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Is There a "Ferguson Effect?" Google Searches, Concern about Police Violence, and Crime in U.S. Cities, 2014–2016

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Abstract
Between 2014 and 2016, the rate of homicide and other violent crime in the United States rose. One hypothesis discussed in the press and by some social scientists is that this increase was tied to political mobilization against police violence: As the Black Lives Matter movement gained support following protests in Ferguson, Missouri, perhaps police officers, worried about the new public mood, scaled back their law enforcement efforts, with crime as a consequence. In this article, we examine the association between public concern over police violence and crime rates using Google search measures to estimate the former. Analyzing data on 43 large U.S. cities, we find that violent crime was higher and rose more in cities where concern about police violence was greatest. We also find that measures of social inequality predict crime rates. We conclude by discussing the implications for future research on the "Ferguson effect" and beyond.

Keywords
crime, police, Internet searches, Black Lives Matter

Among the many remarkable political developments in the United States of the past few years, one will surely stand out to future scholars of race, law, and cities: the significant mobilization against police violence associated with the Black Lives Matter movement. Gaining ground in the aftermath of protests and civil disturbances prompted by the police killing of Michael Brown in Ferguson, Missouri, in August of 2014 and the failure of a Staten Island grand jury later that year to indict the officers involved in the death of Eric Garner, by 2015 the Black Lives Matter movement had become a force to be reckoned with. In the Democratic presidential primaries, all the candidates staked out policy positions on racial inequalities in policing and criminal justice. In cities around the country, mayors and police chiefs were forced to address accusations of police bias, often following incidents caught on video and spread widely through social media. Public opinion shifted as well. A Gallup poll released in June 2015 showed that public confidence in the police had plummeted to record low levels not seen since the trials of the officers who took part in the arrest and beating of Rodney King in 1991 (Jones 2015).

As the Black Lives Matter movement picked up, however, another thread emerged in the public conversation. The year 2015 also saw a non-negligible increase in violent crime in some U.S. cities. Although at the national level crime remained low, with analysts pointing out that after 20 years of declines a floor in crime rates may have been reached around which one would naturally expect some fluctuation, other commentators and public officials expressed alarm. Some linked the uptick to the protest movement against police violence, coining the term *Ferguson effect* to refer to a hypothesized chain of events where (in the most popular version of the argument) public anger at police mistreatment of African Americans would lead police officers to be more circumspect in their behaviors in high-crime neighborhoods with large black populations. As police pulled back from discretionary activity such as "stop and frisk" or investigatory traffic stops, criminals would find expanded opportunities.

The Ferguson effect hypothesis also proved politically powerful. FBI Director James Comey said he believed it to be true. After the targeted killings of five police officers in

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Dallas and three in Baton Rouge, the theme of restoration of law and order—and support for the police—became central to the successful presidential campaign of Donald J. Trump.

Yet as most who have written on the Ferguson effect acknowledge, only a few social-scientific studies test the hypothesis. Pyrooz et al. (2016) ask whether the trajectory of crime rates in 81 cities was altered by the events of August 2014 in Ferguson. Morgan and Pally (2016) look for evidence that the Ferguson protests and unrest and then protests surrounding the death in police custody of Freddie Gray changed patterns of policing and crime in Baltimore. Rosenfeld (2016) studies the rise in homicide in 2015. He considers whether the available evidence supports the theory that declines in police legitimacy lie behind the murder spike that year or whether other hypotheses—such as those to do with a surge in the drug trade—are more plausible.

While these studies are valuable, they share a limitation. All recognize that attitudes toward the police are an important part of the causal chain described by the Ferguson effect hypothesis. But none examines systematically the association between crime and police-related attitudes, in part because local-level attitudinal data have been unavailable.

This article uses a relatively novel methodological technique to explore the association. We estimate changing levels of public concern about police violence in 43 large American cities between July 2014 and June 2016 by examining patterns in Google search activity. We find that the increase in such concern, as registered by searches for phrases like *Black Lives Matter* and *police brutality*, is associated with the increase in certain violent crimes that occurred between 2014 and 2015 and more ambiguously with the further (and more modest) increase that occurred between 2015 and the first half of 2016. At the same time, our models indicate that factors relating to social inequality are linked with violent crime. Violent crime is most prevalent and has risen the most in cities characterized by (among other things) higher levels of residential segregation by race, higher rates of poverty, and lower levels of educational attainment. While the findings on public concern in no way represent proof of the Ferguson effect hypothesis—not least because we have no data on the activities of the police—alongside the findings of Morgan and Pally (2016) and Rosenfeld (2016), they provide empirical warrant for further study of it.

Our article proceeds in three steps. First, we briefly review previous research on the Ferguson effect. Second, we discuss our data, methods, and findings. Third and finally, we address implications for future research.

Research on the Ferguson Effect

Has there been a Ferguson effect? Meaningful discussion of this question begins with recognition of how far crime rates fell in the decades following the early 1990s—what Zimring (2007) calls "the great American crime decline." At that time, the country was in the midst of a crack cocaine epidemic that fueled a wave of gun violence. But crack was not the only driver of high crime rates, which peaked for violence in 1994 at 80 incidents for every 1,000 persons 12 and older (Truman and Langton 2015).[1] In fact, crime had been rising since the 1960s for what social scientists now think were a host of reasons, including the growth of concentrated poverty (Sampson and Wilson 1995), the presence of environmental contagions such as lead linked to violent behavior (Reyes 2007), and inefficient policing that could not keep up with developments on the urban landscape (Zimring 2012). By the late 1970s and 1980s, crime and fear of crime were part of the American way of life, especially in big cities.

Responding to the public clamor to do something, politicians pushed through legislation that considerably increased the severity of punishment for those convicted of violent and property offenses, as well as drug crimes, and ramped up spending on prisons and jails to accommodate the influx of prisoners. As critics of "mass incarceration" have noted (e.g., Alexander 2010), African Americans and to a lesser extent Latino Americans were disproportionately affected by these changes. Imprisonment rates for black and Latino men soared. Crime had already started to trend downward by the time the most far-reaching crime bills were passed, though, and it would continue to drop, eventually reaching lows not seen since the early 1970s. In 2014, there were 20.1 violent incidents nationwide for every 1,000 persons, a 75 percent decline from 20 years prior (Truman and Langton 2015). While advocates of harsh sentencing see this as evidence that tough on crime policies work, the social-scientific consensus is that the crime drop was a consequence of various factors, from incarceration-backed deterrence to improved policing techniques (revolving around targeted deployment of personnel in response to local crime patterns) to gentrification and the revival of America's urban cores.

It is against this backdrop that evidence of a recent uptick in crime is both disturbing and puzzling. It is important to be clear that while the increase that began in 2015 is, for a few cities, large in both percentage and absolute terms, in most places violent crime remains near historic low levels. In his paper on the Ferguson effect and homicide, Rosenfeld (2016) focuses on developments in 56 of the largest cities in the country. He finds that between 2014 and 2015,

> Forty cities experienced homicide increases and 16 saw declines or, in one case, no change. Homicides in 18 of the cities increased by more than 25 percent; the increase exceeded 50 percent in 12 cities. The skewed distribution of the homicide changes indicates that a relatively small number of cities accounted for most of the increase in the sample. (Rosenfeld 2016:7–8)

He goes on to observe—correctly in our view—that "had homicides not risen in these cities, it is likely the homicide increase of 2015 would have generated far less attention and

[1]The peak appears somewhat earlier using other measures.

controversy" (p. 8) since elsewhere the changes were small. The cities that experienced the largest increases in homicide, according to Rosenfeld's analysis, were Baltimore, Chicago, Houston, Milwaukee, Cleveland, Washington, D.C., Nashville, Philadelphia, Kansas City, and St. Louis.[2]

As we discuss in more detail in the following, a comparison of first half 2015 to first half 2016 homicide numbers for the 43 big cities in our sample shows that while some cities experienced larger spikes, the average increase across all cities was 16 percent. In the majority of American cities, homicide and other violent crimes are still quite rare—just about as rare as they have been during any other late-stage point in the long crime drop. Yet in cities where violence is on the rise—and especially in the neighborhoods most affected—it is a matter of great urgency to figure out what's driving the upward movement. In Chicago, for example, there were an astonishing 316 homicides in the first half of 2016—as compared to 414 for the entire year in 2014—along with 1,321 nonfatal shootings and 5,176 reported robberies. By year's end, according to news reports, Chicago had recorded more than 750 murders, a nearly 60 percent increase from 2015 (Bosman and Smith 2016:A1). Not surprisingly, fear of crime in Chicago is high. Do the lessons learned from the "great American crime decline" no longer apply?

The Ferguson effect hypothesis arose as a possible answer to the question of why violent crime was trending upward in some places. As Rosenfeld (2016) notes, the hypothesis was first floated by Samuel Dotson, the chief of police in St. Louis. But it was most fully developed by political commentator Heather Mac Donald. Mac Donald works for the Manhattan Institute, a think tank. In a *Wall Street Journal* op-ed from May 2015—and then in her book, *The War on Cops* (Mac Donald 2016)—Mac Donald, pointing to recent crime statistics and a spate of "riots, violent protests, and attacks on the police," claimed that "the most plausible explanation of the current surge in lawlessness is the intense agitation against American police departments over the past nine months" (Mac Donald 2015). The mechanism she identified was police pullback from discretionary stops and law enforcement activities. One of the police practices thought by some to have contributed to the post-1990s crime drop was "broken windows" policing—a strategy of vigorously enforcing public disorder laws, such as those prohibiting public drinking or panhandling, so that a message would be sent to those contemplating more serious criminal behavior that the eyes of law enforcement were on a neighborhood (Kelling and Coles 1996; cf. Harcourt 2001; Sampson 2012). Mac Donald speculated that broken windows policing was waning as police came to fear that interactions gone awry with citizens could cost them their job, or worse. Pedestrian or traffic stops that might lead to searches for guns or drugs could also be declining in a political climate where police behavior was under intense scrutiny and where senior police officials, responding to pressure from activists, were perceived to be willing to throw line officers under the bus if improprieties were alleged.

While Mac Donald's argument appears politically motivated, it is broadly consistent with social-scientific research on "de-policing." For example, Rushin and Edwards (forthcoming) assess the effect of officer pullback on crime rates by studying what happened in jurisdictions whose police departments were the object of "federally mandated reform" between 1994 and 2016—either put on notice that their activities were being scrutinized or subject to actual federal oversight. The authors find higher than expected crime rates in cities after their police departments become subject to oversight as police withdraw from aggressive and sometimes unconstitutional behavior. They also find that crime returns to expected levels once departments adjust their work routines.

An alternative version of the Ferguson effect thesis focuses less on policing per se than on citizens. Beyond broken windows policing, another police innovation seen as contributing to the crime drop is "problem-oriented policing," which is where police work together with citizens and other local agencies to identify and remediate neighborhood public safety problems (like abandoned houses where drugs may come to be sold) before they spiral into full-blown sources of crime and violence (Braga and Weisburd 2010). Often bundled together with "community policing," problem-oriented policing requires cooperation and trust between citizens and the police, who must be viewed as a legitimate source of authority. Some writing on the Ferguson effect (e.g., Rosenfeld 2016) reason that outrage over police mistreatment of citizens—African Americans in particular—might undermine citizen trust in the police and lead to a crime-inducing decrease in cooperation (for discussion, see Cook 2015; Tyler, Goff, and MacCoun 2015). More routine police activity such as investigating leads following a shooting or tracking down people with arrest warrants could also be affected.

That there has been outrage over police violence is clear. Police mistreatment of African Americans has long been a source of frustration and anger in the black community and has long spurred activism. But even by historical standards, the recent wave of mobilization is notable. The Black Lives Matter movement began when a San Francisco Bay Area–based activist, Alicia Garza, wrote a Facebook post in 2013 lamenting that George Zimmerman had been found not guilty in the death of Trayvon Martin. "I continue to be surprised at how little Black lives matter," she wrote. A fellow activist soon created a Twitter hashtag around that phrase. After the death of Michael Brown, the hashtag became a rallying point for protesters who streamed into Ferguson and

[2]The *New York Times* reported that "the number of murders [nationally] in 2015 was about the same as the 15,399 committed in 2009. Still, the 10.8 percent increase in the murder rate in 2015 is the most since a rise of more than 11 percent from 1967 to 1968" (Williams and Davey 2016:A1).

for others who were already demanding criminal justice reform in their communities (Cobb 2016). An analysis of tweets by Freelon (2016) shows that by August 2014, more than 200,000 people were following the Black Lives Matter movement on social media. This number grew to almost 250,000 by late November of that year, when Darren Wilson, the officer who shot Brown, escaped indictment. As a steady stream of cell phone and body camera videos showing more police killings of unarmed African American men emerged in the months that followed, protests broke out in cities around the country. According to a *Washington Post* database, police officers shot and killed 991 people in 2015 and 963 in 2016.[3] A crowdsourced database indicates that in response, there have been more than 1,500 demonstrations loosely linked to the Black Lives Matter movement, with the largest ones taking place in Chicago, New York, St. Louis, Ferguson, Minneapolis, Washington, D.C., and Oakland.[4] The movement resonated with public opinion. A Reuters/Ipsos poll from early 2015 showed that 37 percent of all Americans, 69 percent of African Americans, and 54 percent of Latinos agreed that "police officers tend to unfairly target minorities" and that trust in the police was especially low among young people (Schneider 2015). By the first quarter of 2016, a Pew survey found that 43 percent of all Americans and 65 percent of African Americans supported Black Lives Matter, with a majority of respondents saying they understood the movement's goals (Horowitz and Livingston 2016). The question is whether the rapid spread of protest and criticism of the police has somehow affected crime rates.

One of the reasons there have been so few studies of the Ferguson effect is the recent nature of the social changes referred to by the hypothesis. While many police departments make crime report data available in real time, the FBI's Uniform Crime Report, which standardizes this information for every jurisdiction in the country, lags behind. Victimization surveys, a more reliable source of data on criminal activity for all violent crimes except homicide (which are almost all reported), are even slower to be released. Cautious researchers have been hesitant to test an explanation for a social phenomenon—an increase in crime—before the usual data are in that would show the phenomenon has actually occurred.

But as police department data are the source for the Uniform Crime Report system, other researchers have felt comfortable using these as the basis for their studies of the Ferguson effect. Pyrooz et al. (2016) assemble information on monthly crime from August 2013 to August 2015. They focus on cities with populations over 200,000 and examine both violent and property offenses. They find that "the total crime rate was decreasing in the 12 months prior to Ferguson" and that there is "no evidence" to support the idea of a "*systematic* change in crime trends in large U.S. cities . . . after the shooting of Michael Brown, and the subsequent social unrest and social media responses" (Pyrooz et al. 2016:3–4). They do find an increase in robberies but declare this "the lone exception" (p. 4) to the pattern of city-level trends in crime continuing along roughly the same linear path before and after Ferguson. Only in a few select cities—including Baltimore, St. Louis, Newark, New Orleans, Washington, D.C., Milwaukee, and Rochester—did homicides pick up after the Ferguson protests, but they note that these were high-crime cities already with characteristics predisposing them to violence, such as a large proportion of residents living in poverty. Without factoring such characteristics into the analysis, Pyrooz et al. (2016) conclude, it would be difficult to tell whether the homicide increase was driven by public concern over policing practices or more typical sociological factors.

Morgan and Pally (2016) take a different approach. Eschewing growth models of the sort used by Pyrooz et al. (2016), they extend the analysis temporally and zoom in on developments in Baltimore. Their study begins from recognition of a disconnect in popular discussions of the Ferguson effect. Police pullback is key to most of these discussions, but the data cited in popular accounts often pertain to crime rates, not police activity. Morgan and Pally remedy this by analyzing crime report and arrest data for the Baltimore Police Department. Their crime report data stretch from 2010 to 2015 and their arrest data from 2013 to 2015. They find that in the period of time between the Ferguson events and the events surrounding the arrest and death of Freddie Gray, there was no meaningful change in crime rates in Baltimore—only "trendless fluctuation" (p. 2). During that same period, however, overall arrests declined by 19 percent. Arrests for minor offenses dropped off the most, which they see as consistent with the idea of a Ferguson effect. It was after the Freddie Gray events that homicides and nonfatal shootings went up, rising 92 percent and 140 percent in just three months, from April to July 2015. Arrests continued to decline, "consistent with the widely discussed conjecture that the Baltimore police pulled back from some routine policing in response to a perceived lack of support from the city's leadership" (p. 3). Morgan and Pally argue that their data do not allow them to conclude that crime increased in the second period *because* of the police pullback in the first and second periods—but they note that the data suggest such an effect. They raise the possibility that in Baltimore "the crime spike is a Ferguson effect that might have remained dormant had it not been ignited by a localized Gray effect" (Morgan and Pally 2016:4).

Rosenfeld (2016) also forefronts issues of timing. After analyzing the nature and extent of the homicide increase in 2015, he considers whether it might be tied to developments in the drug trade. The illicit market for heroin and prescription drugs like Oxycontin has been expanding, as indicated

[3]See https://www.washingtonpost.com/graphics/national/police-shootings/.

[4]See https://elephrame.com/textbook/BLM.

by an upward trend in deaths from heroin and prescription opioid overdoses. But Rosenfeld points out that the heroin market was booming by 2010–2011, whereas the homicide spike did not happen until 2015. "It is not obvious," he writes, "why the increase in homicide would lag at least five years behind the explosive growth in the demand for heroin, if the expansion of urban drug markets spurred the homicide rise" (Rosenfeld 2016:15). A second possibility he explores—one for which there is more evidence—has to do with prisoner release. Rosenfeld points out that imprisonment rates began to fall nationally in 2010 and that the country is now at the point where we are releasing more people from prison than we are locking up new inmates (although the U.S. imprisonment rate remains high in comparative terms). He notes that former prisoners are at increased risk of committing crime and that research shows a lag between time of release and time of reoffending. While this research focuses on robbery and property crimes, it is not implausible that prisoner release trends that started a few years ago could be linked with the rise in homicide rates today, though he concludes that more localized data would be needed to test the theory.

Finally, Rosenfeld (2016) turns to the Ferguson effect idea, fleshing out in particular the legitimate authority interpretation. To do so, he draws on the work of historian Randolph Roth (2009) and crime scholar Gary LaFree (1998), who argue that American homicide patterns are tied to trust in government. Although more proximate causes are involved as well, the claim is that ultimately people resort to murder to settle disputes when they do not believe public officials or the legal system relevant for dispute resolution.[5] In the wake of widely publicized police killings of African American men and protests against racism in policing, there is not much trust in the police in impoverished African American neighborhoods, Rosenfeld observes, citing polls that show large gaps between whites and African Americans in confidence in the police. After Ferguson confidence actually dropped more for whites than for blacks, but both the timing of the homicide spike—coming on the heels of Ferguson and Black Lives Matter—and its location in cities with large and poor African American populations imply to him a connection to perceptions of police legitimacy. Rosenfeld concludes his paper with a call for further study of the topic using new data sources.

Our study follows Rosenfeld's call. Using an untapped data source—Google searches—we ask: Is there evidence directly linking public concern about police violence to the recent increase in crime?

[5]A related body of research examines the "legal cynicism" that may arise in poor neighborhoods where residents perceive they are not being treated fairly by the justice system or where the system is seen to be ineffective. Crime may go up when, as a result of legal cynicism, people withdraw their cooperation from police and the courts. See Desmond, Papachristos, and Kirk (2016); Kirk and Papachristos (2011); and Sampson and Bartusch (1998).

Data and Methods

One limitation in existing work on the Ferguson effect is that measures of public concern about police violence are not factored into statistical models. There is a good reason for this: Surveys and public opinion polls might be seen as the only way to gauge such concern, while the few polls that have been conducted are national in scope and do not allow researchers to get at local variation in attitudes that could be associated with city-specific patterns of criminality. We sidestep this limitation by using Google search activity as a rough indicator of attitudes, in line with the work of Stephens-Davidowitz.[6] In a paper on racial attitudes and the 2008 and 2012 presidential elections, Stephens-Davidowitz (2014) demonstrated that Google search queries can be used to estimate racial "animus" and argued they may complement traditional survey methods in that Google searches are conducted in the relative privacy of one's computer, tablet, or smart phone, such that desirability bias in survey response does not come into play. We turn to Google queries partly for the same reason—in a highly politicized climate, people may not feel comfortable revealing their true feelings about the police to poll takers. More important, search query measures allow us to look at local variation, which we would expect to be meaningful in light of demographic differences across cities and different local histories of police-citizen interaction and conflict.

It is certainly possible that the police could pull back from discretionary law enforcement, potentially triggering an increase in crime, not just because of actual citizen attitudes in a community but also because of perceptions of such attitudes (which may be accurate or inaccurate), or perceptions of attitudes nationally, or perceptions of the local political or legal climate (which may or may not be tied to citizen beliefs.) We analyze the connection to actual concern about police violence on the part of local residents because this is the causal link most often mentioned in discussions of the Ferguson effect, even though data have been scarce.

Our measure of concern about police violence is the frequency of searches in 43 large U.S. cities for phrases that signal an interest in the topic and/or a personal commitment around it. These phrases are *Black Lives Matter*, *police brutality*, *police shooting*, *cop shooting*, *police shootings*, *cop shootings*, *I hate cops*, or *I hate police*. *Black Lives Matter* was an obvious phrase to include given the Ferguson effect hypothesis. *Police brutality*, *police shooting*, *cop shooting*, *police shootings*, and *cop shootings* are phrases that Google indicated

[6]Other studies that use Internet searches to estimate attitudes or public interest include DiGrazia (forthcoming) on anti-immigrant sentiment and Swearingen and Ripberger (2014) on interest in candidates for the U.S. Senate.

were related to one another in their search corpus ("related searches")—that is, phrases often searched for in connection with one another. *I hate cops* and *I hate police* we included to identify Internet users with strongly anti-police views.[7] To measure search frequency, we used Google AdWords, the commercial interface Google offers that allows customers to target advertising to search term activity. We relied on Google AdWords rather than the more popular Google Trends for two reasons: (1) Unlike Google Trends, which shows frequency of search activity for a specified geographic area and time period relative to the highpoint for searches within that area and time period, Google AdWords gives estimates of actual search counts, which fit better into a regression framework; and (2) unlike Google Trends, where the finest geographic resolution is "Demographic Market Areas"—local television markets, as identified by the Nielsen Company—Google AdWords allows us to zoom in on municipal boundaries (or approximations thereof) and hence link these data with city-level crime and demographic information.

Google Trends does have the advantage of adjusting results for trends in overall Google search volume—seasonal spikes in searches, for example, or incremental growth as the number of Internet users in a locale increases. Again taking a cue from Stephens-Davidowitz, we built an AdWords equivalent of the same adjustment, gathering city-specific search frequency data for the generic search term *recipe*—a reasonably proxy for overall Google search volume—and then using this to standardize our police violence-related search measures. (Stephens-Davidowitz [2014] did something similar using the search term *weather*.)[8] Google AdWords allows one to examine search term activity in a moving two-year window. We gathered our data in July 2016 and so have data dating back to July 2014, one month before the shooting of Michael Brown.[9] We standardized by constructing a simple additive index of police violence–related searches for each city under study for each month from July 2014 to June 2016 and then dividing by the number of monthly searches for *recipe* in each of those cities.

How good a measure of public concern about police violence are these Google search data? We think they provide a decent but imperfect measure. On the one hand, it seems entirely plausible that some of those Americans who are worried about police mistreatment of citizens would turn to the Internet for more information. As word of Black Lives Matter began to spread, for example, we would expect some people open to its message to Google the movement so that they could find out more about it. Similarly, people might use Google to research the general topic of police brutality or find and watch for themselves the latest tragic police shooting video. It also seems plausible that people with more strident anti-police views might Google phrases like *I hate cops* in order to connect with online communities of the likeminded and that the views of such persons would not show up in traditional polling or survey data.

On the other hand, Americans who are already well informed about police brutality, either from personal experience or exposure to other sources of news and information (e.g., social media), might not need to do any Googling. There is also the problem that some of the phrases on our list are ones that people are likely to Google only a few times. While someone closely following the issue of police violence might conduct a search for *police shooting* after every incident, we suspect that after gaining initial information from a search query like *Black Lives Matter*, many people would be unlikely to Google it again, such that search frequency would measure the exposure of new people to the movement and could be expected to decline once knowledge saturation levels were reached in the population.[10] Another issue is that we narrowed our search term list to phrases that could in principle have been searched for during any point in the study's timeframe. The list is thus centered on relatively abstract topics rather than specific people or events, whereas the latter (e.g., *Samuel DuBose shooting*—referring to a man killed in 2015 by a University of Cincinnati police officer) might be more common search targets. It is also surely the case that not everyone who Googles phrases like *Black Lives Matter* is concerned about police violence; critics of the movement might make queries for information as well. In addition, some people are simply more active Googlers than others, on this or any other subject, such that our measures might be seen as capturing, at best, the share of active Googlers concerned about police violence, not the share of

[7]We experimented with other search terms. The ones we settled on seemed to capture naturally occurring search activity, though we are not aware of any formal procedures that would allow us to establish their optimality.

[8]For these and other search terms used in the analysis, Google AdWords generates frequencies reflecting how often the terms were searched for by themselves or with common variants.

[9]Two significant downsides of Google AdWords are: (1) The moving two-year window makes it impossible to study anything other than recent phenomena (for us, this means we cannot examine the association between pre-Ferguson spikes of public concern about police violence and earlier crime patterns), and (2) once time has moved on, one cannot go back and generate new data for periods that are now out of the window. The second problem raises questions about replicability. We have dealt with this, to the extent possible, by retaining the original output files produced by AdWords. We double-checked the procedures used to generate these files by having research assistants replicate searches for select cities within the current window. Also note: when we first collected the data, in the summer of 2016, AdWords did not charge for search frequency information. They subsequently revised their terms of service. Now, unless one pays for a "campaign," one can generate only broad search volume ranges.

[10]In a following note, we discuss a version of our models that sidesteps this problem. Relatedly, so far as we are able to tell (Google AdWords was not designed for social science research and aspects of the algorithm are not transparent), search numbers are not adjusted for repeated searches from the same IP address.

all Americans thus concerned. Finally, not every Internet search is conducted using Google.

These problems are real. But we believe that in the absence of a huge and repeated time series survey of American attitudes toward the police—with a sufficiently large sample that reliable estimates could be made of attitudes in particular cities at multiple points in time—Google search data, imperfect though they are, represent the best available measure for our purposes of public concern with police violence. As we will see, the over-time patterns of search activity across the cities in our sample correspond well with national events, such as the Freddie Gray protests in Baltimore. This lends credibility to the notion that Google search data can be used to help track public interest and attitudes. It is also the case, as we will note, that the overall pattern in the search data roughly mirrors that revealed in national-level public opinion polls tracking confidence in the police.

Our outcome variables are violent crimes reported to the police in 2014, 2015 (full year and first half year), and the first half of 2016 in the same 43 cities.[11] Like Rosenfeld, we draw on crime information compiled by the Major Cities Chiefs Police Association (MCCA).[12] Although not every large city is included in the MCCA data—New York City is not, for example (at least in this time period)—the cities represent a large swath of urban America, with a combined population of almost 33 million. The MCCA data in fact cover more large police jurisdictions than this, but we have excluded from our data set most sheriff's departments with urban policing responsibilities (e.g., the Los Angeles County Sheriff's Department) because the geographic boundaries of their jurisdictions do not match up with the municipal boundaries in our Google search data. (The one exception to this is the Jacksonville Sheriff's Office, which primarily serves Jacksonville, Florida, along with a few smaller communities in Duval County.) We also excluded the city of Phoenix, which did not submit complete data to the MCCA, and Wichita, which submitted first half 2015 and 2016 data but not full year 2014 and 2015 data. A full list of cities in our sample can be found in the Appendix.

The MCCA data contain information on reported homicides, rapes, robberies, aggravated assaults, and nonfatal shootings. There is a great deal of missing data for nonfatal shootings, however, so we do not include nonfatal shootings in our final analysis. Our goal is to account for variation in violent crime levels in and across the cities in our sample from 2014 to 2015—when the initial spike in violence was first observed and linked to the Ferguson uprising—as well as from the first half of 2015 to the first half of 2016 (for seasonal comparability). While the 2014 crime reports include crimes that happened in the first half of the year—before our Google search data series begins—we see no problem with accounting for change from a baseline with data on a "treatment" that starts somewhat later.

Our models incorporate a number of adjustment variables. Our lone time-variant adjustment is the number of local police killings of citizens in the period covered by the Google search data series. We might expect concern about police violence to be very much affected by these local incidents. The numbers we use here are from another crowdsourced database tied to the Black Lives Matter Movement, mappingpoliceviolence.org. Unlike the database maintained by the *Washington Post*, this database contains information on all police killings, not just shootings. As for time-invariant adjustments, these are the number of police officers per capita[13] as well as sociodemographic characteristics drawn from the American Community Survey and U.S. census data: population size (2015 estimate), percent of residents who are 15 to 24 (2014), percent African American (2014), percent Latino (2014), percent of residents with a bachelor's degree (2014), percent of young adults (20–24) who are unemployed (2014), and percent of city residents in poverty (2014). We look at the percent of residents who are African American or Latino because if research on police bias is any indication, substantial African American and Latino communities should mean more tension in interactions with law enforcement (Epp, Maynard-Moody, and Haider-Markel 2014; Rios 2011). The other variables speak to either the availability of policing resources or to social disadvantage; the latter has long been shown to be linked with crime rates. We include as well a standard measure of residential segregation—the white-black dissimilarity index[14]—and as a further measure of economic distress, the percent of homes in each city that are underwater (2016)[15] along with the percent of occupied residences that are owner occupied (2010). During the short period covered here, we would not expect significant year-to-year change in these time-invariant measures, and in any event, most of the variables are not available for all the time points in our study.

We structure our data in a panel format and analyze it using both fixed and random effects regression, with a negative binomial specification to deal with the highly disbursed distribution of the crime counts. Since our regression analysis uses four different panels (2014, 2015, first half 2015, and first half 2016), our main search variable in each analysis is

[11]Crime data for the second half of 2016 were not available when we conducted the bulk of our analysis.

[12]For the midyear 2015 and 2016 data, see https://www.majorcitieschiefs.com/pdf/news/mcca_violent_crime_data_midyear_20162015.pdf. For the 2014 and 2015 numbers, see https://www.majorcitieschiefs.com/pdf/news/vc_data_20152014.pdf.

[13]The latest numbers here are from 2012 and reported at http://www.governing.com/gov-data/safety-justice/police-officers-per-capita-rates-employment-for-city-departments.html.

[14]Drawn from http://www.censusscope.org/segregation.html and based on 2010 census numbers.

[15]Drawn from http://files.zillowstatic.com/research/public/NESummary_2016Q2_Public.csv.

the monthly average of the adjusted search term index for each panel. While we report unstandardized numbers when characterizing the extent of the crime increase and trends in searches, our regression models use *z*-score standardized versions of the predictor variables to facilitate model interpretation. We also render the regression coefficients as incidence rate ratios, or the rate at which we expect our dependent variable (homicide and other violent crimes) to increase or decrease per one unit change in our predictors.

Results

The Crime Increase

Before presenting the findings from our regression models, we discuss significant descriptive results. We begin by characterizing the crime increase our models seek to account for. Rosenfeld's (2016) paper does an admirable job describing the 2014 to 2015 increase in homicide. What about change between the first half of 2015 and the first half of 2016? As noted previously, the 43 cities in our sample saw a mean increase in homicide of 16 percent between the two periods, as compared to a gain of 18 percent between the full years 2014 and 2015. As is true for the 2014–2015 data, significant percentage increases were concentrated in a relatively small number of cities. Seventeen of the 43 cities saw increases of 20 percent or more, and 6—Arlington, Boston, Las Vegas, Louisville, Orlando, and San Jose—saw increases of 50 percent or more.[16] (Chicago is just under this mark, at 49.7 percent.) On the other hand, 18 cities saw decreases in homicide. Only 4 of the cities in the sample—Aurora, Louisville, Omaha, and Orlando—experienced homicide gains of more than 20 percent in both 2014–2015 and first half 2015–first half 2016. Given the infrequency of homicide, these percentage changes do not necessarily reflect a large number of incidents.

As mentioned previously, we do not include nonfatal shootings in our regression analysis because many cities do not report them to the MCCA. Among those that do, however, one sees about a 22 percent gain on average between 2014 and 2015 and then a 4 percent gain between the first half of 2015 and the first half of 2016. Of the 10 cities in our data set that reported increases of more than 20 percent in nonfatal shootings between 2014–2015 (out of 23 with nonmissing data), only Charlotte, Fresno, and Louisville saw continued increases of that magnitude between the first half of 2015 and the first half of 2016. Charlotte and Chicago saw the biggest gains during this latter period, with spikes in nonfatal shootings of 64 and 51 percent, respectively.

Moving on to robberies, one observes small upward movement over time. For the cities in our sample, robberies increased 4 percent in 2014–2015 and then 5 percent between the first half of 2015 and the first half of 2016. In the most recent period, 4 cities out of 43 experienced increases in robbery of more than 20 percent: Aurora, Chicago, Fort Worth, and Salt Lake City. The average gain across all the other cities in the sample was 2 percent.

The story is similar for reported rape: small upward movement. There was an 8 percent gain on average in reported rape for the cities in our sample between 2014 and 2015 and a 6 percent gain between the first half of 2015 and the first half of 2016. As with other crime types, these increases were not evenly distributed. In the most recent period, 26 cities saw increases, while 17 saw decreases or no change.

Finally, aggravated assaults rose about 6 percent on average between 2014–2015 and 6 percent again between the first half of 2015 and the first half of 2016. In the most recent period, 16 of the 43 cities experienced either no change or decreases in aggravated assaults.

The upshot of all this is that there is only one type of violent crime—homicide—for which our data show a clear and significant increase from 2014 to 2016 across more than a handful of cities. While increases have been registered in other types of violent crime as well, in many cities these increases are not large and do not appear to be sustained. Homicide seems the most likely candidate for the effect for which a rise in public concern about police violence would be the cause. Accordingly, in the following regressions, we model homicide separately from other violent crimes, constructing an additive index for the latter.[17]

Concern about Police Violence

We turn next to the matter of search frequency. Figure 1 shows total police violence–related search activity over 24 months for the 43 cities under study. The vertical axis displays the adjusted search volume.

Two things stand out to us from this graph. First, there are four obvious surges in search activity, with the timing corresponding to large-scale protest events. While one sees a rise in concern about police violence from the very beginning of the time series to August and September 2014—the time of the initial Ferguson protests—this pales in comparison to the increase that comes in December 2014, when protests were taking off around non-indictments in the death of Eric Garner. The biggest surge by far, however, comes around the Freddie Gray protests in Baltimore in April 2015, when in some cities there are nearly twice as

[16]For Orlando, we have not included numbers from the Pulse nightclub massacre as this is an instance of terrorism.

[17]On its face, a rise in homicide alongside no substantial rise in other violent crimes would seem to be inconsistent with certain versions of the Ferguson effect hypothesis. If the Ferguson effect is a matter of reduced deterrence, for example—of potential criminals being emboldened by the withdrawal of police from the street occasioned by public criticism—why would this affect killers but not robbers? We return to this issue in our conclusion, where we speculate about some of the causal mechanisms that might underlie the associations we report.

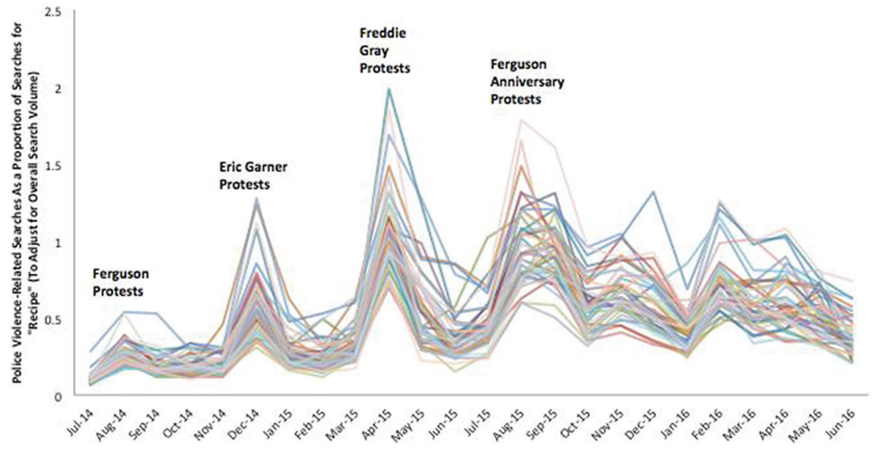

Figure 1. Police violence–related Google searches in 43 large U.S. cities, 2014–2016.

many police violence–related searches as searches for *recipe*. A fourth surge—one that displays more heterogeneity across cities—comes around August 2015, as a second wave of Ferguson protests broke out and Black Lives Matters protestors successfully shut down a campaign event for Senator Bernie Sanders.

These surges are a function of both local/regional and national interest. Newark and St. Louis have the highest search volume during the first surge; Newark, Boston, Washington, D.C., and Baltimore during the second (recall again that New York City is not in our data set); and Baltimore in the third. The city with the highest police violence–related search volume during the fourth surge is Washington, D.C. But most cities trend in the same direction during these events. Because concern about police violence, as indexed by Google search patterns, only goes very high in response to events in Baltimore, we think it could be appropriate to rename the Ferguson effect hypothesis the Baltimore effect.[18] Measured by Google searches, concern about police violence rose dramatically between 2014 and 2015. Across all the cities in our sample, adjusted searches rose 129 percent. Ten cities experienced gains of at least 150 percent in this regard: Cincinnati (199 percent increase), Austin (189 percent), Fort Worth (169 percent), Louisville (160 percent), Las Vegas (156 percent), Chicago (154 percent), Arlington (154 percent), Seattle (151 percent), Philadelphia (151 percent), and Raleigh (150 percent). St. Louis and Baltimore saw smaller increases, of 88 and 112 percent, respectively.

The second thing to note is how much police violence–related searching has dropped off since the surges. At the end of the series, it is higher than at the start but nowhere near peak levels. This could be because of a saturation effect, as discussed previously. It could also indicate that public concern has begun to move on, consistent with research in political science on "issue-attention cycles" (Downs 1972). Polling by Gallup shows that public confidence in the police began to fall in 2014, bottomed out in 2015, and then rebounded by the middle of 2016 (Newport 2016). While, again, the highly partisan political climate may be affecting these polling numbers, they are in line with the issue-attention cycle interpretation—and at the same time suggest that our Google search measure may indeed be getting at attitudes, as Figure 1 shows the approximate inverse of this pattern.

How much Googling was there of police violence–related phrases during the surges? In April 2015, during the Baltimore surge, Google AdWords estimates there were about 17,000 searches in our 43 cities for *Black Lives Matter*, about 32,000 searches for *police brutality*, 39,000 for *police shooting*, 15,000 for *cop shooting*, 2,600 (combined) for *police shootings* and *cop shootings*, and 700 searches (combined) for *I hate cops* and *I hate police*, for a total of about 106,000 searches. This is far below the actual number of Americans who were then concerned about police violence; recall that twice that many were following Black Lives Matter on Twitter alone (though the Twitter data covered the entire United States). While these counts suggest the value of concentrating on relative changes, not absolute levels, it is not the case that only a tiny number of searches is driving our results.

Multivariate Findings

Are these search patterns associated with changes in crime? We begin by considering the 2014 to 2015 panels before moving on to the panels covering first half 2015 and first half 2016.

Table 1 displays the results from a fixed effects negative binomial regression in which Google search activity from 2014

[18]As mentioned previously, Morgan and Pally (2015) discuss the connection between the Ferguson effect and a "Gray effect" in Baltimore.

Table 1. Negative Binomial Fixed Effects Models Predicting Homicide and Other Violent Crime, 2014–2015.

	Homicide	Other Violent Crime
Google searches	1.10***	1.03***
	(.02)	(.01)
Observations	86	86
Akaike Information Criterion	290.0	559.5

Note: Standard errors in parentheses.
***$p < .001$.

and 2015 is used to predict variation in homicide rates and all other violent crimes within the 43 cities in our sample. Most of the variation in these crime data is across cities, not within them. However, the Google search variable is a significant predictor of within-city change in both models. The incidence rate ratios indicate that every standard deviation increase in search activity during this period is associated with a change in homicides by a factor of 1.1—in other words, with a 10 percent rise in homicides. Likewise, a one standard deviation increase in search activity is associated with a rise in other violent crimes of about 3 percent. While this would seem to be prima facie evidence that public concern about police violence is indeed tied to violent crime, we turn next to random effects models that allow us to analyze variation across cities as well and to break out the contribution of our adjustment variables.[19]

Table 2 displays the random effects results for the 2014–2015 panels, with the models nested to compare fit with and without the Google search variable.

Looking first at the homicide models, we see that when the Google search variable is not included, population size and racial segregation are positively associated with homicide, while the percent of city residents with a bachelor's degree and the percent of city residents who are young are negatively associated.[20] These variables remain statistically significant once the Google search variable is introduced, and it too is positively associated with the outcome. Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC), measures of model fit, improve with the fuller model. The better (lower) BIC score for the Google search model is especially notable since it imposes a harsher penalty on the additional parameter than the AIC. From the fuller model, we see that a one standard deviation increase in search activity is associated with an 11 percent rise in homicide. This is indeed meaningful since between 2014 and 2015 the average increase in search activity across all cities amounted to about four standard deviations. The incidence rate ratio for the white-black dissimilarity index is larger; every one standard deviation increase in this measure (14 points, which is about the difference between the level of segregation in Oklahoma City and Newark) is associated with about a 26 percent increase in homicide. Likewise, every one standard deviation increase in the proportion of city residents with a bachelor's degree (10 percentage points, or the difference between Atlanta and less educated Pittsburg) is associated with a decline in homicide by a factor of .80—that is, a 20 percent decline.[21]

The story is somewhat different in the "other violent crime" models. In the restricted model, educational attainment is not a statistically significant predictor. Population size and residential segregation are, along with the percent of dwellings that are owner occupied and the percent of city residents below the poverty line. These all remain significant once the Google search measure is introduced. For that measure, the results mirror those of the fixed effects model. Here a one standard deviation increase in searches is associated with about a 4 percent rise in other violent crime. Introducing this variable improves model fit.

Interactions with the Google search variable are also worth noting, though we do not reproduce the results in tabular form. Several of these interactions are consistent with the Ferguson effect hypothesis. With homicide as the outcome, model fit improves when the search variable is interacted with percent African American, percent Latino, and percent of city residents age 15 to 24. With other violent crime as the outcome, there are a greater number of significant interactions. Model fit measures improve when the search variable is interacted with percent African American, percent Latino, number of police killings, number of police per ten thousand residents, percent of homes under water, population size, and percent of city residents age 15 to 24. To put this in different terms, in 2014–2015 public concern about police violence, as measured by Google searches, was especially associated with crime in big cities with large minority and youth populations and intensive policing.

What about in 2015–2016? Table 3 shows the results of our fixed effects models for these panels. According to the models, in the most recent period there is no statistically significant relationship between public concern about police violence and homicide or other violent crime. This may be

[19]While random effects models do not offer the same benefit as fixed effects models in controlling for all time-invariant variables, Hausman tests indicate that our random effects models are not significantly different in their estimations. For Hausman test statistics, we used ordinary least squares models with logged dependent variables. We also note that Allison and Waterman (2002) have raised doubts about the implementation of fixed effects negative binomial regressions in leading statistical software packages, including the one we used, STATA—which is another reason to consider the random effects models.

[20]The finding from criminological research is that cities whose populations skew young tend toward more crime if youth populations are "disengaged" from mainstream institutions like colleges and universities and the labor market but tend toward less crime where engagement is high (McCall et al. 2013). Our models effectively control for disengagement.

[21]Tests on the full homicide model for 2014–2015—as well as on the full homicide model reported in the following for 2015–2016—show that outlier cities, including Baltimore and Chicago, are not skewing the model estimates and that the panel data display no significant heteroskedacticity or cross-sectional dependence.

Table 2. Negative Binomial Random Effects Models Predicting Homicide and Other Violent Crime, 2014–2015.

	Homicide		Other Violent Crime	
Population	1.60***	1.51***	1.31**	1.35***
	(.11)	(.11)	(.11)	(.10)
Police per 10,000 people	1.31	1.31*	1.13	1.10
	(.18)	(.18)	(.17)	(.15)
Killings by police	0.95	1.03	0.99	1.01
	(.03)	(.03)	(.01)	(.01)
Percent African American	1.01	1.03	1.01	1.02
	(.16)	(.16)	(.16)	(.16)
White-black dissimilarity index	1.27*	1.26*	1.34**	1.30**
	(.13)	(.13)	(.14)	(.13)
Percent Latino	0.89	0.90	1.12	1.10
	(.09)	(.09)	(.11)	(.10)
Percent bachelor's degree	.80*	.80*	1.08	1.08
	(.08)	(.08)	(.12)	(.11)
Percent population 15–24	.86*	.85*	0.87	.85*
	(.06)	(.06)	(.06)	(.06)
Percent young adults unemployed	0.96	0.93	0.97	0.97
	(.09)	(.09)	(.10)	(.10)
Percent of dwellings owner occupied	1.13	1.18	1.32**	1.30**
	(.10)	(.11)	(.13)	(.12)
Homes under water	1.09	1.12	1.07	1.06
	(.11)	(.11)	(.12)	(.11)
Percent below poverty line	1.21	1.22	1.32*	1.34**
	(.13)	(.14)	(.15)	(.14)
Google searches		1.11***		1.04***
		(.02)		(.01)
Observations	86	86	86	86
Akaike Information Criterion	778.0	758.8	1,430.9	1,418.0
Bayesian Information Criterion	814.8	798.1	1,467.7	1,457.3
Hausman chi-square		.2299		.2562

Note: Standard errors in parentheses.
*p < .05. **p < .01. ***p < .001.

Table 3. Negative Binomial Fixed Effects Models Predicting Homicide and Other Violent Crime, 2015 (Quarters 1 and 2) and 2016 (Quarters 1 and 2).

	Homicide	Other Violent Crime
Google searches	1.06	1.04
	(.06)	(.02)
Observations	86	86
Akaike Information Criterion	259.1	530.5

Note: Standard errors in parentheses.

due to the fact that with only half-year data we are losing some variance in our measures.

Table 4 switches back to random effects modeling. Looking first at homicide, the table shows that in 2015–2016 the white-black dissimilarity index was no longer a statistically significant predictor but that educational attainment and population size remained significant, with incidence rate ratios roughly similar to those found in the 2014–2015 models. More police per capita was also positively associated with homicide, while more young people was associated with less homicide. Unlike in the fixed effect models, the random effects models indicate that in the most recent period Google search activity is a significant predictor of homicide, although we see no improvement in model fit between the restricted and fuller models as judged by AIC and BIC.

In the other violent crime models, we see once again there was more crime in larger cities. Where there were more police killings of civilians, there was somewhat less crime. Cities with a more youthful population saw less crime, while cities with more impoverished residents saw more. Public concern about police violence, as measured by Google search activity, was associated with more violent crime, and here there is a small improvement in model fit between the restricted and fuller models.

In line with the relative fragility of the Google search variable as a crime predictor in the 2015–2016 panels, we

Table 4. Negative Binomial Random Effects Models Predicting Homicide and Other Violent Crime, 2015 (Quarters 1 and 2) and 2016 (Quarters 1 and 2).

	Homicide		Other Violent Crime	
Population	1.67***	1.67***	1.56***	1.58***
	(.13)	(.13)	(.10)	(.1)
Police per 10,000 people	1.37*	1.34*	1.11	1.10
	(.20)	(.19)	(.14)	(.13)
Killings by police	.93	.93	.95**	.96**
	(.04)	(.04)	(.02)	(.01)
Percent African American	1.17	1.13	0.99	0.96
	(.20)	(.19)	(.14)	(.13)
White-black dissimilarity index	1.12	1.15	1.15	1.16
	(.13)	(.13)	(.11)	(.10)
Percent Latino	.90	.91	0.99	0.99
	(.09)	(.09)	(.09)	(.08)
Percent bachelor's degrees	.75*	.76*	1.00	1.00
	(.09)	(.09)	(.10)	(.09)
Percent population 15–24	.82*	.80**	.87*	.85*
	(.06)	(.06)	(.05)	(.05)
Percent young adults unemployed	.91	.86	1.02	0.97
	(.09)	(.09)	(.09)	(.09)
Percent of dwellings owner occupied	1.12	1.19	1.14	1.17
	(.11)	(.12)	(.10)	(.10)
Homes under water	1.03	1.08	0.90	0.94
	(.11)	(.12)	(.08)	(.09)
Percent below poverty line	1.19	1.25	1.36**	1.40***
	(.14)	(.15)	(.13)	(.13)
Google searches		1.11*		1.07**
		(.05)		(.02)
Observations	86	86	86	86
Akaike Information Criterion	674.8	672.6	1,314.5	1.308.9
Bayesian Information Criterion	711.6	711.9	1,351.3	1,348.2
Hausman chi-square		.1421		.2850

Note: Standard errors in parentheses.
*$p < .05$. **$p < .01$. ***$p < .001$.

find fewer meaningful interactions. We improved the fit of the homicide model when we interacted Google searches with the percent of city residents who are young and the percent below poverty. With other violent crime as the outcome, Google searches were more predictive only in larger cities and those with bigger Latino populations.

Finally, for all the panels, there is the question of directionality. Where we find an association between crime and police violence-related Google searches, which of the two variables (if either) points to the social fact doing the causal work? The answer could be crime. Perhaps crime began increasing for another reason—for example, because of social inequality, as our models indicate was in fact part of the story—and as a byproduct people became more concerned with issues of fairness and justice in policing. We cannot rule out this possibility. Three things lead us to be skeptical, however. First, if a rise in crime were to have generated a rise in searches around police violence, on the idea that criminal justice issues in general became more salient, it stands to reason that it should also have generated a rise in searches for the term *crime* itself and that crime searches should then be associated with police violence-related searches. However, a Google Trends graph covering the entire United States for the time period of our study and comparing searches for *crime* to searches for *police brutality* and *Black Lives Matter* shows only a weak relationship. *Crime* and *police brutality* have a correlation of .183, while *crime* and *Black Lives Matter* have a correlation of .186.[22] Second, unless one holds the view—for which there is no empirical basis—that political mobilization around the Michael Brown, Eric Garner, and Freddie Gray cases specifically was somehow a result of rising crime rates, then we can infer from the fact that the search spikes in Figure 1 correspond so well to national protest events that relatively autonomous concern with police violence was behind the search

[22]See https://www.google.com/trends/explore?date=2014-07-01%20 2016-06-30&geo=US&q=crime,Black%20Lives%20Matter, police%20brutality.

patterns.[23] Third, the uptick in homicide evident in our data and discussed by Rosenfeld (2016) was a 2015 phenomenon, while the first two spikes in police violence–related searches in our time series occurred in 2014. Consistent with this point, we were able to obtain monthly homicide numbers for several of the cities in our study that saw increases in murder in 2015 (e.g., Baltimore, Chicago, St. Louis, Milwaukee).[24] When we plotted these against the search data, we found that the police violence–related search spikes generally preceded the upticks in homicide (though one series did not "Granger predict" the other.) In Baltimore, for example, we found a rise in searches in April 2015 (corresponding with Freddie Gray's death and civil unrest) and then the beginnings of a rise in murder in May (corresponding with the withdrawal of National Guard troops that had been deployed.) Along these same lines, a recent journalistic analysis of national "assault deaths" in the United States from 2013 to 2015 suggests that the 2015 homicide rise took the form of a more substantial than normal spring and summer escalation (Verbruggen 2016).

Discussion

We think there are two takeaways from our regression models. First, public concern about police violence, as measured by Google search queries, is associated with elevated rates of homicide and other violent crime. The evidence for this association is strongest in the data from 2014–2015 and weaker in the 2015–2016 data.

Second, though it is not the case in every model we ran, we find generally that there is more crime and more of a rise in crime in large cities characterized by racial segregation, lower levels of educational attainment, and poverty.

Concerning the predictiveness of the Google search measure, we would be the first to insist that it is not a standalone test of the Ferguson effect hypothesis. To reemphasize a point we have been making throughout, there are competing ideas in popular discussion and in the emerging scholarly literature as to what the Ferguson effect means. It is often seen to involve "de-policing." But is this driven by heightened public scrutiny in a community? By angry crowds that form on street corners when police stop people? By police fear of being caught on video? By a slowdown in work activity intended to protest the erosion of public support? Or perhaps the Ferguson effect isn't about de-policing but rather about citizen perceptions that affect people's willingness to cooperate with the police? Our findings speak only to the public concern aspect of the thesis.

It is also the case, as we have noted, that measuring public concern about police violence with Google searches is not unproblematic. Beyond the points made previously, we would add here that (1) it is not clear how exactly a rise in Google searches for police violence–related topics translates into conventional social-science concepts like attitudinal change in a population, so it is uncertain how to interpret the substantive meaning of the incidence rate ratios we report—not least because we are measuring Google *searches* for police violence–related phrases, not necessarily the number of individual *searchers*; and (2) given the possibility mentioned previously that for some of our search queries (like Black Lives Matter) there could be a saturation effect, it is unclear whether the aggregate decline in search activity from 2015 to 2016 signals a real decline in public concern or simply that members of the public had by that time acquired enough information to form an opinion.[25] More generally, as is true for all social science research, our empirical findings are to some extent dependent on the conceptual and methodological choices we have made.

Yet despite this complex of issues, we think our results have value. In the final analysis, Google searches *do* seem to get at public concern about police violence, and meaning can be found in the fact that between 2014 and 2015 most clearly, crime rose more in cities where, by our (limited) measure, there was more public concern. This could well be because of police pullback or declining public cooperation. A related possibility, suggested to us by Patrick Sharkey, is that in the aftermath of police violence and then protests in cities like Baltimore and St. Louis—protests that were met with shows of force by local authorities—young people's perceptions of the legitimacy of core social institutions changed. Some who were on the fence about participating in criminal enterprises may have gotten the message that the wider society did not care about them and became more likely to take part in the life of the street. Perhaps this led to a surge in involvement with street gangs. A spike in killings and nonfatal shootings (less so other crimes) could have then ensued as a product of intensified competition between and within gangs in the context of the opioid crisis flagged as potentially significant by Rosenfeld. (This argument harks back to Merton's [1957] theory of anomie and crime; for a more contemporary discussion, see Duneier 1999.)

Another possibility is that our finding of an association between public concern over police violence and a rise in violent crime is spurious. It is surely the case that in some cities,

[23]A qualification is in order here: Oliver (2008) and others argue that crime, mass incarceration, and political mobilization in African American communities are linked in that the build-up of urban law enforcement resources in the 1980s grew out of an earlier effort to contain urban riots and repress the Black Power movement.

[24]If reliable monthly crime data were available for more cities, we could have employed a different design for our study, one with many more panels. A benefit of such an approach would be the possibility of controlling for generic time trends that might be affecting both our predictor and outcome variables. We sought to address this issue in a limited fashion in an alternative version of our models, using dummy variables to represent years. In these models, the effect sizes of our Google search variables were slightly reduced, and the variables were no longer statistically significant. This might be interpreted as suggesting the presence of period effects. More fine-grained data and data stretching over a longer period of time would be required to assess this and other possible interpretations.

[25]Against the saturation effect interpretation, we obtained similar results to those reported here when we reran our models excluding the query *Black Lives Matter*.

racism and racial exclusion are more deeply entrenched than in others. It would not be surprising to discover more people worried about police violence in cities where racial exclusion is entrenched and more people quickly mobilizing around it in response to specific incidents—and also to discover that such cities are conducive to criminality in the sense that among the concrete manifestations of such exclusion are residential segregation by race, poverty, and reduced public investment in education, all of which are associated with crime. On this interpretation, the increase in crime that occurred in the spring and summer of 2015 would reflect not a demonization of the police but a boiling over of long-simmering racial tensions as some city residents—those not given to protesting—took out their frustrations on one another. A great deal more research will be required to identify the mechanisms underlying the associations we report if, in fact, those associations prove robust.

Our results also provide evidence that social disadvantage is the larger context in which violent crime grew between 2014 and 2015 and more slowly between 2015 and 2016. Since our measures of residential racial segregation, educational attainment, and poverty did not change over the course of the time series, they cannot be responsible, in a statistical sense, for year to year increases or decreases in our outcome variables. But there is another way to think of them.

It seems to us both reasonable and productive to characterize cities—and within cities, neighborhoods—as varying not just in their rates of crime but also in their susceptibility to *cycles* of violent criminality. While social scientists have learned much in recent years about how neighborhood context matters for crime, disorder, and the reproduction of poverty (Harding 2010; Sampson 2012; Sharkey 2013), we are also learning from ethnographic and network-based studies that there is an important endogenous component to urban violence: it occurs not simply because an individual perpetrator of violence has been exposed to predisposing social conditions but often as part of a long, escalating chain of social interaction. Gang wars may be the leading example of this, as the work of Papachristos (2009) illustrates. Gang homicides are frequently acts of retaliation for other homicides, such that, sociologically speaking, what we are really seeing are not individual killings but spatio-temporal clusters of linked violence. These dynamics can be understood through the lens of networks and culture but also in terms of the qualities of violence itself. If, as Collins (2008) has argued, humans have a natural aversion to violence, and if, as Luft (2015) has found in her work on the Rwandan genocide, humans overcome this aversion the more they kill or are surrounded by killing, then we should expect that as violence escalates it will bring more violence in its wake.[26] The point we wish to emphasize, in line with ethnographic work by Bourgois (1995), Contreras (2012), and other scholars oriented to political economy, is that there is an obvious exogenous aspect to this endogeneity: structurally based individual propensities for violence aside, cycles of violent crime are more likely to get started in some communities than others.

One way of interpreting our findings on racial segregation, educational attainment, and poverty is as suggesting that even in periods when crime is generally low, it is subject to more upward cyclical movement (of varying magnitude and duration) where one sees socially isolated communities with blocked opportunities. In these settings, cycles of criminality may be triggered by any number of events or processes, from rapid shifts in economic conditions to product innovations in local markets for illicit goods to—potentially—declines in the legitimacy of police authority. If the Ferguson effect proves to be a case of an upward cycle of this sort, then close study of it could reveal important features of urban social dynamics.

[26]In an important but neglected paper on the crime drop that bears on the Ferguson effect, Winship (2004) argued that homicides fell in Boston in the 1990s in part because police officers and ministers trusted each other enough to begin working together to reduce community tensions and ensure that initial incidents of conflict between young men did not turn into larger episodes of violence.

Appendix

Sample Cities
Arlington
Atlanta
Aurora
Austin
Baltimore
Boston
Charlotte-Mecklenburg
Chicago
Cincinnati
Cleveland
Columbus
Dallas
Denver
El Paso
Fort Worth
Fresno
Jacksonville
Las Vegas
Long Beach
Los Angeles
Louisville
Miami
Milwaukee
Nashville
Newark
Oklahoma City
Omaha
Orlando
Philadelphia
Pittsburgh
Raleigh
Sacramento
Salt Lake City

(continued)

Appendix. (continued)

San Antonio
San Diego
San Jose
Seattle
St. Louis
Tampa
Tucson
Tulsa
Virginia Beach
Washington, D.C.

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