GROUP 11

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Abstract

#Hashtags and Bullets: Mapping Citizen Journalism and unarmed U.S. Police Shootings

Uncertainty is an ever-present aspect of cases of police brutality, as the public's reaction is difficult to predict when information is controlled, spread, or distorted by official sources, mainstream media and, recently, citizen journalists. In order to approach this interaction between cases of police brutality, the unpredictability of people’s responses, and the role of citizen journalism (CJ) in this process, we will address the way in which police shootings of unarmed civilians in the United States are covered by CJ on Twitter. By using the data of The Washington Post‘s database of fatal police shootings and comparing it to Twitter activity on the incident, we aim to answer the question: what is the relationship between the level of coverage and certain types of shootings or certain profiles of the victims? By answering it, we expect to discover patterns of coverage that would contribute to broadening the research on areas such as the psychology of social media usage, and the relation between citizen journalism, public debate, and social movements.

Keywords: citizen journalism, unarmed police shootings, social media, Twitter, police brutality.

Introduction

In 1991, Rodney King, a black taxi driver, was savagely assaulted by the police after a high-speed chase in Los Angeles, California. One year later, a wave of violent riots flooded the streets of Los Angeles when the verdict absolved the policemen involved. A footage of the beating taken by a civilian played an important role in spreading the news and generating responses from the public. As Rodney King's case shows, uncertainty is an ever-present aspect of cases of police brutality, because the public's reaction is difficult to predict when information is controlled, spread or distorted by mainstream media and, recently, citizen journalists. Such uncertainty has been increased by the expansion of social media, as civilians can engage more in the production and diffusion of contents without the control and accountability of mainstream journalism or official sources.

This interaction between cases of police brutality, the role of citizen journalism (CJ), and the unpredictability of people's responses has not been sufficiently studied by existing literature. This is why we will address the way in which police shootings of unarmed civilians in the United States are covered by CJ on Twitter. Our objective is to answer the question: *what is the relationship between the level of coverage and certain types of shootings, or certain profiles of the victims?* We will answer it by comparing the data of fatal police shootings compiled by *The Washington Post* with Twitter activity on the incident, identifying possible relations between variables such as race, passivity of the victim, and body cameras on the agents. We will interpret the results in the light of literature on CJ, Twitter usage by Black Americans, and police surveillance. We expect to discover patterns of coverage of the shooting events that will contribute to the research on areas such as the psychology of social media usage, and the relation between CJ, public debate, and social movements.

Literature review

Citizen journalism (CJ) is the gathering of content, editing, publicating, and distributing news content produced by non-professionals without any participation of professional journalists (Nip, 2006; Wall, 2015; Hamilton, 2015). CJ has been broadly studied by scholars, but we will limit to its role in empowering the average citizen and promoting social justice. Journalism is considered necessary to foster democracy by promoting debate on public issues and accountability. However, as scholars such as Tumber (2001), Antony and Thomas (2010), Splichal and Dahlgreen (2016), or Min (2016) acknowledge, traditional journalism has lost its centrality due to the expansion of the Internet and the distrust of the readers given the fact that, while deciding which topics to cover, some issues, such as defects in social justice, local news or information about the political opposition might be intentionally omitted, following the interests of the news conglomerates or the government, with whom mainstream media is normally associated. In this context, CJ opens new possibilities for deliberative democracy which traditional journalism is neglecting (Tumber, 2001; Dzur, 2002; Goode, 2009), as it gives ordinary people the chance to express their views on public issues (Nip, 2006). With the aid of technology, average citizens can gain access to the media systems that were originally restricted by the elites and thus, expand debate on the issues they care about.

As said before, our research is focused specifically on Twitter, whose technological architecture is particularly useful for CJ, as contents are generated by a diffuse group of users in an unorderly fashion (Kwak, Lee, Park, & Moon, as cited by Jang and Pasek, 2015; Hermida, as cited by Vis, 2012). Also, tweets are public and accessible and fit the needs of the contemporary audience that prefers short and fast news because of its limited attention span (Tandoc and Johnson, 2016; Jang and Pasek, 2015). Moreover, Twitter has been proved to be the ideal platform to cover breaking news, especially if they are bad news. However, studies have also shown that attention given to the news on Twitter may be heavily influenced by the coverage of an event in the mainstream media or by cultural aspects of the audience.

Given our main topic of research, we consider pertinent to explore the Twitter use by Black Americans, who have been particularly vocal in police abuse cases. Jackson and Foucault (2015) and Graham and Smith (2016) utilise the concept of counterpublics, as opposed to the idea of the public, to study this phenomenon. As the public, understood as the space where issues of society are defined through debate, excludes certain social groups, marginalised individuals look for other spaces of expression. Those are the counterpublics, "parallel discursive arenas" where they circulate counter-discourses about their identities, interests, and needs (Fraser, as cited by Graham and Smith, 2016). This is consistent with Lee-Won, White and Potocki (2017), who found that Black Americans usage of Twitter is instrumental or goal-driven, most likely to cope with the discrimination they face in everyday life. Furthermore, these three studies depart from the fact that Black Americans constitute a major user demographic in terms of presence and frequency of tweeting.

Finally, we include literature on the recent increase of police surveillance through film recordings, done partly by body cameras worn by police officers and partly by citizens recording and distributing footages. According to Bock (2016) the rise of cop-watching groups is due to the use of social networks and the desire for accountability, especially given the public's distrust of traditional journalism. Farmer's (2016) study suggested that this has made the relationship between police and community more publicized but also more adversarial, so that, even if CJ may help to restrain police misconduct by accountability, this kind of CJ might entail the risk of inciting civilian violence or increase police abuse as officers get irritated by the presence of bystanders recording them in tense situations (Newell, 2013). The same author also investigates the legal nature of CJ and concludes that civilians have the constitutional right to film the police, but that photos and videos taken by citizen journalists can infringe the privacy of the victims.

From the above paragraphs, we identified that our research will add a different perspective to the literature on CJ, racialised Twitter use, and police surveillance by addressing a possible intersection between them through the analysis of the general coverage in Twitter of different types of fatal unarmed police shootings.

Methodology

Our research methodology consisted on the collection of data on unarmed police shootings and social media coverage of those cases and its further analysis through regression analysis via IBM's SPSS Statistics analytics software.

Data collection

Our primary source of data was The Washington Post's database on fatal police shootings, which comprised a time frame from 2015 until the 31st of May, 2017. It contained 2621 recorded fatalities and included variables such as age, gender, race, perceived threat level posed to officer, presence of body camera, among others. For the purpose of our study, and to make the data more manageable, we narrowed this list to consider only the 166 cases where the victim was unarmed.

To measure the coverage, we counted the number of tweets by non-official sources –not politicians, professional journalists, news agencies or the government– and the number of retweets of those incidents from the day of the shooting untill three days after. In addition, we considered context whilst counting the tweets, excluding those that were ambiguously phrased or not clearly referring to the incident.

Analysis

The database of unarmed victims of police shootings and their respective social media coverage was inserted into SPSS, IBM's statistical analytics software. Through SPSS, we ran multivariate linear regressions and analysis of variance (ANOVA) to determine the effects of certain variables on the amount of coverage and their levels of significance as well as the nature of the interactions between the variables.

a) Linear Regression

From the data collected from Twitter, the number of tweets of certain incidents were disproportionately large; for instance, there were over 100,000 tweets about the shooting of Tony Robinson Jr. in March, 2015. For statistical convenience, we scaled the data by adding 1 and then taking their natural logs (ln). By doing so, we obtained a body of results with a reasonable range (0-7) with a consistent spread.

The independent variables such as race, threat levels, tendency of victims to flee, as well as perceived signs of mental illness were transformed into binary factors. For instance, to determine whether the victim is Hispanic or not, we created a variable called "Race_Hispanic" in which case if the value is 1, then we measure the effect of the victim being Hispanic on the coverage of the incident. The same process was applied to the variables gender, body camera (B.C), mental illness signs (M.I. signs), threat levels (threat_level_attack), and tendency to flee (flee_foot). These dummy variables, as they are referred to in statistics, along with "age", were used as our regressors against "ln_x" (natural log of (number of twitter coverage + 1)).

We then performed a multivariate linear regression through the "backward" method, which eliminated the non-significant variables, ultimately leaving us with a regression of the natural log of number of tweets on whether the police officer had a body camera (*B.C*), whether the victim was black (*RaceBlack*), and whether the victim was perceived to be attacking the officer (*threat_level_attack*), yielding the following regression equation:

$$ln(coverage\_via\_twitter + 1) = \alpha_1 B.C + \alpha_2 RaceBlack + \alpha_3 threat\_level\_attack + \gamma$$

Where $\alpha_1, \alpha_2, \alpha_3$ are the correlation coefficients of each of the variables - which represent the nature and magnitude of the effect each variable has on the dependent variable, natural log of the number of tweets.

b) Univariate Analysis of Variance (ANOVA)

The univariate ANOVA allows us to determine if there is an interaction effect between the three independent variables, '*B.C', 'RaceBlack', 'threat_level_attack',* we identified as statistically significant on the continuous dependent variable, '*ln_x'* (natural log of *coverage_via_twitter* + *1*). Following the identification of a significant interaction effect between the three independent variables, we further analysed this interaction effect by 'splitting' the results and isolating one variable at a time, examining the two-way interaction effect. For example, we would control for *B.C* and look at the two-way interaction effects between *RaceBlack* and *threat_level_attack* when *B.C* is 0 and 1.

Results and Discussion

Our results show the nature (positive or negative) and the magnitude (how large or small an effect the variable has on amount of coverage) of the relationships between the amount of Twitter coverage an unarmed shooting incident receives and the variables that we determined to be significant through the analysis. We also examine, through the univariate ANOVA, the three-way interaction effect between the significant variables.

Figure 1: Linear Regression - Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.530[a]	.281	.249	2.47168
2	.529[b]	.280	.253	2.46543
3	.527[c]	.278	.255	2.46169
4	.521[d]	.272	.254	2.46403
5	.509[e]	.260	.246	2.47703

a. Predictors: (Constant), flee_not_fleeing, B.C, M.I.SIGNS, age, RaceBlack, sex, threat_level_attack

b. Predictors: (Constant), flee_not_fleeing, B.C, age, RaceBlack, sex, threat_level_attack

c. Predictors: (Constant), flee_not_fleeing, B.C, age, RaceBlack, threat_level_attack

d. Predictors: (Constant), B.C, age, RaceBlack, threat_level_attack

e. Predictors: (Constant), B.C, RaceBlack, threat_level_attack

From the backward linear regression in Figure 2, we observed the significance level of each model and we decided to proceed with Model '5' whilst keeping in mind the relevance of Model '4', which successfully explained 27.2% (larger than 26.0% of Model '4') of the variance in coverage via Twitter as represented by the value of 'R Square'. This is because Model '5' allows us to see the effects of the independent variables on Twitter coverage more explicitly in the most significant fashion.

Figure 2 : Backward Linear Regression - Coefficients

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	4.011	.993		4.038	.000
	B.C	1.734	.536	.222	3.233	.001
	flee_foot	.251	.490	.035	.511	.610
	sex	-.653	.882	-.052	-.741	.460
	M.I.SIGNS	.217	.484	.031	.449	.654
	threat_level_attack	-.904	.409	-.154	-2.207	.029
	age	-.028	.018	-.109	-1.588	.114
	RaceBlack	2.387	.406	.405	5.881	.000
2	(Constant)	4.049	.987		4.101	.000
	B.C	1.753	.533	.225	3.286	.001
	flee_foot	.255	.489	.036	.521	.603
	sex	-.666	.880	-.053	-.757	.450
	threat_level_attack	-.883	.406	-.150	-2.176	.031
	age	-.028	.018	-.107	-1.569	.119
	RaceBlack	2.371	.403	.402	5.879	.000
3	(Constant)	4.032	.985		4.095	.000
	B.C	1.753	.532	.225	3.294	.001
	sex	-.611	.871	-.049	-.701	.484
	threat_level_attack	-.884	.405	-.151	-2.185	.030
	age	-.028	.018	-.106	-1.562	.120
	RaceBlack	2.397	.399	.407	6.005	.000
4	(Constant)	3.504	.633		5.534	.000
	B.C	1.791	.529	.229	3.388	.001
	threat_level_attack	-.937	.397	-.160	-2.359	.020
	age	-.029	.018	-.111	-1.644	.102
	RaceBlack	2.407	.398	.409	6.043	.000
5	(Constant)	2.582	.296		8.729	.000
	B.C	1.828	.531	.234	3.444	.001
	threat_level_attack	-.919	.399	-.157	-2.304	.023
	RaceBlack	2.429	.400	.412	6.071	.000

a. Dependent Variable: ln_x

Based on model '5', we obtained the linear regression equation :

$$ln(coverage\_via\_twitter + 1) = \alpha_1 B.C + \alpha_2 RaceBlack + \alpha_3 threat\_level\_attack + \gamma,$$

where $\alpha_1 = 1.828$, $\alpha_2 = 2.429$, $\alpha_3 = -0.919$ and $\gamma = 2.582$

Upon algebraic manipulation and computation, we obtained an equation with a direct relationship between the independent variables and dependent variables :

$$Coverage\_via\_Twitter = \beta_1 B.C. + \beta_2 RaceBlack + \beta_3 threat\_level\_attack + \delta$$

where $\beta_1 = 69.05$, $\beta_2 = 136.83$, $\beta_3 = -7.945$ and $\delta = 12.22$

This model suggests that there will be on average 69.05 more tweets with the presence of a body camera, 136.83 more tweets if the victim is identified as black, and 7.945 less tweets if the victim is perceived to be attacking the officer. These results resonate with the studies about the influential Twitter usage of Black Americans and their group affiliation, and also with the growing interest in police surveillance by video footages identified by the aforementioned authors.

Univariate ANOVA

For completeness, we used Model '4' to run a univariate analysis of variance, and discovered a significant relationship between the 3 independent variables *'RaceBlack'*, *'B.C.'* and *'Threat_Level_Attack'* (refer to column "Sig." in Figure 3). Generally, a significant level value less than 0.05 is considered statistically significant.

Figure 3: Univariate ANOVA

Tests of Between-Subjects Effects

Dependent Variable: ln_x

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	494.567[a]	8	61.821	11.487	.000
Intercept	470.650	1	470.650	87.454	.000
age	27.492	1	27.492	5.108	.025
RaceBlack	116.479	1	116.479	21.644	.000
threat_level_attack	3.411	1	3.411	.634	.427
B.C	72.942	1	72.942	13.554	.000
RaceBlack * threat_level_attack	.081	1	.081	.015	.903
RaceBlack * B.C	9.378	1	9.378	1.743	.189
threat_level_attack * B.C	30.927	1	30.927	5.747	.018
RaceBlack * threat_level_attack * B.C	54.801	1	54.801	10.183	.002
Error	839.546	156	5.382		
Total	3267.261	165			
Corrected Total	1334.112	164			

a. R Squared = .371 (Adjusted R Squared = .338)

Threat of attack

Figure 4: Univariate ANOVA - Tests of Between-Subjects Effects - Split 'Threat_Level_Attack'

Tests of Between-Subjects Effects

Dependent Variable: ln_x

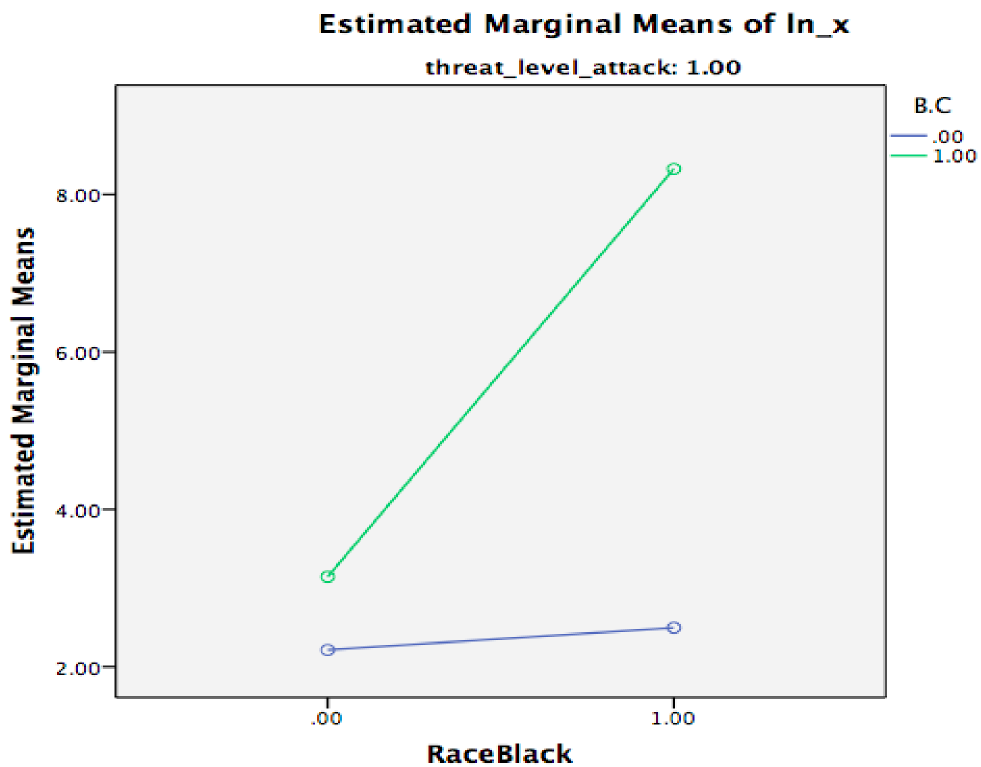
threat_level_attack	Source	Type III Sum of Squares	df	Mean Square	F	Sig.
.00	Corrected Model	255.275[a]	3	85.092	12.062	.000
	Intercept	1057.077	1	1057.077	149.839	.000
	RaceBlack	85.457	1	85.457	12.113	.001
	B.C	10.388	1	10.388	1.472	.228
	RaceBlack * B.C	9.366	1	9.366	1.328	.252
	Error	705.474	100	7.055		
	Total	2428.486	104			
	Corrected Total	960.749	103			
1.00	Corrected Model	166.763[b]	3	55.588	18.312	.000
	Intercept	426.142	1	426.142	140.385	.000
	RaceBlack	48.608	1	48.608	16.013	.000
	B.C	74.360	1	74.360	24.497	.000
	RaceBlack * B.C	39.102	1	39.102	12.882	.001
	Error	176.060	58	3.036		
	Total	842.562	62			
	Corrected Total	342.823	61			

a. R Squared = .266 (Adjusted R Squared = .244)

b. R Squared = .486 (Adjusted R Squared = .460)

From our test of between-subjects effects that splits the attacking threat level, we observe the significance of *'RaceBlack'*, *'B.C.'* and *'RaceBlack'***'B.C.'* when the *'Threat_Level_Attack'* is non-zero.

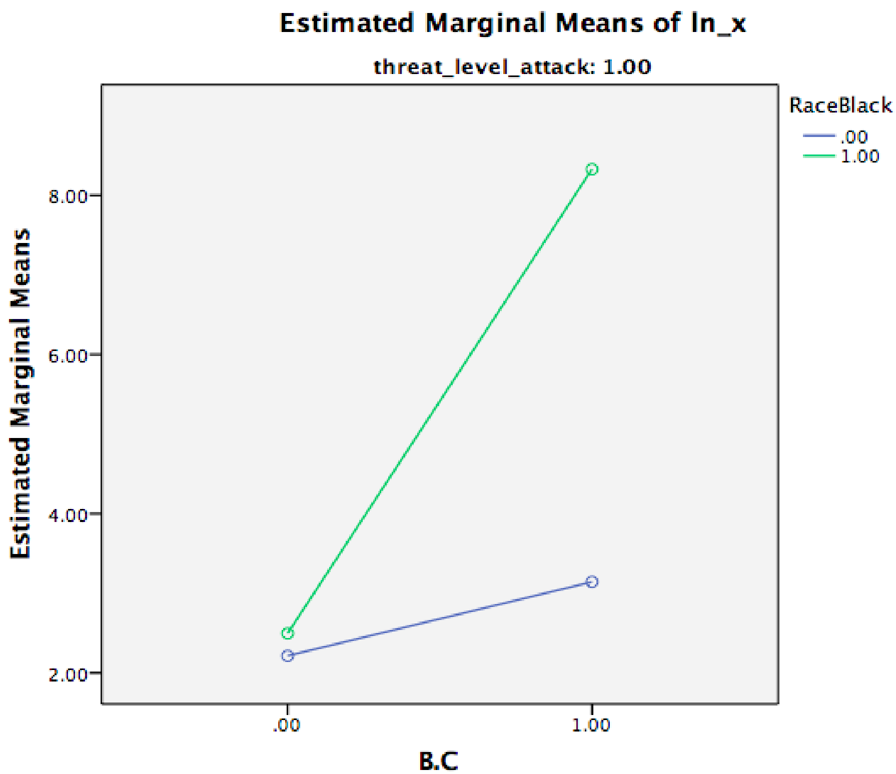
Figure 5: ‘ln_x’ against ‘RaceBlack’ based on varying ‘B.C.’ (Threat_Level_Attack = 1)



From our test between-subject effects, under non-zero attacking threat levels, we proceeded with a profile plot with the *‘ln_x’* against *‘RaceBlack’* where we used *‘B.C.’* as separate lines. From Figure 5, when the *‘Threat_Level_Attack’* is non-zero, we conclude that:

1. When *B.C.* is zero, *ln_x* increases by a small magnitude when we switch from a non-black to a black victim.
2. When *B.C.* is non-zero, *ln_x* increases by a large magnitude when we switch from a non-black to a black victim.

Figure 6: ‘ln_x’ against ‘B.C.’ based on varying ‘RaceBlack’ (Threat_Level_Attack = 1)



Again, under non-zero attacking threat levels, we proceeded with a profile plot with the *‘ln_x’* against *‘B.C.’*,where we used *‘RaceBlack’* as separate lines. From Figure 6, then, we conclude that:

1. When the individual is non-black, as we switch from zero B.C. to non-zero B.C., *ln_x* increases by a small magnitude.
2. When the individual is black, as we switch from zero B.C. to non-zero B.C., *ln_x* increases by a large magnitude.

Body camera

Figure 7 : Univariate ANOVA - Tests of Between-Subjects Effects - Split 'B.C.'

Tests of Between-Subjects Effects

Dependent Variable: ln_x

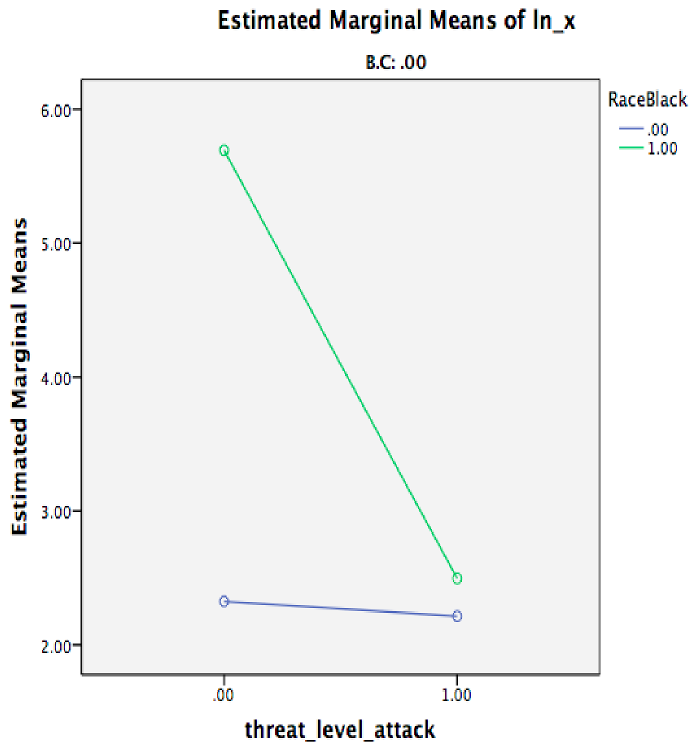
B.C	Source	Type III Sum of Squares	df	Mean Square	F	Sig.
.00	Corrected Model	281.991[a]	3	93.997	21.042	.000
	Intercept	1237.236	1	1237.236	276.972	.000
	RaceBlack	101.732	1	101.732	22.774	.000
	threat_level_attack	83.494	1	83.494	18.691	.000
	RaceBlack * threat_level_attack	72.750	1	72.750	16.286	.000
	Error	607.514	136	4.467		
	Total	2226.757	140			
	Corrected Total	889.505	139			
1.00	Corrected Model	79.284[b]	3	26.428	2.122	.126
	Intercept	576.690	1	576.690	46.300	.000
	RaceBlack	60.367	1	60.367	4.847	.038
	threat_level_attack	3.640	1	3.640	.292	.594
	RaceBlack * threat_level_attack	15.557	1	15.557	1.249	.276
	Error	274.020	22	12.455		
	Total	1044.291	26			
	Corrected Total	353.304	25			

a. R Squared = .317 (Adjusted R Squared = .302)

b. R Squared = .224 (Adjusted R Squared = .119)

From our test of between-subjects effects that splits *'B.C.'*, we observed the significance of *'RaceBlack'*, *'threat_level_attack'* and *'RaceBlack'**'threat_level_attack'* when *'B.C.'* = 0.

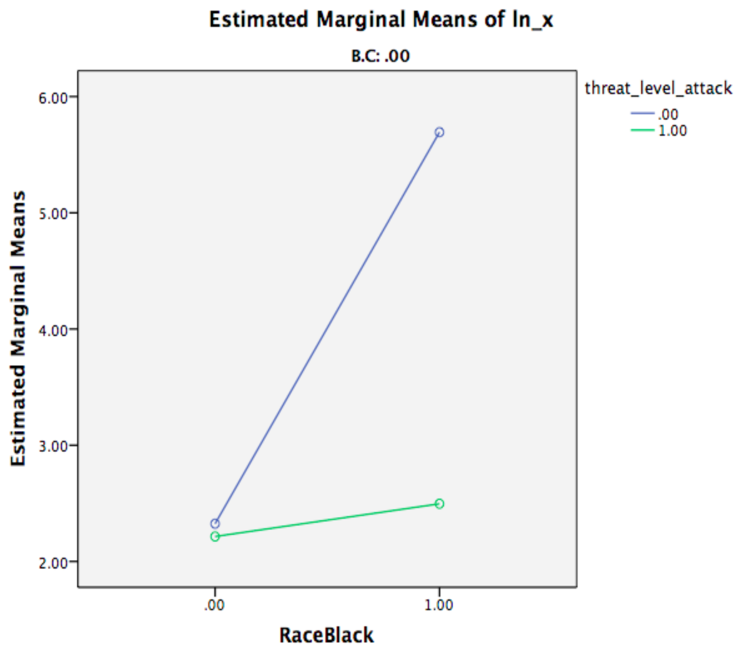
Figure 8 : 'ln_x' against 'Threat_Level_Attack' based on varying 'RaceBlack' (B.C. = 0)



Following through from our test between-subject effects, when *'B.C.'* is zero, we proceeded with a profile plot with *'ln_x'* against *'threat_level_attack'* where we used *'RaceBlack'* as separate lines, from which we concluded:

1. When the individual is not black, as we switch from a non-zero *'threat_level_attack'* to zero *'threat_level_attack'*, '*ln_x'* decreases by a small magnitude.
2. When the individual is black, as we switch a non-zero *'threat_level_attack'* to zero *'threat_level_attack'*, '*ln_x'* decreases by a large magnitude.

Figure 9 : 'ln_x' against 'RaceBlack' based on varying 'Threat_Level_Attack' (B.C. = 0)



Following through from our test between-subject effects, when *'B.C.'* is zero, we proceeded with a profile plot with *'ln_x'* against *'RaceBlack'* where we used *'threat_level_attack'* as separate lines, from which we concluded:

1. When the *'threat_level_attack'* is zero, as we switch from non-black individuals to black individuals, *'ln_x'* increases by a large magnitude.
2. When the *'threat_level_attack'* is non-zero, as we switch from non-black individuals to black individuals, *'ln_x'* increases by a small magnitude.

Black race

Figure 10 : Univariate ANOVA - Tests of Between-Subjects Effects - Split 'RaceBlack'

Tests of Between-Subjects Effects

Dependent Variable: ln_x

RaceBlack	Source	Type III Sum of Squares	df	Mean Square	F	Sig.
.00	Corrected Model	34.379[a]	3	11.460	2.419	.071
	Intercept	296.615	1	296.615	62.611	.000
	threat_level_attack	2.205	1	2.205	.465	.497
	B.C	15.132	1	15.132	3.194	.077
	threat_level_attack * B.C	1.350	1	1.350	.285	.595
	Error	473.742	100	4.737		
	Total	1163.298	104			
	Corrected Total	508.121	103			
1.00	Corrected Model	192.792[b]	3	64.264	9.140	.000
	Intercept	1099.323	1	1099.323	156.356	.000
	threat_level_attack	.818	1	.818	.116	.734
	B.C	76.621	1	76.621	10.898	.002
	threat_level_attack * B.C	74.317	1	74.317	10.570	.002
	Error	407.793	58	7.031		
	Total	2107.750	62			
	Corrected Total	600.585	61			

a. R Squared = .068 (Adjusted R Squared = .040)

b. R Squared = .321 (Adjusted R Squared = .286)

When we split 'RaceBlack' into binary variables, we observe no significance between the dependent variable and the independent variables in both cases. Therefore, we did not proceed with any possible profile plots.

Limitations

The data on coverage was distorted by some very large numbers in a small minority of cases, resulting in possible significant outliers reducing the efficacy of the ANOVA. In addition, even the 'best' fit model explains less than 30% of the variance in coverage, which is significant in a statistical sense, but raising doubts nevertheless.

Furthermore, there is potentially omitted variable bias due to the lack of data on some other possible factors such as the influence of mainstream media content on social media content.

Finally, whilst model 4 from Figure 2 generates a larger set of values and explains the variance slightly better, this route requires a more complex approach (i.e. best-fit projection through linear algebra).

Conclusion

In general, our results indicate that there are four variables that have statistically significant relationships with the amount of social media coverage an incident receives - age, race, and threat level of the victims, as well as the presence of a body camera on the police officer.

Of these four variables, the victim being black and the presence of a body camera, displayed strong, positive correlations with the amount of coverage an incident receives. In contrast, higher age and viable threat posed to officer displayed strong, negative correlations with the amount of coverage received.

Furthermore, in cases where the victims were perceived to be attacking the police officer, if the race of the victim was black, there was a sharper increase in social media coverage than when the victim was of non-black racial background, when there was a body camera. Conversely, whilst coverage was still higher for black victims, if there was no body camera, the difference was not significant.

Additionally, in cases where there was no body camera, if the victim was black, the coverage decreased sharply when there was a threat posed to the officer as opposed to when the victim was non-black. Conversely, when there was no threat posed, coverage increased sharply when the victim was black as opposed to when the victim was non-black.

In general, our literature review agrees with our findings on Black Americans particular and influential activity on Twitter and the idea of counterpublics, as it offers them a space to express themselves and participate in public debate. This, as much of the literature on CJ has argued, contributes to deliberative democracy. Also, our results are consistent with the growing interest in police surveillance through video recordings, which in turn is related to a desire for accountability, one of the democratic ideals.

Whilst we are unable to draw conclusions of causal relationships, our research can augment the existing research and serve as a point of reference for future research on citizen journalism and its evolving influence on the level of public debate.

Moreover, our research can be used to further examine the psychology of social movements and social media as their mode of transmission.

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