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The disproportionate impact of post-George Floyd violence increases on minority neighborhoods in Philadelphia

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ABSTRACT

In early 2020 the Coronavirus (COVID-19) pandemic swept across the globe, impacting the criminal justice system in myriad ways. The effects of this significant societal upheaval were then exacerbated by unprecedented and extended protests and social unrest following the murder of George Floyd. This analysis seeks to clarify the disproportionate impacts on communities of color in Philadelphia (Pennsylvania) neighborhoods. This analysis considers all acts of violence, weighted by severity, and examined across the natural societal boundaries of the city for a seven-year period, while controlling for temporal trends and seasonality. Analysis using a fixed effects cross-sectional panel design of different racial/ethnic groups in the city finds that the increase in violent harm experienced by the city disproportionately impacted Hispanic communities, and one neighborhood specifically. In other words, during and following the 2020 'Summer of Racial Reckoning', violence rose across Philadelphia, but increased more so in the Upper Kensington neighborhood. Possible reasons for this are discussed.

1. Introduction

Starting in spring of 2020 and continuing through 2022, violent crime increased significantly across much of the US. Within weeks of the country commencing a lockdown to stem the spread of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2, or COVID-19), the murder of George Floyd in Minneapolis, Minnesota sparked a wave of protests which were among the largest in American history (Buchanan et al., 2020). Initially, reductions in "burglaries, larcenies, and drug crimes in 2020 coincided with the stay-at home mandates and business closings during the early months of the pandemic" (Rosenfeld and Lopez Jr, 2022: 16). But rates of violence, and especially gun violence, increased (Schleimer et al., 2022). Over time, some types of property crime have returned to pre-pandemic levels, but violence has remained higher than before COVID-19 (Council on Criminal Justice, 2023).

The public wrath and protests following the murder of George Floyd were reminiscent of similar outrage after the officer-involved deaths of Eric Garner in New York City and Michael Brown in Ferguson, Missouri, in 2014. The latter incident provided the eponym for the 'Ferguson effect', an argument that intense scrutiny of police after a high-profile incident can drive de-policing and discourage officers from engaging in proactive police work (Pyrooz et al., 2016; Wolfe and Nix, 2016). While evidence confirms some Ferguson-related 'depolicing' (Shjarback et al., 2017), the criminogenic impact appears to work indirectly, by first damaging police legitimacy. This subsequently had an impact on—in particular—Black homicide victimization rates, rather than Hispanic homicide rates (Gaston et al., 2019).

Considering shifts in neighborhood murder rates more broadly, over a longer time frame and for several cities, (Krivo et al., 2018, p. 57) observed that predominantly Black (≥ 70%) neighborhoods were the most likely ethnoracial type of urban neighborhood to be included in a group with high and increasing homicide rates. As MacDonald et al. (2022) point out, racial inequalities in violence rates are connected to areas with concentrations of unemployment, poverty and disadvantage, all related to decades of systemic racism and its associated segregation and underinvestment (Peterson and Krivo, 2010). MacDonald et al.'s (2022) study of blocks within Philadelphia crime hotspots showed a significant increase in post-pandemic gun violence within the top 10 % of block groups, areas disproportionately Black and Hispanic. This confirms previous research that changes in homicide affect African Americans disproportionately (Sharkey and Friedson, 2019) and corroborates the work of Wolff et al. (2022) who found differential impacts of the George Floyd protests on shootings in New York City boroughs.

The current study has modest goals: to describe the city-wide parameters of any increases in violence in Philadelphia since 2020, and, as importantly, any ethnoracial-linked neighborhood disparities in those

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increases. Previous research has examined the impact of recent social upheaval at coarse levels such as counties (Gaston et al., 2019), zip codes (Schleimer et al., 2022) or whole boroughs (Wolff et al., 2022), or more focused areas such as census blocks (MacDonald et al., 2022). Rather than use large administrative units or areas designed for census collection, this article explores neighborhoods, definable places with "clear physical definitions, organized local institutions, and a communal pattern of activities" (Brower, 1996; Kallus and Law-Yone, 2000, p. 815).

It also expands on the previous gun violence research by incorporating a wider definition of violence, using a harm weighting to produce a violent harm score for each neighborhood. This generates a single monthly harm value that combines a broader range of community-reported violence, including non-gun violence and domestic abuse. A further contribution of this study is it disaggregates impacts by racial and ethnic neighborhood composition, focusing on the two largest non-white groups in Philadelphia, Black and Hispanic residents.

This study employs a fixed effects cross-sectional panel design incorporating controls for temporal trends, seasonality, and serial autocorrelation at the neighborhood level. Because fixed effects models are used, average neighborhood-level spatial outcome variation is discarded. The focus is on temporal and spatiotemporal outcome variation.

In brief, study findings are threefold. First, there is a significant citywide neighborhood violence increase for the post-George Floyd as compared to the pre-George Floyd period. Second, the neighborhood violence increase is markedly higher in predominantly Hispanic neighborhoods. This finding aligns with some previous work on ethnically linked community violence shifts over time but diverges from other recent work (noted above) that situated violence increases in Black neighborhoods. Finally, model comparisons suggest the impact of the murder of George Floyd as a better correlate for neighborhood violence than the onset of the national pandemic response. That said, future research is sketched to help determine whether post-Covid community routine activity shifts, or post-Floyd related policing shifts like de-policing, are the dynamics linking to these violence increases.

2. Research strategy

2.1. Data

Philadelphia, Pennsylvania was chosen for this study due to access to multiple years of spatially referenced crime data, the existence of a crime harm index, and the availability of spatially referenced neighborhood boundaries. The 2019 American Community Survey five-year demographic data were areally interpolated from the block group level (table B03002) to a shapefile of 158 Philadelphia neighborhoods created by Philadelphia company Azavea (2014, now owned by Element 84) to represent Philadelphia's community boundaries. Census units and city administrative boundaries may be easy to use; they may not, however, reflect the social meaning and within-group homogeneity of neighborhoods (Foster and Hipp, 2011). While there are no official neighborhoods in the "City of Neighborhoods" (Washington, 2012), the map employed in this study has undergone numerous revisions and is reflective of the city's distinct residential areas. 2019 neighborhood populations ranged from 67 to 52,992, with an interquartile range of 3388 to 13,558. Researchers scoured neighborhood and community association websites and maps, and used that information to adjust city administrative information (Azavea, 2013). The international airport was removed from the analysis due to lack of population, leaving 157 neighborhoods for analysis. It is worth noting that this number differs considerably from the 384 census tracts and 1336 block groups in Philadelphia for the target year (based on the 2010 census), often used as proxies for neighborhoods. 2019 was chosen for census capture as it represents the median year of the analysis. Following Peterson and Krivo's (2010) classification rules (see also Krivo et al., 2009), neighborhoods whose population was at least 70% Black-non-Hispanic (n = 37) were classified as predominantly Black, and neighborhoods at least 70% Hispanic, were classified as predominantly Hispanic (n = 3). Asian neighborhood racial composition ranges from 0% to 62%, but this highest value is an outlier; the next to highest value is 39%. Neighborhoods whose Asian population was 10 % or higher (n = 39) were classified as Asian. All three ethnoracial binary classifications are mutually exclusive.

Harm scores were positively skewed. Given interest in a cross-level interaction between ethnoracial composition and post-Floyd months, logging the outcome is *not* recommended (Hannon and Knapp, 2003). Instead, multiple Winsorized versions of harm scores were created (Tukey and McLaughlin, 1963). The version reported here Winsorized 18 high values back to a maximum value of 4979, where outcome values were relatively continuous. Patterns of statistical significance/non-significance, and significance levels were unaffected by the version of the outcome examined: raw harm, or three different versions with either 3, 10 or 18 high values Winsorized.

Two dichotomous variables represented specific exogenous 'shocks' (Curiel, 2023) that are hypothesized to impact violent crime. First, the global COVID-19 pandemic had criminological repercussions in numerous countries (Ceccato, Kahn, Herrmann, & Östlund, 2022; Chen, Kurland, Piquero, & Borrion, 2023). In the US, the government declared a public health emergency in February 2020, corresponding to the 50th month of the time series, and a dichotomous *covid* variable (0/1) reflects that shock.

Similarly, the murder of George Floyd by a police officer in Minneapolis, Minnesota on May 25, 2020, sparked nationwide protests more expansive than the response after the 2014 death of Michael Brown in Ferguson, Missouri. Multicity evidence suggests that after high-profile incidents such as these, 'de-policing' occurs whereby police officers reduce proactive activity and especially work that is self-initiated (Cheng and Long, 2022). Like the *covid* variable, a *floyd* dichotomous (0/1) variable reflects before and after that event, commencing at month 53 of the time series (May 2020).

The *covid* and *floyd* variables strongly correlate (0.928). The analyses reported here suggest that the final model with *floyd* was preferred over the model using *covid;* see details below. That said, parallel analyses were completed using the *covid* predictor and cross-level interactions. *Covid* results, both in terms of patterns of significant versus non-significant impact, and in terms of significance level, were closely comparable. Any departures from comparable results are noted in footnotes.

Violent crime data were provided by the Philadelphia Police Department, and included all homicides, rapes, robberies, arsons, cases of child or domestic abuse, and simple and aggravated assaults. Incidents potentially resulting from initiation by police were excluded, such as justifiable homicide by police officer or aggravated assault on police officers. Because schools were closed during COVID-19, assaults on teachers, school employees, or students were also excluded as the data were not consistently recorded across the entire study. The data contained X and Y coordinates and were aggregated to their relevant Philadelphia neighborhood. From more than five million crime incidents in the database for 2016–2022, 195,460 incidents were identified related to violence; however, 2307 records did not have coordinates, and a further 277 could not be mapped to a neighborhood. This resulted in 192,876 recorded violent incidents in the analyses that follows.

Each crime incident was assigned a numeric weighting representing an estimate of incident harm. Crime harm indices emerged in Cambridge (Sherman et al., 2016) and have been created for numerous locations such as New Zealand (Curtis-Ham and Walton, 2017), Denmark (Andersen and Mueller-Johnson, 2018), and California (Mitchell, 2019). The usual approach is to estimate the harm caused by a crime from the severity of the punishment recommended for a first conviction sentence for that crime. A crime harm index for Philadelphia, derived from Pennsylvania State Sentencing guidelines (Ratcliffe, 2015) and subsequently refined (Ratcliffe and Kikuchi, 2019) was made available for this study. Violence harm scores range from 342 for homicide to 15 for simple assaults. The total harm associated with violence was aggregated by month and neighborhood, resulting in a panel of 157 neighborhoods each containing 84 monthly sums of the total violence harm in the neighborhood. Descriptive statistics for the original version and the most sizably Winsorized version of total violence harm appear in Table 1. The average monthly harm value for a Philadelphia neighborhood was 682.1 (SD = 850.2). Demographic data related to race and ethnicity associated with each neighborhood were used to construct dichotomized indicators of ethnoracial segregation for predominantly Black non-Hispanic and predominantly Hispanic neighborhoods, based on the widely used (Peterson and Krivo, 2010) ≥ 70% cutpoint.[1]

Contrast coding (Hardy, 1993) was used to construct the cross-level interaction terms. Take the *Black x Floyd* interaction for example. If an observation *was* from a predominantly Black neighborhood, it was coded +0.5 if the observation corresponded to the post-Floyd period, and − 0.5 if it corresponded to the pre-Floyd period. Non-predominantly Black neighborhoods were coded 0. The *b* weight for the term ignores all the neighborhood-months coded 0, and reports on the harm difference for Black neighborhoods in the pre- versus post-Floyd era. There were three cross-level interaction terms: pre- versus post-Floyd for predominantly Black neighborhoods; pre- versus post-Floyd for predominantly Hispanic neighborhoods, and pre- versus post-Floyd for neighborhoods 10% Asian or higher. (Analyses using the at-least-20% Asian cutpoint for the crosslevel interactions yielded similar non-significant impacts for this term.) Note that population is not included as a predictor since analyses discard all between-neighborhood outcome variation in the fixed effects analysis. Statistical analyses relied on Stata v. 18 and Stata addon *xtscc* (Hoechle, 2007) as well as R 4.2.1 (R Core Team, 2022) packages *tidycensus* (Walker and Herman, 2023), *areal* (Prener and Revord, 2019), and *multcomp* (Hothorn et al., 2008) packages. Descriptive statistics for all the aforementioned variables are shown in Table 1.

2.2. Analytic approach

An intraclass correlation coefficient (r_{icc}) of 0.869 (or 0.871 for the Winsorized outcome) indicated very high neighborhood variance in the monthly harm score (Fig. 2). Nonetheless, since the focus here is on change over time, and the conceptual goal is to separate these shifts as cleanly as possible from neighborhood differences, a fixed effects cross sectional panel analysis was carried out rather than a mixed model with random effects (Allison, 2009). The panel variable was the neighborhood identifier, and the time variable was months, centered.

A challenge with any time series analysis or panel with multiple repeated measures is serial autocorrelation, because additional time periods in panel data are not independent of previous time points (Cameron and Trivedi, 2010). The specific analysis used was the Stata (v. 18) command *xtscc* (Hoechle, 2007). This approach "obtain[s] … standard errors that allow autocorrelated errors of general form, rather than restricting errors to be AR(1)", allows for fixed effects analyses and, as needed, allows "error correlation across panels" (Cameron and Trivedi, 2010: 274), i.e., spatial autocorrelation. The estimates generated with the fixed effects option "produces the standard within [neighborhood] estimator but then finds standard errors that are robust to both spatial (across panels) and serial autocorrelation of the error" (Cameron and Trivedi, 2010: 278).[2]

Fixed effects *xtscc* models include the following predictors: the centered months variable to control for an overall linear trend, dummy variables for February through December to simultaneously control for seasonal effects and different month lengths; a dummy variable for *floyd* (=1 from May 2020 onwards) and the three contrast-coded cross-level interaction terms. For the parallel *covid* analyses the dummy variable for *covid* was = 1 from February 2020 onward, and the three cross-level interaction terms were constructed similarly.[3] Post-estimation margins plots for interactions provide additional details.

Although only one final model (4) is of central interest, a model sequence identified the contribution of *floyd* without controlling for a general linear trend (Model 1), and the linear trend without controlling for *floyd* (Model 2). Model 3 entered both the general linear trend and *floyd*. Model 4 then added the three cross-level interaction terms.

A Wald test statistic for the "joint statistical significance of a subset" of predictors gauged whether the three ethnoracial interactions, as a set, contributed significantly to the model (Cameron and Trivedi, 2010: 89). In the *floyd* analysis all VIFs were at or lower than 4.34 and all tolerances >0.231. The strongest correlation was between *linear* and *floyd* (r = 0.84).

3. Results

Although only a few months separated the onset of the *covid* era from the onset of the *floyd* era, AIC and BIC differences confirmed that the full model with *floyd* and the corresponding cross-level interactions performed better than the full model with *covid* and its corresponding cross-level interactions. Both indicators were 16.9 lower for the *floyd* model, providing "very strong" evidence (Long, 1997: 112) that this is the preferred model for investigating changes in neighborhood violent crime harm. Subsequently, results for the *floyd* models appear in Table 2 and are discussed below.

Following the murder of George Floyd, Philadelphia's neighborhoods, citywide, suffered from significantly more violent crime harm (b = 50.9; $p < .01$, Model 1). Even after controlling for the seven-year linear trend in monthly harm changes, the impact remained significant (b = 48, $p < .05$; Model 3).

If the events surrounding George Floyd's murder are not considered, the city's neighborhoods experienced significant monthly increases in violent crime harm (b = 0.88, $p < .05$, Model 2).

The Wald test confirmed the joint significance of the three ethnoracial cross-level interaction terms as a set (F (3, 83) = 5.22; $p < .01$).

[1] Thirty-seven predominantly Black neighborhoods were dispersed throughout many sections of the city including North Philadelphia (e.g., Logan, Strawberry Mansion), West Philadelphia (e.g., Mantua, Mill Creek) and Southwest Philadelphia (e.g., Bartram Village, Eastwick, Elmwood, Paschall). These neighborhoods were also socioeconomically diverse, ranging from middle income (e.g., Wynnefield) to lower income (e.g., Cobbs Creek). By contrast, three predominantly Hispanic neighborhoods (Fairhill, McGuire, and Upper Kensington) formed a tight spatial cluster in a lower income section of North Philadelphia east of Broad Street and just south of Roosevelt Boulevard. Thirty-nine neighborhoods which were at least 10 % Asian also were spread throughout different parts of the city, but several of these were located either in or close to the Greater Northeast section of Philadelphia (e.g., Oxford Circle, Mayfair), or in the Chinatown region (e.g., Chinatown, Center City East), or in South Philadelphia (e.g., Lower Moyamensing, Passyunk Square). Additional analyses (detailed results not shown) used a more stringent cut point, equal to or >20% Asian, to classify neighborhoods as Asian (n = 10 neighborhoods).

[2] Jeff Wooldridge, a well-known econometrician (Wooldridge, 2002) in a Statalist post on June 19, 2023, commented in response to a query "I would use the user-written command -xtscc- … It essentially allows any N. If you choose the fe option with xtscc then you're doing fixed effects but getting a serial correlation and heteroskedasticity-robust standard error" [https://www.statalist.org/forums/forum/general-stata-discussion/general/1717500-how-to-interpret-drastic-differences-in-significance-panel-data/page2].

[3] The Wald test with the test command (Baum, 2006: 94–98) confirmed that the curvilinear time trend variable made a non-significant addition to the model, either before or after adding the three cross-level interactions. Consequently, it was dropped from the model series.

Table 1
Descriptive statistics.

Variable		Variable name	Min	Max	Mean	SD
Dependent variables						
	Harm score	*harm*	0	7,189	682.112	850.234
	Winsorized (18 values) harm	*harm4979*	0	4,979.5	681.243	845.254
Predictors						
	Floyd (=1 starting May 2020)	*floyd*	0	1	0.381	0.486
	Covid (=1 starting Feb, 2020)	*covid*	0	1	0.417	0.493
	February	*febdum*	0	1	0.083	0.276
	March	*mardum*	0	1	0.083	0.276
	April	*aprdum*	0	1	0.083	0.276
	May	*maydum*	0	1	0.083	0.276
	June	*jundum*	0	1	0.083	0.276
	July	*juldum*	0	1	0.083	0.276
	August	*augdum*	0	1	0.083	0.276
	September	*sepdum*	0	1	0.083	0.276
	October	*octdum*	0	1	0.083	0.276
	November	*novdum*	0	1	0.083	0.276
	December	*decdum*	0	1	0.083	0.276
	Linear trend (months, centered)	*linear*	−41.5	41.5	0.000	24.248
	Curvilinear trend (linear*linear)	*curvilin*	0.250	1722.250	587.917	525.757
Interaction terms						
	Floyd/Predominantly Black	*blafloefx*	−0.5	0.5	−0.028	0.241
	Floyd/Predominantly Hispanic	*hisfloefx*	−0.5	0.5	−0.002	0.069
	Floyd/≥ 10% Asian	*asnfloefx*	−0.5	0.5	−0.026	0.231
	Floyd/≥ 20% Asian	*asn3floefx*	−0.5	0.5	−0.008	0.126
	Covid/Predominantly Black	*blacovefx*	−0.5	0.5	−0.020	0.242
	Covid/Predominantly Hispanic	*hiscovefx*	−0.5	0.5	−0.002	0.069
	Covid/≥ 10% Asian	*asncovefx*	−0.5	0.5	−0.018	0.232
	Covid/≥ 20% Asian	*asn3covefx*	−0.5	0.5	−0.005	0.126

Note: $N = 13{,}188$ (84 months across 157 neighborhoods).

Within the set of three interactions, Model 4 results show that only the *Floyd x Hispanic* interaction proved significant (b = 262.5; $p < .001$).[4] More details appear in the margins plot in Fig. 1. In predominantly Hispanic neighborhoods, prior to May 2020, average monthly violent crime harm, 550.59, was significantly below the seven-year violence average. In the post-Floyd period, however, neighborhood monthly violent crime harm scores in predominantly Hispanic neighborhoods soared to an average of 813.1, significantly above the overall violence average for the entire series (an overall increase of 47.7%).

Other margins plots (details not shown) indicated that violent crime harm increases seen in predominantly Black neighborhoods were far more modest. Pre-Floyd, monthly violent harm averages were slightly below the overall average (670). Post-Floyd, they were slightly above (693) the overall average. The story was similar in neighborhoods with at least a 10% Asian residential population; violence averages were 676 pre-Floyd and 687 post-Floyd.[5]

It is noteworthy that in Model 4 the main effect for Floyd became weaker but remained significant using a one-tailed test (b = 35.5; t = 1.84; p = .034, one tailed).[6] In short, working with the difference in coefficients, 70.9% of the impact of *floyd* on neighborhood harm scores was a main effect, and 29.1% of the *floyd* harm impact was moderated by neighborhood ethnoracial composition, with most of that moderating impact occurring in predominantly Hispanic neighborhoods.[7]

In other results, all models estimated a serial autocorrelation structure of AR(3), suggesting monthly violent crime harm shifts were somewhat sticky over time. Turning to months, compared to January, neighborhood violent crime harm scores were significantly higher for June–October after controlling for other factors, and significantly lower for February, the shortest month of the year.

4. Discussion

As stated earlier, the goal of this article has been to take advantage of extant neighborhood structure—along with an existing crime harm index—and describe the impacts of the exogenous shocks of 2020 on the city's neighborhoods and on communities of color. It has not been to try and explain these impacts with a barrage of explanatory variables, but rather just clarify the devastating and disproportionate impacts of the violence increase since 2020. MacDonald et al. (2022) examined shooting incidents in 'hot' block groups in Philadelphia, Los Angeles, and New York, concluding a surge in gun violence across 2020–21 was concentrated in hot spots characterized as containing a disproportionate number of Black and Hispanic residents. The current study *partially* corroborates their analysis by considering all acts of violence, disaggregated by ethnoracial neighborhood composition, weighted by severity, and examined across the current societal boundaries of the entire city.

First, we identified a significant citywide post-Floyd neighborhood violent crime harm increase. This impact is somewhat reduced when moderating effects linked to community ethnoracial composition are taken into account, but it still represents a statistically significant increase. Even with ethnoracial moderation taken into account, model 4 shows that 70.9% of the impact of *floyd* on neighborhood harm scores was a citywide effect. The entire city has suffered.

At the same time, location within the city mattered. Our work reiterated the community criminology literature and specifically the work of Peterson, Krivo and colleagues on the racial/spatial divide (Krivo et al., 2018; Peterson and Krivo, 2010) in that we found *shifts* in violence as well as static violence patterns are threaded by race and ethnicity. The set of three cross-level ethnoracial interactions added significantly to

[4] With less severely Winsorized harm outcomes, the b weight for this interaction increased in size. For example, for the "plain" un-Winsorized outcome, b = 341.70; $p < .001$.

[5] If at least 20% Asian was used to define Asian neighborhoods, although the harm change was non-significant, the direction with this cutoff was negative; 690 pre-Floyd and 672 post-Floyd.

[6] Models using the *covid* main effect and interactions rather than the *floyd* main effect and interactions did generate a difference in significance level for the main effect. With *covid* Model 4, b = 23.06, se = 24.13, $t < 1$, p, one tailed, = 0.17.

[7] (1 – (35.449/49.980))

Table 2
Predicting neighborhood violent crime harm changes

Variable	Model 1		Model 2		Model 3		Model 4	
Floyd	50.910	**			47.980	*	35.449	
	(15.195)				(18.587)		(19.228)	
	3.35				2.58		1.84	
February	−88.616	**	−89.495	**	−88.686	**	−88.686	**
	(18.903)		(18.622)		(18.860)		(18.860)	
	−4.69		−4.81		−4.70		−4.70	
March	−34.982		−36.740		−35.122		−35.122	
	(20.254)		(20.884)		(20.264)		(20.264)	
	−1.73		−1.76		−1.73		−1.73	
April	−25.547		−28.184		−25.757		−25.757	
	(25.539)		(28.524)		(25.770)		(25.770)	
	−1.00		−0.99		−1.00		−1.00	
May	43.665		47.422		43.805		43.805	
	(25.306)		(24.882)		(25.156)		(25.156)	
	1.73		1.91		1.74		1.74	
June	53.278	*	56.156	*	53.347	*	53.347	*
	(22.163)		(22.847)		(22.101)		(22.101)	
	2.40		2.46		2.41		2.41	
July	66.144	**	68.144	**	66.144	**	66.144	**
	(21.792)		(22.532)		(21.757)		(21.757)	
	3.04		3.02		3.04		3.04	
August	71.735	**	72.856	**	71.666	**	71.666	**
	(18.295)		(20.507)		(18.390)		(18.390)	
	3.92		3.55		3.90		3.90	
September	47.764	**	48.005	*	47.624	**	47.624	**
	(16.826)		(18.239)		(16.815)		(16.815)	
	2.84		2.63		2.83		2.83	
October	88.439	**	87.802	**	88.230	**	88.230	**
	(20.767)		(22.539)		(20.716)		(20.716)	
	4.26		3.90		4.26		4.26	
November	10.794		9.277		10.515		10.515	
	(17.499)		(18.805)		(17.499)		(17.499)	
	0.62		0.49		0.60		0.60	
December	1.175		−1.220		0.827		0.827	
	(19.680)		(19.533)		(19.511)		(19.511)	
	0.06		−0.06		0.04		0.04	
Linear trend			0.879	*	0.070		0.070	
			(0.340)		(0.397)		(0.397)	
			2.59		0.18		0.18	
Interaction terms								
Floyd/Predominantly Black							22.186	
							(31.653)	
							0.70	
Floyd/Predominantly Hispanic							262.504	**
							(70.947)	
							3.70	
Floyd/≥ 10% Asian							10.561	
							(22.445)	
							0.47	
Intercept	642.362		661.7413		643.5821		649.848	
	(16.088)		(16.585)		(17.343)		(17.339)	
N	13,188		13,188		13,188		13,188	
F	21.75		14.53		20.30		20.18	

Note: Outcome = neighborhood level Winsorized violent crime harm. Fixed effects cross-sectional panel design using Stata add-on command *xtscc*. All models control for a serial autocorrelation structure of AR(3). $T = 84$ months. $N = 157$ neighborhoods. Interaction terms use contrast coding (−0.5 / 0 / +0.5). Table shows b weight / (se) / *t*-test. ** p < .01, * p < .05.

violence prediction. That said, results here do not precisely align with their previous work since the specific community configuration linked to increasing violence here was neighborhoods that were predominantly Hispanic. Findings to date have largely suggested it is predominantly Black rather than predominantly Hispanic neighborhoods most at risk of increasing homicide over time. For example, Krivo, et al. (2018: 57) found that "94% of neighborhoods that had high and rising homicide are predominantly Black". Of course, the disparate findings could arise from numerous differences between their study and this one, including a different outcome measure, different sized neighborhood units, a different analytic approach, different years considered, multiple cities versus one city, and yearly changes versus monthly changes.

Why predominantly Hispanic neighborhoods and not predominantly Black neighborhoods? It is worth pointing out that predominantly Black neighborhoods did suffer a harm increase, but it was much smaller, and not statistically significant. This divergence from the existing literature may be due to a different distribution of neighborhoods, or it may be due to greater variance in the distribution of harm across Black and Hispanic neighborhoods. The bottom left of the Fig. 2 main graph shows predominantly white neighborhoods with low average harm scores. As the color changes towards red, average neighborhood harm per month increases (the midpoint of the color scale between blue and red is scaled to twice the mean monthly neighborhood harm score, and the cutoff for 'predominantly' is shown at 70% in a dashed yellow line). Two dark red neighborhoods stand out. With 78% Hispanic residents, the predominantly Hispanic Upper Kensington neighborhood has the highest

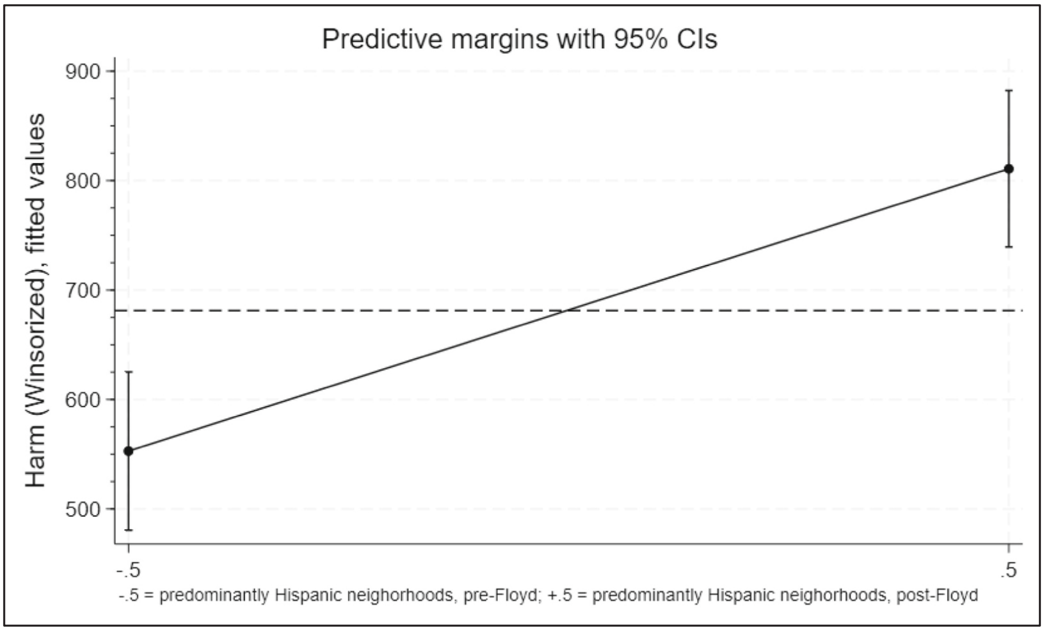

Fig. 1. Margins plot for cross-level interaction with predominantly Hispanic, pre- and post-Floyd.
Note: Margins plot from Table 2, Model 4 results. Horizontal reference line references average Winsorized harm score, all neighborhoods, all months. Harm score had 18 values Winsorized back to a maximum value of 4979.

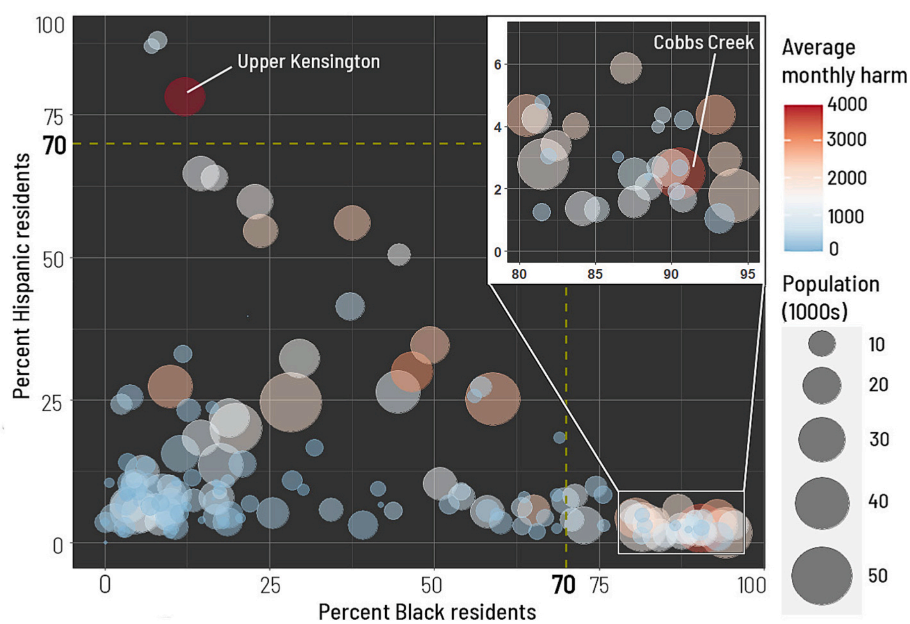

Fig. 2. Average monthly violence harm score by neighborhood Black and Hispanic residency rates, Philadelphia, 2016–22. Note: Axes expanded in inset graphic to improve clarity.

average monthly harm score in the city (3950). And in the lower right, the Cobbs Creek neighborhood has a 90% Black residency and an average monthly harm score of 3580. Nevertheless, Black neighborhoods in Philadelphia are far more diverse geographically and socioeconomically. Many neighborhoods with majority Black residency are low harm areas, as shown in the figure. This variance may explain the lower overall harm increase across predominantly Black neighborhoods.

Another possibility may be related to differential changes in policing. As explained earlier, the *floyd* variable (and interactions) was statistically preferred over the *covid* variable. This isn't to negate the impact of the COVID-19 pandemic on crime rates, but it does recognize the likelihood that changes to police strategies, stops and enforcement also may have driven the observed results, as has been observed in New York City (Kim, 2023). A few weeks into the pandemic, and just over a month shy of the murder of George Floyd, police in Philadelphia limited detention arrests across a range of lower level activities, including narcotics arrests (Marin and Briggs, 2020). As a result, the Kensington neighborhood saw a significant reduction in proactive police activity which may have consequently created an opportunity for greater violence to flourish. Kensington is not just a largely Hispanic area, it is also home to the largest drug market on the United States' east coast (Johnson et al., 2020; Ratcliffe and Wight, 2022). The extensive violence and narcotics issues plaguing the area necessitated the creation of a new police district dedicated to the Kensington neighborhood in early 2021 (Vitarelli, 2021). The area therefore has unique problems and is a place where, more so than in other parts of the city, police actions may have contributed substantially to suppressing violent crime harm.

Results here suggest that although the sizable and ongoing neighborhood urban violence racial disparities between predominantly Black non-Hispanic versus predominantly White non-Hispanic locales persist across the city of Philadelphia, and indeed across the country, within Philadelphia's predominantly Black communities themselves, their reported violent crime harm (as defined here) did not significantly intensify over time following the murder of George Floyd.

Study limitations merit consideration. First, the ecological fallacy is always a potential issue in spatial studies, in that we should not infer individual characteristics from ecological conditions (Robinson, 1950). In other words, just because the models predict that an area with a greater representation of a racial or ethnic minority population will have increased levels of violence, does not mean we should assume that members of those demographic groups are either the offenders or targets of the violence. Related to this, the model uses crime *victimization* data, overwhelmingly reported by the public. It says nothing about the identity or status of the offenders in those cases. Furthermore, the modifiable area unit problem should be considered. This is where the results of an analysis can change when researchers either aggregate individual events (like crimes) to differing number of aggregation areas (the scale problem), or choose different borders and administrative areas to subdivide an overall area (the zonation problem) (Green and Flowerdew, 1996; Openshaw, 1984). Unfortunately, there is no single solution to these issues (Larson, 1986). At least in this study, community-identified boundaries are chosen for the neighborhoods; however, the reader should be aware that using different aggregation units may affect the analysis. Subsequently, we took an analytically conservative approach in that the current work controlled for ongoing spatial disparities in violence. Further, we controlled for significant serial autocorrelation, and other concerns typically arising in cross sectional panel designs.

Notwithstanding the caveats above, this article has considered the fallout from what has been called the 2020 'Summer of Racial Reckoning' (Chang et al., 2020). While some have argued that—at least in terms of policing reform—there has been no racial reckoning (Lowery, 2023), that is a debate for elsewhere. For now, the community impact during and after the spring of 2020 is clearer. The response from, and impact on, the criminal justice system of the 'tandem' effects of the COVID-19 pandemic and the events following the murder of George Floyd (Piquero, 2021; Wolff et al., 2022) had a disproportionately negative impact on communities of color. Considering all communities of color as a group, community ethnic and racial composition significantly shaped post-Floyd violent harm impacts. This ethnoracial dynamic operated most clearly and specifically in Philadelphia's predominantly Hispanic neighborhood of Upper Kensington. Piquero (2021: 397) notes "the health, familial, and economic toll of the pandemic has been disproportionately" borne "by communities of color", and –at least in Philadelphia—he is partially right. In Philadelphia, in addition to the citywide adverse impact, it has been Hispanic communities that have experienced the most significant increases in the intensity of violence post-George Floyd, violence that, as of the time of writing, continues.

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