utilized descriptive statistical analysis including frequency tables and crosstabs. I also employed OLS regressions to directly test the above hypotheses, while accounting for control variables.

Results

Initially, an in-depth analysis of the dataset is necessary to understand the full context of the results of this study. The dataset itself included 250 tweets from the 67 general election gubernatorial candidates collected by Politwoops. Table 10 highlights the gender disparity in the dataset. Of the 250 total tweets, 230 (92%) were retracted by male candidates; only 20 (8%) were retracted by female candidates. However, this is unsurprising, considering the disparity in the profile of the candidates in the dataset.

Table 10: Descriptive Statistics of Gubernatorial Tweets

		Male	Female	Democrat	Republican
Total Tweets	N= 250	230(92%)	20(8%)	136 (54.4%)	114 (45.6%)
Candidate Level	N= 67	31 (46.3%)	36 (53.7%)	114 (45.6%)	129 (52.9%)

Table 10 also shows a gender disparity at the candidate level highly similar to the one apparent at the tweet level. Of the 67 total candidates, 61 were males and 6 were females. The percentages of male and female candidates in the dataset is almost identical to the percentage of tweets retracted by males and females. 91% of the candidates were male and 9% were female, while 92% of the tweets were retracted by males and 8% were retracted by females. Thus, the large disparity in tweet retraction between males and

females is likely not due to gender differences in use of Twitter, but instead is due to the unfortunately low number of female gubernatorial candidates.

Table 10 also shows frequency analysis of the partisan identification of the candidate retracting each tweet. Of the 250 retracted tweets, 114 were retracted by Republicans and 136 were retracted by Democrats. Consequently, 45.6% of the tweets in the dataset were retracted by Republicans and 54.4% were retracted by Democrats. On the surface, this is not a huge disparity between the two major political parties, but it is an approximately 9% difference, which does raise questions about differences in tweet retraction between the two major political parties.

As is the case with gender, the candidate percentages for partisan identification are extremely similar to the percentages of tweets retracted by each party's candidates. 31 of the 67 candidates in the dataset were Republicans, while 36 were Democrats. This yielded a dataset with 46.3% of the candidates being Republicans and 53.7% being Democrats, which was again almost identical to the 45.6% of tweets retracted by Republicans and 54.4% of tweets retracted by Democrats.

Thus, the dataset seems to be relatively well balanced in the areas of gender and partisan identification based upon the similarities between the number of tweets retracted and the number of candidates in the dataset.

In terms of age, the dataset also appears to be relatively well balanced. Table 11 shows that the minimum age in the dataset is 42 and the highest is 76. This creates a range of 34 years. The mean age of the dataset is 57.36 and the median is 58.00, which demonstrates that the mean and median are extremely close to one another. Additionally,

both the mean and the median are situated about halfway in between the minimum and maximum value. Thus, this dataset appears to be ideal for analyzing a vast range of ages and their relationships to tweet retraction patterns among gubernatorial candidates.

Table 11: Descriptive Statistics of Gubernatorial Candidate Age

N	250	
Mean	57.36	
Median	58	
Minimum	42	
Maximum	76	
Range	34	

Of even greater interest is the regression analysis of the variables in question.

Separate OLS regressions analyze the frequency of deleted tweets, the amount of time before the tweets were deleted, and the electoral outcomes of the candidates who retract.

The primary components of this study are represented by the OLS regression results depicted in Tables 12 and 13.

Table 12 shows OLS regression results for the number of deletions made by a candidate. It considers all four primary independent variables, as well as the control variables of incumbency and favorability. Cowart (1973) argues that voters are more likely to make choices consistent with party ID when their party's candidate was an incumbent (as cited in Piereson, 1977). Consequently, including incumbency as a control variable allows for a clearer examination of the true relationship between deletion and partisan identification. Similarly, candidates who are favored to win may not keep as close a watch over their Twitter presence, and including a control variable for the favorability of that candidate may help to mitigate this relationship in the final results.

The main finding of this regression is the lack of statistically significant findings. Not a single hypothesis is supported by the results of the OLS regression depicted in Table 12 because these results fail to achieve statistical significance. Thus, these results point toward a lack of relationship between the examined demographic factors and the rate and which gubernatorial candidates retract their tweets.

Table 12: OLS Regression for Frequency of Deletion by Candidate

	Coeff.	SE	Sig.
Age	-0.033	0.069	0.637
Female	-1.172	1.647	0.481
Democrat	1.154	1.106	0.302
Incumbent	0.830	1.274	0.518
Competitiveness	0.291	0.350	0.410
Favored	-1.803	1.201	0.140
Constant	4.602	4.041	.261
N	67		

Table 13 employs a similar model to Table 12. It depicts OLS regression results for the time between publication and deletion of a tweet. Specifically, the independent variable considers whether the candidate waited more or less than one hour to delete the tweet. It considers the same independent and control variables as the previous regression, but because the previous regression considers the patterns of each candidate and this regression considers the patterns of each tweet, it also introduces 4 additional control variables that deal with the timing and content of the tweets: whether the tweet contains a link, whether the tweet contains a hashtag, whether the tweet contains a mention of another user, and how many days before the election the tweet was deleted. As the table shows, the regression finds statistically significant results to support H₁'s prediction that

Democratic candidates will retract more quickly than Republican candidates. It shows a negative relationship with the binary variable of whether the deletion took more than one hour. Thus, this means Democrats are more likely to delete within one hour than Republicans are. This finding is statistically significant at the .01 level.

Table 13 also shows statistically significant effects for two control variables. The number of days until the election has a positive relationship with the amount of time it takes to delete, meaning that the closer to the election, the more likely a candidate is to take longer than one hour to delete a tweet. Interestingly, however, candidates who were favored showed a negative relationship with the amount of time it takes to delete, meaning that candidates who are favored are more likely to delete within an hour. This finding initially seems counterintuitive, as more vulnerable candidates would seem more likely to retract quickly. However, this finding could be reflective of how successful a campaign is: if a candidate is favored, his or her campaign is likely performing well, and thus would be more likely to catch mistakes quickly.

Table 13: OLS Regression for Timing of Deletion by Tweet

	Coeff.	SE	Sig.
Age	0.002	0.005	0.639
Female	0.145	0.109	0.184
Democrat	-0.199	0.065	0.002
Incumbent	-0.045	0.069	0.514
Competitiveness	-0.014	0.022	0.531
Favored	-0.177	0.072	0.015
Days til Election	0.003	0.001	0.019
#	-0.048	0.060	0.430
Mention (@)	-0.057	0.062	0.356
Link	0.036	0.066	0.584
Constant	0.262	0.297	0.379
N	67		

After examining the results of this study, there is some evidence to conclude that the answer to this question may be yes. However, considering that only timing of tweet retraction produced statistically significant results with any of the independent variables, it is likely that demographic factors do not have a measurable effect on the number of tweets gubernatorial candidates delete. Certain demographic factors, however, be related to how long it takes a gubernatorial candidate to delete a tweet.

Initially, H_1 must be rejected due to a lack of statistical significance. There is no evidence to support the presence of any relationship regarding gender. In the frequency regression, the results actually trend away from the direction of the hypothesis, yet there is no statistical significance to support these findings. Similarly, in the timing regression, the relationship indicated by the regression actually trends in the opposite direction, but has no statistically significant support.

There is partial support for H₂. While Democrats are not shown to retract with a higher frequency than Republicans, Democrats did retract significantly more quickly than Republican candidates, suggesting that partisan identification may play a role in gubernatorial tweet retraction practices. It is possible that this trend results from Democrats' historic advantage in social media. Though with Republicans quickly closing this gap, it would be interesting to see if these partisan tweet retraction trends hold true over time. If so, the differences may not be attributable to skill in utilization of social media, but another factor entirely.

Both components of H₃ must be rejected due to a lack of statistical significance. The frequency regression finds results that actually trend toward the opposite direction of the hypothesis, but this finding fails to achieve statistical significance. The regression for speed of deletion shows weak positive results that barely register, and also fails to achieve statistical significance. Thus, there is no evidence to support this hypothesis, nor currently any evidence to support a relationship between age and retraction patterns for gubernatorial candidates.

Finally, both components of H₄ must be rejected due to a lack of statistical significance. The frequency regression does trend toward the hypothesis that candidates in more competitive races will retract more frequently, but there is no statistical significance to support this trend. In terms of speed of deletion, not only does the timing regression fail to achieve statistically significant results in one direction or another, but the results also trend in the opposite direction of the hypothesis. Thus, there is no evidence to support this hypothesis, and currently no evidence to support any relationship between competitiveness and retraction patterns.

The results of study two highlight that the only demographic trend present in gubernatorial tweet retraction is a positive relationship between membership in the Democratic Party quicker tweet retraction. This demonstrates a relationship between party ID and speed of retraction. No other relationships exist between gubernatorial candidates' gender, age, or party ID and the frequency or speed of retraction.

CHAPTER 5

DISCUSSION & CONCLUSION

As the nature of political campaigns becomes more closely intertwined with technology, the study of tweet retraction provides fascinating implications for political science. This analysis helps provide the basis for understanding tweet retraction as a political mechanism, but yields significant gaps in understanding which future research should address.

In regards to study one, the ultimate conclusion must be that gender may affect frequency of deletion, and age positively correlates with the time until retraction. However, this data presents significant gaps in understanding. The evidence is inconclusive as to the true motivational factors behind retraction. Future research should examine more closely the relationship between gender and tweet retraction to discern more concrete patterns and a possible explanation for why this is the case.

Future scholarship would also be apt to examine whether a relationship exists between other factors and frequency of deletion. Such factors include whether the member is running for reelection, incumbency, the competitiveness of the race, the number of followers the member has, and whether the member's Twitter account is maintained by the member or by a campaign staffer. This final factor could be a fascinating study in itself. It is highly possible that the nature of both tweeting and tweet

retraction are dramatically different when executed by the candidate than by a staffer. Staffers may be shown as quicker to retract or more discerning than candidates when choosing which messages to retract. Only future analysis can answer these questions.

In addition to frequency of deletion, there are many more significant elements to tweet retraction. Future scholarship could examine the types of tweets members delete and the content of those tweets. Additionally, I expect analysis of the dates and times tweets are most frequently deleted would yield interesting results if utilized as components of an independent variable rather than a control. For example, several tweets were retracted on the day of the Supreme Court ACA ruling in June 2012. Future research would do well to cover these factors specifically. Content analysis could determine which types of tweets are most common and when tweets are most likely to be retracted.

While only gender proved to be a statistically significant demographic factor affecting frequency of retraction, and only age was found to affect time until retraction, these findings provide a valuable starting block to spark future research. After effectively concluding that age does not affect frequency of candidate tweet deletion, we as a discipline can move on to analyze further aspects of tweet retraction in the future, such as the impact of gendered deletion on electoral politics.

In regards to study two, the lack of relationship between variables is particularly interesting in a few cases. First, the lack of relationship between gender and frequency of deletion is of notable interest as it contrasts with Congressional data. Though study one shows a relationship between gender and frequency of deletion for members of Congress,

the lack of relationship in a gubernatorial setting, as well as the lack of a relationship in a dataset that includes both incumbents and challengers, means that issues such as office or incumbency may play a stronger role in retraction than gender. The lack of relationship between age and time taken to delete a tweet is also of note because it too contrasts with Congressional data in study one. My findings indicated that older members of Congress would take longer to delete, yet this finding was not reproduced in gubernatorial data. Again, this may indicate that the office sought or incumbency status may be more important to retraction patterns than age.

Because these two findings differ from what study one would suggest, and because the evidence produced in this study regarding partisan identification was not found in the previous Congressional study, one or both of two outcomes is likely true. First, different factors are important in retraction patterns between gubernatorial and Congressional races. Second, this difference in findings may suggest that demographic factors are not what drive retraction. Rather, structural political factors such as incumbency, competitiveness, office sought, and favorability seem likely to be the driving force behind retraction patterns. This points to a bevy of future possible research questions on this topic.

Perhaps the most promising finding of this study is the nature of timing patterns. Results of study two show that negative tweets are retracted faster than more neutral or positive tweets, while all tweets are retracted more slowly closer to Election Day. These findings produce fascinating implications and questions for future research. A number of possible explanations exist as to why tweets are retracted more slowly closer to Election Day. Campaigns may be more discerning in the days immediately preceding an election.

The more careful a campaign is with its messages, the less likely a retraction is necessary. Alternatively, the campaign may be operating under significantly more stress and have less time available to even notice an error in a tweet until days or weeks later. Either way, it is likely only qualitative analysis of direct interviews with candidates and their staff will reveal the answer.

An additional important analysis that should be conducted regarding tweet retraction is whether it has any measurable effect on electability. Because evidence has suggested that Twitter use can impact the outcome of a race (Lamarre & Suzuki-Lambrecht, 2013), it would be prudent to determine if that relationship extends to tweet retraction. This may or may not have a causal relationship, especially considering the self-censoring effects Politwoops has produced. Many representatives are well aware that Politwoops exists. Some even go so far as to use it as a political tool. With so many interlocking factors, the effects of Politwoops on electoral environments and outcomes warrant further analysis. With this in mind, politicians may be forced to become more discerning. If Politwoops does soar to political popularity, candidates will be forced to operate with heightened awareness of their social media actions.

Similarly, it is still incredibly unclear how tweet retraction impacts public sentiment. Twitter and Facebook have recently become hotbeds of political activity through which the public often develops opinions. Their frequency of use to discuss candidates makes them prime research tools. Politwoops could serve a similar function by providing a deeper window into the messages politicians choose to delete. In this way, the database could exacerbate the growing scrutiny surrounding politicians' online activities. However, Politwoops' status as a research database means it functions much

differently than a social media platform itself. While publicly available tweets can certainly impact voters' opinions on a candidate, it is unclear whether Politwoops has any degree of similar power. The database is certainly at a disadvantage. Unlike Twitter, it is not a widely known platform, and the average citizen does not visit Politwoops each day. Voters can quite easily stumble upon political tweets that remain on Twitter, but once these tweets are deleted, voters must actively seek them out. Future research focused on the voter apathy toward seeking out such information could demonstrate that Politwoops holds very little power outside the world of academia. Despite Politwoops' good intentions of bringing transparency to political tweeting, the database's message may ultimately go unheard.

Finally, it is important to note the tumultuous history of the Politwoops project.

Newman (2016) explains that Politwoops was shut down by Twitter in October of 2015 because "preserving deleted Tweets violates [Twitter's] developer agreement" (para 1). Fortunately, Politwoops' access to Twitter's "application program interface (API)" was restored in January of 2016 (Newman, 2016, para 2). Because this outage caused controversy as well as gaps in data collection, it could have tremendous impacts on the future of research in this field. Politwoops' conflict-laden relationship with Twitter also raises fascinating implications for platform-based political research. Any social media research database such as Politwoops depends to a certain degree on the social media platform itself.

Ultimately, these findings uphold the notion that examining tweet retraction patterns is a valuable field of study. If, indeed, structural factors are more important to determining tweet retraction patterns, tweet retraction may have an even closer

relationship with the outcome of elections than previously thought. This area of research is still relatively new, and once years of data can be compiled and examined in an aggregate fashion, tweet retraction is sure to demonstrate interesting patterns and findings that may drive our conversation on Twitter for years to come.

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