Do Police Brutality Stories Reduce 911 Calls?

Reassessing an Important Criminological Finding

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Abstract

This paper reassesses the prominent claim from Desmond, Papachristos, and Kirk (2016) that 911 calls plummeted – and homicides surged – because of a police brutality story (the Jude story). The results in DPK depend on a substantial outlier 47 weeks after the Jude story, the final week of data. Identical analyses without the outlier final week show that the Jude story had no statistically significant effect on either total 911 calls or violent crime 911 calls. Modeling choices which do not extrapolate from data many weeks after the Jude story – including an event study and "regression discontinuity in time" – also find no evidence that calls declined, a consistent result across predominantly Black neighborhoods, predominantly White neighborhoods, and citywide. Finally, plotting the raw data demonstrates stable 911 calls in the weeks around the Jude story. Overall, the existing empirical evidence does not support the theory that publishing brutality stories decreases crime reporting and increases murders.

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INTRODUCTION

"Police Violence and Citizen Crime Reporting in the Black Community" (Desmond, Papachristos, and Kirk 2016; henceforth DPK) examines how Milwaukee 911 calls change following a February 2005 police brutality story (the Jude story).[i] Building on legal cynicism scholarship (Sampson & Bartusch 1998; Kirk & Papachristos 2011), DPK finds that the Jude story had a "clear and significant impact on citizen crime reporting" by reducing 911 calls (870). Moreover, the paper strikingly suggests that the Jude story caused a 32% increase in homicides, saying that "by driving down 911 calls," publicized cases of police violence "thwart the suppression of law breaking, obstruct the application of justice, and ultimately make cities as a whole, and the black community in particular, less safe" (869-870). These are extraordinary claims: learning that police officers beat Frank Jude caused Milwaukee residents to systematically stop reporting crime, frustrating police efforts to solve homicides and leading to a substantial increase in murders.

But 911 calls probably did not decline because of the Jude story. I show this in three main ways. First, plotting the raw data shows that 911 calls were quite stable around the Jude story.[ii] Second, DPK's findings depend entirely on a statistical outlier 47 weeks after the Jude story, the final week of data. Estimating the same model without this outlier week shows no changes in 911 calls. Third, alternative methods less sensitive to extrapolation from many weeks after the story produce no evidence that calls declined.

Though police killings have deleterious social consequences (e.g. Bor et. al 2018), they may not hamper crime reporting. Brutality events like the Jude story often occur in contexts of high legal cynicism stemming from cumulative perceived injustices during routine interactions (Kwak, Dierenfeldt, & McNeeley 2019). Indeed, studies of other police brutality events have found no (White, Weisburd, & Wire 2018) or short-lived (Kochel 2015: 3) effects on legal cynicism. Moreover, despite elevated legal cynicism, residents of racially-isolated, disadvantaged neighborhoods disproportionately call 911, even conditioning on crime rates, because they rely on police protection (Hagan et. al 2018) and often reconcile general distrust of police with strategies of "situational trust" (Bell 2015).

PLOTTING DATA: DO CALLS DECLINE AFTER THE JUDE STORY?

DPK posits that the Jude story undermined police legitimacy among Milwaukee residents, particularly in Black neighborhoods, causing an abrupt decline in 911 calls persisting for many months. Extrapolating from the model coefficients of an interrupted time series regression DPK (867-868) states that "the police beating of Frank Jude resulted in a net loss of approximately 22,200 911 calls reporting crime... Over half (56 percent) of the total loss in calls occurred in black neighborhoods. For comparison purposes, there were approximately 110,000 police-related 911 calls… during this time period."[iii] Given that statistical models estimated this dramatic decline in 911 calls, one would expect 911 calls to decline in the weeks following the Jude story, particularly in Black neighborhoods, if the models are approximately correct.

In an interrupted time series design, plotting the time-series helps "identify the underlying trend, seasonal patterns and outliers" (Bernal, Cummins, and Gasparrini 2017: 351). The natural first comparisons are the weeks just before and after the Jude story, where we are more confident that the story caused any observed changes.

[FIGURE 1 HERE]

Figure 1 (top) plots the weekly 911 calls per Census Block Group (CBG) five weeks before and after the Jude story for Milwaukee as a whole (left) and Black neighborhoods (right).[iv] Instead of declining when the Jude story was released, 911 call patterns appear remarkably stable for the five weeks following the Jude story (if anything, there is a small increase). Figure 1 (middle) zooms out slightly, showing 911 calls for the 20 weeks before and after the Jude story for Milwaukee as a whole (left) and Black neighborhoods (right). Calls declined in the twenty weeks prior to the story and increased in the 20 weeks following the story (again opposite the claims in DPK). Figure 1 (bottom) plots the data over the complete period analyzed in DPK. The Jude story occurred in early February and calls appear to follow the normal seasonal trend.

This visual inspection of the data yields several important insights. First, none of these plots suggest that calls declined dramatically – or at all – in the weeks following the Jude story. Call patterns after the story are notably unremarkable. Second, contrary to claims of a disproportionate reduction in calls in Black neighborhoods (870), call patterns in Black neighborhoods do not trend differently from all Milwaukee neighborhoods after the Jude story (though Black neighborhoods exhibit higher average call rates). Third, a statistical outlier appears in the final week of data – corresponding to December 25, 2005 to December 31, 2005. This outlier proves highly influential.

SENSITIVITY OF RESULTS TO ONE OUTLIER

That the raw data and predictions of the statistical models in DPK differ so starkly suggests that the models may be misspecified. Model parameters can be distorted by the influence of outliers (Aguinis, Gottfredson, and Joo 2013), leading to predictions overfitted to extreme values (see Online Appendix Figure A1 for visual evidence of overfitting the final week). DPK includes data from March 1, 2004 to December 31, 2005, a period of 95 weeks – 48 weeks before and 47 weeks after the Jude story. Week 95, the last week of data – 47 weeks after Jude – has a much larger call rate of 4.87 per CBG than all other weeks (the second largest is 4.2, and the prior week's rate was 3.27).[v]

Dropping this single week at the periphery of the data (Week 95) changes the negative interaction between the linear trend and the Jude story (the main finding in the paper) to a positive and non-significant one, as shown in Table 1, which reports the results from DPK (left) and an identical model including identical data except for the final week (right). While the linear trend after the Jude Story was negative and significant, it becomes positive and non-significant after omitting the final week. The quadratic trend also changes signs (and becomes non-significant) when one omits data from 47 weeks after the story broke.

[TABLE 1 HERE]

Given the large influence of an outlier at the edge of the dataset, I systematically explored the estimated effect of the Jude story by varying the weeks included in the regression. I estimated the same model parameters on subsets of data ranging from 7 weeks (3 weeks before and 4 weeks after the Jude story) to 107 weeks (54 weeks before and 53 after the event). Each of these models has the same specification and controls as DPK: a linear trend prior to Jude, an intercept shift at the time of Jude, and a linear trend as well as a quadratic trend after the Jude story. That is, each is a negative binomial fixed-effects regression with the linear part as follows:

$$\eta_{ij} = \alpha_i + \mu_j + \beta_1 W_j + \tau S_j + \beta_3 (W_j \cdot S_j) + \beta_4 (W_j^2 \cdot S_j) + \Sigma\Gamma_{\mathrm{i}} + \gamma C_{ij} + \log(Pop_i) + \epsilon \qquad (1)$$

The dependent variable is the number of calls in block group i in week j. α_i represents block-group specific intercepts conditioned out of the likelihood function, μ_j represents month dummies, Γ_{I} represents the vector of census demographic covariates (percent poverty, Black, renter, and Hispanic) with coefficients Σ,[vi] C_{ij} is the weekly crime count per CBG, and $\log(Pop_i)$ represents the exposure variable (adjusting total calls by population). W_j denotes the weeks since January 4, 2004 and S_j is an indicator variable equaling 1 if the week falls after the story.

[FIGURE 2 HERE]

Figure 2 plots z-statistics for the three parameters representing the Jude story effect – a change in intercept (τ), a change in linear slope (β_2), and a new quadratic slope (β_3) – across bandwidths. The intercept representing the average change in call levels after the story never statistically differs from zero. However, depending on the bandwidth, one obtains positive and significant, negative and significant, or null results for the linear and quadratic interactions. The change in the linear trend of calls after Jude – the crux of the paper – is never negative and significant until the final Week 95 is included, when it abruptly shifts downward (and the quadratic term similarly shifts abruptly).[vii]

TWO ROBUST ALTERNATIVE APPROACHES

This high degree of sensitivity to events well after the Jude story stems from the analytic approach in DPK, which weights data from 47 weeks after the Jude story as equally influential as data one or two weeks later. This strategy introduces substantial model dependence into the trend variable interactions, as "the greater the distance from a counterfactual to the available data, the more model-dependent inferences can be about that counterfactual" (King and Zheng 2007: 232). Model dependence concerns are compounded by the atheoretical modeling of a linear trend prior to Jude and a linear trend and new quadratic trend afterwards. This modeling decision was chosen to minimize the Bayesian Information Criterion, a measure of model fit itself decisively influenced by Week 95 (Online Appendix Table A4). Other model specifications, including a symmetrical linear/quadratic trend, do not suggest that calls declined (Online Appendix Figure A1; bottom row).

I present two alternative approaches that are less sensitive to extrapolation from many weeks away from the Jude story. First, I estimate a fully-dynamic event study with CBG fixed-effects and leads and lags for each week relative to the Jude story (Jacobson, LaLone and Sullivan 1993; Borusyak and Jaravel 2017). That is, I estimate the following model:

$$C_{ij} = a_i + \sum_{k=-48}^{47} \left(\tau_k \, D_{ij}^k\right) + \epsilon_{ij} \qquad (2)$$

Where C_{ij} represents 911 calls in CBG *i* in week j, α_i is a CBG fixed effect, and D_{ij}^k is an indicator variable equal to 1 when week *j* equals *k*, which indexes weeks before and after the Jude story and equals zero when the Jude story is released. Standard errors are clustered by CBG. I omit the week just prior to Jude, when k=-1 to make each coefficient τ_k represent the average changes in calls in week *k* relative to the week prior to Jude. If, as DPK describes, the Jude story resulted in a sharp decline in calls that slowly dissipated, τ_k will be large and negative just after the Jude story (when *k* is equal to and just larger than zero) and approach zero as *k* increases. I estimate Equation 2 separately for Black and White neighborhoods to test heterogenous effects.

Second, I estimate a "regression discontinuity in time" (Hausman and Rapson 2018) which more heavily weights data closer to the story. I estimate local linear regressions at varying bandwidths around the release of the Jude story, with a triangular kernel used in the local linear fitting and standard errors clustered by CBG.[viii]

[FIGURE 3 HERE]

Both approaches find no evidence calls declined after the Jude story (Figure 3). The event study estimates (Figure 3; top row) show that 911 calls were stable for many weeks following the Jude story and then increased relative to the week prior to Jude. This is confirmed by an F-test that the lead indicators for the first four weeks following Jude are jointly different from zero, which fails to reject the null hypothesis of no difference for all Milwaukee CBGs ($p \approx 0.60$), Black neighborhoods ($p \approx 0.98$), and White neighborhoods ($p \approx 0.68$). Moreover, comparing Figure 3's plotted coefficients for White and Black Neighborhoods shows that, when calls do diverge from pre-Jude levels (such as when k = 20, twenty weeks after the story), it is because calls *increased and increased more* in Black neighborhoods (consistent with Figure 1). Similarly, the regression discontinuity estimates (Figure 3; bottom row) provide no evidence that calls decreased. Across all bandwidths (two weeks to 15 weeks), using either calls per CBG or calls per capita as outcomes, and for White neighborhoods, Black neighborhoods, and all Milwaukee neighborhoods, the estimated change in calls is indistinguishable from zero.

CONCLUSION

DPK argues that brutality stories dampen citizen-crime reporting and increase homicides by activating legal cynicism. But the underlying evidence has several critical issues, including total sensitivity of results to a single outlier 47 weeks after the story. Implementing any of the three conventional procedures for outlier remediation (Aguinis, Gottfredson, and Joo 2013) yields a null effect: deletion of the outlier (Table 1; Table A2; Figure 2), model re-specification accounting for outliers (Table A3; Figure A1), and more robust alternative (Figure 3) all show no significant impact of the Jude story on 911 calls. Moreover, the key empirical claim that 911 calls declined after the Jude story is not reflected in the raw data – which show stable call rates for many weeks. Because DPK has generated significant public and scholarly interest, and police violence and oversight have considerable policy relevance, these issues are particularly concerning. It is plausible that police brutality stories reduce crime reporting, particularly among Blacks, but this remains an open question.

ENDNOTES

[i] This comment focuses on the Jude story, DPK's central empirical section.

[ii] DPK graciously shared replication materials at the CBG-week level. Replication materials for this comment are available on the Harvard Dataverse: https://doi.org/10.7910/DVN/YHSKQR.

[iii] Replication data indicate 190,000 calls during the study period.

[iv] Following DPK, Black neighborhoods are CBGs with at least 65% Black residents. White neighborhoods are similarly defined.

[v] The origin of this end-of-year spike is unclear. It could be because this final week of 2005 includes New Year's Eve, when some reports describe surging 911 calls (Putrelo 2018). A similar influential spike appears 52 weeks earlier in DPK's Milwaukee data, the final week of 2004, six weeks before the Jude story. However, all of 14 other cities for which I collected 911 police calls have fewer calls on the last seven days of the year (Online Appendix Table A1).

[vi] While unit fixed-effects would typically absorb these time-invariant census covariates, they can be estimated because Stata's conditional negative binomial fixed effects model does not control for all stable covariates (Allison & Waterman 2002).

[vii] Specifications controlling for the final weeks of 2004 and 2005 with dummy variables, instead of omitting them, also produce no evidence that the Jude story caused calls to decline (Online Appendix Table A3).

[viii] These estimations were implemented using the *rdd* package in R.

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TABLES

TABLE 1: Outlier Changes Signs and Significance of Interaction Term Parameters

Variable	**Total Calls, *DPK***	**Total Calls, *dropping final week***
Weeks Pre-Jude	0.036***	0.020*
	(0.008)	(0.008)
Jude Story	-0.009	-0.009
	(0.034)	(0.034)
Weeks Post-Jude	**-0.088*** **	**0.010**
	(0.021)	**(0.022)**
Weeks Post-Jude (Squared)	**0.002*** **	**-0.001**
	(0.000)	**(0.000)**
Weeks before event	48	48
Weeks after event	47	46

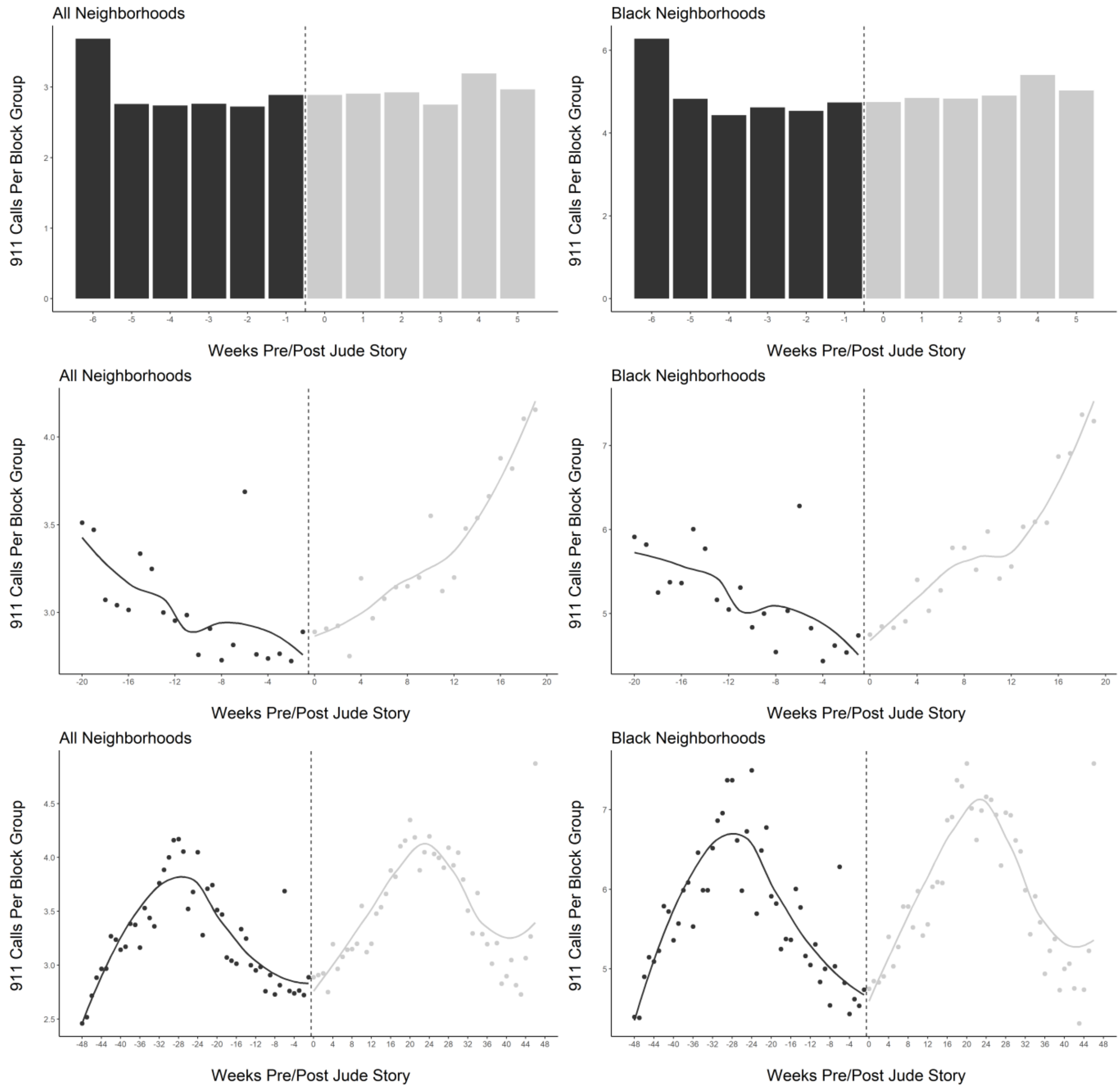
*p< .05; **p< .01; ***p< .001 (two-tailed test).

Estimates of Jude story on total 911 calls from DPK (left) and estimates of same model on same data except for the final week (right) with important differences bolded. Online Appendix Table A2 shows the same pattern with violent crime calls. To be consistent with DPK, coefficients and standard errors for Weeks Pre-Jude, Weeks Post-Jude, and Weeks Post-Jude (Squared) are multiplied by 10 here and throughout. The Weeks Post-Jude coefficients with and without the outlier week are statistically significantly different from one another according to the formula given by Clogg, Petkova, and Adamantios (1995):

$$z = \frac{\beta_2 - \beta_1}{\sqrt{(SE\beta_2)^2 + (SE\beta_1)^2}} \approx \frac{0.010 - -0.088}{\sqrt{(0.022)^2 + (0.021)^2}} \approx \frac{0.098}{0.030} \approx 3.2$$

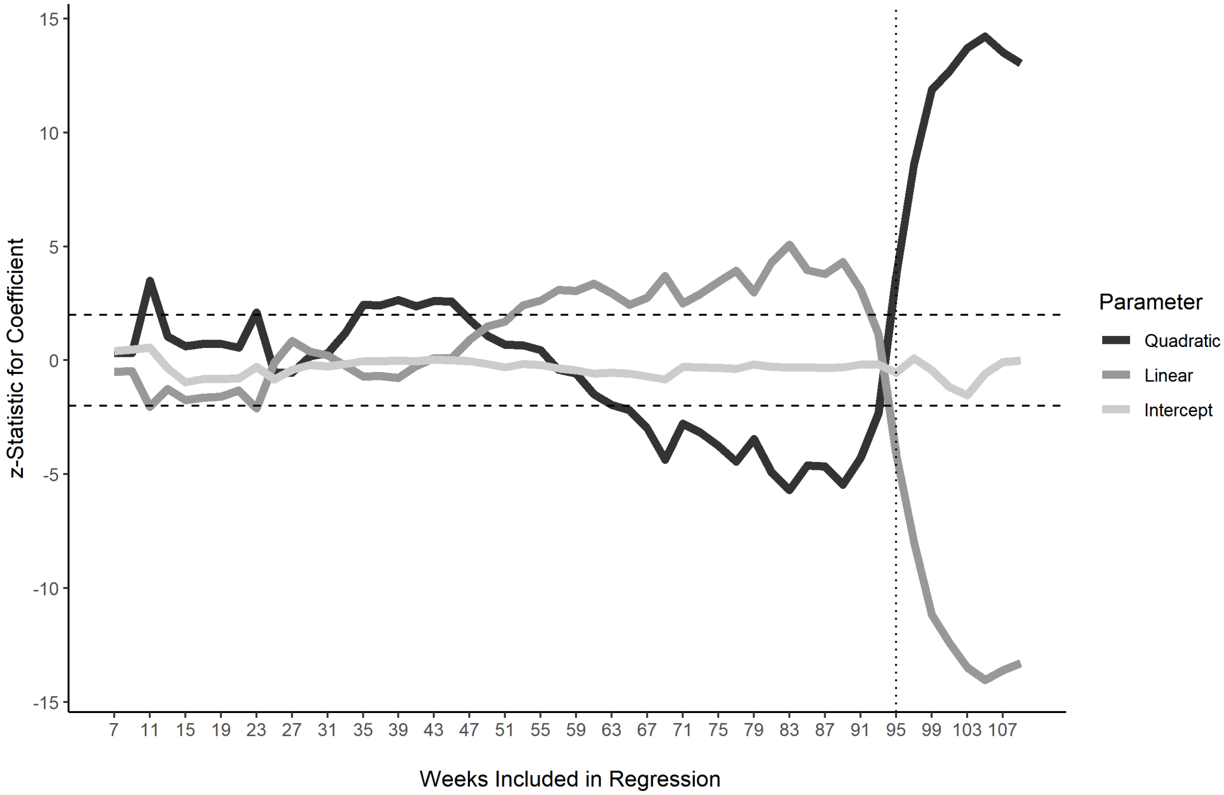
FIGURES

FIGURE 1: 911 CALLS PER BLOCK GROUP IN ALL MILWAUKEE (LEFT) and BLACK NEIGHBORHOODS (RIGHT).



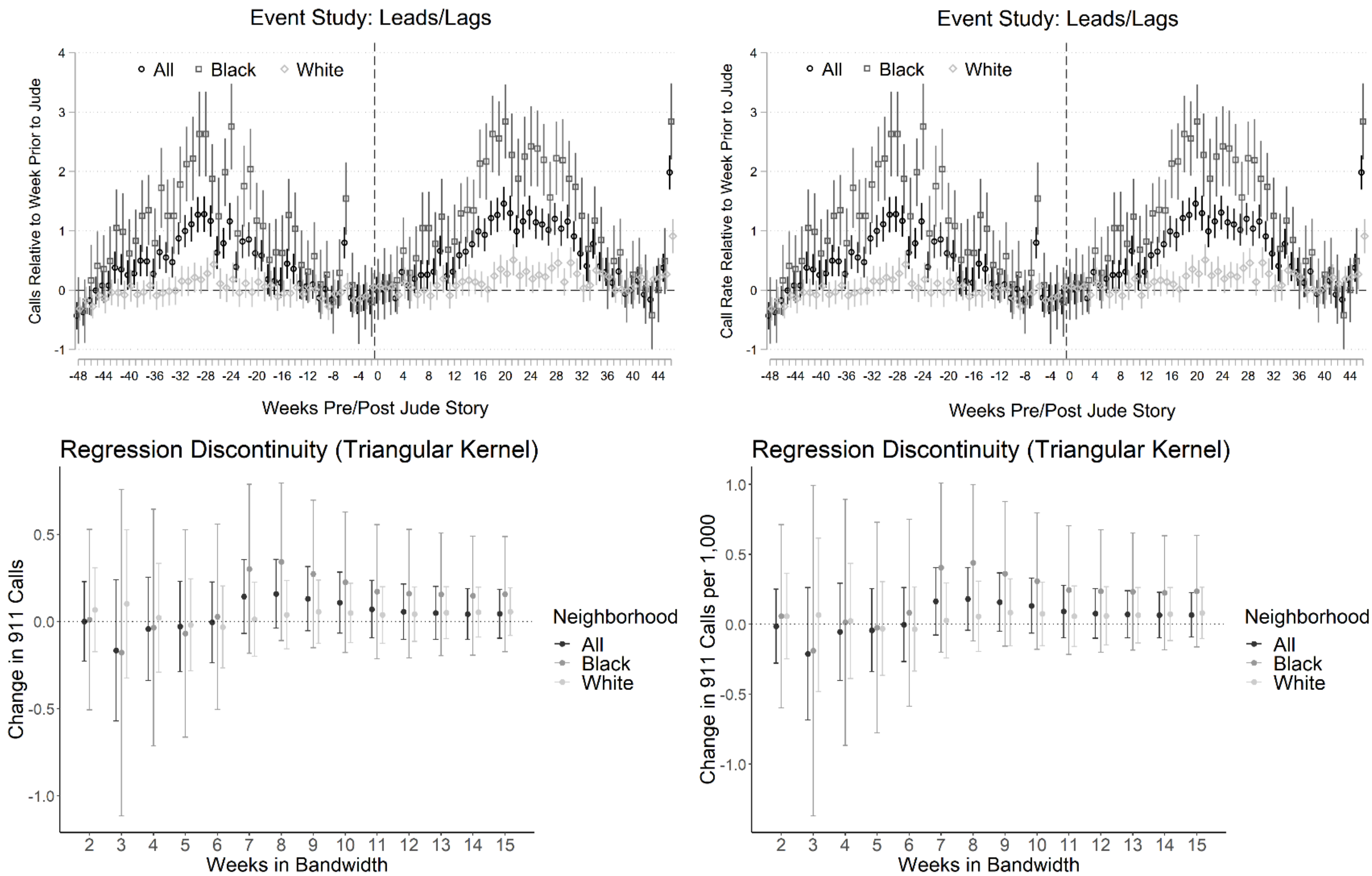
Average 911 calls per Block Group in Black neighborhoods for five weeks (top), 20 weeks (middle), and 48 weeks (bottom) prior and subsequent to the Jude story for all (left) and Black (right) Milwaukee neighborhoods. Smoothed curves are loess fits.

FIGURE 2: **PARAMETER ESTIMATES VARYING WEEKS IN REGRESSION**



This Figure shows the z-statistics for the effect of the Jude Story on the mean rate of calls (intercept; "Jude Story" coefficient), the interaction between the Jude story and the linear trend (linear; "Weeks Post-Jude" coefficient), and the quadratic trend (Quadratic; "Weeks Post-Jude Squared" coefficient), varying the weeks included in the regression. Dashed horizontal lines at z = +/- 2 indicate conventional statistical significance thresholds. Dotted vertical line indicates the bandwidth shown in the paper (95 weeks). All model specifications are the same as DPK; Table 2 Column 1.

FIGURE 3: EVENT STUDY AND RDD ESTIMATES OF JUDE STORY



The top row plots the average weekly changes in 911, with 95% confidence intervals, for each week relative to the week prior to the Jude story (see Equation 2). The bottom row plots the marginal average treatment effects of the Jude story with 95% confidence intervals for regression discontinuity specifications at the indicated bandwidths. The IK bandwidths are between 3 and 4 weeks. Plots on the left use 911 calls per CBG as the dependent variable; those on the right use calls divided by CBG population in thousands as the dependent variable.

SUPPLEMENTARY APPENDIX: Supplementary Tables & Figures

Table A1: Average Daily Calls on New Year's Eve versus other days

City	New Year's Eve	All Other Days	Number of Years
Baltimore	1730	2034	4
Burlington	16	19	7
Cincinnati	1199	1378	4
Detroit	852	905	3
Hartford	165	185	3
Las Vegas	180	220	3
Los Angeles	2209	2296	4
Nashville	1348	1599	2
New Orleans	792	872	8
Orlando	660	690	8
Sacramento	660	747	2
San Diego	1253	1413	2
Seattle	305	319	10
Virginia Beach	556	622	2

City	December 24-31	All Other Days	Number of Years
Baltimore	1446	2039	4
Burlington	14	19	7
Cincinnati	1296	1588	4
Detroit	782	908	3
Hartford	153	185	3
Las Vegas	176	221	3
Los Angeles	2020	2256	4
Nashville	1415	1601	2
New Orleans	784	873	8
Orlando	616	691	8
Sacramento	620	749	2
San Diego	1153	1417	2
Seattle	274	319	10
Virginia Beach	496	624	2

Tables show, for 14 cities with 911 call data readily available online, the average number of daily 911 calls on New Year's Eve compared to all other days (top) and the average number of daily 911 calls for the last seven days of the year compared to all other days. Number of years indicates the number of New Year's Eves in the data. Averages are rounded to the nearest integer. To the extent possible from the provided data fields, calls were subset to deduplicated citizen-initiated police 911 calls by omitting traffic calls, alarm, calls and police-initiated 911 calls, but substantial heterogeneity likely remains between cities in the calls recorded in these data. In every city, calls are lower on the last seven days of the year, so the end-of-year spikes in these Milwaukee data anomalous.

Table A2: Outlier Changes Signs and Significance of Interaction Terms (Violent Crime)

Variable	**Violent Crime Calls, *DPK***	**Violent Crime Calls, *dropping final week***
Weeks Pre-Jude	0.019	-0.002
	(0.015)	(0.014)
Jude Story	-0.021	-0.020
	(0.065)	(0.066)
Weeks Post-Jude	**-0.177****	**0.011**
	(0.040)	**(0.041)**
Weeks Post-Jude (squared)	**0.003*****	**-0.000**
	(0.001)	**(0.000)**
Weeks before event	48	48
Weeks after event	47	46

*p< .05; **p< .01; ***p< .001 (two-tailed test).

Estimates of Jude story on violent crime calls from DPK (left) and estimates of same model on same data except for the final week (right) with important differences bolded. The Weeks Post-Jude coefficients with and without the outlier week are statistically significantly different from one another (Clogg, Petkova, and Adamantios 1995):

$$z = \frac{\beta_2 - \beta_1}{\sqrt{(SE\beta_2)^2 + (SE\beta_1)^2}} \approx \frac{0.011 - -0.177}{\sqrt{(0.041)^2 + (0.040)^2}} \approx \frac{0.188}{0.057} \approx 3.3$$

Similarly, the Weeks Post-Jude (squared) terms are significantly different:

$$z = \frac{\beta_2 - \beta_1}{\sqrt{(SE\beta_2)^2 + (SE\beta_1)^2}} \approx \frac{-0.000 - 0.003}{\sqrt{(0.000)^2 + (0.001)^2}} \approx \frac{0.003}{0.001} \approx 3.0$$

Table A3: Controlling for Outlier Changes Significance and Model Fit

Variable	**Total Calls, *DPK***	**Total Calls, Week 95 Dummy**	**Total Calls, end-year dummies**	**Total Calls, end-year dummies, No Jude Story**
Weeks Pre-Jude	0.036*** (0.008)	0.020* (0.008)	0.020* (0.007)	0.013*** (0.001)
Jude Story	-0.009 (0.034)	-0.008 (0.034)	0.005 (0.034)	
Weeks Post-Jude	**-0.088*** (0.021)**	**0.009 (0.021)**	**-0.007 (0.022)**	
Weeks Post-Jude (Squared)	**0.002*** (0.000)**	**-0.001 (0.000)**	**-0.000 (0.000)**	
Last Week of 2004			0.212*** (0.030)	0.238*** (0.029)
Last Week of 2005		0.485*** (0.028)	0.498*** 0.028	0.469*** (0.029)
N	56,145	56,145	56,145	56,145
BIC	**208325.2**	**208059.6**	**208022.1**	**208007**

*p< .05; **p< .01; ***p< .001 (two-tailed test).

Estimates of Jude story on total 911 calls from DPK (left column) and estimates of an otherwise identical model on the same data including dummy parameters for the last weeks of 2004 and 2005 (middle columns) with important differences bolded. Models with both end-of-year dummies have better model fit (with BIC reduced by more than 300). Omitting all parameters associated with the Jude story further improves model fit (right column). The Weeks Post-Jude coefficients with and without the outlier week are statistically significantly different from one another (Clogg, Petkova, and Adamantios, 1995):

$$z = \frac{\beta_2 - \beta_1}{\sqrt{(SE\beta_2)^2 + (SE\beta_1)^2}} \approx \frac{-.0006683 - -.00879}{\sqrt{(.002153)^2 + (.0021469)^2}} \approx \frac{0.008}{0.003} \approx 2.7$$

The Weeks Post-Jude (Squared) terms similarly differ:

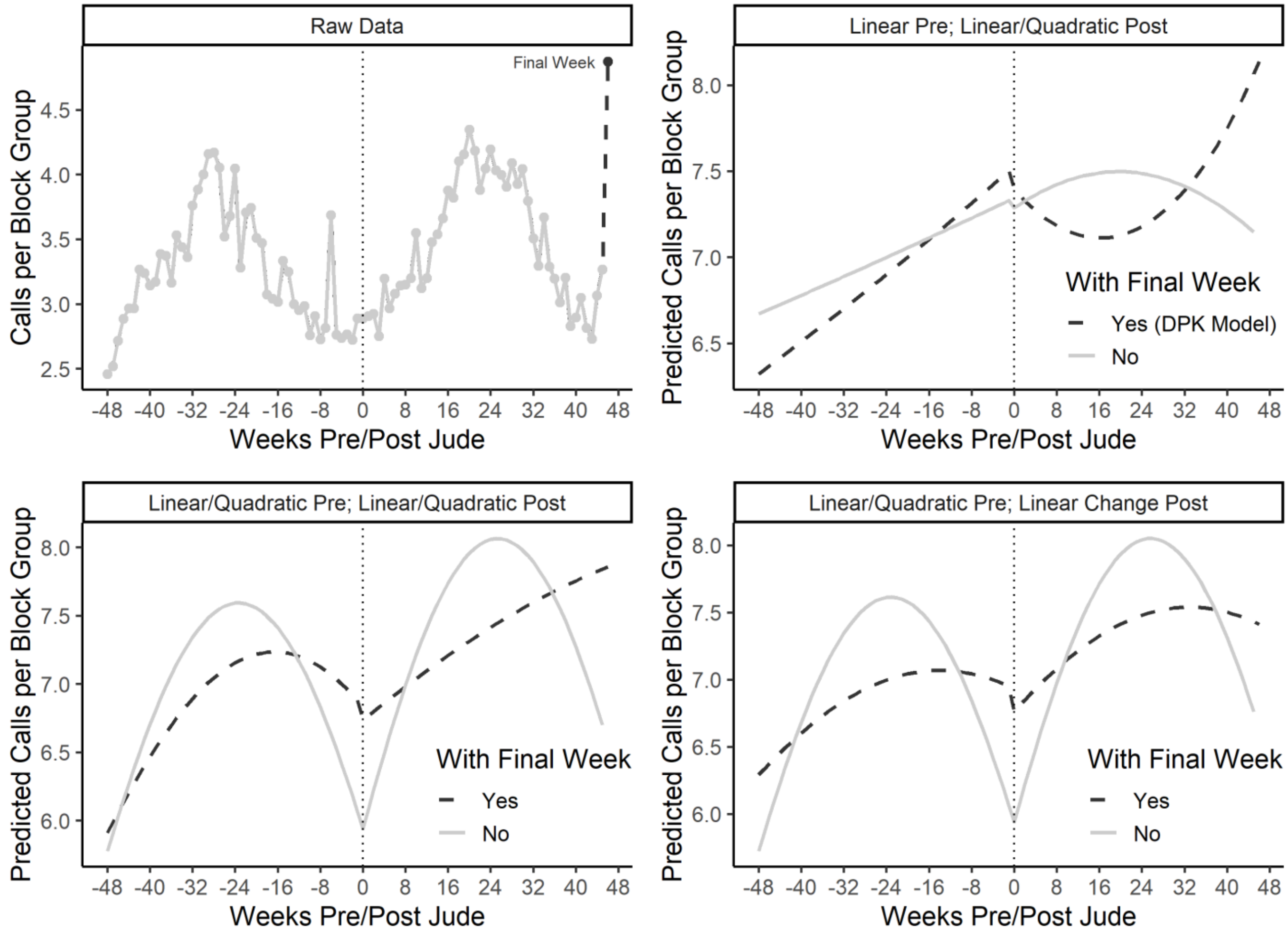
$$z = \frac{\beta_2 - \beta_1}{\sqrt{(SE\beta_2)^2 + (SE\beta_1)^2}} \approx \frac{0.0001505 - -0.0000294}{\sqrt{(.0000403)^2 + (0.0000431)^2}} \approx 3.0$$

Table A4: Outlier Influences functional form for time

Model	Drop Week 95	df	AIC	BIC (N = CBG * Week)
Linear Pre; Linear/Quad post	No	21	208137.6	**208325.2**
Linear/Quad Pre; Linear Post	No	21	208150.2	208337.9
Linear/Quad Pre; Linear/Quad Post	No	22	**208134.8**	208331.3
Linear Pre; Linear/Quad Post	Yes	21	205351.1	205538.6
Linear/Quad Pre; Linear Change Post	Yes	21	**205329**	**205516.4**
Linear/Quad Pre; Linear/Quad Post	Yes	22	205330.5	205526.9

This Table reports fit statistics (AIC and BIC) for models with different model specifications of the effect of the Jude story. Smaller AIC and BIC indicate better fit. The italicized specification denotes specification in DPK. Bolded specifications are best fitting for a model estimated on the same data. As in DPK, these specifications always include a change in intercept parameter for the Jude story, though dropping this parameter improves model fit.

Figure A1: Raw Data and Predicted Values Across Specifications



Top left plot shows the raw call data and remaining plots show predicted values from different models using Stata's *margins* command, as in DPK. Dashed black lines include the final week, while solid gray lines omit the final week. The top right plot shows predicted values from DPKs model's specifications (linear before Jude, linear and quadratic after Jude), while the bottom row uses a symmetric linear/quadratic specification (left) and a linear/quadratic specification with the linear term allows to change after the story. As in DPK, predicted values are on a different scale than the raw data because Stata's conditional negative binomial fixed effects model does not estimate the Block Group unit intercepts.