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Do Police Brutality Stories Reduce 911 Calls? Reassessing an Important Criminological Finding

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Table S1. 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 to 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

Table S1 shows, 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 are anomalous.

Table S2. Outlier Changes Signs and Significance of Interaction Terms (Violent Crime)

Variable	**Violent Crime Calls, *DPK***	**Violent Crime Calls, *Dropping Final Week***
Weeks Pre-Jude	.019	–.002
	(.015)	(.014)
Jude Story	–.021	–.020
	(.065)	(.066)
Weeks Post-Jude	**–.177****	**.011**
	(.040)	**(.041)**
Weeks Post-Jude (squared)	**.003*****	**–.000**
	(.001)	**(.000)**
Weeks before Event	48	48
Weeks after Event	47	46

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

Table S2 shows 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 Haritou 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 S3. 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	.036*** (.008)	.020* (.008)	.020* (.007)	.013*** (.001)
Jude Story	–.009 (.034)	–.008 (.034)	.005 (.034)	
Weeks Post-Jude	**–.088*** (.021)**	**.009 (.021)**	**–.007 (.022)**	
Weeks Post-Jude (Squared)	**.002*** (.000)**	**–.001 (.000)**	**–.000 (.000)**	
Last Week of 2004			.212*** (.030)	.238*** (.029)
Last Week of 2005		.485*** (.028)	.498*** .028	.469*** (.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).

Table S3 shows 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 et al. 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 S4. Outlier Influences Functional Form for Time

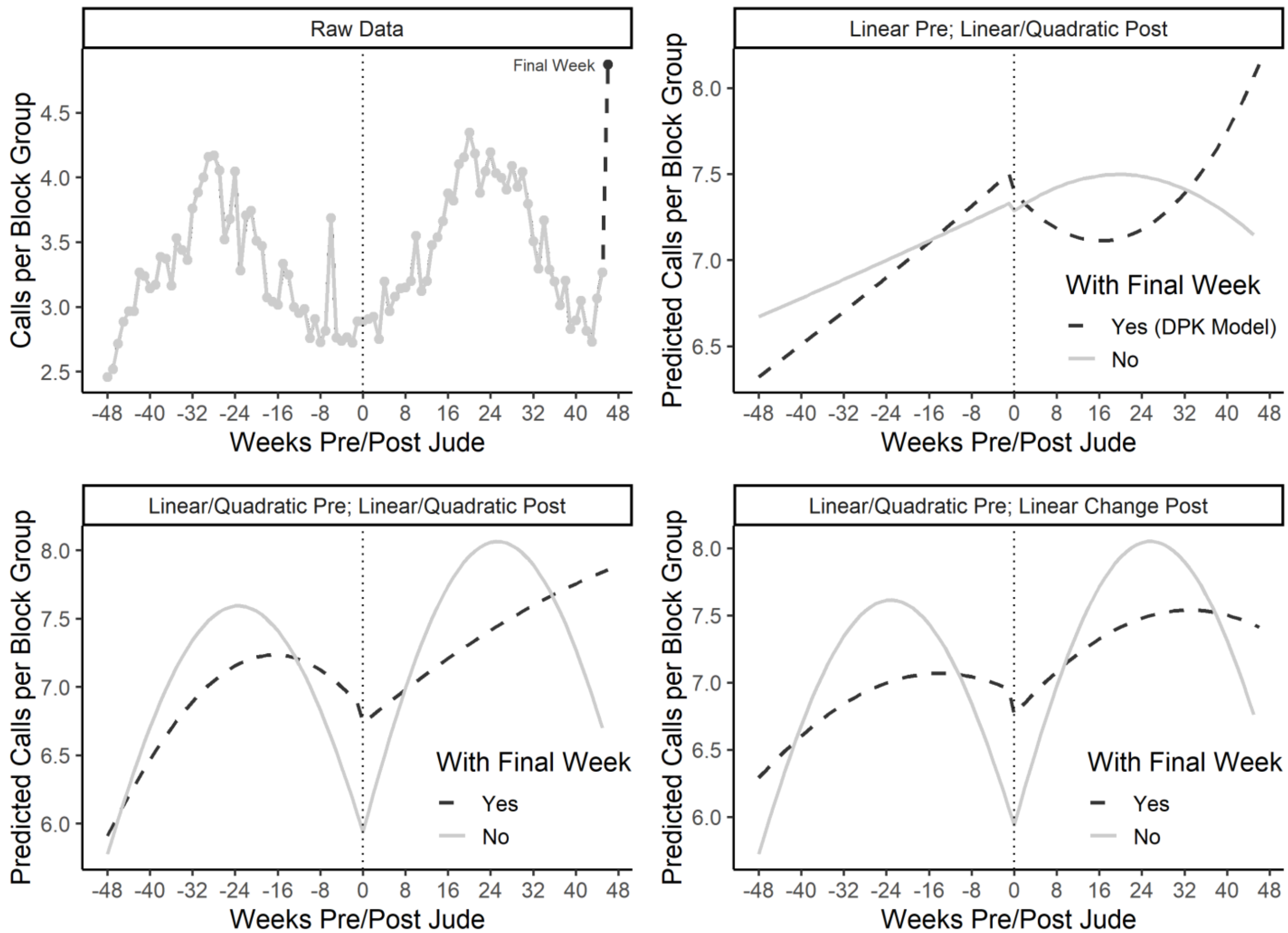
Model	Drop Week 95	df	AIC	BIC (N = CBG × Week)
Linear Pre; Linear/Quad post	No	21	208137.6	**208325.2**
Linear/Quad Pre; Linear Post	No	21	208150.2	208337.9
Linear/Quad Pre; Linear/Quad Post	No	22	**208134.8**	208331.3
Linear Pre; Linear/Quad Post	Yes	21	205351.1	205538.6
Linear/Quad Pre; Linear Change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

Table S4 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, although dropping this parameter improves model fit.

Reference

Clogg, Clifford C., Eva Petkova, and Adamantios Haritou. 1995. "Statistical Methods for Comparing Regression Coefficients between Models." *American Journal of Sociology* 100(5):1261–93.

Figure S1. Raw Data and Predicted Values across Specifications



The top left plot of Figure S1 shows the raw call data; the remaining plots show predicted values from different models using Stata's *margins* command, as in DPK. Dashed black lines include the final week; solid gray lines omit the final week. The top right plot shows predicted values from DPK's model's specifications (linear before Jude, linear and quadratic after Jude), and the bottom row uses a symmetric linear/quadratic specification (left) and a linear/quadratic specification with the linear term allowed 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.