Temporal and Spatial Shifts in Gun Violence, Before and After a Historic Police Killing in Minneapolis

Spatial and Spatio-temporal Epidemiology Revision Memo

Thank you for the opportunity to revise our manuscript for consideration in *Spatial and Spatio-Temporal Epidemiology*. We found the comments to be incredibly helpful, and we have made substantial revisions to our manuscript accordingly. This revision has involved changes to the manuscript text (e.g., adding significantly more detail regarding model specification and estimation), presentation of new analyses (e.g., including socioeconomic status, presenting models with and without police indicators), and the addition of new sensitivity analyses (e.g., expanding our analysis of murder rates as a supplementary measure of violence, considering a combined outcome that includes assault and unintentional firearm injuries). Below, we list each of the Reviewers' points followed by a detailed description of what we did to address each comment (in italics).

Reviewer #1: The authors attempted to determine the impact of the police murder of George Floyd in Minneapolis on firearm violence, and examine the spatial and social heterogeneity of the effect. However, the authors have only been partially successful in achieving their objectives. In fact, I have a few comments, all of them major.

1.- Although it is true that in their models the authors include random effects that collect unobserved confounders and that in their models to assess spatial heterogeneity in the post-killing effect across communities they include the percentage of black people, the authors do not include other important confounders as the socioeconomic level.
Authors should perform a sensitivity analysis including these confounders.

Thank you for this comment. We agree that socioeconomic status could be a potential confounder, especially considering its strong spatiotemporal relationship to racial demographics. We therefore include median household income, as measured by the 5-year American Community Survey estimates, as a control in our primary RE specifications. Our conclusions are robust after the inclusion of a measure of SES in the specifications, and we think this revision strengthens the validity of our conclusions. We add the following prose in the methods section detailing the inclusion of the measure:

"We also acquire ZCTA-year data on percent Black and median household income from the American Community Survey 5-year estimates. Percent Black, which serves as our proxy for structural racism and disadvantage in our tests of spatial heterogeneity below, and we include median household income as a measure of socioeconomic status to control for the interrelationships between class and race (p. 6-7)".

2.-The authors find spatial heterogeneity in post-killing effects.
But did this inequality exist before? In all ZCTA? The gap was the same?
They should do a pre-George Floyd analysis as well, to see if pre and post are comparable.

We thank reviewer 1 for their comments here, and the push to clarify the heterogeneity pre-treatment and the heterogeneity in the post-killing effect. The focal spatial heterogeneity we discuss in the paper concerns differences in the post-killing effect (which captures the pre-post change in the rate of firearm assaults net of observed covariates) across ZCTA-level covariates, and this effect is exclusive to the post-treatment period. However, reviewer 1's comment also speaks to spatial differences in firearm assault incidence in the pre-killing period. We now devote greater discussion to the raw spatial differences highlighted in the first panel of Figure 2 ("Pre-Killing" panel), as well as the spatial differences captured in the main effect ("Percent Black") in the RE interaction model (Model 5). More specifically, we find spatial concentration of firearm injury incidence in the pre-killing period, and we add further discussion of these patterns in the manuscript. In response to reviewer 1's comments, we also added description of the pre-treatment spatial patterns in Figure 2 and added a sentence interpreting and contextualizing the main effect in Model 5. These changes were made to make explicit and clarify the spatial patterns pre-treatment, as well as clarifying that while there were observable pre-treatment spatial patterns, these existing inequities were exacerbated by the police killing of Mr. Floyd.

Description of pre-killing pattern in Figure 2: "In the Pre-Killing period (first panel of Figure 2), the ZCTAs do exhibit a spatial pattern, with the average ZCTA having a pre-killing firearm assault injury rate of .067 per 100,000, but with the rates ranging from 0 to 3.16 per 100,000."

Description of pre-killing pattern in Model 5: "The main effect of percent Black captures the spatial heterogeneity in firearm assault injury incidence by percent Black in the pre-killing period. This term is statistically significant and positive, indicative of higher levels of violence in Black neighborhoods in the pre-killing period, consistent with the spatial heterogeneity depicted in Figure 2."

3.- Authors should include, in the discussion, at least one paragraph of limitations. How they have influenced their results, how they could have been avoided and why they have not done so if it were the case.

We thank reviewer 1 for pushing us to expand upon the limitations of our study. We expand our discussion of the limitations of our analysis by discussing the limits inherent in our study in terms of a) generalizability, b) causal inference assumptions, and 3) the scope of potential moderating influences left uncaptured in our models. Our expanded discussion in the discussion section is as follows:

"Our study, however, is not without its limitations. First, we caution that our data and analysis are limited to a single jurisdiction in a period of large-scale social change in response to COVID-19, economic recession, and social unrest. Second, our interrupted time series design relies upon the assumption that the change in firearm incidence in the week of the police killing is unrelated to unmeasured time-varying characteristics. If other unmeasured contemporaneous changes also drove the increase in firearm injury, the validity of our estimates would be threatened. Finally, we explore only one mechanism of effect heterogeneity, percent Black, and the impacts of police violence on communities could perhaps vary amongst other social or economic dimensions. Although a full exploration of the mechanisms for this increase is beyond the scope of our analysis, the localized and racialized patterns we observe are consistent with accounts based on structural racism, legal estrangement and legal cynicism. Further research is clearly needed to elucidate these processes, but the pattern of findings is consistent with the

idea that police violence impacts vulnerable communities by destabilizing social order and threatening public safety (p. 16-17)."

Reviewer #2: This is an important and interesting analysis, and the writing is clear and concise. I have some questions about the specifications of the statistical models (noted below), but most of the main findings are clearly supported by the descriptive data, with the models serving primarily as confirmation, so I do believe that the conclusions the authors arrive at are justified. Beyond these questions about model specification, my comments are mostly minor.

Major comments:

More information about the model specifications and fitting procedures is warranted. In particular, how were the seasonality variables entered into the model? For concreteness, it would be useful to write out the full statistical model (perhaps in the appendix). Additionally, what fitting strategy and software was used to estimate these models?

Thank you for this comment. We add approximately one page of detail in the Statistical Method section about our interrupted time series model design and assumptions, providing the equations for each estimated model in the primary specifications. In addition, we include a discussion of the focal parameters in each model. We also make explicit how the seasonality variables are measured and incorporated in the model both in the formulas and the new Table 1, which describes the variables in our data. Finally, we also include a description of the statistical software used and the fitting strategies involved. In short, we made significant revisions to our Statistical Method section to further describe our study design, modeling strategy, and estimation procedures.

I don't entirely understand the reasoning behind including both model 1 and 2. I expect the temporal pattern of firearm assault injury for the city as a whole to be pretty similar to the shared temporal pattern among ZCTAs. You could potentially observe different patterns on a local level as opposed to a more aggregate level if there are large shifts in population within the city over the study period, but I think that's unlikely to be the case in this context, particularly in the period the authors are most interested in around George Floyd's murder.

Thank you for this comment. The key difference between the AR(1) time series models (Models 1+2 in Table 2) and the RE models (Models 3, 4, and 5 in Table 2) are as you describe: the AR(1) models compare Minneapolis as a whole pre-post, and the RE panel models compare pre-post within each ZCTA. Our reasoning for including both sets of models is to a) identify how firearm injury incidence changed on average in Minneapolis overall (Models 1+2), and b) to examine how the temporal discontinuity for certain neighborhoods may be heterogeneous (Models 3, 4, + 5). We have added text in the Statistical Methods section to better explain the added value of both models to readers:

"Overall, the AR(1) interrupted time series models describe how firearm injury incidence changed on average across Minneapolis before and after the police killing of Mr. Floyd (p. 8)."

"Subsequently, we estimate a random-effects model on ZCTA-week panel data to corroborate and extend the findings of the overall Minneapolis AR(1) interrupted time series models by using within-ZCTA comparisons. The panel structure of the data allows us to examine the spatial heterogeneity of the police killing on firearm injury incidence across ZCTAs. In other words, these models allow for the examination of how the pre-post difference in firearm injury incidence was heterogeneous across space in Minneapolis (p. 9)."

Related to the previous two points, I find it very surprising that the results are so different in magnitude between models 1 and 2. The coefficients on "Post-Killing" and on "Post-Killing 3 Months" are nearly two orders of magnitude larger in model 2 than in model 1. This suggests to me that there's something fundamentally different about the model specification that impacts the interpretation of these coefficients, which I think needs to be stated more clearly. As currently written, the authors simply note that the results of model 2 "corroborate" the results of model 1, presumably based on the consistency of the direction of the effects rather than the size.

We thank reviewer 2 for their close eye to detail. Our initial manuscript presented estimates in the pooled Minneapolis time series model as a rate per 1,000 (rather than per 100,000, as in model 2) and the table had been mislabeled. For consistency and ease of interpretation we now estimate all models using the firearm assault injury incidence per 100,000. The coefficients now are on an identical scale and exhibit much smaller differences in magnitude, and we make this measure explicit in the methods section and in the model table headings. We also adjust the discussion of the figures and models in the results section to reflect these changes.

What was the reasoning behind using three months as the time window to investigate post-killing? Would it be possible to instead include dummy variables in the model for each month post-killing? This would allow you to more specifically investigate the pattern of decline in firearm assault injuries following the initial spike.

We thank reviewer 2 for their comments regarding our time parameterization post-treatment. We did not have a specific theoretical or empirical motivation for choosing 3-months post-treatment to examine the change to the immediate post-treatment period. Inspired by reviewer 2's comments, we reparameterize our interrupted time series models in two ways: 1) to have a linear post-treatment slope, and 2) include time dummies for each month post-treatment as suggested by reviewer 2. The linear post-treatment parameterization indicates a modest weekly decreasing rate of firearm injury incidence in the post-treatment period. The specifications with the monthly dummy parameterization generally indicate a decreasing trend through three months post-killing, followed by a leveling off and modest increase before decreasing further in the 7+ months post-killing window. We utilize the the linear post-treatment slope in our primary specifications as this parameterization closely follows conventional modeling strategies in interrupted time series designs[1], and utilizes the weekly variation available in firearm injury incidence. In addition, we include the parameterization with the monthly dummy variables in a table in the appendix and is also included below:

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[1] Bernal, J. L., Cummins, S., & Gasparrini, A. (2017). Interrupted time series regression for the evaluation of public health interventions: a tutorial. *International journal of epidemiology*, *46*(1), 348-355.

Table A4: Interrupted Time Series Models of Firearm Assault Injuries

<table>
<tr><th></th><th colspan="5">Firearm Assault Injuries</th></tr>
<tr><th></th><th colspan="5">Rate per 100,000</th></tr>
<tr><th></th><th>AR(1) TSR</th><th>AR(1) TSR</th><th>RE HLM</th><th>RE HLM</th><th>RE HLM +Int.</th></tr>
<tr><th></th><th>(1)</th><th>(2)</th><th>(3)</th><th>(4)</th><th>(5)</th></tr>
<tr><td>T</td><td>0.001
(−0.0001|0.002)</td><td>−0.001
(−0.003|0.001)</td><td>0.003
(0.0004|0.005)</td><td>0.002
(−0.0004|0.004)</td><td>0.001
(−0.002|0.004)</td></tr>
<tr><td>COVID - State of Emergency</td><td>−0.148
(−0.786|0.490)</td><td>−0.063
(−0.706|0.580)</td><td>−0.520
(−2.114|1.074)</td><td>−0.352
(−1.951|1.246)</td><td>−0.313
(−2.052|1.427)</td></tr>
<tr><td>COVID - Stay at Home</td><td>−0.016
(−0.712|0.681)</td><td>−0.032
(−0.732|0.669)</td><td>0.081
(−1.659|1.821)</td><td>−0.037
(−1.781|1.707)</td><td>0.028
(−1.869|1.926)</td></tr>
<tr><td>Post-Killing</td><td>2.545
(1.614|3.477)</td><td>2.556
(1.619|3.493)</td><td>1.611
(−0.716|3.938)</td><td>1.617
(−0.715|3.950)</td><td>0.563
(−2.040|3.166)</td></tr>
<tr><td>1 Month Post</td><td>−0.699
(−1.906|0.509)</td><td>−0.853
(−2.080|0.374)</td><td>−0.013
(−3.029|3.003)</td><td>−0.067
(−3.090|2.956)</td><td>0.052
(−3.237|3.342)</td></tr>
<tr><td>2 Months Post</td><td>−1.241
(−2.454|−0.028)</td><td>−1.538
(−2.785|−0.292)</td><td>−0.902
(−3.931|2.127)</td><td>−1.059
(−4.096|1.977)</td><td>−0.972
(−4.276|2.331)</td></tr>
<tr><td>3 Months Post</td><td>−2.128
(−3.345|−0.911)</td><td>−2.355
(−3.596|−1.114)</td><td>−1.248
(−4.288|1.791)</td><td>−1.331
(−4.377|1.715)</td><td>−1.338
(−4.652|1.977)</td></tr>
<tr><td>4 Months Post</td><td>−1.871
(−3.085|−0.656)</td><td>−2.021
(−3.252|−0.790)</td><td>−1.176
(−4.210|1.858)</td><td>−1.145
(−4.185|1.896)</td><td>−1.156
(−4.464|2.153)</td></tr>
<tr><td>5 Months Post</td><td>−2.121
(−3.334|−0.907)</td><td>−2.111
(−3.339|−0.884)</td><td>−1.372
(−4.402|1.658)</td><td>−1.353
(−4.391|1.684)</td><td>−1.401
(−4.706|1.903)</td></tr>
<tr><td>6 Months Post</td><td>−1.330
(−2.548|−0.111)</td><td>−1.337
(−2.566|−0.108)</td><td>−0.249
(−3.292|2.794)</td><td>−0.304
(−3.355|2.746)</td><td>−0.179
(−3.498|3.140)</td></tr>
<tr><td>7+ Months Post</td><td>−2.489
(−3.672|−1.307)</td><td>−2.485
(−3.674|−1.295)</td><td>−1.527
(−4.480|1.426)</td><td>−1.524
(−4.484|1.435)</td><td>−1.566
(−4.786|1.654)</td></tr>
<tr><td>MPD Use of Force t-1</td><td></td><td>−0.732
(−2.145|0.680)</td><td></td><td>−0.130
(−0.184|−0.077)</td><td>−0.123
(−0.175|−0.070)</td></tr>
<tr><td>MPD Stops t-1</td><td></td><td>−0.182
(−0.415|0.050)</td><td></td><td>0.035
(0.019|0.051)</td><td>0.077
(0.055|0.098)</td></tr>
<tr><td>MPD OIS t-1</td><td></td><td>−30.131
(−68.210|7.948)</td><td></td><td>−2.053
(−13.048|8.942)</td><td>−1.773
(−13.202|9.657)</td></tr>
<tr><td>AR(1)</td><td></td><td></td><td></td><td></td><td>0.00001
(−0.00001|0.00002)</td></tr>
<tr><td>Median HH Income</td><td></td><td></td><td></td><td></td><td>0.038
(0.014|0.062)</td></tr>
<tr><td>Percent Black</td><td></td><td></td><td></td><td></td><td>0.063
(0.032|0.094)</td></tr>
<tr><td>Post-Killing X Percent Black</td><td>0.722
(−0.029|1.474)</td><td>1.263
(0.178|2.348)</td><td>0.878
(−1.039|2.794)</td><td>0.924
(−1.006|2.854)</td><td>−0.320
(−2.715|2.076)</td></tr>
<tr><td>SD(ZCTA)</td><td></td><td></td><td>0.817</td><td>0.922</td><td>0.504</td></tr>
<tr><td>SD(Residual)</td><td></td><td></td><td>5.353</td><td>5.364</td><td>5.578</td></tr>
<tr><td>Observations</td><td>261</td><td>217</td><td>5,993</td><td>5,928</td><td>5,460</td></tr>
<tr><td>R^2</td><td>0.436</td><td>0.485</td><td></td><td></td><td></td></tr>
<tr><td>Log Likelihood</td><td></td><td></td><td>−18,582.870</td><td>−18,396.930</td><td>−17,161.870</td></tr>
<tr><td>Akaike Inf. Crit.</td><td></td><td></td><td>37,203.730</td><td>36,837.860</td><td>34,373.740</td></tr>
<tr><td>Bayesian Inf. Crit.</td><td></td><td></td><td>37,331.000</td><td>36,984.990</td><td>34,538.870</td></tr>
<tr><td>Residual Std. Error</td><td>0.447 (df = 244)</td><td>0.448 (df = 197)</td><td></td><td></td><td></td></tr>
<tr><td>F Statistic</td><td>11.808*** (df = 16; 244)</td><td>9.761*** (df = 19; 197)</td><td></td><td></td><td></td></tr>
</table>

Models include controls for seasonality. 95% Confidence Intervals in parentheses

The descriptive statistics in the appendix using the weekly murder rate, and MPD murder event data are really interesting as support to the argument made using hospitalization data in the main text. Is there any reason not to run the statistical models on these data to further make the point that the patterns are substantively similar across different outcomes/data sources?

Thank you for your support in using the MPD Homicide data to extend our analyses into a longer series and add robustness to our findings across different outcomes and data sources. We agreed that including identical models with the homicide would be a useful addition to our appendix. We therefore estimated each interrupted time series specification on the MPD homicide data, as well as adding prose to the appendix contextualizing and discussing these models. In general, the overall patterns we observe in the hospital data are corroborated with the alternative murder rate measure from the MPD, with fairly large discontinuous increases followed by modest weekly decreases post-killing. However, we find a much smaller interaction effect. While this could indicate that the post-killing effect for murders was more global, or were heterogeneous along axes other than race, we suspect that this is because the MPD data spatially locates violence where it took place as opposed to where those injured reside (as in the MHA data). For example, downtown ZCTAs (e.g., 55402) had a higher increase in murders, but these often *involve non-residents in these ZCTAs. Such ZCTAs have a relatively advantaged residential population but experienced a larger discontinuity in murder rate, and could be suppressing the broader spatial pattern. We describe this analysis as follows in the text:*

"The spatiotemporal visualizations above are corroborated by interrupted time series models at both the city-week and ZCTA-week levels. Similar to Table 2 in the main text, a significant increase in murders was observed, followed by modest linear decreases in the post-killing period across all specifications. However, the interaction term in Model 5, albeit similar in direction to that of Table 2 Model 5, is less strong, suggesting perhaps that the spatial heterogeneity in the post-killing effect was moderated by a factor other than racial demographic composition. However, we caution against overinterpreting this effect, as downtown ZCTAs (e.g., 55402) had a higher increase in murders, but these often involve non-residents in these ZCTAs. Such ZCTAs have a relatively advantaged residential population but experienced a larger discontinuity in murder rate, and could be suppressing the broader spatial pattern (p.23)."

For the sensitivity analysis using unintentional injuries, if the concern is about misclassification of assaults as accidents, I think it may make more sense to combine assaults and unintentional injuries for the purposes of the sensitivity analysis. Similarly, you might want to consider firearm injuries where intent was undetermined (though I'm not sure how common these are in your data; this may not be as important).

Thank you for this comment. We agree with reviewer 2 that it would be better to combine assaults and accidents, as previous research shows how assaults can be misclassified as accidents.[2] *We construct a measure to test the robustness that is expressed as (total_assaults+total_accidents)/total_pop*100000, and use this newly constructed measure to examine the robustness of our findings. The results of these analyses substantively corroborate the findings of the primary figures and models. Given reviewer 2's suggestion to construct a measure of firearm injuries of undetermined intent, we also went back to the Minnesota Hospital Association discharge data and constructed a measure of the rate of undetermined firearm injuries as an additional sensitivity check on the analyses. However, the amount of undetermined firearm injuries was very low (on average only about 3% of total firearm injuries, excluding suicide) but did exhibit a rise, albeit smaller in magnitude, post-killing (which makes sense given the much smaller base rate). In sum, the alternative measures of firearm injury incidence (assault+unintentional, undetermined) all exhibited post-killing increases, and all exhibited significant treatment heterogeneity by level of percent Black (interaction models) consistent with the primary assault only specifications. We include these robustness checks in the appendix.*

Minor comments:

[2] Miller, M., Azrael, D., Yenduri, R., Barber, C., Bowen, A., MacPhaul, E., ... & Rowhani-Rahbar, A. (2022). Assessment of the accuracy of firearm injury intent coding at 3 US hospitals. *JAMA Network Open*, *5*(12), e2246429-e2246429.

What was the reasoning behind using ZCTAs as the unit of analysis? Usually this is a matter of convenience—eg, some data are available only by ZIP code, and using ZCTAs facilitates merging these data with census data sources—but, at least from the description of the data sources, that does not seem to be the case in this analysis.

ZCTAs are the lowest level of aggregation available in the hospital administrative data, from which we construct our focal dependent measures. Fundamentally, we are trying to be as resolute to a "neighborhood" given the confines of our data. We add clarification in the methods section to reflect this data construction decision.

"We situate our panel at the ZCTA-level because the Minnesota Hospital Data's lowest level of geography available is the ZCTA, and does not include more resolute information on the residences of those injured (p. 6)."

It would be useful to include a table summarizing the different sources and any necessary processing of these data sources corresponding to the variables in the statistical model. This information is also included in the text, but there's enough different sources to make it difficult to keep track of, so a reference table would be a useful addition.

Inspired by reviewer 2's comment, we constructed a table that relays each variable in the analysis, its source data, and how it is measured. We agree that although the information is included in the text, the amount and variety of data sources intimates that a table summarizing this information would be a welcome addition to the manuscript. The table is as follows:

Table 1: Variables and Data Sources in all Analyses

Variable	*Data Source*	*Measurement*
Firearm Assault Injury Rate	MHA Discharge Data	Injuries per 100,000
Firearm Assault+Unintentional Injury Rate*	MHA Discharge Data	Injuries per 100,000
Firearm Undetermined Injury Rate*	MHA Discharge Data	Injuries per 100,000
Murder Rate*	MPD Crime Data	Murders per 100,000
T		Linear Week Count
Post-Killing		0 pre-5/25/2020; 1 post-5/25/2020
T Post-Killing		Linear Week Count post-5/25/2020
COVID – State of Emergency	COVID-19 US Policy Database	0 pre-3/13/2020; 1 post-3/13/2020
COVID – Stay at Home	COVID-19 US Policy Database	0; 1 within 3/28-2020-5/28/2020
Mean Temperature Maximum	MNDNR Weather Data	Degrees Fahrenheit
Snowfall	MNDNR Weather Data	Inches
Precipitation	MNDNR Weather Data	Inches
Dark Before 12	Suncalc R Package	Hours of dark before midnight
Proportion of School Days	Minneapolis Public Schools	School days/7
Use of Force$_{t-1}$	MPD UOF Data	Lag rate per 1,000
Stops$_{t-1}$	MPD Stops Data	Lag rate per 1,000
Officer Involved Shootings$_{t-1}$	MPD OIS Data	Lag rate per 1,000
Median Household Income	ACS 5-Year Estimates	USD
Percent Black	ACS 5-Year Estimates	(Black Pop/Total Pop)*100

*Denotes variable exclusively used in robustness checks in appendix.

In a few locations (eg, 199, 204), the authors allude to the lack of attenuation in the models "after" controlling for changes in police behavior, but they do not show any models or results before controlling for these changes. I actually think it would be a useful comparison to show both the before and after, but alternatively the authors could simply update this language.

Thank you for this comment. We agree that a presentation of both the interrupted time series AR(1) models and the ZCTA-week RE interrupted time series models without our indicators of police behavior would be a useful comparison to highlight the lack of attenuation in the post-killing coefficient. We include these model specifications in the primary results tables as well as the appendix tables. The general pattern is the post-killing discontinuity is not attenuated, or only marginally attenuated, after including time-varying measures of police behavior.

We appreciate the reviewers taking time to offer such constructive comments and suggestions and thank them for this work. Our paper is much stronger because of their efforts.